Worker Reallocation during the Great Resignation*

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Abstract

In 2021 the number of quits in the United States increased 25% relative to pre-pandemic, totaling 47.8 million. However, the Great Resignation was different in magnitude but not in kind. Using data from the Current Population Survey, I find that, compared to workers who quit before the pandemic, workers who quit during the Great Resignation (a) went to roughly the same industries after leaving their jobs (b) had on average same age and education background (c) did not leave the labor force at significantly higher rates, and (d) experienced higher nominal wage growth. Finally, I show that the increase in quits and job openings observed in the data is what a canonical search model with two simple additions would predict after the impressive labor market recovery in 2021.

Key words: great resignation, quit, pandemic.

Journal-classification: E24,E60.

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1 Introduction

By the end of 2021, the United States had its tightest labor market since the end of World War II. The economy had 1.8 job openings per unemployed person, a standard measure of labor market tightness, which represents its highest number since 1946 (Michaillat and Saez (2022) and Appendix figure A1). The recovery from the COVID-19 recession was strikingly fast. After the unemployment rate jumped 10 percentage points in April 2020, the labor market recovered faster than any other recession of the past 70 years (Appendix figure A2). In fact, according to the NBER Business Cycle Dating Committee, it was the shortest U.S. recession on record.

In this paper, I argue that the impressive increase in labor market tightness is the main factor behind the 30% increase in the quits rate between December 2019 and December 2021. This increase in the quits rate (percentage of workers quitting) was led by workers who, after quitting their jobs, went to work for new employers instead of leaving the labor force or becoming unemployed. Figure 1 shows that the quits rate - total quits as a percentage of employment - was 3% in December 2021, its highest rate since the Job Openings and Labor Turnover Survey (JOLTS) started measuring it in December 2000. This phenomenon received substantial media attention[1] and was named the "Great Resignation"[2]. To the best of my knowledge, this is the first paper that studies the reallocation patterns of workers who quit their jobs during the Great Resignation.

Several factors contributed to the fast labor market recovery. First, the fiscal policy response was approximately $5.4 trillion between 2020 and 2021 (IMF, 2022), which is an outstanding amount in historical context. President Obama's CEA Chair described, at the time, the fiscal policy response to the 2008 financial crisis as "the boldest countercyclical fiscal action in American history" (Romer, 2010), which 'only' amounted to $1 trillion (Blinder and Zandi, 2010). Furthermore, the rapid development of vaccines and possibly even the loss of fear from the virus helped the economy almost fully reopen one year after the March 2020 outbreak.

Finally, the composition of unemployed workers was also conducive to a rapid recovery. Chodorow-Reich and Coglianese (2021) argue that the percentage of workers on temporary layoff[3] is a critical determinant of unemployment rate dynamics. They find that unemployed workers on temporary layoff are more than twice as likely to find a job than those not on layoff and that 90% who became unemployed in April 2020

[1] See Yamada and Miller (2022),Rosalsky (2021),Wells and Ballentine (2022), and Goldberg (2022)

[2] This term was probably coined by organizational psychologist Anthony Klotz (Fox, 2022)

[3] These are unemployed individuals that are classified by the Current Population Survey (CPS) as being 'temporary layoff' if (1) were available to work in the survey reference week (2) had either received a recall date from their employer or had been given indication that they would be recalled in the next six months.

were on temporary layoff[4]. Forsythe et al. (2022) show that this spike in temporary layoffs was almost immediately followed by a spike in transitions from unemployment to employment in what appears to be recalls. Therefore, these facts combined help explain why the unemployment rate rapidly declined a few months after the pandemic started, from 14.7% in April to 8.4% in August. For context, the economy took almost 8 years after the Great Recession to have a decline of similar magnitude. The paper proceeds as follows.

Figure 1: Evolution of Number of Quits as a Percentage of Employment (quits rate)

Notes: The y-axis refers to the number of workers (seasonally adjusted) who quit their jobs as a percentage of total employment. Source: JOLTS

Section 2 describes the two data sources I use in this paper: Job Openings and Labor Turnover Survey (JOLTS) and Current Population Survey (CPS). While JOLTS is an establishment survey that does not provide information on workers, CPS is a household survey that follows workers throughout time and can be used to identify workers who quit their jobs during the Great Resignation. Moreover, I provide several reasons why the quits rate series between both surveys are different. Finally, I do not find evidence that workers who leave the labor force after quitting their jobs are driving the Great Resignation.

Section 3 provides basic facts about the Great Resignation and is divided into three parts. First, I show that, between 2021 and 2019, the quits rate increased in all industries except one and that there is substantial heterogeneity even among the biggest industries. Second, workers' main destinations after quitting are the same industries

[4]For the role of temporary layoffs during the pandemic see also Kudlyak and Wolcott (2020) and Hall and Kudlyak (2020), and for a more historical analysis see Fujita and Moscarini (2017).

they were working for before quitting. For example, 71% of workers that quit their jobs in the Education and health services industry end up working in the same industry one month after quitting. Perhaps even more surprisingly, the reallocation of workers after quitting during the Great Resignation shows similar patterns to before the pandemic. The percentage of workers who left their industry after quitting in 2021 has a 0.9 correlation with the same percentage in 2019. This finding is consistent with the fact that, by July 2022, industries' employment shares (at the 2-digit level) did not change relative to pre-pandemic (Forsythe et al., 2022). Third, I find that, compared to workers who stayed at their jobs, quitters are (a) 5.3 years younger, (b) more than twice as likely to have multiple jobs, (c) earn 1.69 fewer dollars per hour, and (d) have significantly higher wage growth.

Section 4 shows in a simple search model that the massive increase in labor market tightness during 2021 is the main driver behind the Great Resignation. The mechanism is straightforward. During the recovery, there was a historical increase in job openings, which made it easier for workers who already had jobs to find another and quit. The model is Mercan and Schoefer (2020) variation of the canonical Diamond-Mortensen-Pissarides (DMP) search model, and features on-the-job search where workers can quit their jobs, and firms can repost jobs vacated by those who quit. I calibrate the model to match the U.S. economy in December 2020, and then show that a shock of the same size as the U.S. labor market experienced in 2021 can correctly explain a significant fraction of the increase in the quits rate, vacancies, and other outcomes. Section 5 concludes.

Related literature

The paper is related to extensive literature that studies labor markets in the U.S. during the COVID pandemic. Forsythe et al. (2020) show that job openings collapsed 44% between February and April of 2020. However, by the end of 2021, vacancies recovered to their pre-pandemic level and increased by 60% relative to 2019 (Appendix figure A3). Forsythe et al. (2022) find that almost half of the decline in the employment-to-population ratio is due to expected declines in employment from an aging population structure and that the remaining half is due to workers aged +65 exiting employment at higher rates than before the pandemic. Furthermore, they show that the pandemic did not lead to a massive reallocation of workers as expected (Barrero et al., 2020). They find that industries and occupations' employment shares (at a 2-digit aggregation) are at the same levels as before the pandemic. However, they do find greater reallocation when looking at a 3-digit level of aggregation for both industries and occupations.

Domash and Summers (2022) present historical data and show that the number of vacancies per unemployed achieved an all-time high in December 2021 compared to the last 60 years. Furthermore, they argue that while supply-side indicators of labor market tightness (employment to population rate) imply modest levels of labor market slack, demand-side indicators (job vacancy rate and quits rate) imply an extremely tight labor market. Michaillat and Saez (2022) argue that since May 2021, labor markets have been inefficiently tight as the ratio of vacancies to unemployed is greater than one. Chetty et al. (2020) report that while employment for high-wage workers was almost back at pre-pandemic levels a few weeks after the initial shock, low-wage workers experienced significantly larger job losses that persisted for several months. Goda and Soltas (2022) find that workers with week-long Covid-19 related absences are 7 percentage points less likely to be in the labor force one year after than those who did not miss a week of work for health reasons. Moreover, they calculate that the labor force supply was reduced by 500,000 workers (0.2 percent of employment) due to Covid-19 induced health problems.

2 Data

This paper mainly uses the Job Openings and Labor Turnover Survey (JOLTS) and the Current Population Survey (CPS). JOLTS is the most important publicly available dataset in the United States to understand how separations evolve at the national and state level. However, given that JOLTS is an establishment survey, it does not provide information on the type of workers who quit their jobs. Therefore, I use the CPS household survey to identify quitters during the Great Resignation and find some basic facts about them, such as income, wage growth, and industry of origin and destination.

2.1 Job Openings and Labor Turnover Survey

The Job Openings and Labor Turnover Survey (JOLTS) is a monthly survey carried out by the U.S. Bureau of Labor Statistics (BLS). The sample consists of approximately 20,700 business establishment units in the nonagricultural sector located across all 50 states and the District of Columbia. The sample unit is an establishment at a single physical location. The sample of establishments is stratified by ownership (private or public), census region (Northeast, Midwest, South, and West), industry sector, and size class, where firms with more than 5,000 employees are included with virtual certainty.

Most sampled establishments remain in the survey for 36 months and, after completing this time, are not sampled again for at least three years. For the first five months, interviews are carried out via Computer Assisted Telephone Interview (CATI). This methodology allows sufficient time for the establishment to learn JOLTS definitions. After this initial period, respondents are encouraged to self-report either by web or email for the remainder of their time at the survey. The survey reports four main series: employment, separations, openings, and hires. The separations category is subdivided into three, which include "Layoffs and discharges", "Quits", and "Other separations". To construct the monthly quits series, JOLTS asks each establishment to report how many workers voluntarily left their job in the past month. The survey explicitly requires that retirements are not to be included in this measure, as they belong to the "Other separations" category.

