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Labor Force Exiters around Recessions: Who Are They?*

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Abstract

This paper identifies workers who experience a job separation during a recession and tracks their labor force status in the following year using the Current Population Survey. Workers are classified as exiters if they leave the labor force shortly after their job loss and non-exiters if they do not. The pool of exiters is disproportionately female, less-educated, and older. During the pandemic recession, there were even more older workers in the exiters pool, although they were less likely to report being retired compared to in the Great Recession. In addition, statuses were more persistent during the Great Recession: for both exiters and non-exiters the majority were in the same labor force status a year later. I then use the patterns of these samples of job-separators to estimate the propensity of being re-employed in a year and apply the estimates to the general out-of-work pools during the two recessions. I find that changes in the likelihood of being re-employed as well as the composition of individuals out of work are important for understanding the differences between the labor market in the two recessions.

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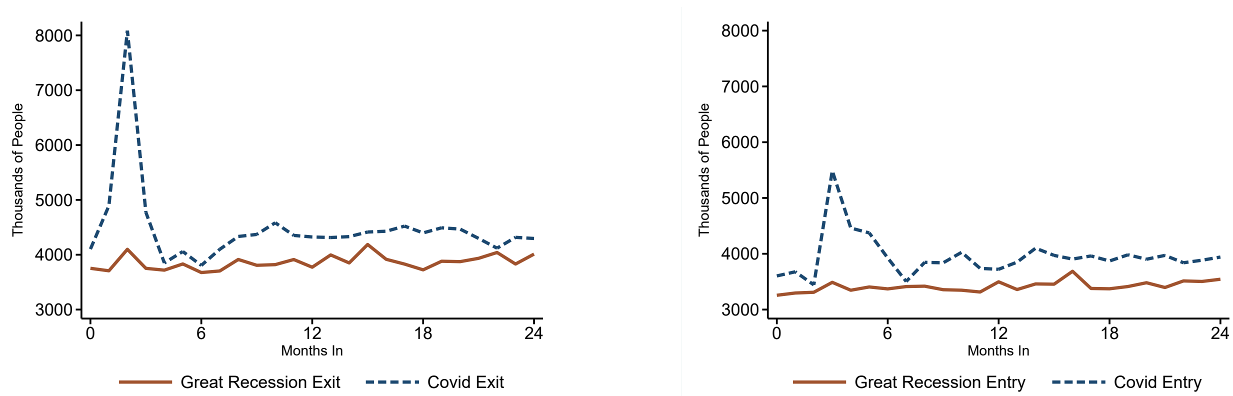
1 Introduction

Job separations are a prominent feature of the labor market in and around recessions. Upon being separated, there are many different paths that workers take afterwards. Some quickly go back to their old jobs or find new ones, some spend considerable time searching for work, and others leave the labor force entirely. Although some of these labor force exits are permanent, many eventually re-enter the labor force. Nevertheless, both the COVID-19 and Great Recessions spurred declines in labor force participation. Whether and how long it takes for these individuals to return are of great interest to policymakers.

Figure 1: Labor Force Flows: COVID-19 vs. Great Recession

(a) Exit (b) Entry



“Exit” refers to the number of monthly flows from employment or unemployment to out of the labor force and “entry” refer to the number of monthly flows from out of the labor force to employment or unemployment. The starting points are December 2007 for the Great Recession and February 2020 for Covid. Source: Current Population Survey (CPS) and author’s calculations.

Figure 1 depicts the monthly number of labor force exits (left panel) and entries (right panel) following the start of both the Great Recession and the pandemic recession. The two recessions exhibit different patterns in both types of flows. The pandemic recession had large spikes of both exit and entry in certain months, tied closely with broad changes in pandemic-related shutdowns. There were also differences in churn: in terms of both entry and exit, more people were moving across the non-participation margin in every month during the pandemic recession compared to the Great Recession. This paper aims to understand who underlies the patterns in these figures and the paths they took to get there.

Specifically, I examine the labor force status patterns of people who lose their jobs in recessions, with an emphasis on comparing the Great Recession with the recent pandemic-related recession. I then use their patterns to estimate the likelihood of being re-employed again within a year as a function of labor force status, individual characteristics, and reason for being out of work, and apply these estimates to a broader sample.

I begin by pinpointing a sample of workers in the Current Population Survey (CPS), who can be observed losing their jobs during either one of the recessions. I record their labor force status each month starting from employment and classify them as either a labor force "exiter" or "non-exiter" based on their employment status at the end of their four-month panel. I then compare the observable characteristics of exiters, non-exiters, and those who became employed again by the end of the four months. I find that in both recessions, exiters were more female, older, less-educated, and similar to non-exiters and terms of racial composition. In the Great Recession, non-exiters skewed male, in comparison to a 50/50 split in the pandemic recession. The age distribution of the exiter pools was also different: it skewed older in the pandemic recession, but less of the exiters in the 55-64 age group reported being retired compared to in the Great Recession.

