Quits, Layoffs, and Labor Supply

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Abstract

We develop a framework in which the circumstances of an employment separation (quit or layoff) and destination (unemployment or non-participation) inform estimates of labor supply elasticities and how they change over time. The participation choices of laid off workers critically shape our analysis. In the model, laid off workers who exit the labor force are close to the margin of re-entry. Using monthly CPS data, we compute labor market transition rates by destination and reason and document that over a third of laid off workers exit the labor force and this share is procyclical. Combining data and theory we find that 25-30% of layoffs selectively target workers near the margin of participation. We conclude by demonstrating how these flows can be used to track movements in labor market slack not captured in the unemployment rate.

1 Introduction

The elasticity of the extensive margin of labor supply is a critical input into Macroeconomic analysis. It helps determine how changes in policy impact labor markets and, subsequently, the economy as a whole. It also affects how economists understand movements in Macroeconomic aggregates like employment, unemployment, and non-participation over the business cycle. Labor market flows between employment, unemployment, and non-participation contain critical information about labor supply elasticities that traditional aggregate metrics often mask. We argue that the distribution of employment surplus—the net value individuals place on working versus not working—fundamentally shapes both observed labor market flows and unobserved labor supply elasticities. Workers with low but positive employment surplus constitute a "marginal

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workforce" whose labor supply decisions are highly responsive to economic conditions. These workers drive much of the cyclical volatility in participation rates and unemployment, creating complex dynamics that traditional approaches struggle to capture.

Our key insight is that labor supply decisions after a layoff offer a uniquely valuable window into this marginal workforce. A worker who separates due to a layoff would likely have continued working in their previous job, indicating that they operated with positive but potentially small employment surplus. The labor supply decisions of laid-off workers over the business cycle have not been studied much but, we argue, carries perhaps the most information about the extensive margin of labor supply. The majority of prior studies have used data only on labor market flows by destination and often have assumed employment to unemployment (EU) flows to be layoffs and employment to non-participation (EN) flows to be quits. We instead construct direct measures of labor market flows by destination and reason, quit or layoff, and find that 35% of laid-off prime-age workers exit the labor force rather than search for new employment. This fact suggests that these workers were near the margin of participation. Their subsequent choices—whether to search in unemployment or exit to non-participation—reveal valuable information about labor supply elasticities across the workforce.

The distribution of employment surplus is not the end of the story in understanding the extensive margin of labor supply. We must also understand what factors would impact the net value of working versus not working, particularly for marginal workers. The wage elasticity is only one of many factors. Responses to changes in non-employment income, the difficulty of finding a job, or unemployment benefits; and how these all move over the cycle; is also critical. And more so for marginal workers since individuals firmly attached, or detached, from the labor force are less responsive to these changes. This emphasizes the desire for a structural model of labor supply since a single parameter cannot capture all of these effects. It also motivates our use of the business cycle as one source of validation of our model- can we capture how participation decisions change over the cycle without directly targeting them? This is a good type of test of the model since we are interested in applying it to business cycle analysis.

We develop a framework incorporating both selective and non-selective quits and layoffs, where the degree of selection depends on the employment surplus distribution. Quantitatively, we find that around one-third of layoffs selectively target workers with low employment surplus, and these workers make up a disproportionate share of the unemployed. This selection is crucial for accurately interpreting labor market flows, as it implies that the behavior of laid-off workers is not representative of the entire workforce but provides vital information about the marginally attached.

Our model successfully reproduces key cyclical patterns in the data, particularly the countercyclical nature of labor supply after layoffs. During recessions, the share of laid-off workers exiting the labor force decreases substantially, with at most 25% of this decline attributable to changes in demographic composition. This countercyclical labor supply amplifies unemployment fluctuations, with our calculations showing that holding participation decisions constant would

reduce cyclical unemployment volatility by 25-30%.

This framework yields several novel insights. First, factors affecting labor supply generate surprising movements in aggregate variables. For instance, a pure positive wealth effect that decreases labor supply will increase unemployment through higher churning of marginal workers, despite reducing overall employment. Second, unemployment insurance extensions primarily operate through participation choices of laid-off workers rather than search intensity of the unemployed. Third, marginal workers' labor supply decisions are key to understanding why unemployment overstates labor market slack during recessions.

We realize policy makers sympathetic to our findings may prefer a less precise but more practical tool to track the contribution of participation decisions to the unemployment rate. For this reason we construct a "participation-neutral" unemployment series that strips out the effects of changing participation decisions and layoff selection. This series reveals that actual unemployment often leads our counterfactual measure, suggesting that participation choices respond to increase unemployment before demand conditions deteriorate. This was precisely the case in the unemployment dynamics 2022-2025 where demand factors contributed little to the steady renormalization of unemployment rates until mid-2024.

The paper proceeds as follows: In the next section we will highlight the relation of our paper to the existing literature; section 2 details how we use CPS monthly data to construct labor market flows by destination and reason and provides a number of robustness checks; section 3.1 gives an overview of the constructed data series; in section 4 we will introduce our model and provide quantitative results which help inform estimates of labor supply elasticities in sections 5 and 6; the last two sections of the paper demonstrate the importance of the flows to track unemployment dynamics and understand different recessions.

Literature Review Our paper contributes to the empirical and theoretical literature that examine labor market flows between employment, unemployment, and non-participation.

Labor Market Flows and Transitions. A rich literature following work by Abowd and Zellner (1985) and Blanchard and Diamond (1990) has analyzed gross flows and transition rates between the labor market states. This body of research aims to understand the evolution of labor market flows across time, cross-sections, and business cycles. Shimer (2012) utilizes flow data on employment-unemployment transitions to construct job-finding and job-loss probabilities, assessing their relative importance to unemployment rate fluctuations. Similarly, Elsby et al. (2015) and Elsby et al. (2019) employ data on flows between employment, unemployment, and non-participation to analyze the contribution of each flow to labor force participation rate fluctuations. Others, such as Garibaldi and Wasmer (2005), Krusell et al. (2017), Cairó et al. (2022), and many more have used gross flows data to inform macroeconomic models of labor markets.

Marginal Workers and Labor Force Attachment. Our focus on marginal workers connects to literature examining labor force attachment. Jones and Riddell (1999) and Jones and Riddell (2006) identify a group of non-employed individuals who report wanting work but are not actively searching. This "waiting" group has transition rates to employment that are higher than other non-participants but lower than the unemployed. Flinn and Heckman (1983) test whether unemployment and non-participation are behaviorally distinct states and find that unemployed workers have significantly higher job-finding rates than non-participants. Building on this, Krueger et al. (2014) examine the long-term unemployed and find that many become marginally attached to the labor force, cycling between active search and non-participation.

Our analysis of marginal workers also relates to Barnichon and Figura (2015), who demonstrate that compositional changes in the unemployed population—including shifts in labor force attachment—substantially affect aggregate matching efficiency. Similarly, Hornstein et al. (2014) develop a framework where non-participants' heterogeneous labor force attachment influences aggregate job-finding rates.

Selection in Quits and Layoffs. Gibbons and Katz (1991) offer empirical evidence for selection in layoffs, showing that workers displaced by plant closings face shorter unemployment durations and smaller wage losses than those laid off for other reasons. More recently, Mueller (2017) finds that laid-off workers have substantially lower pre-displacement wages than those who quit, supporting the selection hypothesis. Chodorow-Reich and Karabarbounis (2016) document cyclical patterns in the opportunity cost of employment, and Mui and Schoefer (2021) show that selection into unemployment varies systematically over the business cycle.

Unemployment Dynamics and Slack. Our work contributes to understanding unemployment movements not directly related to labor market slack. Ahn and Hamilton (2021) decompose unemployment fluctuations into flows related to entry, exit, and duration, finding significant variation unrelated to aggregate demand.