2.2 Current Population Survey

2.2.1 Survey overview

The Current Population Survey is a monthly survey jointly sponsored by the U.S. Census Bureau and the BLS. Its sample is designed to provide labor force and demographic characteristics on the civilian noninstitutional population aged 16 or over for every U.S. state and the District of Columbia. The survey consists of state-based independent samples, where a sample is constructed for every state and the District of Columbia. California and New York have two samples, and the rest of the states have one. The CPS sample is a multistage stratified sample of about 72,000 housing units. The housing units are selected from 852 sample areas.

After a household is selected, it will be interviewed eight times in what is known as the 4-8-4 design. The household is interviewed throughout 4 consecutive months, followed by an 8-month pause, and then comes back to the sample to be interviewed 4 consecutive times again. The households exiting the sample - those interviewed in the fourth and eighth interviews - are in the outgoing-rotation group. This group is important because CPS asks households for extra information, such as hourly wage, in these interviews.

2.2.2 Construction of quits rate from the CPS

The worker that quits at month t has three possible destinations: another employer (Q^{EE}), unemployment (Q^{EU}), and exit the labor force (Q^{EN}). The quits rate published by BLS from JOLTS data implicitly includes all of them. However, CPS data only allows the construction of a quits series that includes the first two. Although there is no transparent methodology for imputing the Q^{EN} quits, I will provide evidence in section 2.4 suggesting that the Great Resignation is not driven by workers quitting their jobs to exit the labor force.

A first approximation of the Q^{EE} quits rate is the employer-to-employer transition probability introduced by Fallick and Fleischman (2004). Their paper suggests to use the PUIODP1 - which I will refer to as SAMEMP from now on - question in CPS, which asks the following:

Last month, it was reported that you worked for (employer's name). Do you still work for (employer's name) (at your main job)?

To compute the employer-to-employer transition probability at month t, EE_t, they count the "No" answers to the question at month t and divide this sum by the total number of people employed at month $t-1$. Unfortunately, there was a sudden increase of missing answers to SAMEMP beginning in January 2007 and accelerating in 2009. The missing answers' percentage increased from 4% to around 9% in 2019. Therefore, Fallick and Fleischman's methodology, which treats missing answers as stayers, is problematic given that the EE transition probability is small (around 2% when discarding missing answers).

Fujita et al. (2021) – FMP from now onwards - point out that the introduction of the Respondent Identification Policy (RIP) is the most important factor behind the increase in missing answers since 2007. This policy allows the original respondent ('RIP respondent') to decide if the interviewer can share his previous answers with other household members if the RIP respondent is not available in a future interview. The 2021 CPS Interview manual explains the following: "If the original respondent, which we refer to as the "RIP respondent," wishes their information to be confidential, and they are not available for a subsequent interview, you cannot conduct dependent interviewing." Therefore, this would impede the interviewer from asking the RIP respondent's spouse all the questions that require dependent interviewing, which the SAMEMP question requires.

FMP points out that "one concern for our purposes is that employed and job-mobile respondents are more likely to answer No to the RIP question, suggesting that they have some confidentiality concerns about their work situation, primarily about their earnings." They propose a selection model that imputes the EE transition probability for workers with missing answers based on several characteristics correlated with the EE probability before the introduction of the RIP policy in 2007.

On the other hand, the Q^{EU} rate can be directly measured from CPS using the PELKLL20 question, which asks:

Did you lose that job, or was it a temporary job that ended?

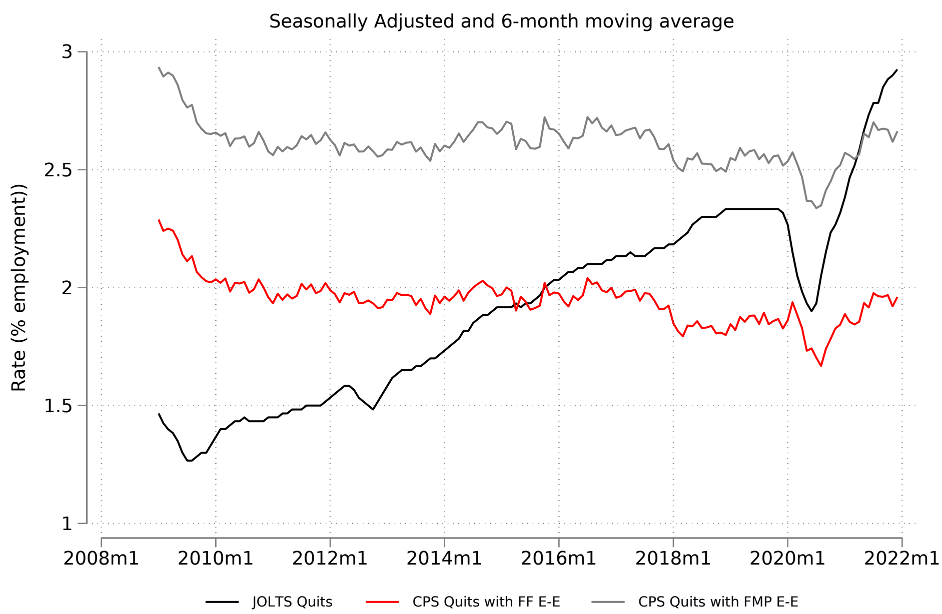
The interviewees are asked to choose from the following three options: "Lost job", "Quit job", or "Temporary job ended". Given that this question is asked to workers that are unemployed (but not on layoff) and who were working or left the military service before they started to look for a job, I can construct a quits to unemployment series by counting the number of workers who answered "Quit job".

2.3 Comparison of quits rates between CPS and JOLTS

Figure 2 compares the evolution of JOLTS quits rate and two quits rate series constructed from CPS data. Both CPS series only include quits Q^{EE} and Q^{EU}, as workers who quit their job to leave the labor force Q^{EN} cannot be properly identified from CPS data. The difference between the two of them lies in how Q^{EE} quits are imputed, FF refers to Fallick and Fleischman (2004) methodology, where workers with missing values to the SAMEMP question are treated as "stayers", and FMP refers to Fujita et al. (2021) where a selection bias correction model is used to impute the Q^{EE} probability for those workers with missing answers. The monthly variations between the two are highly correlated, and their main difference relies on the level of the quits rate.

Ideally, a quits rate series constructed from CPS and JOLTS would look the same. Unfortunately, as figure 2 shows, this is not the case. There are several reasons why a quits rate constructed from CPS data might differ from the rate published by BLS calculated with JOLTS data. First and more importantly, as was previously mentioned, both CPS quits rate series do not include Q^{EN} quits. Nevertheless, I provide evidence in Section 2.4 that suggests that Q^{EN} quits are not driving the Great Resignation.

Figure 2: CPS vs JOLTS quits rates



Notes: The y-axis refers to the number of workers, who were employed in month $t-1$ and quit their jobs in month t. If the change of status (different employer or unemployment) happened in month t it is assumed that the quit also happened in that month. FF refers to Fallick and Fleischman (2004) methodology where workers with missing values to the SAMEMP question are treated as "stayers", and FMP refers to Fujita, Moscarini, and Postel-Viney (2022) where a selection bias correction model is used to impute the EE probability for those workers with missing answers.

Furthermore, their population of interest is entirely different. While CPS surveys households, JOLTS sample consists of business and government establishments. This could produce differences in several dimensions. For example, if a worker quits his job at month t and moves out from the selected household, the worker would no longer be in the CPS sample in month $t+1$. Therefore, CPS cannot observe the quit because the worker left the sample. On the other hand, this quit would be included in JOLTS because the establishment, where the worker used to have a job, is the one being interviewed and not the worker himself.

FMP reports that around 1.3% of workers employed at month $t-1$ live in a new address at month t. Given that Q^{EE} rate constructed from CPS is about 2% of employment, the effects of geographical attrition are potentially dramatic. Using data from the Survey of Income Participation Program (SIPP), they calculated that around 0.1% of those workers who were employed last month moved for "job-related reasons". Hence, they conclude that geographical attrition does not pose a significant problem. However, the actual fraction is probably much higher than 0.1% for at least two reasons.

First, 0.21% of workers employed last month report to have moved to a different state which suggests that they probably had to leave their previous job. Second, the SIPP question[5] asks for the main reason for moving to the new residence. It could be the case that the main reason for moving was not a "job-related reason"- for example, "cheaper housing", "change in marital/relationship status", or "other family-related reason"- but the worker still had to leave his job before moving out.

Furthermore, CPS only asks if the worker moved to a different employer than last month in their main job. If the worker has multiple jobs and he quits a secondary job but keeps his main job, CPS would not pick up this quit while JOLTS would do. However, this feature cannot explain any systematic difference between CPS and JOLTS quits rates. I have calculated that, in any given month, less than 0.1% of workers quit a secondary job and keep their main job.

Finally, there are several reasons to believe their sampling errors can differ. On the one hand, JOLTS sample is significantly bigger. In a typical month, the CPS sample includes 50,000 employed workers, meaning that with a 2% quits rate, we would only expect to observe 1,000 workers who quit their job per month. JOLTS sample includes around 20,000 establishments per month, translating to a significantly higher number of employees sampled given that JOLTS includes almost all employers with more than 5000 employees in the sample.