The structure of the CPS allows me to follow-up on these workers one year after their initial job loss. I look at their status in their last month of the survey and compare it with where they were four months after the job loss. I find that statuses were more persistent during the Great Recession: the majority of exiters stayed out of the labor force and the majority of non-exiters were unemployed. The pandemic recession looked much different, with one-third of the exiters and 60% of the non-exiters having gone back to work.

In the last section of the paper, I estimate logit models for returning to employment in the last month of the survey for exiters and non-exiters, both in the Great Recession and the pandemic recession. This group of workers is interesting because it is representative of the matches that were in tact before the recession hit. Thus it is a group who policymakers may be interested in getting back to work. Using the CPS for this exercise is also useful because it is the most up-to-date micro data on employment with a panel dimension. The results of this estimation reflect differences in behavior of the workers who lost their jobs during the two recessions: exiters who become re-employed tend to be younger, not have young children at home, and female. Non-exiters who become re-employed tend to be more educated and have left their old jobs voluntarily. I apply these estimates from the exiters and non-exiters sample to the broader out-of-work pools over the two recessions, which combines the measure of behavior with the composition of people who recently separated from their jobs. Despite the fact that exiters returned more quickly after the pandemic recession, the composition of the out-of-labor force pool in the aftermath suggests that the rest may return more slowly.

1.1 Related Literature

This paper relates to the large literature on labor market flows, specifically in and out of non-participation. For example, Elsby, Hobijn and Şahin (2015) show how these flows account for a substantial part of unemployment fluctuations. This paper dives into who makes these flows and the roles they play as workers eventually find (or not find) new jobs. In studying the paths workers take in the data, Hall and Kudlyak (2019) use the CPS in a similar way. They string together each worker's monthly observations of labor force status in order to understand what "types" of workers comprise the population in terms of their labor market flows.

This paper also complements the existing research on the effects of COVID-19 on the labor market. A few related examples that have major empirical components and that use the CPS are Hall and Kudlyak (2021), Cortes and Forsythe (2020), and Forsythe et al. (2020). Chodorow-Reich and Coglianese (2021) also have a related method that projects the distribution of unemployment durations.

The rest of this paper proceeds as follows. Section 2 discusses the data and how its structure is used to analyze the employment status patterns of people who lose their jobs during recessions. Section 3 investigates the patterns of employment transitions for different categories of workers. Section 4 presents estimates of one-year ahead re-employment probabilities and 5 concludes.

2 Data and Methodology

2.1 The CPS

The analysis is based on monthly data from the Current Population Survey (CPS), which is the official source of the jobs report created by the Bureau of Labor Statistics. The monthly files are provided by IPUMS.

The CPS has a rotating panel structure, which is key to the objective of this paper. Households are surveyed for four months, then are rotated out of the survey for eight months, and then are surveyed for the final time for four more consecutive months. The respondents' survey answers correspond to the week that spans the 12th of each month. In each of the eight months, respondents self-report their employment status as well as other information about themselves and their household, which will be used throughout this paper. In the CPS, an individual is considered employed (E) if they were working for pay, unemployed (U) if they did not have a job, have actively looked for work in the prior 4 weeks, and were currently available for work, and out of the labor force (N) if they were neither employed nor unemployed.

2.2 Sample Selection: Exiters, Non-Exiters, and Re-Employed

I begin by comparing two samples of workers: those who lost their jobs in the Great Recession and those who lost their jobs during the more recent pandemic recession. These samples are selected and further split up based off of the employment statuses that each worker experiences during their first four months in the survey.

I would like to identify people who can actually be observed separating from their jobs so I start by limiting the sample to only people who were employed for their first month in the survey. I then want to maximize the number of times they are surveyed consecutively after their job loss, so I then require that they are reported as unemployed or out of the labor force in their second month in the survey. This initial sample of job-losers is selected for people who enter the survey in February or March 2020 for the pandemic recession and anytime between December 2007 and June 2009 for the Great Recession (the official dates of the recession according to the National Bureau of Economic Research). In the case of the pandemic recession, focusing on these two months captures the large spike in separations that occurred at the onset of the pandemic. This group is also interesting because it represents the workers whose jobs were intact before the recession, a benchmark for comparing labor market progress over the recovery.

I then further split these two groups based on their labor force status in the fourth consecutive month. If the worker ended up out of the labor force, they were called an "exiter." If the worker stayed in the labor force but was unemployed, they were called a "non-exiter." The key distinction between these two groups is that the exiters have given up searching for a job which means we may expect them to be slower to go back to employment, if at all, compared to the non-exiters. Finally, if the worker was employed again, they were called "re-employed." Table 1 summarizes the possible sequences of labor force status that workers in the sample may exhibit.