We contribute to the "unemployment volatility puzzle" literature pioneered by Shimer (2005) and further explored by Hagedorn and Manovskii (2008), Ljungqvist and Sargent (2017), and Mitman and Rabinovich (2019). We contribute by showing that layoffs are more frequent and less cyclically volatile than flows from employment to unemployment, and that labor supply appears to be countercyclical on the margin.

Mukoyama et al. (2018) document countercyclical search intensity, suggesting that labor supply behavior—rather than just demand factors—shapes unemployment fluctuations. The role of unemployment insurance in distorting unemployment measures of slack has been investigated by Rothstein (2011) and Farber and Valletta (2015), who find that UI extensions modestly increase unemployment duration but primarily through reduced labor force exits rather than reduced job finding. This aligns with our finding that marginal workers are more likely to report as unemployed when benefits are more generous.

2 Data

2.1 Data source

We use monthly data from the Current Population Survey (CPS) basic monthly files (BMS) from January 1978 to December 2024. The CPS is a rotating panel survey of approximately 60,000 households, sponsored jointly by the U.S. Census Bureau and the U.S. Bureau of Labor Statistics (BLS). While primarily designed for cross-sectional analysis, the CPS's rotating panel structure allows us to match individuals across consecutive months, enabling the computation of month-to-month labor market transitions.

2.2 Methodology

We classify flows from employment to both unemployment and non-participation by reason of separation. The goal is to newly classify four distinct flows:

- Employment to unemployment due to a quit (EUQ)
- Employment to unemployment due to a layoff (EUL)
- Employment to non-participation due to a quit (ENQ)
- Employment to non-participation due to a layoff (ENL)

The CPS short panel follows a 4-8-4 structure which allows us to observe individuals for 4 continuous months, followed by an 8-month break, and then another 4-month period. Due to the option of observing individuals for two consecutive months, researchers have frequently used the CPS to compute gross flows and transition rates (Abowd and Zellner (1985), Shimer (2012), Elsby et al. (2015), and many others). Most commonly, researchers have computed flow rates between the three labor market states employment (E), unemployment (U), and non-participation (N) to create a matrix of nine flow rates as shown in Table 1. The flows have been used to understand fluctuations in job finding and job loss rates, or to study the evolution of stocks such as the unemployment rate or employment-population ratio using a stock-flow analysis.

From	To		
	E	U	N
E	f_{EE}	f_{EU}	f_{EN}
U	f_{UE}	f_{UU}	f_{UN}
N	f_{NE}	f_{NU}	f_{NN}

Table 1: Standard approach of flow rates in the CPS

The standard approach often interprets flows between employment and unemployment as layoffs and flows between employment and non-participation as quits. We show this convention

is not accurate. Flows into both unemployment and non-participation consist of both layoffs and quits.

We follow the standard methodology of computing gross flows with an important difference: we compute flow rates from employment to both unemployment and non-participation *by reason of separation*. Thus, we not only get employment to unemployment (EU) and employment to non-participation (EN) rates, but also employment to unemployment due to a quit (EUQ), employment to unemployment due to a layoff (EUL), employment to non-participation due to a quit (ENQ), and employment to non-participation due to a layoff (ENL), such that

$$f_{EU} = f_{EUQ} + f_{EUL}(+f_{EUO}) \tag{1}$$

$$f_{EN} = f_{ENQ} + f_{ENL}(+f_{ENO}) \tag{2}$$

Few papers distinguish separations into non-participation by quits and layoffs. Table 2 shows the contribution of this distinction to the standard approach of using the CPS to calculate flows. While this seems like a minor change, it allows researchers to use this data in important ways, such as (i) analyzing what fraction into unemployment and non-participation is due to a layoff vs. a quit; and importantly (ii) accurately observing total quits and total layoffs into non-employment, i.e

$$\text{Quits} = f_{EUQ} + f_{ENQ} \tag{3}$$

$$\text{Layoffs} = f_{EUL} + f_{ENL} \tag{4}$$

From	To		
	E	U	N
E	f_{EE}	$f_{EUQ} + f_{EUL}$	$f_{ENQ} + f_{ENL}$
U	f_{UE}	f_{UU}	f_{UN}
N	f_{NE}	f_{NU}	f_{NN}

Table 2: Our contribution to the standard approach

2.3 Decomposition into Layoffs and Quits

2.3.1 Unemployment

We are going to keep this section brief, since the distinction of a layoff or quit into unemployment in the CPS has been used in previous literature. In CPS IPUMS (Flood et al. (2023)), the variable to classify a separation into unemployment as a quit, layoff, or other is readily available and harmonized for all sample months. The survey asks all unemployed individuals why they became unemployed and distinguishes between workers who had lost jobs (due to temporary layoff, involuntary job loss, or ending of a temporary job), those who had quit jobs, those who were re-entering the labor force after an extended absence from the work force, and those who were seeking their first jobs (new entrants). We use these answers and classify a separation into unemployment as a layoff or quit as follows:

- Layoff: `Job loser/on layoff`, `other job loser`, `temporary job ended`
- Quit: `Job leaver`

2.3.2 Non-participation

Expanded questions on reasons nonparticipants left the labor force were added to the CPS in 1967 following recommendations in a 1962 report by the President's Committee to Appraise Employment and Unemployment. Subsequent research has argued that the answer to these questions is informative about future labor supply. For example, Deutermann Jr (1977) finds that nonparticipant prime age men who left their last job due to economic reasons or layoff are more likely to expect to return to the labor force within a year than those whose job ended for other reasons.[1]

The variable coding reason for leaving the last job is not easily available on CPS IPUMS for non-participants, those not actively searching for a job. This instead requires work with the raw or non-harmonized CPS data. The next paragraphs will outline the process to distinguish separations into non-participation by reason of separations, i.e layoff or quit.

The question asked to individuals to inquire their reason of non-participation has slightly changed over the years, but is a close variant of:

`Why did ... leave that job?`

Before 1994, the question is asked to all non-participants who fulfill the following criteria: (1) currently not in the labor force, but worked for pay within the last five years, and (2) in the outgoing rotation group (ORG), which means the individuals are in month of sample 4 or 8. After 1994, the question is asked to individuals who (1) are currently not in the labor force, but worked for pay within the last 1 year, and (2) are in the outgoing rotation group (ORG). We restrict our sample to anyone who has worked in the past 12 months for the entire time period.[2] The possible answer choices to the question have changed over time and we harmonize the answers across all months and years and define a layoff or quit as follows:

- Layoff: `Temporary, seasonal or intermittent job completed`, `Slack work/business conditions`
- Quit: `Personal or family (including pregnancy)`, `Return to school`, `Health`, `Retirement or old age`, `Unsatisfactory work arrangements`

There are additional separations where the question asking the reason why the last job ended is not asked. These include, for example, retirements. We label these separations as other, but

[1] See Schwab (1974) for men age 58-63.

[2] In theory, since we are looking at individuals who make a transition from employment in the previous month to non-employment in the current month, all individuals should fulfill this requirement, but a very small number reports not having worked in the past 1 year and we do not include them.

the reader should think of them as "unknown" since these separations such as retirements can certainly be preceded by an involuntary layoff as well as a planned quit.

2.4 Linking over Time & Variable Construction

We employ linking and variable construction methodologies in order to come as close as possible to the construction used in IPUMS.

We follow Madrian and Lefgren (1999) when linking individuals across two consecutive months and verify match quality based on sex and age.[3] This method ensures that when we aggregate our flows to broad E-N and E-U rates, we recover the same transition probabilities that would be computed from IPUMS harmonized CPS data. In the CPS, the unique household and person identifier corresponds to the physical address of the individuals and therefore being able to match an individual does not necessarily imply matching the same individual but rather two individuals living at the same physical address in subsequent months. Personal characteristics, such as age and sex, which do not change over two subsequent months (or by not more than one in the case of age) and help to reduce false matches. Once we matched individuals across two subsequent months based on the above criteria, we use the matched data to compute the numbers of individuals in each labor market state in a given month.