On the other hand, although both surveys have seen their response rate dropped in recent years, as of March 2022, CPS' response rate (74%) is higher than JOLTS' (68%). The latter dropped significantly since the pandemic's start, from 84% in January 2020 to the 68% mentioned before[6]. JOLTS response rates problems seem to have come to

[5]EHC_WHY:*What was the main reason [insert name] moved to [insert address]?*

[6]These percentages refer to what BLS calls the "final release" response rate, which counts firms that

stay as its response rates for establishments that are asked to start participating in the survey - called initiation response rate - have dropped from 42 percentage points from January 2020 to March 2022 (from 65% to 23%).

2.4 Are workers leaving the labor force after quitting?

The analysis in this and the following section does not include workers who, after quitting their jobs, decide to leave the labor force. CPS data only allows me to identify employer-to-employer (Q^{EE}) and employer-to-unemployment (Q^{EU}) transitions. This data limitation is potentially problematic because a quits rate that is only constructed from these two types of transitions does not exhibit the same big increase than the quits rate calculated from JOLTS (Figure 2).

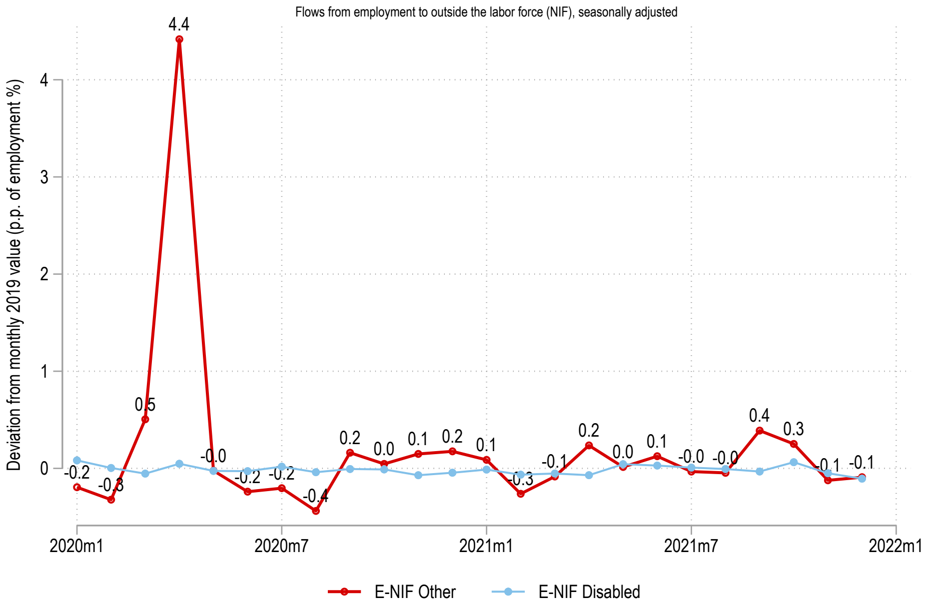
There are at least two reasons why these two series might differ. First, as Section 2.2.2 explained, this could be because of substantial differences between the surveys. Second, it might be the case that the CPS quits rate does exhibit the same rise as JOLTS' quits rate precisely because the former excludes Q^{EN} quits. If this were true, workers who leave the labor force[7] after quitting their jobs would be driving the Great Resignation.

The CPS classifies those who are not in the labor force into three categories: "Retired", "Disabled", and "Other". By definition, those working at month $t-1$ and retired at month t did not quit their jobs, they retired. Therefore, the eligible workers who might have quit their jobs to leave the labor force are those working at month $t-1$ and belong in month t to the "Disabled" or "Other" category. However, the number of workers (as a percentage of employment) that in 2021 left their jobs to leave the labor force and join either one of these two categories has barely increased relative to 2019 (Figure 3). This finding suggests that the increase in the quits rate cannot be explained by workers leaving the labor force after quitting.

did not answer the survey before the preliminary release date but did send a response before the final release date.

[7]All those who are neither employed nor unemployed are included in the labor force group. Note that for a person to be classified as unemployed it needs to have actively looked for a job (or been temporarily layoff) in the 4-week period prior to the survey week. Therefore, the not-in-labor force group inclues some individuals who want a job, are available to work and have looked for a job in the past 12 months, who are classified by Census as being marginally attached to the labor force.

Figure 3: Montly difference (relative to same month in 2019) in the percentage of workers that are not in the labor force at month t and were employed at month $t-1$



Notes: The y-axis shows the monthly difference (relative to same month in 2019) in the percentage of workers (employment measured from CPS) that are not in the labor force at month t and were employed at month $t-1$. The figure does not include those workers who went from being employed to be retired because these workers, by definition, could not have quit their jobs.

The distribution of monthly transitions within the eligible group shows interesting patterns. CPS asks a large fraction of their sample, "What best describes your situation?". I plot in Appendix Figure A4 what those among the eligible answered to this question after they were no longer employed. During 2020, while the percentage of individuals in the eligible group "In School" declined, those in the "Other" category rose dramatically. School closures probably caused the decline, and the increase was likely led by workers who might have stopped looking for work after being laid off.

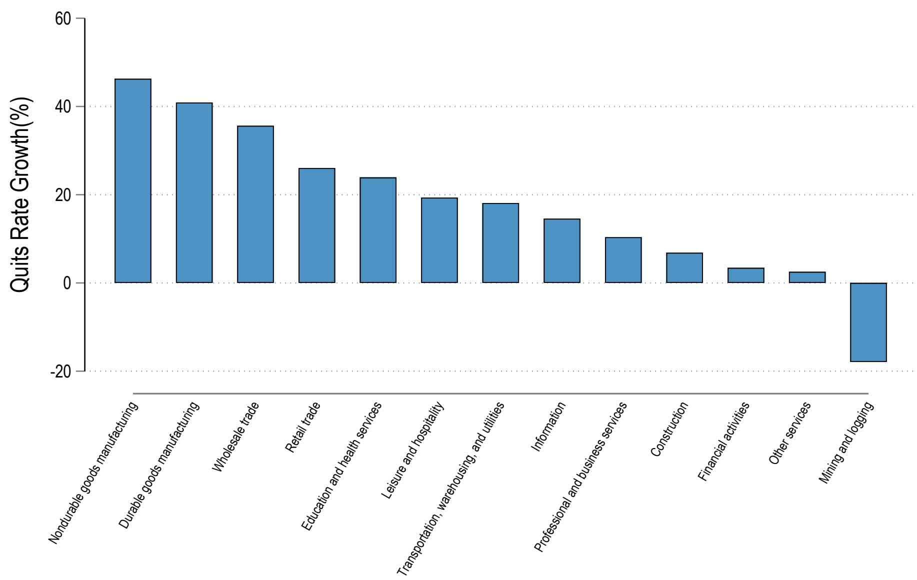
However, the figure shows the opposite patterns in 2021 (when the Great Resignation started). In 2021 the percentage of workers that transitioned from employed at month $t-1$ to the "Other" category at month t declined steeply, and who answered "In School" rose by the end of the year. Moreover, none of the other categories ("Taking care of house or Family" and "Disabled/ill") are at significantly higher levels than before the pandemic, which suggests that the increase in the quits rate is not driven by Q^{EN} quits. Therefore the Great Resignation is probably mainly driven by employer-to-employer quits, which did increase as shown in shown figure 2.

3 Basic facts about the Great Resignation

3.1 Where are workers quitting *from?*

The Great Resignation is a widespread phenomenon that affected the entire economy. Except for Mining and logging, every industry had positive growth in the quits rate (quits as a percentage of employment) between 2021 and 2019. However, as Figure 4 shows, there is substantial heterogeneity across sectors. While some sectors (Financial activities, Other services, and to some extent, Construction) barely experienced any growth in their quits rate, other industries had massive increases. For example, the quits rates in Durable and Nondurable goods manufacturing increased by 40% and 46%, respectively. The two biggest industries in the United States by the percentage of total employment[8] are Education and health services (18.8%) and Professional and business services (16.6%). However, the Education and health services' quits rate increased more than twice as much (23.9% vs. 10.4%).

Figure 4: Growth of quits rate between 2021 and 2019



Notes: The y-axis refers to the growth rate between the average quits rate (quits/employment) by sector between 2021 and 2019. Data extracted from JOLTS.

Although it is difficult to know for sure, the 35% increase in the quits rate in the Wholesale trade sector could be driven by workers at Amazon's warehouses, as these

[8]According to the average seasonally adjusted total number of employees in 2019.

facilities are classified in this sector. Times (2021) reports that, even before the pandemic and the surge in demand for Amazon products and services that came with it, Amazon lost about 3 percent of its hourly associates each week. Furthermore, they found that two years after Amazon opened a new facility, the county's turnover rate (of warehousing and storage employees) rose an average of 30 percentage points.

The quits growth rate can be calculated using levels or rates. Figure 4 calculates it using the quits rate, which is the percentage of workers quitting their jobs in a given year. However, instead of using a relative measure of quits, one could also use the number of quits. In Appendix figure A6, I show that, for almost all industries, the differences across these two methodologies do not matter. The exception is Leasure and hospitality, which has a 19.4% increase in the quits rate but only a 1.9% increase in the number of quits. This difference is because Leisure and hospitality, by December of 2021, still had an approximate 10% employment drop relative to before the pandemic.