Month in Survey			
1	2	3	4
E	U or N	E or U or N	E or U or N

Table 1: Possible labor market statuses for individuals in the sample

The rotating panel setup of the CPS also ensures that some of these individuals are re-surveyed exactly 12 months after their first month in the survey. This enables a longer-term follow-up on these workers after their initial job loss.[1]

3 Labor Market Transitions of Job-Separators

3.1 After 4 Months

Before examining what types of workers comprise each group, I summarize the breakdown of the job-separators as constructed above into the three groups, and compare between the pandemic recession and the Great Recession. Table 2 reports these percentages.

	Pandemic Recession	**Great Recession**
Exiters	29%	39%
Non-exiters	25%	17%
Re-employed	46%	44%
N obs. unweighted	1842	7548
N obs. weighted	5,817,250	16,233,539

Table 2: Composition of job-separators sample during the two recessions
This table summarizes the composition of job separators during the pandemic recession and the Great Recession based on the labor force status of their fourth consecutive month in the CPS. Exiters had status N, non-exiters had status U, and re-employed had status E. Everything is reported using the CPS' composite weights.

The table shows that in both recessions, people who lost their jobs were about equally likely to be employed again within three months.[2] However, the split between exiters and non-exiters is different. The Great Recession saw a lot more exiters among people who separated from their jobs. In contrast, in the pandemic recession, job separators who were not quickly re-employed we almost equally split between exiters and non-exiters. These differences may reflect the persistency of the two downturns: the pandemic was seen as a much more temporary shock which may have kept workers on the sidelines ready for work.

I now explore further what types of workers were in these groups. Table 3 shows the composition of exiters, non-exiters, and re-employed according to gender, age, race, education,

[1]Note that, especially for the Great Recession, the observed job loss may not be the only one they experienced during the downturn, but rather the initial one that was recorded while they were in the CPS.

[2]The CPS does not ask about employers, so it is impossible to know whether they went back to their original jobs. However, later I check whether they switched industries which could serve as a lower bound for how many found different jobs.

	Pandemic Recession			Great Recession		
	Exiters	Non-exiters	Re-employed	Exiters	Non-exiters	Re-employed
Male	40%	48%	49%	41%	61%	50%
Female	60%	52%	51%	59%	39%	50%
Older than 55	38%	20%	26%	30%	13%	21%
Had Been on Temporary Layoff	23%	85%	64%	3%	18%	12%
Had Children Age 12 or Younger	16%	18%	23%	19%	25%	24%
White	76%	74%	78%	79%	77%	81%
Black	12%	10%	12%	14%	15%	12%
Asian/Pacific Islander	8%	10%	5%	5%	4%	4%
Other or Two or More Races	4%	6%	6%	3%	4%	3%
Less than High School Diploma	16%	13%	12%	24%	20%	21%
High School Diploma	28%	27%	27%	32%	39%	31%
Some College	29%	33%	34%	27%	27%	28%
Bachelor's Degree or Higher	27%	27%	27%	17%	14%	20%

Table 3: Features of job-separators during the two recessions
This table summarizes the demographic characteristics of job separators in each of the two recessions. Each row represents the percentage of exiters/non-exiters/re-employed who had that feature. Everything is reported using the CPS' composite weights.

whether they were at any point on temporary layoff after the job loss, and whether they had children in their household. Note that the statistics in this table reflect the make-up of who was in each group during each recession (thus, in each column the rows in each group sum to 100%) and do not represent the likelihood that someone with a given set of characteristics will be an exiter, a non-exiter, or re-employed. On the other hand, the numbers here do reflect the features of workers who lost their jobs in the first place.

I first turn to the broad differences between the types of job-separators. Exiters tend to be more female than male, reflecting the lower labor force attachment of women. They also tend to have more older workers and slightly more less-educated workers. People who have young children in their household comprised the smallest parts of the exiters pool. Finally, the groups do not differ much in terms of racial composition.

Next, I analyze the differences between the two recessions. The disparities between men and women were most prominent in the Great Recession, where 61% of non-exiters were male and about 60% of the exiters were female. In the pandemic recession, there was a more even split among the non-exiters. This may reflect the ongoing trend of declining male labor force participation.