For all labor market states with the exception of layoffs and quits into N, we simply count how many individuals are in each labor market state.[4] Since only individuals in the outgoing-rotation groups are asked about their reason for non-participation, we only have a subset of individuals responding to the question. We assume that the distribution of individuals by reason for non-participation is the same across all individuals in that month and use the share of quits and layoffs from the outgoing rotation groups multiplied by the total E-to-N transition rate to compute the number of layoffs for all other individuals making an employment to non-participation transition. Thus, we obtain flows numbers for individuals transitioning due to a layoff from E to N, and individuals transitioning due to a quit from E to N.

Once we have the numbers of individuals in each labor market state we compute flow rates between the different states. We compute the transition rates as the number of individuals with labor market state I in the previous month and labor market state J in the current month relative to all individuals with labor market state I in the previous month, such that

$$f_{IJ} = IJ_t / I_{t-1} \tag{5}$$

where $I = \{E, U, N\}$ and $J = \{E, U, N, UL, UQ, NL, NQ\}$ to obtain flow rates as shown in table 2.

Lastly, we seasonally adjust the data using the X-13ARIMA-SEATS seasonal adjustment program provided by the U.S. Census Bureau.

[3] We are not matching based on race since the answers have to this question has changed drastically over time.

[4] Consistent with best practices advise by IPUMS, we do not use weights in constructing the flow series.

2.5 Robustness

DeNUNifying the Data One common concern when linking individuals or household in the CPS data is that unemployment and non-participation are misclassified. Different methods have been proposed to address the classification errors in recorded labor market states to correct for potentially spurious transitions. One adjustment strategy was proposed by Abowd and Zellner (1985) which adjusts transitions by relying on the usage of the re-interviewed households and individuals. Since this method has been documented to have short-comings, we will use the deNUNification method developed in Elsby et al. (2015) and recode frequent unemployment to non-participation cyclers. In particular, we remove all individuals which make one of the following labor market transitions: non-participation to unemployment to non-participation (NUN), or unemployment to non-participation to unemployment (UNU).

Table 3 shows that excluding these potentially misclassified transitions has no effect on the main statistics in this paper. The averages of the important timeseries are unchanged and the correlations with the unemployment rate are statistically identical.

Statistic	Main Data	DeNUNified Data
Averages		
Quits	0.85	0.84
Layoffs	1.27	1.27
Total Separations	2.11	2.11
Layoffs share N	0.35	0.35
Quit share N	0.85	0.85
EN	1.55	1.54
EU	1.09	1.09
Correlation with Unemployment Rate		
Quits	-0.4642	-0.4588
Layoffs	0.8343	0.8157
Total Separations	0.7219	0.7077
Layoff share N	-0.6364	-0.6256
Quit share N	-0.1560	-0.1296
EN	-0.0611	-0.0438
EU	0.8258	0.8029
Corr(EQ,EL)	-0.4518	-0.4486

Table 3: Comparison with deNUNified data

Choice of moving average filter In the main text, all timeseries were smoothed using a 6-month centered moving average smoother. We will show in the following that the choice of the smoothing parameter as well as whether it is centered or not does not change the data in any significant way. The following figures plot our layoff and quit series for four different smoothing techniques. 6-month centered is the standard we use in the main text, which means we include

the previous 3 months, the current month, and three forward terms. 4-month centered and 8-month centered are constructed equivalently. 3-month lag only includes the previous 3 month as well as the current month but does not use any lead months.

We see that the different lengths really only affect the pandemic period, as it was so short but so extreme. It does not seem to affect other recessions or expansions. We checked including both lags and leads versus only including leads to make sure the most recent data are not significantly affected by the moving average filter. As we can see in the following figures, we see no difference between the two methods for the most recent observations.

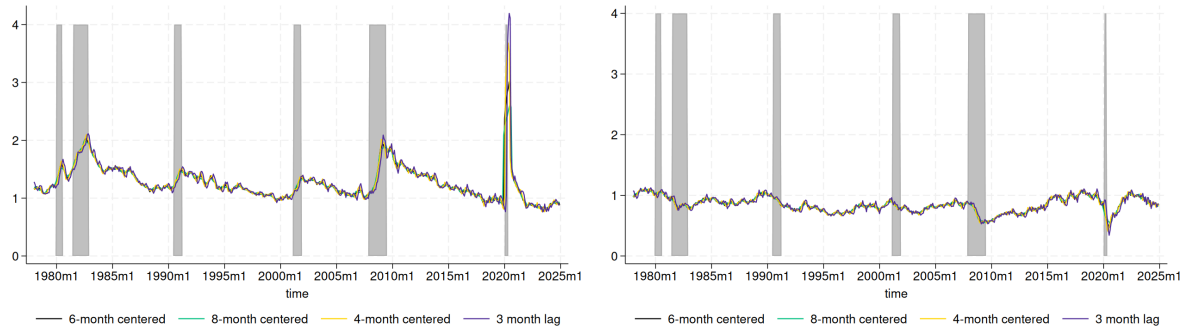


Figure 1: Comparison of moving-average filter for quit and layoff series

Layoffs from permanent vs. temporary jobs When we harmonize the data to compute the layoff rate, the possible answer choices of unemployed and non-participating individuals in the CPS can be grouped in two categories: layoffs from a temporary job or from a permanent job. The former category includes everyone who reports losing their job because a temporary, seasonal, or intermittent job ended. The latter includes all other job losers.

Figure 2 shows that the business cycle pattern of layoffs is driven by layoffs from permanent jobs and the majority of layoffs are from permanent jobs. Interestingly, layoffs from temporary jobs are mildly procyclical, i.e. decline during periods when unemployment is high.

Because layoffs from permanent jobs are strongly countercyclical and layoffs from temporary jobs are mildly procyclical, recessionary periods are charaterized by an increase in the share of layoffs from a permanent job.

Reason for non-participation vs. activity in non-participation Our main data contribution in this paper is to be able to separate all employment to non-participation flows by reason, i.e. whether it was due to a layoff or quit, and then subsequently compute total layoff and quit series from employment.

One variable that is harmonized from 1994 onwards, readily available from CPS IPUMS, and has been used as a proxy for the layoff/quit decision by other researchers asks individuals about their activity in non-participation. We will show in the following that the answers to this variable do not give any indication as to whether the individual has lost or quit their most

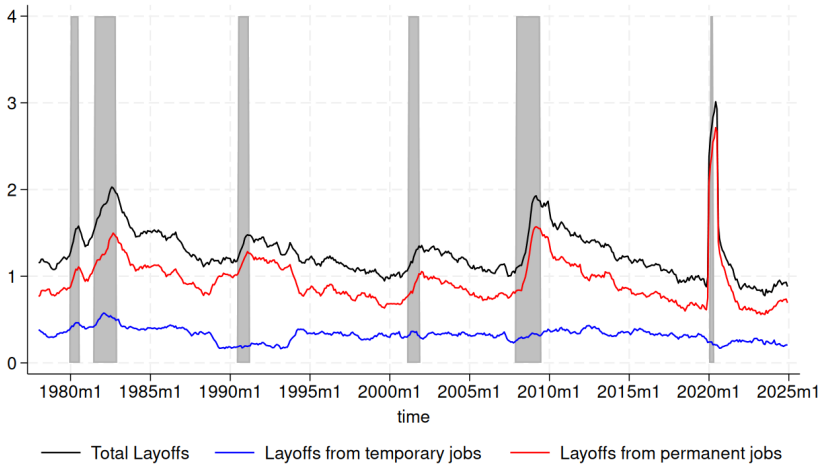


Figure 2: Layoffs from temporary vs permanent jobs

Activity	Layoffs into N	Quits into N
Disabled/Ill	6%	12%
School	8%	18%
Family	49%	52%
Other	33%	15%
Unknown	4%	3%

Table 4: Activity in non-participation by reason for non-participation

recent job.[5]

All individuals who are currently non-participating are asked about their major activity while being not in the labor force. The possible answers are disabled, ill, in school, taking care of house or family, and other. We grouped disabled and ill together and added a category unknown for all individuals for whom the answer was missing. Since the data is only available starting in 1994, we restrict our sample to only include months starting in 1994. Table 4 shows that half of all individuals currently not in the labor force list taking care of their house or family as their major activity. This is true for both individuals who responded having lost their job and quit their job. While there are some differences in the other categories among job losers and quitters, there is no correlation between the reason for leaving employment into non-participation and the major activity after leaving employment into non-participation.