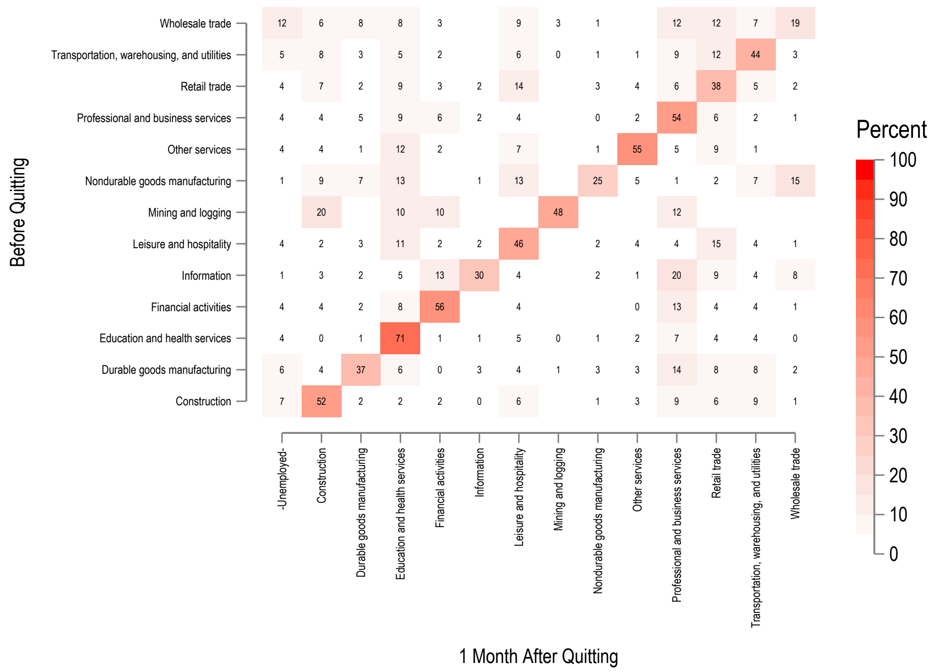
Unfortunately, JOLTS does not have data on quits at the occupation level because it only asks establishments for the total number of quits in the past month. Therefore, it is impossible to know from which occupations workers are quitting using JOLTS data.

3.2 Where are workers quitting *to?*

JOLTS cannot be used to determine where workers are going after quitting their jobs because it is an establishment survey. However, CPS does not have this problem as it follows households across several months. Therefore, if a worker quits at month t, unless the worker moved or abandoned the survey, CPS allows us to compare industries before and after the quit, that is, at months $t-1$ and t.

The Census Bureau defines industry as "the kind of business conducted by a person's employing organization". Therefore an accountant working for a hospital would be classified as working in the Education and health services industry. Figure 5 uses CPS micro data for all quits in 2021 to show the origin and destination of workers between quits. For every industry, the workers' main destinations after quitting are the same industries they worked for before quitting. There is substantial variation across sectors regarding what extent this phenomenon is important. For example, 71% of workers that quit their jobs in the Education and health services industry end up working in the same industry one month after quitting. However, this number is only 19% for Wholesale trade.

Figure 5: Where do workers go after quitting?



Notes: Percent refers to the percentage of workers on a given row (industry before quitting) that went to a particular column (industry after quitting). Rows might not sum to 100% due to rounding. Origin and destination of workers were calculated from CPS micro data for all quits in 2021.

Perhaps even more surprisingly, the reallocation of workers after quitting during the Great Resignation shows similar patterns to what was observed before the pandemic. First, the percentage of workers who left after quitting the industry they were working for in 2021 has a 0.9 correlation with the percentage of workers that left their industries after quitting in 2019 (Appendix Figure A7). Second, the correlation between the percentage of workers that went from industry A to industry B in 2021 and the same percentage in 2019 is 0.96 (Appendix figures A9 and A8).

3.3 Who is quitting?

The CPS micro data contains rich information on several economic and demographic characteristics of those who quit their main jobs in 2021. Several interesting facts arise from a simple test of differences in means between those who quit their jobs in 2021 and those who did not. First, workers that quit their jobs during the Great Resignation earn (before quitting) 1.69 dollars less on average than those who did not quit, and they are 4 percentage points more likely to be paid by the hour.

Furthermore, workers who quit their jobs are 5.3 years younger than those who did not. Moreover, they are twice as likely to have two or more jobs as those who did

Table 1: Do workers that quit their jobs earn less?

	Avg. Quitters	N	Avg. Stayers	N	Difference
Hourly wage	23.26	1675	24.95	59142	-1.69***
Paid by hour (dummy)	0.60	1742	0.56	62259	0.04***

Notes: * 0.1 ** 0.05 *** 0.01. The ttest was carried out assuming that quitters and stayers have different variances. Quitters are defined as those who quit their main job in 2021. Stayers are defined as those who did not left their main job in the same period. In the case of quitters, both variables were measured in the month before quitting

not quit. This is consistent with the fact that many industries that have experienced a substantial increase in the quits rate also have a high percentage of workers who hold multiple jobs relative to other industries. For example, Education and health services and Leisure and hospitality are the two industries with the highest fraction of multiple job holders (Appendix figure A10), and both had an increase in the quits rate of around 20%.

Perhaps surprisingly, there are no significant differences between workers who quit their job in 2021 and those who did in 2019 across several dimensions. Both groups have, on average, the same age and education level. Even though those who quit in 2019 are more likely to have multiple jobs, this difference is small (11% vs 10%). These findings align with the fact that both groups of workers exhibit similar reallocation patterns (section 3.2). They leave their industry at about the same rate, and the reallocation flows aggregated up to the industry of origin level are highly correlated.

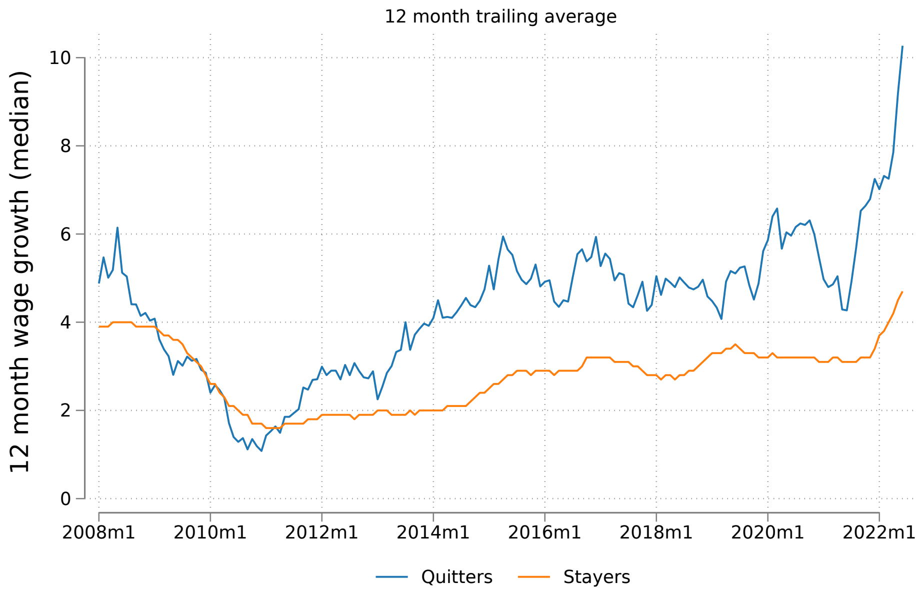
Table 2: Difference in means Between Quitters and Stayers

	Quitters 2021	N	Stayers 2021	N	Difference
Age	38.68	6276	43.99	363599	-5.31***
At least bachelor's degree (dummy)	40.78	6276	41.12	363599	-0.33***
Multiple Jobs (dummy)	0.10	6276	0.05	363599	0.05***
Number of Jobs	1.11	6276	1.06	363599	0.06***
Total hours (usual week)	36.25	6276	37.31	363599	-1.06***
Total hours (last week)	36.48	6276	37.77	363599	-1.29***
	Quitters 2021	N	Quitters 2019	N	Difference
Age	38.68	6276	39.06	7084	-0.38
At least bachelor's degree (dummy)	40.78	6276	40.76	7084	0.02
Multiple Jobs (dummy)	0.10	6276	0.11	7084	-0.01**
Number of Jobs	1.11	6276	1.13	7084	-0.01**
Total hours (usual week)	36.25	6276	36.52	7084	-0.27
Total hours (last week)	36.48	6276	37.07	7084	-0.59**

Notes: * 0.1 ** 0.05 *** 0.01. The ttest was carried out assuming that quitters and stayers have different variances. Quitters are defined as those who quit their main job in 2021 or 2019. Stayers are defined as those who did not left their main job in the same period and are still on the next month. In the case of quitters, variables were measured in the month before quitting

Finally, I find strong evidence that suggests that workers who quit are moving up the wage ladder. Workers who quit their job have significantly higher wage growth than those who did not quit and stayed at their jobs. This finding goes in line with what the literature has previously found. Haltiwanger et al. (2018) show that workers tend to flow from low-wage to high-wage firms via employer-to-employer moves, and Hazell and Taska (2022) find that wages for new hires are rigid downwards and flexible upwards. These findings are also consistent with several poaching models that find an increase in wages through employer-to-employer quits (Moscarini and Postel-Vinay (2008) and Moscarini and Postel-Vinay (2013)).