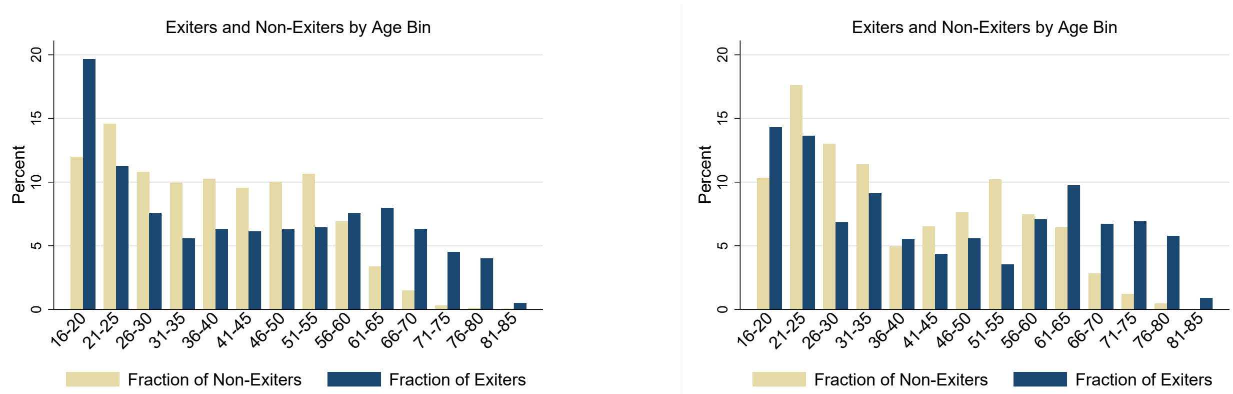
The role of temporary layoffs was quite different in the two recessions as well: they were much more common in the pandemic recession. As a result, both the non-exiter and the re-employed group were dominated by workers who had at one point reported themselves as on temporary layoff during their unemployment spells: 64% of those who quickly went back to work and 85% of those who were still searching after 3 months were on temporary layoff. Although less common in the Great Recession, these workers still made up a non-trivial part of the non-exiters group. In both recessions, but especially in the Great Recession, these workers made up much smaller parts of the exiter pool.

With respect to education, the pandemic recession had more highly-educated workers losing their jobs across the board. There, the three groups had relatively similar compositions, but in the Great Recession, the group of workers who were quickly re-employed leans more educated than the other two groups during that recession.

The age dimension also exhibits clear differences in the two downturns. From Table 3, nearly 40% of exiters during the pandemic recession were near or close to retirement age, in comparison to 30% during the Great Recession. This indicates that many of the people who left the labor force in the first few months after the pandemic hit were on the older side. This tendency may have been more pronounced than in the Great Recession because of health-related risks or appreciating asset values.

Figure 2: Exiters and Non-Exiters by Age

(a) Great Recession (b) Pandemic Recession



"Exit" refers to flows from employment or unemployment to out of the labor force and "entry" refer to flows from out of the labor force to employment or unemployment. The starting points are December 2007 for the Great Recession and February 2020 for Covid. Source: Current Population Survey (CPS) and author's calculations.

To explore further the age distribution within the exiter and non-exiter group, Figure 2 plots the proportion of exiters and non-exiters that are in each 5-year age bin from the two recessions. In both recessions, the distribution of exiters is clearly shifted to the right. The

Great Recession had more very young workers in its exiter pool and the pandemic recession had less workers in both pools who were middle-aged.

	Pandemic Recession	**Great Recession**
Less than 25 Years	1%	1%
25-34 Years	3%	4%
35-44 Years	5%	5%
45-54 Years	12%	13%
55-64 Years	36%	62%
65 Years and Older	88%	88%

Table 4: Percentage of exiters who are retired by age group
Retirement status here is based on the respondent's last month in their four-month stint in the survey. Everything is reported using the CPS' composite weights.

The CPS also asks respondents why they are out the labor force, providing a way to examine how many of these exits, especially among older workers, may be retirements. Table 4 presents the fraction of exiters in each age group who report being retired. These numbers are remarkably similar with the exception of the 55 to 64 age group. It appears that during the pandemic, workers close to retirement age who lost their job were less likely to retire within 3 months as compared to the Great Recession. However, with respect to workers over 65, there did not appear to be an higher propensity to retire upon a job loss after the pandemic hit. So even though there were more older workers within the exiter pool during the pandemic, the ones who were not quite at the typical retirement age had less of a propensity to retire compared to their counterparts in the Great Recession. This finding casts doubt on the story of accelerating early retirements during the pandemic.[3]

Retirement, as well as other out-of-labor force states and unemployment, are not absorbing states. It is highly possible that workers who recently lost their jobs will transition to another state over the next year. That is what the next section explores.

3.2 After 1 Year

I follow-up on the sample of job-separators by linking them with their responses when they re-enter the survey eight months after their first four-month spell. This allows for a longer-horizon analysis of their labor force status after their initial job loss and is also a way of measuring the persistence of their status right before they rotated out of the survey for the first time.

[3] "Early" here means with respect to age. It is possible that the pandemic spurred retirements that would not have happened as quickly absent the pandemic.

	Pandemic Recession				Great Recession			
	Employed	Unemployed	Not in Labor Force	Switched Industries	Employed	Unemployed	Not in Labor Force	Switched Industries
Exiters	34%	8%	**58%**	57%	15%	3%	**81%**	52%
Non-exiters	60%	**14%**	27%	39%	21%	**68%**	11%	59%

Table 5: Labor force status of exiters and non-exiters in the year after their initial job loss The rows represent the types of job-separators as defined in the last section and the columns "Employed" through "Not in Labor Force" represent their labor force status from their final month in the CPS. These columns sum to 100% in each row. "Switched Industries" reports the proportion of employed workers whose 2-digit NAICS industry differed from that of their first-observed job in the CPS. Everything is reported using the CPS' composite weights.