[5]The variable is called nilfact and available for everyone 15+ years of age on CPS IPUMS from 1994 onwards. For this analysis we will restrict our sample to the working-age population only because the original unharmonized variable only includes people up until 49 years of age since it's not meant to include retired individuals.

2.6 Validation with Panel Study of Income Dynamics (PSID) and Survey of Income Programs and Participation (SIPP)

Our classification of flows in the CPS data produces results that are similar to other commonly studied panel data sets such as the PSID and SIPP. Both of these datasets also include quits and layoffs without an unemployment spell and help to understand the scope of these events that we are unable to classify in the CPS but appear in the JOLTS.[6]

Since the three household surveys cover different time periods and are asked at different frequencies, we will adjust the CPS, which covers the longest time period and the highest frequency, to be comparable to the other two surveys. The numbers in Table 5 derived for the CPS are for the years 2002-2023. The PSID sample spans the years 2002-2018.[7] For comparison to our main CPS sample, we restrict to prime age only. We use the latest available data for the SIPP which covers the years 2019 to 2023 and is at monthly frequency.

The top three rows of Table 5 show the share of quits by destination and the bottom three rows show the share of layoffs by destination. We can see that the CPS and PSID produce very similar numbers. The SIPP is close as well and produces similar business cycle pattern but covers a shorter time period. We focus our comparison on the PSID and CPS since they consider comparable time periods and include both expansionary and recessionary times.

Looking at quits, we see that in both surveys around 87-88% of the flows to non-employment go to non-participation and this share changes little in recessions. Looking at layoffs, we see that 32-35% of the flows to non-employment go to non-participation and that this share declines by between one fourth to one third in recessions.

	Total Flows			to Non-Employment				
	PSID		SIPP	CPS		PSID		SIPP
	All	Recessions	All	All	Recessions	All	Recessions	All
QN	0.452	0.547	0.416	0.866	0.854	0.882	0.874	0.791
QU	0.060	0.079	0.110	0.133	0.146	0.118	0.126	0.209
QE	0.507	0.391	0.474					
Q	1	1	1	1	1	1	1	1
LN	0.248	0.199	0.241	0.359	0.310	0.320	0.242	0.389
LU	0.527	0.623	0.373	0.643	0.689	0.680	0.758	0.611
LE	0.225	0.179	0.387					
L	1	1	1	1	1	1	1	1

Table 5: Share flowing to Destination: (N)on-Participation, (U)nemployment, and directly to another (E)mployer by type of flow: (Q)uit or (L)ayoff. PSID: 2002-2018; SIPP: 2019-2023

Table 5 also shows what we miss in the CPS data. We miss 50% of quits which flow directly to a new employer and 22% of layoffs that flow directly to a new employer. Both of the shares

[6]The PSID and SIPP are smaller samples and are released with a lag which is why we focus on the CPS.

[7]The PSID is biennial during this time and the results are similar if we restrict to only responses for the past year as a check on recall error.

flowing directly to a new employer decline in recessions.

2.7 Prime-age vs. Working-age population

All data results and statistics in the main text are for the prime-age population, those between 25 and 55 years old, only. We provide all results for the working-age population, those 16 years and older, in the appendix. We focus on the prime-age population because our main focus is on the labor supply decisions of marginal workers that are not necessarily driven by education or retirement choices.

3 Motivation

3.1 An Overview of Quits and Layoffs

Figure 3 plots the full time series of the monthly quit and layoff rates to non-employment from 1978-2024 as a percent of total employment for the prime-age population (25-55 years old) in the United States. We see that the layoff rate generally exceeds the quit rate but the two converge

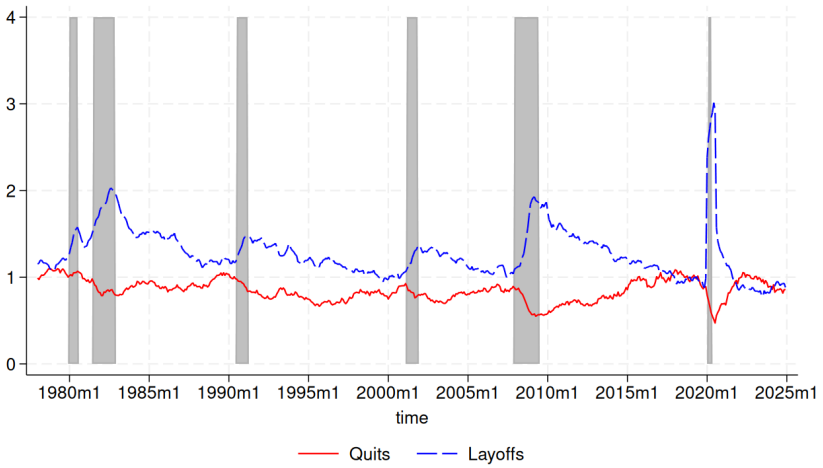


Figure 3: Monthly Quit and Layoff Rates (as a percent of employment) (Monthly seasonally-adjusted data and 6-month centered moving average)

during recessionary periods. On average, 40% of all separations to non-employment are quits and 60% are layoffs. In the average month, about 0.9% of all workers quit their job. Both series display clear business cycle patterns which we will discuss in more detail in section 3.2.

Figure 4 plots flows from employment to non-employment by destination: unemployment or non-participation. These are the standard flows considered in prior research studying the cyclical properties of the labor market. Traditionally, employment to unemployment (EU) flows have been interpreted as layoffs, and flows from employment to non-participation (EN) as quits. Comparing the EU and EN rates to our quits and layoffs series, we see that flows to non-participation exceed those to unemployment whereas layoffs exceed quits. Of all workers separating to non-employment each month, 60% move to non-participation and 40% move to unemployment,

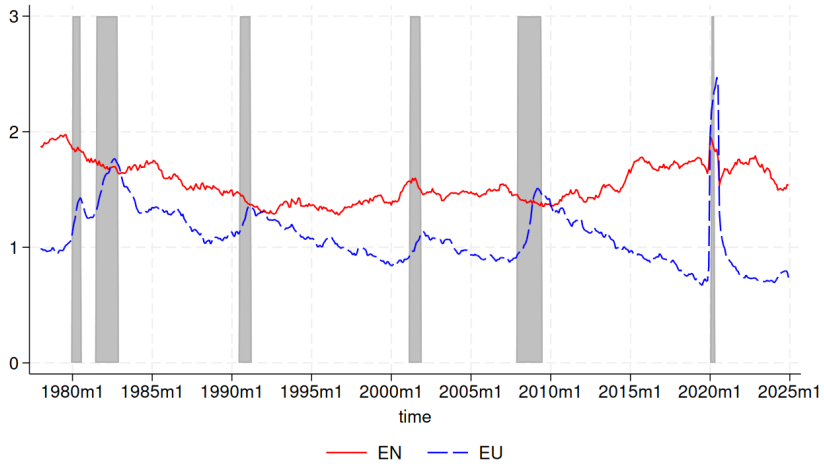


Figure 4: Flow Rates from Employment to Non-Participation (EN) and to Unemployment (EU) (as a percent of employment) (Monthly seasonally-adjusted 6-month centered moving average data)

whereas our data shows that about 40% are quits and 60% are layoffs. Comparing Figure 4 and Figure 3, it is obvious that these flows are related but not the same.