Figure 6: 12-month wage growth: Quitters vs. Stayers



Notes: Wage growth for quitters is calculated from CPS, and wage growth for stayers comes from Atlanta FED wage tracker. In both cases wage growth is calculated for the unweighted median worker. Quitters are defined as those who quit in interviews 6, 7 or 8. Stayers are defined by Atlanta FED as those who (1) did not quit in interviews 6,7 or 8 and (2) did not change industry or occupation between interviews 4 and 8.

4 Model

In this section, I argue that the increase in labor market tightness during 2021 is the crucial factor behind the increase in quits during the Great Resignation. The mechanism is simple. According to the NBER Business Cycle Dating Committee, this recession was the shortest U.S. recession on record. The rapid recovery led to a massive increase in job openings and labor market tightness (openings per job searcher). In the model, an increase in labor market tightness implies a higher probability that any given searcher (employed or unemployed) finds a job. Therefore, the probability that a worker who already has a job finds another one and quits is also higher.

The model is based on Mercan and Schoefer (2020) (MS) with minor changes[9]. They add two changes to the standard Diamond-Mortensen-Pissarides (DMP) model. First, the pool of searchers comprises not only unemployed but also employed workers. The latter can accept outside offers and quit their jobs. Second, firms can repost jobs that were vacated by quits. Therefore, job openings are composed of new and reposted old vacancies. This mechanism leads to a vacancy chain: workers quit their jobs and leave behind vacant jobs, which firms repost. Some of these reposted jobs are filled by employed searchers who need to quit their job to change employers, which leads to more vacancies, and so forth. Vacancies lead to more vacancies.

4.1 Environment

Time is discrete, and there is a unit mass of workers with risk neutral preferences and discount factor β, who are either employed or unemployed ($e_t + u_t = 1$). Firms are single-worker jobs, owned by workers. There is a one-time sunk cost per new job created, $k(n_t)$, where n_t is the number of new jobs. These new jobs, by definition, are initially vacant since they have just been created. If $k(n_t) > 0$, firms would repost jobs vacated by quits. Jobs are exogenously destroyed with probability δ. After a job is destroyed, the worker goes into unemployment, and that job cannot be reposted. $\rho = \frac{r}{r+n}$ is the fraction of total vacancies that are classified as quit-driven replacement hiring, where r are reposted old jobs and n consist of new vacancies.

$M(s,v) = \mu s^{\eta} v^{1-\eta}$ is a standard Cobb-Douglas matching function that determines the number of matches between searchers and firms, where $s = u + \lambda e$ is the number of agents searching for jobs, v the number of vacancies, and μ the matching efficiency. Labor market tightness $\theta = v/s$ is defined as vacancies per searcher. All unemployed workers search with an intensity equal to 1, while employed workers search with intensity λ[10]. The job finding probability for an *unemployed* worker is $f(\theta) = M/s$, and for an *employed* worker is $\lambda f(\theta)$. On the other hand, the probability that a *vacancy* finds a job is $q(\theta) = M/v$.

The timing of events within period t is as follows

1. The state of the economy s_t is realized, including unemployment u_t and vacancies inherited from last period $\tilde{v}_t$

[9] Their model incorporates two extra parameters. First, σ which is the probability that a match is exogenously dissolved after the match. Second, firms repost jobs vacated by quits with probability γ. The version of the model I will use in this paper assumes that $\sigma = 0$ and $\gamma = 1$.

[10] How to interpret λ? If only 10% of employed workers search for jobs but they do it with twice the intensity of unemployed workers then $\lambda = 0.1 * 2 = 0.2$

2. Employed workers consumed a bargained wage w_t and produce y_t. On the other hand, unemployed workers receive unemployment benefit b.

3. Firms create new jobs n_t at a cost $k(n_t)$ each, and pay flow cost κ per vacancy. This determines market tightness $\theta_t = v_t/(u_t + \lambda e_t)$.

4. $f(\theta_t)u_t$ of unemployed workers find jobs, $\lambda f(\theta_t)e_t$ of employed workers quit their jobs and change employer.

5. Fraction of δ of workers lose their jobs exogenously destroyed and become unemployed.

Laws of motions

$$u_t = \underbrace{(1-(1-\delta)f(\theta_{t-1}))\,u_{t-1}}_{\text{stay unemployed}} + \underbrace{\delta(1-u_{t-1})}_{\text{EU: job destruction}} \tag{1}$$

$$v_t = \underbrace{n_t}_{\text{new}} + (1-\delta)\left\{\underbrace{(1-q(\theta_{t-1}))\,v_{t-1}}_{\text{unfilled}} + \underbrace{\lambda f(\theta_{t-1})e_{t-1}}_{\text{reposted: EE}}\right\} \tag{2}$$

Value functions

The state of the economy is $s = (u_t, v_t)$. The worker's problem when unemployed, where b refers to opportunity cost of moving from unemployment to employment, is the following:

$$U(s) = b + \underbrace{\beta(1-\delta)f(\theta)E[W(s')]}_{\text{becomes employed}} + \underbrace{\beta\,(1-(1-\delta)f(\theta))\,E[U(s')]}_{\text{continues unemployed}} \tag{3}$$

The worker's problem when employed:

$$W(s) = w(s) + \underbrace{\beta\delta E[U(s')]}_{\text{becomes unemployed}} + \underbrace{\beta(1-\delta)\left(\overbrace{1-\lambda f(\theta)}^{stay} + \overbrace{\lambda f(\theta)}^{quit}\right)E[W(s')]}_{\text{continues employed}} \tag{4}$$

The firm's problem incorporates three value functions: newly created jobs, vacancies, and jobs. The inclusion of $k(n)$ is what makes this model different. If $k(n) = 0$, then the model is a standard DMP where vacancies are not reposted. This case implies that new jobs and vacancies are perfect substitutes. However, if the cost of creating a new job is positive, $k(n) > 0$,then firms will repost vacancies. That is, after an employee quits, instead of paying $k'(n)$ to create a new job, the firm will repost the vacancy, as is common for actual firms to do.

$$N(s) = V(s) - k(n) \tag{5}$$

A vacancy entails flow cost κ and it matches with a worker with probability $q(\theta)$. If the vacant does not find a match, it will be carried out to next period. In Mercan and Schoefer (2020)'s model, a fraction σ of matches are exogenously dissolved at the end of the period. I assume that $\sigma = 0$, so matches can only be dissolved endogenously by workers quitting.

$$V(s) = -\kappa + \beta(1-\delta)\left[\underbrace{q(\theta)E[J(s')]}_{\text{vacant finds a match}} + \underbrace{(1-q(\theta))E[V(s')]}_{\text{vacant does not find a match}}\right] \tag{6}$$

A job produces output y and pays wage w. If the match is dissolved by a worker quitting, the job always enters next period as a vacancy[11].

$$J(s) = y - w(s) + \beta(1-\delta)\left[\underbrace{\lambda f(\theta)E[V(s')]}_{\text{match is dissolved by quit}} + \underbrace{(1-\lambda f(\theta))E[J(s')]}_{\text{match is preserved}}\right] \tag{7}$$

As is usually the case in DMP, the model imposes a free entry condition in job creation. A newly created job has value $N(s) = V(s) - k(n)$, which implies that the value of a vacancy equals its cost.

$$V(s) = k(n) \tag{8}$$

Wage determination mechanism

The model assumes that after quitting, the worker bargains with the firm as if his outside option is unemployment. Define joint match surplus as

$$S(s) = \underbrace{J(s) - V(s)}_{\text{Surplus for firm}} + \underbrace{W(s) - U(s)}_{\text{Surplus for worker}} \tag{9}$$

Wages are determined by generalized Nash bargaining between the firm and the worker. This implies that the worker, which has a bargaining power $\phi \in (0,1)$, and firm linearly share the joint match surplus in the following way:

$$\phi S(s) = W(s) - U(s) \tag{10}$$

[11] Mercan and Schoefer (2020) model has the parameter γ, which is the share of vacancies that can be reposted. I set this parameter to 1 due to simplification, and also because this share is potentially very high in the United States.

$$(1-\phi)S(s) = J(s) - V(s) \tag{11}$$

4.2 Calibration

The model period equals one month. Under a standard Cobb-Douglas matching function, $M(s,v) = \mu s^{\eta} v^{1-\eta}$, η is the elasticity of total matches to the total search effort, which I set $\eta = 0.5$ as standard. Discount factor $\beta = 0.9967$ implies an annual interest rate of 4%. I set the worker's bargaining power $\phi = 0.5$ to satisfy Hosios's condition. Furthermore, I set b, the opportunity cost of moving from unemployment to employment, equal to 0.715, which is the midpoint of the range calculated in Chodorow-Reich and Karabarbounis (2016).

I set the remaining parameters using the generalized method of moments (GMM) such that all parameters target different U.S. labor market outcomes in December 2020, right before the Great Resignation starts. I find $\mu = 0.424$ by targeting a UE rate, $(1-\delta)f(\theta)$ in the model, of 22.6%. Furthermore, targeting a steady-state unemployment rate $EU/(EU+UE)$ of 6.7% unemployment rate disciplines $EU = \delta = 0.016$, where δ is the probability that a job is exogenously destroyed. I target a ratio of vacancies per unemployed $\frac{v}{u} = 0.6$, the same vacancies per unemployed the U.S. had in December 2020. Finally, I target a employer-to-employer quits rate, $\lambda f(\theta)$, of 1.89%[12] and find $\lambda = 0.083$.