For this, I focus on exiters and non-exiters (i.e., just the workers who had not been re-employed at the end of their first four months), Table 5 reports the percentage of these two categories of workers who were employed, unemployed, and not in the labor force in their final month in the CPS.

The chart reveals that labor force statuses were more persistent in the Great Recession. In the Great Recession, 81% of exiters were still out of the labor force over a year after their job loss. This figure was 58% during the pandemic. In fact, after the pandemic recession, 34% of exiters had gone back to employment. To get a lower bound on whether these workers went back to their old jobs, the table reports the percent of those re-employed found jobs in an industry different from their previous one. In both recessions, a bit over half of the exiters who had found jobs switched industries, meaning that at least this many went to jobs that were different from their old ones.

Turning to the non-exiters, in the Great Recession 68% of them were still unemployed a year later. Note that although the incidence of long-term unemployment was high following the Great Recession, it is possible that some of these workers held short-lived jobs during the time they rotated out of the CPS. An additional 11% of the non-exiters left the labor force entirely. Turning to the pandemic, only 14% of the non-exiters were still unemployed. In contrast, the majority of them (60%) had returned to employment. The remaining 27% left the labor force entirely – this was a much less common path during the Great Recession (11%). Among the workers who went back to employment, 59% had switched industries during the Great Recession compared to only 39% in the pandemic. The latter may reflect the possibility that many of these transitions back to employment were temporarily laid off workers being recalled.

In sum, the takeaway here is that workers who lost their jobs in the Great Recession experienced "stickier" labor force statuses, as evidenced by the large bolded diagonal elements of the transition matrix in Table 5. In contrast, during the pandemic there were additional, non-immediate exits, as well as entries, which is consistent with the greater amount of churn evident in Figure 1.

	% of Exiters who Returned One Year Later		**% of Non-exiters who Left One Year Later**	
	Pandemic Recession	Great Recession	Pandemic Recession	Great Recession
Male	42%	30%	18%	14%
Female	42%	29%	35%	25%
Less than High School Diploma	29%	25%	22%	23%
High School Diploma	47%	29%	22%	18%
Some College	46%	29%	32%	18%
Bachelor's Degree or Higher	37%	34%	26%	10%
Less than 25 Years	63%	36%	45%	22%
25-54 Years	48%	34%	17%	16%
55-64 Years	43%	24%	25%	14%
65 Years and Older	15%	16%	37%	57%
Has Children Age 12 or Younger	42%	29%	28%	19%
No Children Age 12 or Younger	38%	32%	21%	15%

Table 6: Characteristics of workers whose labor force status changed between their two CPS rotations
For the first two columns, each row reports the percentage of exiters in that demographic group who returned to the labor force in their follow-up survey. For the second two columns, each row reports the percentage of non-exiters in that demographic group who later left the labor force in their follow-up survey. Everything is reported using the CPS' composite weights.

What types of workers experienced these labor force status changes over their year in the CPS? Table 6 addresses this question. Each entry in the first two columns presents the percentage of exiters of each demographic group who returned to the labor force one year later. All the numbers in the "Pandemic Recession" column are higher than the ones in the "Great Recession" column because of the increased churn, but young workers and workers with children seemed especially likely to come back in the aftermath of the pandemic recession.

The last two columns display the proportion of non-exiters of each demographic group who went on to leave the labor force by the time they rotated out of the CPS. Again, the numbers in the pandemic recession are generally higher, but there are some notable differences. Young and highly educated workers were a lot more likely to leave after one year compared to their counterparts in the Great Recession. The major exception to this pattern was with workers older than 65: they were much more likely to delay their exits in the Great Recession, possibly because they had no obvious reason to do so early on like in the pandemic.

4 Using Transitions to Predict One-Year Ahead Employment Probabilities

The analysis so far has shown how the limited panel dimension of the CPS can be used to track the outcomes of people who lose their jobs in recessions for a year after their job loss. In this section, I use the samples of job-separators in the pandemic recession and in the Great Recession to estimate the probability of being employed in one year for a worker as a function of their current labor force status and demographic characteristics. Although this is a very specific sample of people, they are a group of great interest. They represent people who were in jobs before the recession hit and thus are easier to get back in during the recovery, compared to new entrants or people re-entering after a long time out of the labor force. A benefit of using the CPS in this way is that it provides the most up-to-date picture of labor force transitions in the U.S. economy. Other data sets that enable similar exercises (such as the SIPP) typically take many years to become available. This means that they are of little use to policymakers that seek to understand the latest patterns in labor force participation among people who suffered job losses during the recession and apply them to the current pool of workers without jobs.