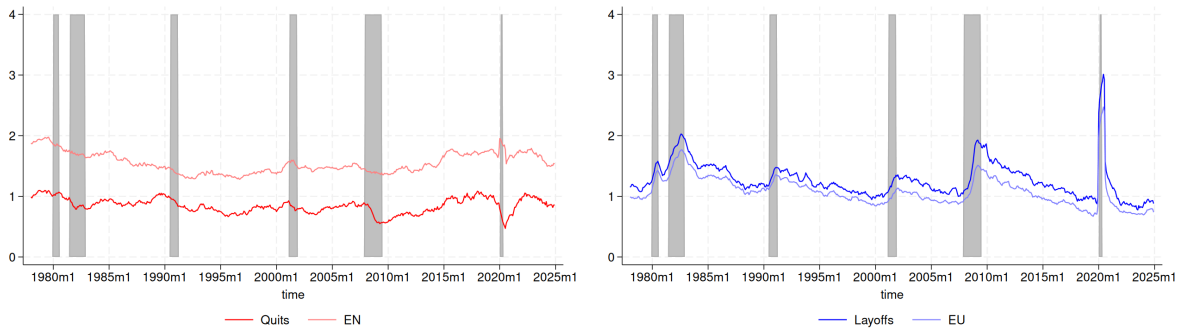


Figure 5: Comparison of Quits and EN flows (left) and Layoffs and EU flows (right)

Notably, figure 5 shows that the rate of EN flows is around 80% higher at a monthly frequency than the quit rate. There are also clear cyclical differences, with the quits rate more volatile than the EN transition rate. Additionally, our layoff series exceeds the EU transition rate by about 20%. Figures 6 and 7 allude to the reason for these discrepancies. A significant share of workers choose non-participation after a layoff, which contributes to EN flows being significantly larger than quits in the data. This share decreases during recessions leading EN flows to be less volatile than the the other rates.

Specifically, 35% of laid off workers move to non-participation in any given month. For workers who quit, the share who move to non-participation is much higher at over 85%. Clearly, not all movements to non-participation are due to a quit decision as was previously assumed. This means that classifying flows from employment to non-participation as quits understates the level of lay-offs by 35%, which will be especially important for estimating labor supply elasticities and considering business cycle fluctuations.

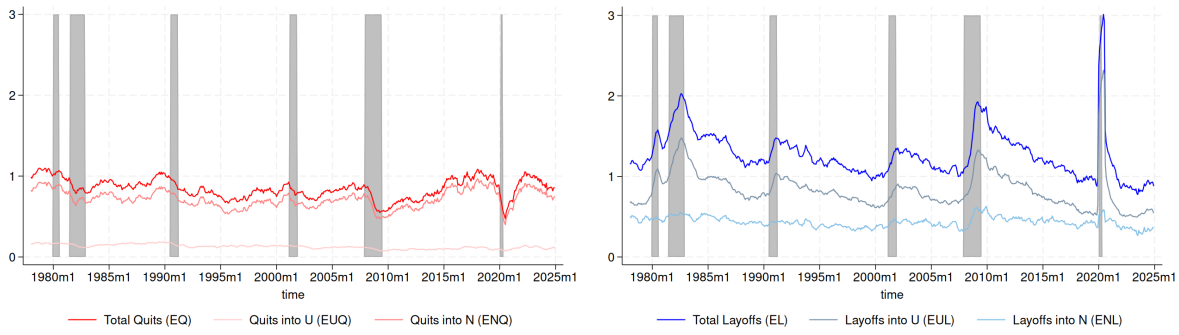


Figure 6: Monthly Quits (left) and Layoffs (right) by Destination

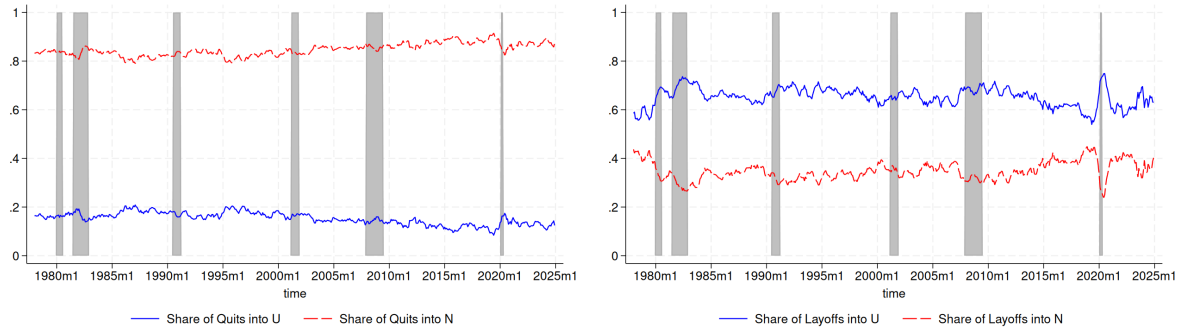


Figure 7: Share of Quits (left) and Layoffs (right) by Destination

3.2 Business Cycle Statistics

The flow rates shape business cycle properties of stocks, such as the unemployment rate or employment-population ratio, and also help us understand how labor supply choices vary over the business cycle and shape labor supply elasticities.

We start by illustrating how quits and layoffs evolve over the business cycle in Table 6.

Statistic	Quits			Layoffs			Total sep.
	to U	to N	Total	to U	to N	Total	to (U+N)
Corr(x, y)	-0.1565	-0.4830	-0.4642	0.8175	0.7504	0.8343	0.7219
SD(x)/SD(y)	0.0192	0.0845	0.0913	0.2193	0.0632	0.2745	0.1492

Table 6: Business cycle correlations of each flow (x) with the unemployment rate (y)

The first row of Table 6 shows the correlation of each flow rate with the unemployment rate. The table confirms that quits and layoffs move in opposite directions over the business cycle as shown graphically in Figure 3. Table 7 shows that quits and layoffs are negatively correlated over the entire observation period.

For comparison, EU and EN flows do not show a strong correlation as the correlation coefficient between the two is 0.0130. Quits decrease in times when unemployment increases, and thus, are procyclical. Layoffs, on the other hand, are countercyclical and increase when

Statistic	
Corr(EQ, EL)	-0.4581
SD(EQ)/SD(EL)	0.3324

Table 7: Business cycle correlations of quits and layoffs

the unemployment rate is high. Quits into both unemployment (U) and non-participation (N) decrease in recessions but quits into N are the main contributor for the overall decline in quits. Layoffs into unemployment increase more than layoffs into non-participation in a recession which is important to understand the finding that the share of laid off workers exiting the labor force declines in recessions.

Table 8 shows the business cycle properties of EU and EN flow rates and compares them with the statistics for layoffs and quits which are taken from Table 6. The first two columns compare EU flow rates with our layoff series and we see that the cyclicality of these two series is similar in magnitude and countercyclical. This is a lucky coincidence. The ambitious researcher who looks only at EU transitions which are layoffs but continues to classify all EN as quits would fare worse and find a cyclicality which is too low compared to the cyclicality of the layoffs.

Statistic	Layoffs	EU	Quits	EN
Corr(x, y)	0.8343	0.8258	-0.4642	-0.0611
SD(x)/SD(y)	0.2745	0.2260	0.0913	0.1145

Table 8: Business Cycle correlation of EU and EN flow rate with Unemployment Rate

The second two columns show more stark differences for quits and EN rates (those the standard methods could not distinguish and assumed to be quits). While quits are strongly procyclical, they decrease in recessions, the EN transition rate is only mildly procyclical. The reason for that difference in cyclicality is that around 40% of all EN transitions are actually precipitated by layoffs. We have seen in Table 6 that layoffs are strongly countercyclical and work to offset the procyclicality of quits into non-participation. We therefore strongly recommend using the quit and share of layoffs into non-participation series rather than the EN transition rate in order to analyze how labor supply choices shape job destruction and labor supply elasticities over the business cycle.