Table 3: Calibration and Model Fit

Parameter	Value	Source
β	0.9967	Mercan and Schoefer (2020)
η	0.5	Standard (2020)
ϕ	0.5	Hosios condition
ρ	0.8	Mercan and Schoefer (2020)
b	0.715	Chodorow-Reich and Karabarbounis (2016)
μ	0.2844	GMM
κ	0.4164	GMM
λ	0.0984	GMM
δ	0.0132	GMM

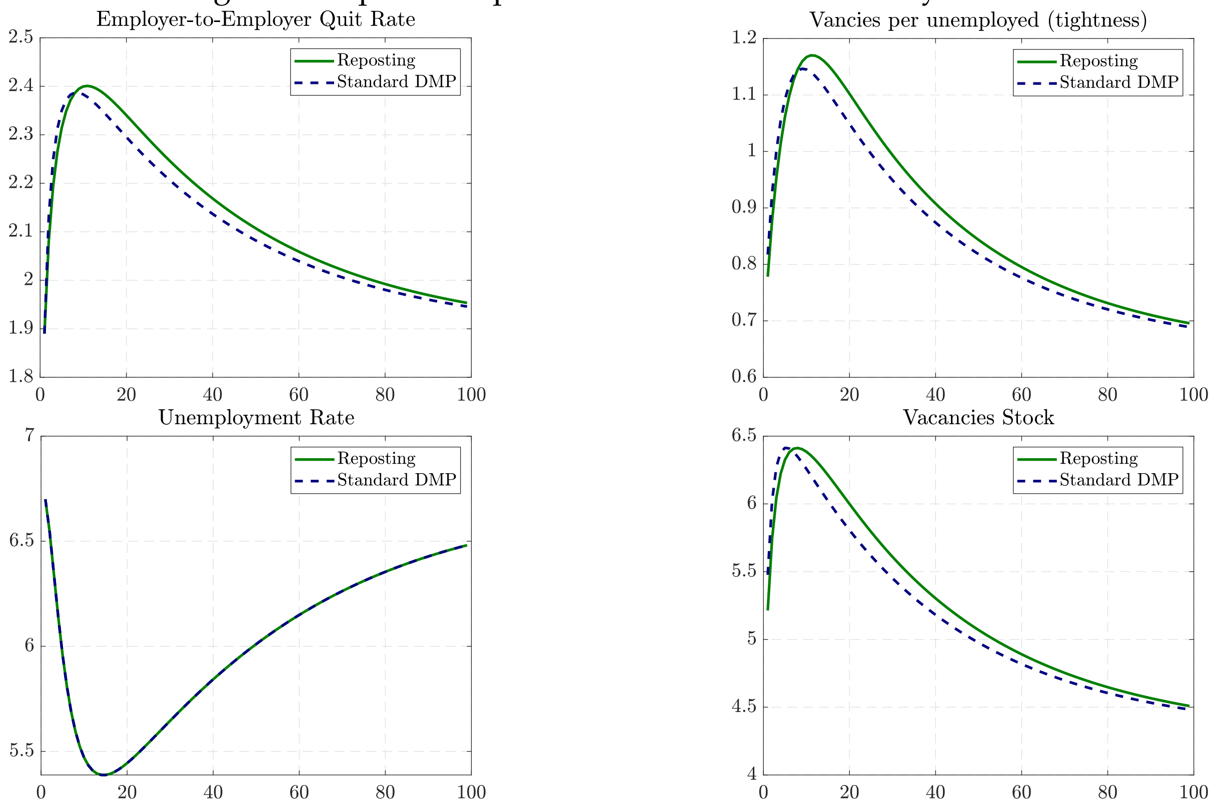
[12]The December 2020 employer-to-employer quits rate constructed from CPS (assuming those with missings answers are stayers) is 1.54%, and the same rate but using Fujita et al. (2021) methodology is 2.23%. The latter number is probably overestimating the employer-to-employer quits rate because JOLTS quits rate number for that month - which includes quits to unemployment and quits to outside the labor force - is 2.4%. Therefore, Fujita et al. (2021) methodology would imply that 93% of quits are employer-to-employer quits. Therefore I choose 1.89%, which is the average between what both methodologies find.

4.3 Aggregate effects of labor demand shock in the quits rate

From December 2020 to December 2021, the U.S. labor market had a strong recovery. The unemployment rate fell 2.8 percentage points - from 6.7% to 3.9% - and the job-finding rate for unemployed workers had a 5.8 percentage points increase in a single year - from 22.6% to 28.4%. Figure 7 shows how the employer-to-employer quits rate (Q^{EE}) and other variables change after a labor productivity shock - parameter y in the model.

Instead of choosing an arbitrarily large shock, I chose the size of the labor productivity shock to increase the job-finding probability of unemployed to a similar magnitude to what was observed in the U.S. during 2021. I calibrated the model so that, before the shock occurs, the steady state level of the unemployment rate, quits rate, labor market tightness, and job-finding probability for those unemployed match with their values (extracted from the data) in December 2020.

Figure 7: Impulse Responses after Labor Productivity Shock



Notes: The figure shows the response of several labor market outcomes to a 22.5% temporary increase - in terms of its standard deviation - in labor productivity. The size of the productivity shock was chosen so that it produces a demand shock - measured by the increase in the job-finding probability for those unemployed- of similar magnitude than what was observed from December 2020 (22.6%) to December 2021 (28.4%) - an increase of 5.8 percentage points.

Table 4 compares the predicted change of the labor market outcomes in Figure 7 to the observed change in the data. The employer-to-employer quits rate observed in the data in December 2021 features a range of values to reflect the uncertainty around its actual value, as it is likely that CPS is underestimating it. I construct the bounds using the missings value imputation developed by Fujita et al. (2021). However, their imputation relies on which variables were correlated with employer-to-employer mobility before the percentage of missing values increased dramatically after 2007. Therefore, it is likely that the demographic and economic characteristics that were correlated with E-E mobility before 2007 are not good predictors 15 years after. Furthermore, the uncertainty around the employer-to-employer quits rate also comes with other problems inherent to the CPS design, such as the inability to identify workers who quit their jobs and move to a different address, as explained in Section 2.3.

The changes in the model are calculated from the initial steady state - which was calibrated to match the U.S. labor market in December 2020 - to period 12. The model can explain a significant portion of the variation in all the labor market outcomes analyzed. For example, it predicts that during 2021 the employer-to-employer quits rate should have increased by 25.5%, a value well inside the range of the observed change.

Table 4: Does the model correctly explain the labor market dynamics during 2021?

	Data			Model
Labor market outcomes	Dec 2020	Dec 2021	Change	Change
quits rate E-E (%)	2.18	[2.43,2.78]	[11.68%,27.5%]	25.4%
Job openings per unemployed	0.64	1.81	182%	77%
Job openings (MM)	6.938	11.448	65%	43.5%
Unemployment rate (%)	6.7	3.9	-41.8%	-23.2%
Unemployed exit rate (MM)	22.6	28.4	25.7%	25.7% (target)

Notes: The change in the model was calculated from initial steady state to period 12. The initial steady state was calibrated to match U.S. labor markets in December 2020. The size of the shock was disciplined to match the increase in the job-finding probability of those unemployed. All variables values from data are seasonally adjusted. The employer-to-employer quits rate in December 2020 and the lower bound in December 2021 have the following characteristics (a) seasonally adjusted (b) six-month moving average (c) missings value imputed using Fujita et al. (2020) methodology. The upper bound in 2021 equals its value in December 2020 plus the increase observed in the quits rate reported by JOLTS between December 2020 and December 2021 (0.6 pp).

5 Concluding remarks

To the best of my knowledge, this is the first paper that provides empirical evidence of the reallocation patterns during the Great Resignation. I show that workers' main destinations after quitting are the same industries they were working for before quitting. For example, 71% of workers that quit their jobs in the Education and health services industry end up working in the same industry one month after quitting. Perhaps even more surprisingly, the reallocation of workers after quitting during the Great Resignation shows similar patterns to before the pandemic. The percentage of workers who left their industry after quitting in 2021 has a 0.9 correlation with the same percentage in 2019. I also find that, compared to workers who stayed at their jobs, quitters are (a) 5.3 years younger, (b) more than twice as likely to have multiple jobs, (c) earn 1.69 fewer dollars per hour, and (d) have significantly higher nominal wage growth.

Finally, I use the Mercan and Schoefer (2020) variation of the canonical Diamond-Mortensen-Pissarides (DMP) search model to argue that the massive increase in labor market tightness during 2021 is the main driver behind the Great Resignation. I calibrate the model to match the U.S. economy in December 2020, and then show that a shock of the same size as the U.S. labor market experienced in 2021 can correctly explain a significant fraction of the increase in the quits rate, vacancies, and other outcomes.