4.1 Methodology

The idea here is to estimate logit models for the probability of being employed after one year for both exiters and non-exiters in the pandemic recession and the Great Recession. The samples are the exiters and non-exiters who can be linked between their two stints in the CPS. The outcome variable is derived from the transitions in Table 5 and the explanatory variables are a variety of demographic characteristics and self-reported reasons for why the respondent is out of work.

More formally, let $y_i^N = 1$ if exiter i was employed again in their last month in the CPS. Let $\mathbf{X_i^N}$ be a vector of observable characteristics for this worker. Similarly, let $y_i^U = 1$ if non-exiter i was employed again in their last month in the CPS, and let $\mathbf{X_i^U}$ be a vector of observable characteristics for this worker. I obtain parameter estimates $\widehat{\beta^{\mathbf{N}}}$ and $\widehat{\beta^{\mathbf{U}}}$ from the following:

$$\Pr(y_i^\ell = 1|\mathbf{X_i^\ell}) = \text{logit}^{-1}(\beta^\ell \mathbf{X_i^\ell}) = \frac{1}{1 + e^{-\beta^\ell \mathbf{X_i^\ell}}}, \quad \ell = \{U, N\} \tag{1}$$

$\mathbf{X_i^N}$ contains indicators for gender, education level (less than high school, high school diploma, some college, bachelor's degree or higher), a quadratic in age, and the respondent's reason for being out of the labor force (retired, disabled or ill, in school, taking care of house, or other). $\mathbf{X_i^U}$ is the same, except it replaces the reason for being out of the labor force with the reason for being unemployed (laid off, temporary job ended, job-leaver, re-entrant, and new entrant). This model is estimated separately for the exiters and non-exiters in the pandemic recession and the Great Recession, so in total, four separate times.

Next, I use the estimates $\widehat{\beta^{\mathbf{N}}}$ and $\widehat{\beta^{\mathbf{U}}}$ to calculate the probability of being employed in one year for workers in the CPS in any given month following the recession. The idea is that the patterns of these workers who can be tracked can be applied to the rest of the unemployment or out-of-labor force pool to understand how quickly the rest may go back to work.

To obtain predictions based on the unemployment pool in month t, I focus on workers who are unemployed in month t but can be linked back to their responses from month $t-12$ and were employed then. This step ensures that the sample is most similar to the non-exiters who by construction, lost their job in the past year. Let the vector of characteristics for this group of workers be $\tilde{\mathbf{X_i^U}}$. I apply a similar restriction to the out-of-labor force pool in month t, keeping only workers who were employed in month $t-12$. This restriction also has the benefit of not creating predictions for workers who are very unlikely to go back to work, like people who have long been retired, for whom the patterns of exiters are not informative. Denote these workers' characteristics by $\tilde{\mathbf{X_i^N}}$.

4.2 Results

Table 7 reports the estimates of $\widehat{\beta^{\mathbf{N}}}$ and $\widehat{\beta^{\mathbf{U}}}$ from the job-separators of the pandemic recession. The relative magnitudes reveal which characteristics make a worker more or less likely to be employed again in a year conditional on losing their job and then leaving the labor force (exiters) or staying in the labor force (non-exiters).[4]

The results reveal that after leaving the labor force after a job loss, workers who are retired, have children 12 or younger at home, female, and/or with low education have low probabilities of being re-employed again within a year. If they do not leave the labor force shortly after the job loss, the workers most likely to be re-employed tend to not have children 12 and younger, are female, highly-educated, and had left their old job voluntarily.