3.3 Importance of Labor Supply Decisions

Being able to observe the destination of a worker who got laid off or quit gives a unique insight into the choices workers make in non-employment.

Table 20 shows how the destination of quits and layoffs vary over the business cycle. In times when the unemployment rate is high, the share of layoffs and quits into non-participation decline. We see that the share of layoffs into non-participation is strongly negatively correlated with the unemployment rate. This indicates that while both layoffs into unemployment and non-

Statistic	Share of Layoffs into N	Share of Quits into N
Corr(x, y)	-0.6364	-0.1560
SD(x)/SD(y)	0.0213	0.0143

Table 9: Business Cycle correlation of the share of layoffs and quits into N with the unemployment rate

participation increase in recessions, the increase is larger for layoffs into non-participation. The share of quits that flow into non-participation decreases when the unemployment rate increases. We have seen the reason for that in Table 6: quits into non-participation strongly decline and by more than quits into unemployment during recessions, thus shifting the share of quits towards quits into unemployment. These findings from Table 20 suggest that laid off workers become more attached to the labor force in recessions as more workers choose to remain unemployed after losing their job. Employed workers too become more attached as fewer workers quit their job to non-employment.

The increase in the propensity of laid off workers to remain in the labor force during a recession works to increase the cyclical volatility of unemployment. The magnitude of this effect can be understood by computing an alternative series of unemployment where the share of laid-off workers leaving the labor force is fixed and constant over time.[8] We will do this in two ways to create a range. The first we will call a lower bound and assumes that the newly classified unemployed workers have the same job finding rate as actual unemployed workers. The second we will call an upper bound and assumes that the newly classified unemployed workers have the same job finding rate as the non-participants. The following formalizes the first series for concreteness, and the second is constructed analogously. Let the constructed series be denoted as $\hat{u}$, the fixed share of laid off workers entering unemployment as $\bar{s}$, the actual series without hats, and the actual flow rates by $\lambda^{source,destination}$ and $\lambda^{source,reason,destination}$ for quits and layoffs. The series is then constructed as:

$$\begin{aligned} \hat{u}_{t+1} &= \hat{u}_{t-1}(1 - \lambda^{ue}_{t-1} - \lambda^{en}_{t-1}) + e_{t-1}(\lambda^{equ}_{t-1} + \bar{s}(\lambda^{elu}_{t-1} + \lambda^{eln}_{t-1})) + n_{t-1}\lambda^{nu}_{t-1} \\ \hat{u}_0 &= u_0 \end{aligned}$$

The correlation between the two constructed series and the actual unemployment series are high at 0.980 and 0.914 for the lower and upper bounds, respectively, but the cyclical variances over the entire time period are 39-43% lower and closer to 30% lower when excluding the pandemic recession. Table 10 displays this calculation for all the recessions in our data. To illustrate this point: the unemployment rate increased 4.63 percentage points in the Great Recession but would have increased only 3.4-3.6 percentage points if the share of laid off workers exiting the labor force would have been held constant. That's a decrease of roughly 25%.

[8] This constant share is chosen to maximize the correlation between the alternative series and the true measured CPS unemployment.

Increase in Unemployment during Recessions					
	1980 & 1981-82	1990-91	2001	2007-09	2020
Actual	4.9	1.6	1.6	4.8	11.3
Fixed Share Layoffs to U	3.0-3.5	1.1-1.2	0.9-1.0	3.4-3.6	4.5-5.1
Percent difference	29-38	29-31	36-42	25-29	55-60

Table 10: Second rows: range of hypothetical unemployment rate if the share of laid-off workers is time invariant. Percent difference: how much of the increase in unemployment is from more laid off workers going to unemployment

3.4 The Role of Composition Effects over the Business Cycle

We showed in the previous section that the share of individuals who leave the labor force after job loss declines during recessions. This section will investigate how much of this is due to a change in the composition of laid-off individuals in recessions or changes within different groups of laid-off workers. We do this by computing the counterfactual share of layoffs that flow into non-participation during each of the previous five recessions. In doing so, we perform a shift-share analysis similar to Elsby et al. (2015).

We compute a counterfactual timeseries for the share of layoffs that flow into non-participation based on observed characteristics of individuals. In particular, share_{it}^{eln} is the weighted average of the fraction of laid-off workers exiting the labor force for the different demographic groups of laid-off workers:

$$\text{share}_t^{eln} = \sum_i \omega_{it} \text{share}_{it}^{eln} \tag{6}$$

where ω_{it} is the share group i among all laid-off workers in time t. In order to decompose the change in share_t^{eln}, we fix ω_{it} for each group i to the 12-month pre-recession average of ω_{it}, which we call ω_i^C. The counterfactual share of laid-off workers leaving the labor force, share_t^C, is computed as follows

$$\text{share}_t^C = \sum_i \omega_i^c \text{share}_{it}^{eln} \tag{7}$$

We calculate three different counterfactual analyses; by gender, race, and education, such that $i = \{\text{men}, \text{women}\}$, $i = \{\text{white}, \text{black}\}$, or $i = \{\text{high school at most}, \text{college and more}\}$. Note, due to the number of observations, we cannot analyze any interactions of the three groups, e.g. black women.

Table 11 compares the actual change in the share of individuals who leave the labor force after job loss to the counterfactual change for each recession. We can see that in general the composition of the laid-off workers during recessions contributed little to the observed change in the share of laid-off leaving the labor force. For all three counterfactual experiments, we see declines in the share of layoffs into non-participation with percentage point changes similar in magnitude to the actual decline. Table 12 shows that while the importance of changes in the

Recession	Actual change in pp	Counterfactual change		
		Gender	Race	Education
Jan 1980 - Jul 1980	-0.0867	-0.0640	-0.0704	-0.0914
Jul 1981 - Nov 1982	-0.0870	-0.0657	-0.0926	-0.0921
Jul 1990 - Mar 1991	-0.0628	-0.0467	-0.0589	-0.0598
Mar 2001 - Nov 2001	-0.0508	-0.0502	-0.0556	-0.0507
Dec 2007 - Jun 2009	-0.1307	-0.1034	-0.1315	-0.1368

Table 11: Actual and counterfactual change (in pp) in the share of layoffs into non-participation

composition varies across the different groups and recessions, changes within groups contribute at least 75% to the decline in the share of layoffs into non-participation and is significantly higher for most recessions and groups other than Gender.

Recession	Actual change in pp	Counterfactual change		
		Gender	Education	Race
Jan 1980 - Jul 1980	-0.0867	-26.18%	-18.80%	+5.42%
Jul 1981 - Nov 1982	-0.0870	-24.48%	+6.44%	+5.86%
Jul 1990 - Mar 1991	-0.0628	-25.64%	-6.28%	-4.78%
Mar 2001 - Nov 2001	-0.0508	-1.18%	+9.45%	-0.19%
Dec 2007 - Jun 2009	-0.1307	-20.89%	+0.6%	+4.67%

Table 12: Actual and counterfactual change (in percentage) in the share of layoffs into non-participation

Thus, the changes in labor supply decisions during recessionary periods is not a simple story of different people in the laid-off pool but rather a story about changes in people's labor supply decisions over the business cycle. It is worthwhile noting that our results differ from previous research[9] which has found that the pool of unemployed differs substantially in recessionary times from normal times. However, in our analysis we focus on everyone who is laid-off, i.e. we include individuals in unemployment *and non-participation*. Additionally, this section only controls for differences between individual based on observable, rather coarse, demographics. We will use the model to check how many layoffs are selectively targeted.