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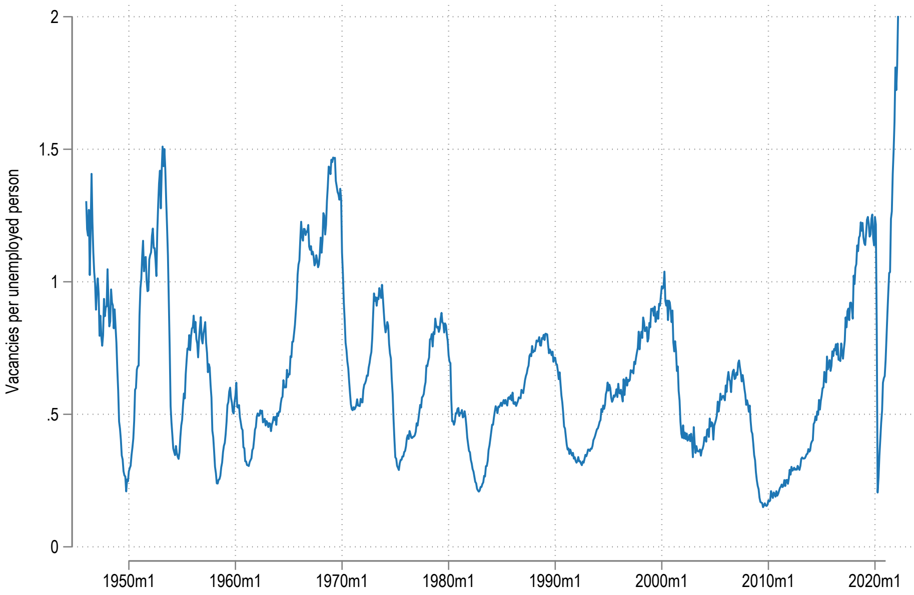
Appendix

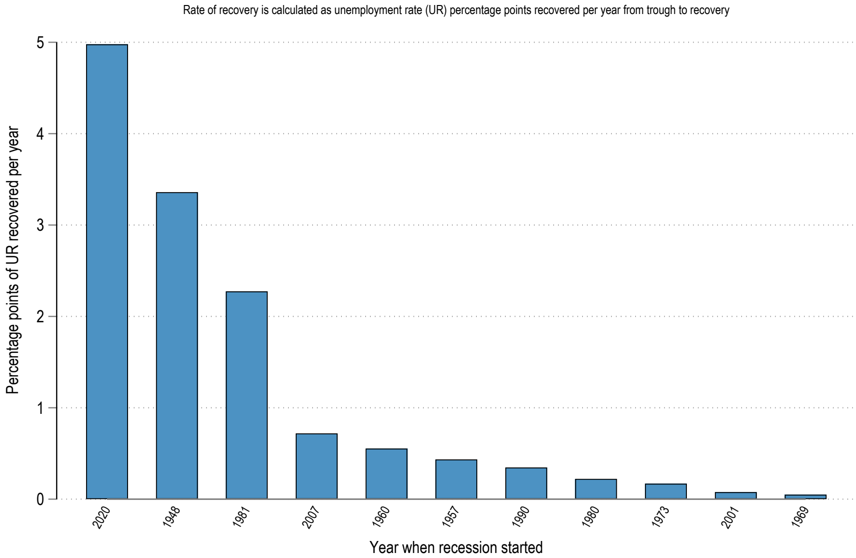
A Introduction

Figure A1: Historical evolution of U.S. Labor Market Tigthness: 1946-2022



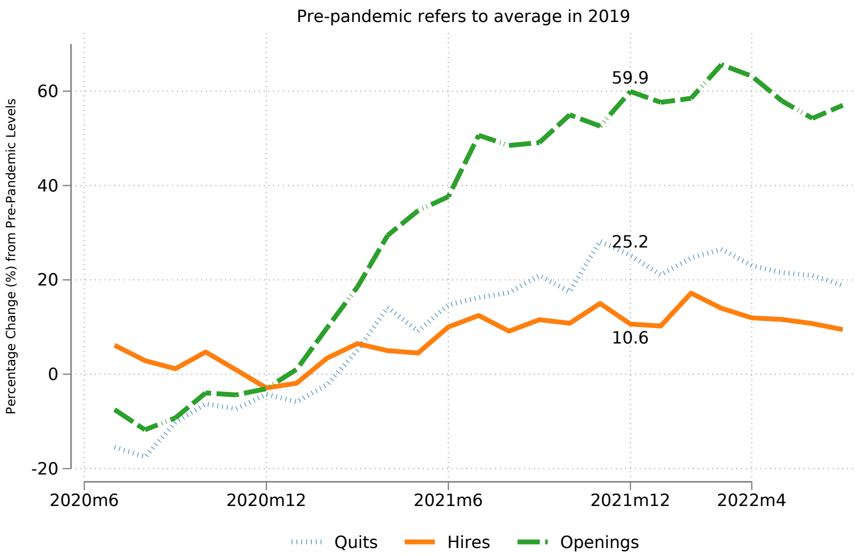
Notes: The y-axis refers to the number of vacancies per unemployed person (a measure of labor market tightness) in the United States. The period is from January 1946 to March 2022. Data was extracted from Michaillat and Saez (2022), who use data from BLS and Petrosky-Nadeau and Zhang (2021). All data is seasonally adjusted.

Figure A2: Unemployment Rate Speed of Recovery for all U.S. Recessions since 1948



Notes: The y-axis refers to the rate of rate of recovery for all recession since 1946. The recession years come from NBER. The rate of recovery is defined as the number of percentage points (per year) that it took the economy to achieve its pre-recession level of unemployment rate. The number of years is calculated since the trough (defined by NBER as "a month when economic activity reaches a low point and begins to rise again for a sustained period). The 1953 recession is not included as it never achieved its pre-recession unemployment rate peak (2.6%).

Figure A3: Evolution of JOLTS components relative to 2019

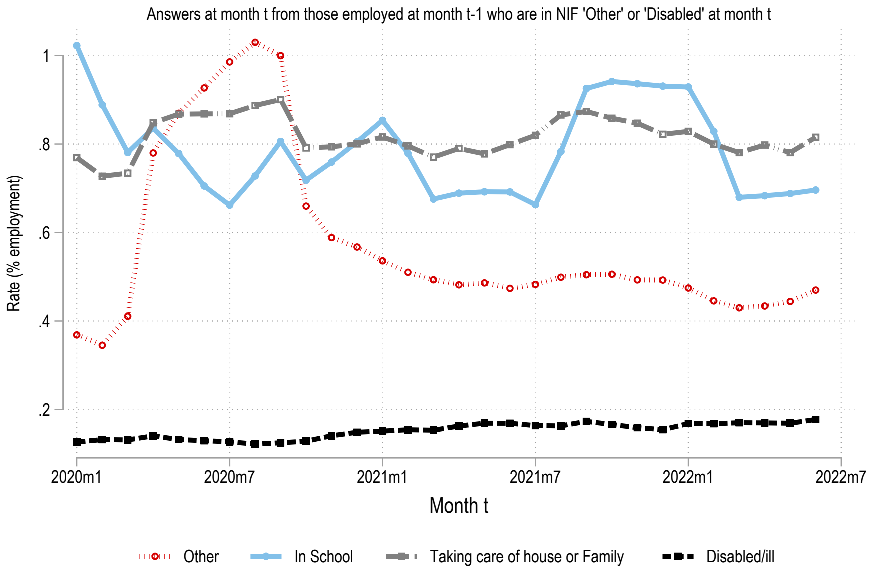


Notes: Data is extracted from JOLTS

B Data

B.1 Is the Great Resignation explained by workers leaving the labor force?

Figure A4: Answers to: "What best describes your situation at this time?"

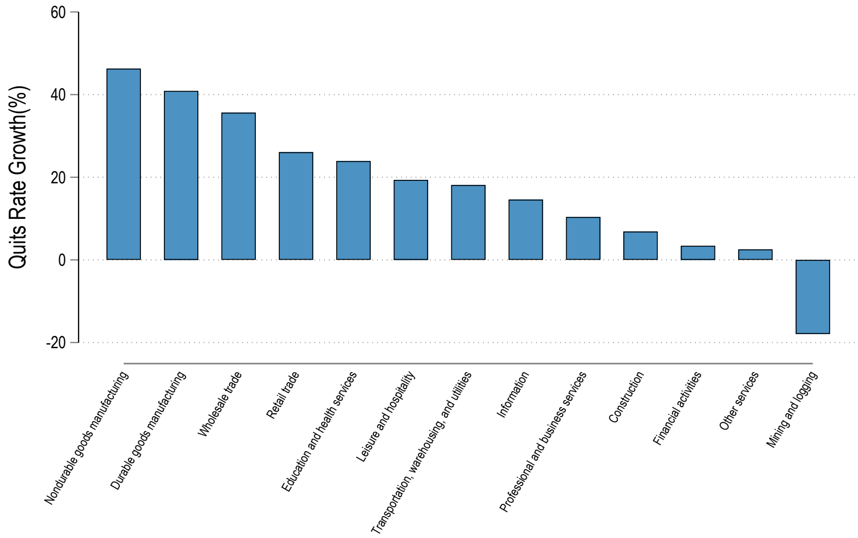


Notes: The y-axis shows the 6-month trailing average as a percentage of employment of answers to the CPS question "What best describes your situation at this time?". This question is asked to (1) those with ages between 14 and 49 or (2) those older than 49 who are not employed, but the figure only plots the answers to those above 16 years old who are not in the labor force at month t (NIF categories "Other" or "Disabled") and were employed at month $t-1$. The figure does not include those workers who went from being employed to be retired because these workers, by definition, could not have quit their jobs.