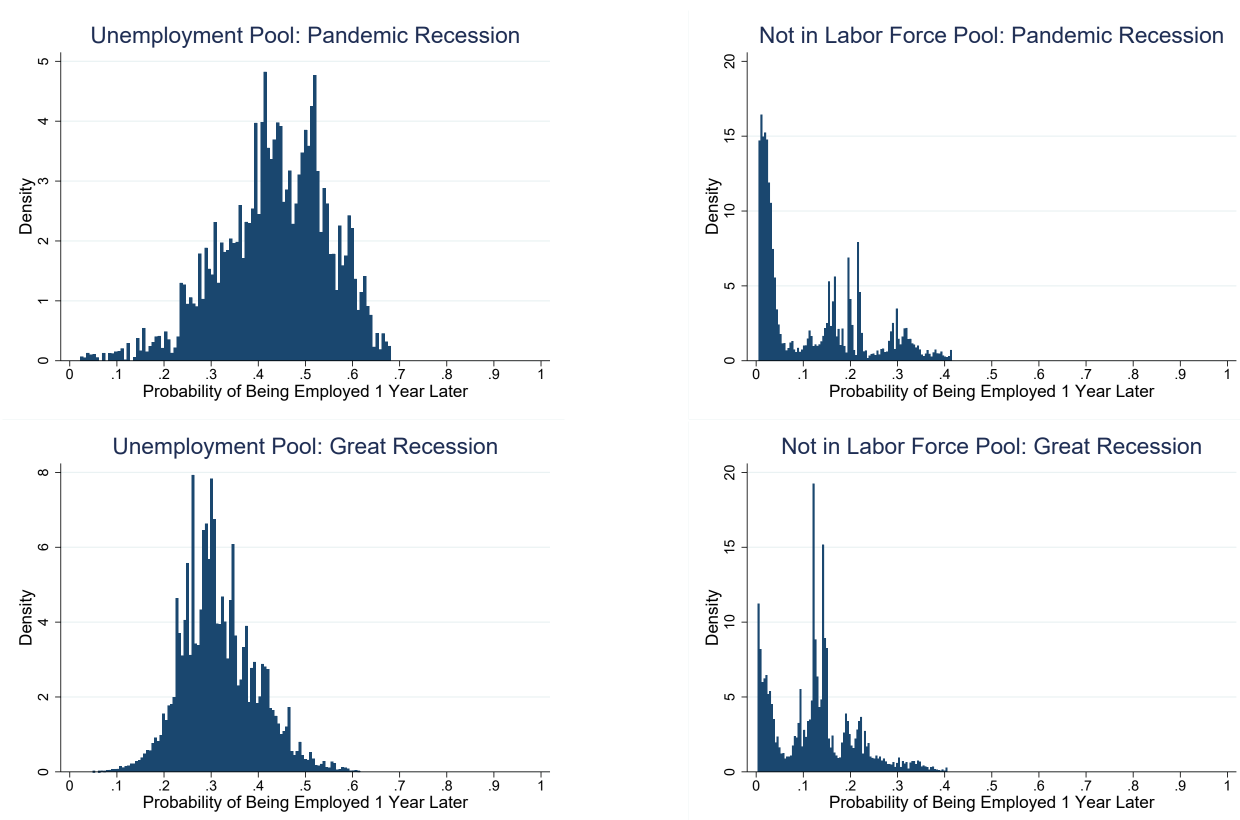
Table 8 reports the same set of results for the Great Recession. The results for workers

[4]Note that these results convey different information than Table 3. That shows the distribution of worker characteristics conditional on being an exiter or non-exiter, where as Tables 7 and 8 enter into the probability re-entering employment in a year conditional on being an exiter or non-exiter, and on characteristics.

who left the labor force are qualitatively similar to their counterparts in the pandemic. For workers who did not leave the labor force, people who had young children or were laid off involuntarily were more likely to go back to employment, in contrast to the pandemic recession.

The results presented so far reflect differences in behavior between the two recessions and between workers who did and did not leave the labor force after their job loss, conditional on the characteristics of those who were out of work. Next, I combine this information with the composition of the out-of-work pools over the two recessions to create a bigger-picture explanation for the different patterns of the employment recovery.

Figure 3: Distribution of One-Year Ahead Employment Probabilities



Densities of the probability of being employed again within one year, based on the estimates $\widehat{\beta^{\mathbf{U}}}$ and $\widehat{\beta^{\mathbf{N}}}$, but applied to the workers in the unemployment and not in labor force pools with characteristics $\tilde{\mathbf{X}}_{\mathbf{i}}^{\mathbf{U}}$ and $\tilde{\mathbf{X}}_{\mathbf{i}}^{\mathbf{N}}$, as described above.

The histograms in Figure 3 represent the distributions of $\Pr(y_i^\ell = 1|\tilde{\mathbf{X}}_{\mathbf{i}}^{\ell})$ in the pandemic recession and the Great Recession, where $\ell = \{U, N\}$.[5] The N to E probabilities are generally

[5]There is a long literature about estimating unemployment hazard rates as a function of various characteristics of the unemployed. This exercise can be thought of as estimating the one-year hazard rate for a very specific group of workers: those who experienced a recent job loss around either the Great Recession or

lower than the U to E probabilities, which makes sense because out-of-the labor force spells tend to last much longer than unemployment spells and are often absorbing states.

Comparing across the two recessions, the U to E probabilities are on average higher during the pandemic recession (44% vs 32%), consistent with the patterns we saw previously in which non-exiters in the pandemic recession were more likely to return to employment after a year. These differences come from both differences in behavior for non-exiters during the two recessions, measured by $\widehat{\beta}^{\mathbf{U}}$ and differences between the composition of the unemployed in the aftermath, measured by $\tilde{\mathbf{X}}_{\mathbf{i}}^{\mathbf{U}}$.

On the other hand, the probabilities for the out of the labor force pools are close on average (12% vs. 13%). This means that, on average in both recessions, workers who left the labor force and had not gone back after a year since their job loss exhibited similar probabilities of going back within the next year. This is despite the fact that exiters returned a lot more quickly after the pandemic recession, as in Table 5. This suggests that the composition of workers in the out-of-labor force pool must have shifted towards workers who were less likely to go back after the pandemic recession and towards workers who were more likely to go back after the Great Recession.