3.5 Taking Stock

Before we introduce the model in the next section, let us briefly summarize the important take-aways from our quit and layoff series. EU and EN flows are not a good metric to study labor supply choices of individuals as they mask important notions about the reasons of the separation in non-employment. Our data shows that about 35% of all prime-age workers will choose non-participation after a layoff. This share significantly drops during recessions. Additionally, quits fall during recessions. These data facts suggest that the choices of laid-off workers offer important

[9]See e.g. Elsby et al. (2015) and Mueller (2017)

insights into the evolution of labor supply choices over the business cycle and are useful informing estimates of labor elasticities.

4 Model

4.1 Overview

We enrich a standard heterogeneous agent model of aggregate labor market dynamics to include features related to labor supply and selection which help us to understand and estimate labor supply elasticities. The foundation is similar to Krusell et al. (2017) and features gross worker flows across three labor market states: employment (E), unemployment (U), and nonparticipation (N). To this we add a notion of quits and layoffs, each of which can happen at random or through endogenous choices of individuals thereby determining the extent of selection in job separation as well as labor supply.

4.2 Environment

Time is discrete and the economy is populated by a unit measure of heterogeneous workers. The aggregate state (Z) can be high (normal times) and low (recession) to produce business cycles, and follows a standard Markov process.

Preferences Consider an individual with preferences given by

$$E_t \sum_{t=0}^{\infty} \beta^t [\log(c_t) - \alpha e_t - \gamma s_t], \tag{8}$$

where $c_t \geq 0$ is consumption in period t, $e_t \in \{0, 1\}$ is employment status, and $s_t \in \{0, 1\}$ is a discrete variable reflecting whether the individual engages in active job search. The parameters $\alpha > 0$ and $\gamma > 0$ represent the disutilities of work and active search, respectively, while $0 < \beta < 1$ is the discount factor. There is no on-the-job search, individuals can only engage in active search if they are currently non-employed.

Budget Constraint and Earnings Individuals cannot borrow but can accumulate assets a that offer a return r. The budget constraint is:

$$c_t + a_{t+1} = (1 + r)a_t + y_t$$
$$a_t \geq 0$$

Flow earnings, denoted by y_t, depend on the individual's labor market status. An employed worker's labor earnings are the product of her idiosyncratic labor productivity z and the market wage per efficiency unit of labor services w:

$$y = w(Z) \cdot z \tag{9}$$

A key element of our model is that an individual's return from market work is stochastic. We model this as an idiosyncratic shock to market productivity, z_t, which follows an AR(1) process in logs:

$$\log z_{t+1} = \rho_z \log z_t + \varepsilon_{t+1}, \tag{10}$$

where the innovation ε_{t+1} is normally distributed with mean zero and standard deviation σ_ε.

Non-participants receive home production income h , which is constant across all individuals: $y = h$.

The model includes a Unemployment Insurance program (UI) that captures key features of the US system. To be eligible ($e = 1$) for UI, a worker must have previously been employed and experienced a layoff, as defined in the next section. Individuals who voluntarily quit their jobs are not eligible ($e = 0$). To receive benefits, an individual must engage in active search ($s = 1$) and incur the search cost γ. UI benefits have finite duration. An eligible individual loses their eligibility each period with probability $\mu(Z)$.

The value of the unemployment benefit is given by the following formula

$$b(z, Z) = \begin{cases} b_0(Z)z & \text{if } b_0(Z)z \leq \bar{b}(Z) \\ \bar{b}(Z) & \text{otherwise} \end{cases}$$

where $\bar{b}$ is the maximum benefit amount and b_0 is the replacement rate.

Additionally, there is a means-tested consumption floor c_{min} representing safety net programs. This payment is available to all agents whose period resources $a + y$ fall below the consumption floor.

4.3 Labor Market Transitions and Employment Dynamics

Job Loss: Quits and Layoffs. Employed workers can lose their job each period in four different ways. Some we will classify as quits and others as layoffs. There is no on the job search and so any job loss results in a transition to non-employment.

First, the worker may quit. An endogenous quit comes about when a worker assesses the value of non-participation or unemployment to be higher than continuing at work and leaves their job. Once separated he or she can choose whether to search for a new job in unemployment or go to non-participation for however long they like. There is also an exogenous shock q that forces a worker to quit into non-participation until the shock goes away. We will call this type of worker to be constrained. They cannot make labor market choices and must stay in non-participation. This shock is meant to capture individuals very far from the margin of the labor market for reasons we do not model explicitly such as disability, child birth, or the ample resources of a second earner. This shock follows a Markov process where $1 - q^0$ is the probability that a constrained individual remains constrained and $1 - q^1$ is the probability that an unconstrained individual becomes constrained.

Alternatively, the worker may be laid-off. As is standard in search models, there is a probability δ that a worker is laid-off exogenously and this probability is common across all workers

but varies with the aggregate state (Z). We call these types of lay-offs "non-selective". The other type of lay-off is called "selective" and is generated by a shock p. This shock has a random arrival rate of $\lambda^p(Z)$ and upon arrival requires the worker to pay a utility cost p of remaining employed. This is a simple way to capture selective firings of low-surplus workers within the firm. While both a selective lay-off and an endogenous quit target low-surplus workers, the layoff is completely transitory to the worker. It is meant to represent pressures idiosyncratic to the firm causing it to cut its least productive workers even though those workers could have a positive surplus elsewhere. It is essentially a match quality shock. An endogenous quit, by contrast, is a separation initiated by a worker who does not have a positive employment surplus at any job and will result in the worker choosing to make an employment to non-participation transition. The endogenous selective layoff can result in the worker choosing either unemployment or employment.

The rich set of transitions between labor market states is key to our analysis, and so we summarize them here:

1. **Selective (Endogenous) Quits**: Employed individuals choose to quit if the surplus of employment relative to non-employment is negative. These are the quits of marginal workers who are relatively close to participating if policy or their circumstances change.

2. **Non-Selective (Exogenous) Quits**: With probability $1 - q^1$, a worker is forced into non-participation where they remain until the shock is removed. These are the quits of non-marginal workers who are far from participating despite changes in policy or their circumstances.

3. **Selective (Endogenous) Layoffs**: With probability $\lambda_p(Z)$, a worker must pay a one-time utility cost p to continue an employment match. If they refuse, they are laid off. This will endogenously generate layoffs of marginal workers with low employment surplus who are more likely to choose to exit the labor force after the layoff.

4. **Non-Selective (Exogenous) Layoffs**: With probability $\delta(Z)$, a worker is forcefully laid off. This will equally generate layoffs of workers who are strongly attached, with high employment surplus, as it will generate layoffs of those marginally attached with low employment surplus.

Labor Market Frictions Both non-participants and the unemployed must wait to receive a job offer before moving to employment. The offer arrival rate for the unemployed is $\lambda_u(Z)$ and is greater than the arrival rate for the non-participants, $\lambda_n(Z)$. Both rates are assumed to be higher in expansions than in recessions.

4.4 Value Functions

The state variable of an individual is $(a, z, q; Z)$, where a are assets, z is their idiosyncratic productivity, q is whether they are exogenously constrained from participation and Z is the

aggregate state. An unemployed worker will have an additional state for their UI eligibility, e.