C Basic facts about Great Resignation

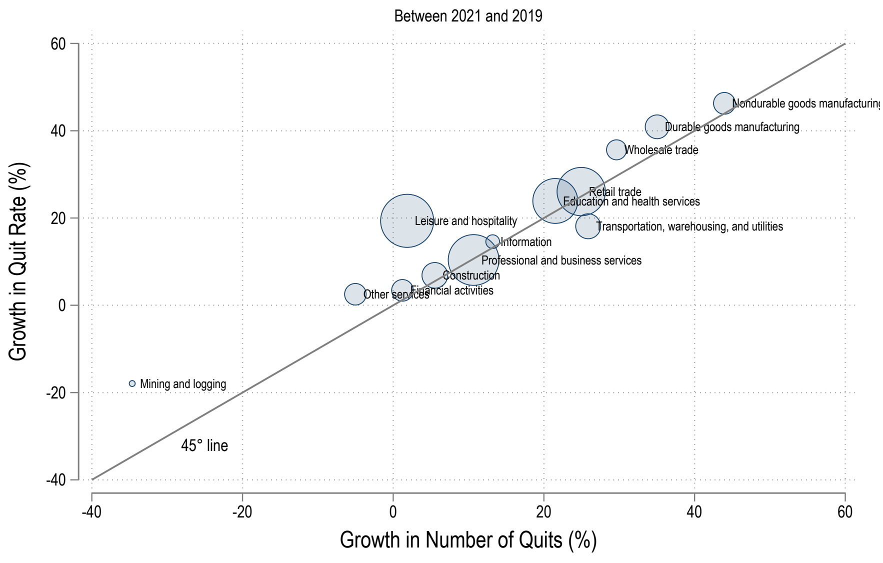
C.1 Where are workers quitting *from?*

Figure A5: Growth of Quits (in levels) between 2021 and 2019



Notes: The y-axis refers to the growth rate between the total number of quits by sector between 2019 and 2021. Data extracted from JOLTS.

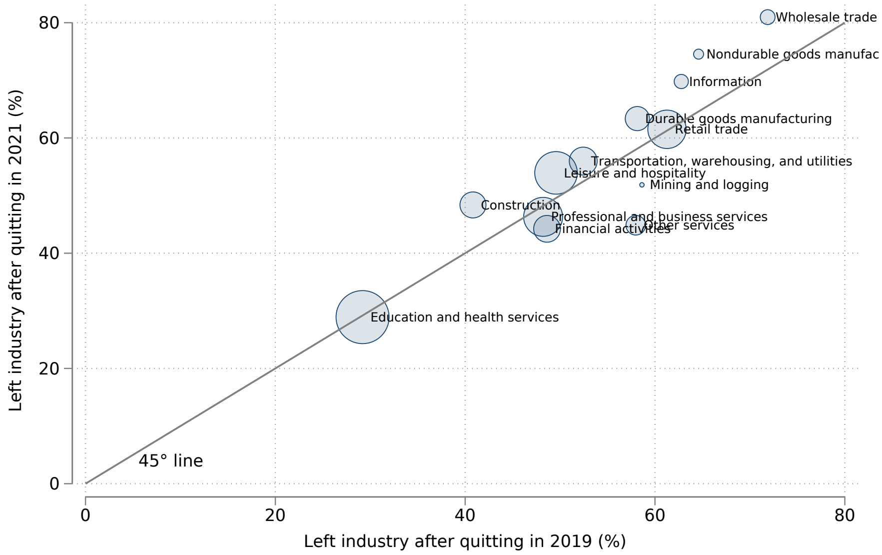
Figure A6: Comparison of Growth Rates: number of quits vs. quits rate



Notes: The y-axis refers to the growth rate calculated from the quits rate (quits/employment), and the x-axis refers to the growth rate of quits in levels (thousands of quits). Both growth rates are calculated between 2021 and 2019.

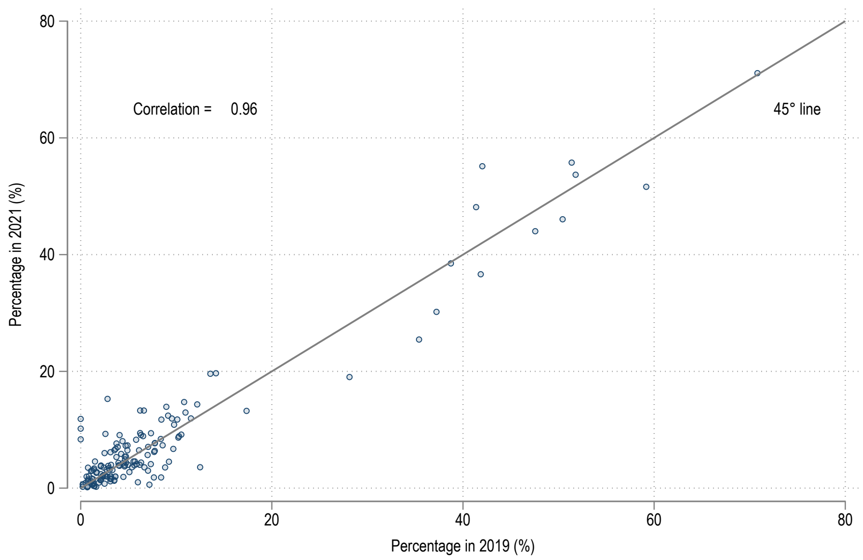
C.2 Where are workers quitting *to?*

Figure A7: Percentage of workers who left their industry after quitting



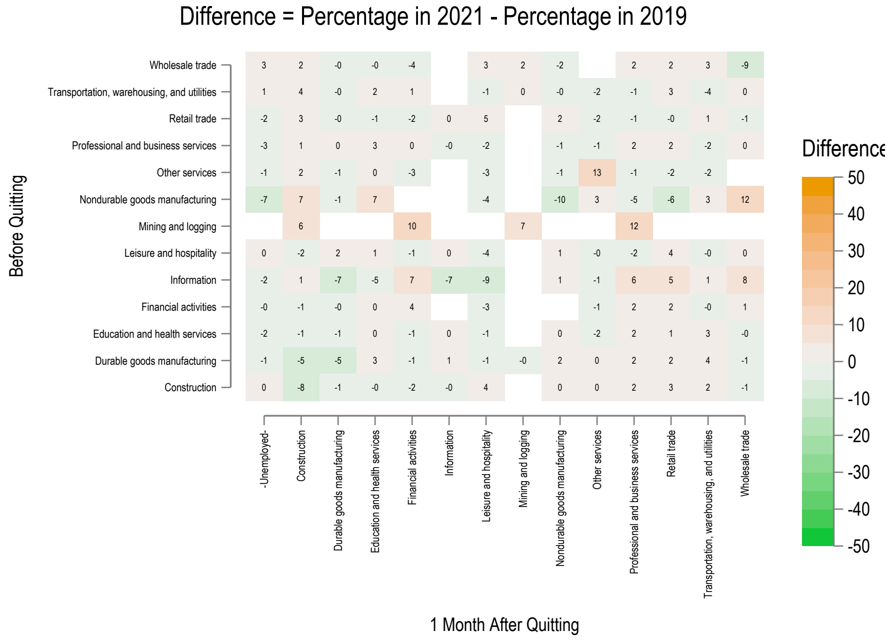
Notes: The y-axis (x-axis) refers to the percentage of workers from a given industry that, after quitting in 2021 (2019), went to a industry different than the one they were working on before quitting. Origin and destination of workers were calculated from CPS micro data for all quits in 2021 and 2019. Industry refers to the industry where the worker had its main job.

Figure A8: Where do workers go after quitting? Comparison between 2021 and 2019 - Scatterplot



Notes: Percentage in 2021 (2019) refers to the percentage of workers on a given row (industry before quitting) that went to a particular column (industry after quitting) in 2021 (2019).

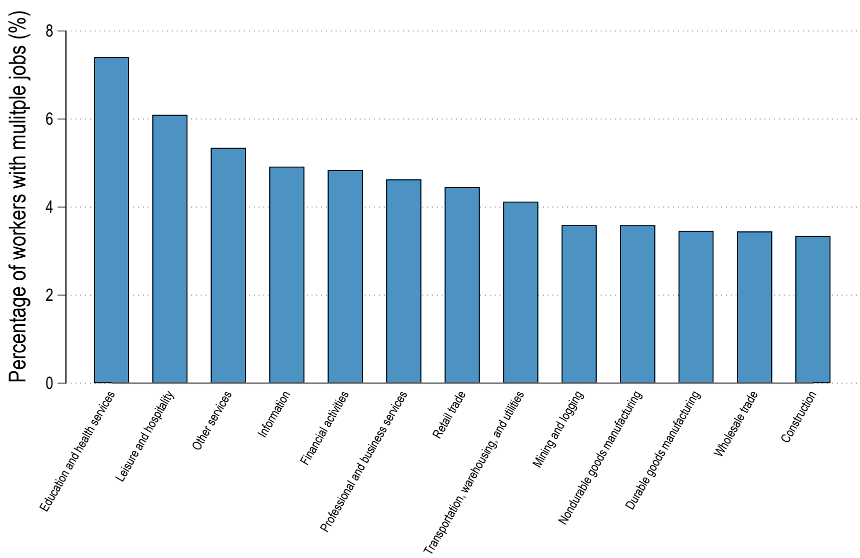
Figure A9: Where do workers go after quitting? Comparison between 2021 and 2019 - Heatmap



Notes: Percentage in 2021 (2019) refers to the percentage of workers on a given row (industry before quitting) that went to a particular column (industry after quitting) in 2021 (2019). Difference refers to the difference, in percentage points, between 2021 and 2019 in the percentage of workers coming from industry A and going to industry B after quitting. Origin and destination of workers were calculated from CPS micro data for all quits in 2021 and 2019.

C.3 Who is quitting?

Figure A10: Percentage of workers with multiple jobs - 2019



Notes: The y-axis shows the percentage of workers that hold more than 1 job in 2019. The percentage was calculated using BLS composition weights.