A few caveats are in order regarding this method's usefulness for predicting future employment on the aggregate level. First, the patterns that govern transitions into employment may change beyond the first year after a recession hits. For instance, the pandemic job separators sample was based on observations from February 2020 to June 2021, which was an unusual span of 16 months: it is not obvious that people who were still out of work beyond that period would behave like workers who lost their jobs in 2020. In addition, the estimates here only apply to workers who had a recent job loss. However, employment growth can also come from new labor force entrants or people who have been out of work for longer than a year. The value-added of this method comes from the use of the limited panel dimension of the CPS to get real-time longer-horizon pictures of employment status transitions and distinguishing differences in the behavior of those who lost their jobs from their characteristics. This distinction sheds some light on the comparison of the employment recovery after different recessions.

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the pandemic recession.

5 Conclusion

In this paper, I investigated the patterns in labor force transitions of workers who lost their jobs during the pandemic recession and in the Great Recession. I used the panel dimension of the CPS to group workers by their labor force status after 4 months and followed up on them one year later to see how this status further evolved. I find that in both recessions, workers who left the labor force shortly after their job less (exiters) tended to be more female, less educated, and older. The age distribution was especially skewed older during the pandemic recession. Another key difference between the two recessions was the persistence of labor force statuses: in the aftermath of the pandemic people who left the labor force were more likely to come back than in the Great Recession and vice-versa. The subsequent employment recoveries depend on the composition of individuals who are out of work as well as their behavior: measuring and combining these two objects can provide up-to-date indications of where the labor market may go in the short-term.

	(1) Exiters	(2) Non-exiters
Retired	-1.988***	
	(0.00374)	
Disabled or Ill	-0.644***	
	(0.00415)	
In School	-0.283***	
	(0.00298)	
Taking Care of House	-1.000***	
	(0.00300)	
Has Children Age 12 or Younger	-0.133***	-0.336***
	(0.00225)	(0.00366)
Female	-0.129***	0.0379***
	(0.00146)	(0.00292)
High School Diploma	0.348***	0.0969***
	(0.00209)	(0.00443)
Some College	0.428***	0.388***
	(0.00189)	(0.00467)
Bachelor's or Higher	0.421***	0.510***
	(0.00231)	(0.00508)
Age	0.0565***	0.109***
	(0.000270)	(0.000618)
Age × Age	-0.000877***	-0.00151***
	(0.00000293)	(0.00000735)
Laid=Off		-0.0257***
		(0.00457)
Temporary Job Ended		-0.356***
		(0.00544)
Job Leaver		0.197***
		(0.00517)
Re-Entrant		-0.440***
		(0.00411)
New Entrant		-0.581***
		(0.00659)
Constant	-1.680***	-1.929***
	(0.00578)	(0.0126)
Observations	11874	742

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Logit estimates: pandemic recession
This table shows the estimates of $\widehat{\beta^{\mathbf{N}}}$ in the first column and $\widehat{\beta^{\mathbf{U}}}$ in the second column. The base categories are "Other" for reason out of the labor force or unemployed, and "less than high school degree" for education. All results used the CPS' composite weights.

	(1) Exiters	(2) Non-exiters
Retired	-1.956***	
	(0.000627)	
Disabled or Ill	-1.139***	
	(0.000854)	
In School	-0.573***	
	(0.000497)	
Taking Care of House	-1.083***	
	(0.000501)	
Has Children Age 12 or Younger	-0.0782***	0.135***
	(0.000357)	(0.000551)
Female	-0.173***	0.181***
	(0.000264)	(0.000472)
High School Diploma	0.285***	0.0614***
	(0.000352)	(0.000645)
Some College	0.417***	0.281***
	(0.000329)	(0.000684)
Bachelor's or Higher	0.531***	0.587***
	(0.000393)	(0.000780)
Age	0.0685***	0.0172***
	(0.0000451)	(0.000101)
Age × Age	-0.00101***	-0.000424***
	(0.000000501)	(0.00000123)
Laid=Off		0.475***
		(0.000696)
Temporary Job Ended		0.0102***
		(0.000787)
Job Leaver		0.384***
		(0.000892)
Re-Entrant		-0.201***
		(0.000630)
New Entrant		-0.304***
		(0.00109)
Constant	-2.077***	-1.074***
	(0.000943)	(0.00194)
Observations	578231	39303

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Logit estimates: Great Recession
This table shows the estimates of $\widehat{\beta^{\mathbf{N}}}$ in the first column and $\widehat{\beta^{\mathbf{U}}}$ in the second column. The base categories are "Other" for reason out of the labor force or unemployed, and "less than high school degree" for education. All results used the CPS' composite weights.

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