We express an individual's decision problem recursively using the following value functions. For the employed:

$$\begin{aligned} W(a,z,q;Z) = \max_{c\geq 0, a'\geq 0} \log(c) - \alpha + \beta E_{z',q';Z'}\Big[&(1-\delta(Z))J(a',z',q',0;Z') \\ &+ \delta(Z)V(a',z'q',1;Z')\Big] \\ \text{st} \quad & c + a' = (1+r)a + w(Z)z \end{aligned}$$

where $J()$ is the value for an individual with an employment opportunity:

$$\begin{aligned} J(a,z,q,e;Z) = \lambda_p(Z)[(1-q)\max\{W(a,z,q;Z) - p, V(a,z,q,0;Z)\} + qN(a,z,q;Z)] \\ + (1-\lambda_p(Z))[(1-q)\max\{W(a,z,q;Z), V(a,z,q,0;Z)\} + qN(a,z,q;Z)] \end{aligned}$$

and $V()$ is the value for an individual without an employment opportunity:

$$V(a,z,q,e;Z) = \max\{U(a,z,q,e;Z), N(a,z,q;Z)\}$$

An employed individual incurs the utility cost of work α and with probability $\delta(Z)$ they are forcefully laid-off, i.e. experience a non-selective (exogenous) layoff. In that case they can choose between active search, unemployment, or leaving the labor force.

If they do not experience a traditional job loss shock, with probability $\lambda_p(Z)$ they might have to pay the one-time match quality cost p and leave employment if the value of employment net of the cost is negative. Even if they do not experience this selective layoff, they might leave employment due to a selective quit, the value of non-employment exceeds the value of employment, or because they are forced into non-participation with probability $(1-q)$.

For the unemployed:

$$\begin{aligned} U(a,z,q,e;Z) = \max_{c\geq 0, a'\geq 0} \log(c) - \gamma + \beta E_{z',q',e';Z'}\Big[&\lambda_u(Z)J(a',z',q',e';Z'). \\ &+ (1-\lambda_u(Z))V(a',z',\gamma',e';Z')\Big] \\ \text{st} \quad & c + a' = (1+r)a + e\cdot b(z;Z) + I(c)\underline{c} \\ & I(c) = \begin{cases} 1 & \text{if} \quad (1+r)a + e\cdot b(z;Z) < \underline{c} \\ 0 & \text{o/w} \end{cases} \\ & e' = (1-\mu(Z))e \end{aligned}$$

An unemployed individuals has to pay the search cost γ, with probability $\lambda_u(Z)$ a job offer arrives, whereas with probability $1-\lambda_u(Z)$ the individual remains in non-employment in the following period. The individual will receive UI benefits $b(z,Z)$ if they are eligible in the current period.

For the non-participants:

$$\begin{aligned} N(a,z,q;Z) = \max_{c\geq 0, a'\geq 0} \log(c) + \beta E_{z',q';Z'} \Big[& \lambda_n(Z) J(a',z',q',0;Z') \\ & + (1-\lambda_n(Z)) V(a',z',q',0;Z') \Big] \\ \text{st} \quad & c + a' = (1+r)a + d_h \end{aligned}$$

Lastly, non-participants will remain non-employed unless they receive a job with probability $\lambda_n(Z)$.

4.5 Key Mechanisms

There are several mechanisms which are crucial for explaining the cyclical patterns of worker flows between the three labor market states employment, unemployment, and non-participation.

1. **Composition effects**: During recessions, the composition of the unemployment pool shifts toward more attached workers (those who were employed and experienced exogenous separations), who are less likely to transition to nonparticipation. This helps explain why the U-to-N flow rate is procyclical despite the participation rate being procyclical.

2. **Option value of employment**: There is an option value to remaining employed for individuals, as finding employment after quitting involves search costs and time. When labor market frictions decrease during good times, this option value decreases, contributing to flows from employment to non-participation.

3. **UI eligibility dynamics**: In bad times, a higher fraction of unemployed workers are eligible for UI benefits due to higher separation rates. This affects the incentives for active versus passive search.

4.6 Aggregate Shocks and Business Cycle Dynamics

Aggregate shocks to job finding and job loss are the primary drivers of business cycles in the model. We model the aggregate state as a two-state Markov process with states labeled "good" (G) and "bad" (B).

In good times, job-finding rates (λ_x^G) are higher and the job-separation rate (δ^G) is lower:

$$\lambda_s^G = \lambda_s^*, \quad \lambda_s^B = \lambda_s^* - \varepsilon_x \qquad \text{for} \quad s \in \{u, n\} \tag{11}$$

$$\delta^G = \delta^*, \quad \delta^B = \delta^* + \varepsilon_\delta \tag{12}$$

where λ_s^* and δ^* are the steady-state values, and ε_s and ε_δ control the cyclicality of these parameters. The finding rates are specific to whether the searcher's labor market state x is unemployment or not in the labor force.

Selective quits may also vary over the business cycle. The arrival of a job continuation cost shock p is $\lambda_p(Z)$ and may be higher or lower in good times than in bad. We will see later that

the cyclicality of this parameter determines how much recessions change the composition of layoffs towards higher or lower productivity workers.

Finally, to mimic the behavior of UI in the US in most business cycles since 1976, the probability of losing UI eligibility varies with the aggregate state and $\mu^G > \mu^B$, reflecting the longer duration of benefits during recessions.

4.7 Labor Supply

The key mechanisms in our model, composition effect, option value of employment, and UI eligibility dynamics, shape workers' labor supply choices. All of these choices hinge upon the net surplus of employment relative to non-participation and of unemployment relative to non-participation.

1. **Selection into endogenous flows**: The net value of participation is higher for individuals with high productivity or low assets. High productivity individuals have a lower replacement rate in their earnings from unemployment benefits (capped) and home production (a constant). This pushes the net flow value of employment higher and is more likely to compensate for the utility cost of searching for a job or the flow utility cost of employment. The same logic is true for low asset individuals. All else equal, they have a greater increase in flow consumption when employed.

   Low productivity or high asset individuals, on the other hand, are workers with lower net values of employment. These workers are the ones who transition out of employment due to an endogenous selective quit or due to an endogenous selective layoff. The latter occurs when a job continuation cost shock arrives and the net value was positive but lower than the shock cost p.

2. **Layoffs to Non-participation**: Both endogenous selective layoffs and exogenous random layoffs may result in a flow to either unemployment or to non-participation under some parameter values. This is more likely to occur for workers with low, but positive net values of employment. A worker who was happy to continue working until a layoff chooses to exit all together because searching for a job in unemployment is costly. Searching results in lost home production and an utility cost of search. It is more likely that a low productivity worker exits after a layoff because they find these costs too high to justify searching in unemployment both because their net surplus of employment is low but also since unemployment benefits depend on your prior wage but home production is a constant.

3. **The impact of recessions on participation flows**: Recessions are complicated in the model and their qualitative impact on participation and the labor supply elasticities of the unemployed and of non-participants depends on many factors.

   - *Endogenous Selective Quits and Layoffs.* Higher job loss rates work to lower the net value of employment which could raise quits but lower job finding rates introduce

job hording motives to keep a job that otherwise would have negative surplus if the worker expects the surplus to be positive again soon. The same logic holds for selective layoffs except more generous unemployment benefits also work to increase selective layoffs.

- *Incentives for laid off workers to Stay in the Labor Force.* Lower job finding rates and higher layoff rates reduce the incentives for a laid-off worker to search in unemployment but more generous unemployment benefits raise these incentives.
- *Selection effects on the share of laid off workers who exit the labor force.* An increase in exogenous layoff rates during a recession would decrease the exit rate after a layoff simply by changing the composition of laid off workers towards higher net employment surplus types. An increase in selective layoffs during a recession would counter this effect.

Critically, these mechanisms provide rich, time-varying extensive margin labor supply elasticities that vary across labor market statuses.

4.8 Calibration

We calibrate our model to match key labor market moments for the U.S. economy. The length of a period is set to two weeks. We set r to provide an annualized interest rate of 3% and β to $1/(1+r)$.

The log productivity process is set to provide an annualized standard deviation of $\sigma_z = 0.25$ and persistence of $\rho_z = 0.85$. The wage per efficiency unit is normalized to $w = 1$ regardless of the aggregate state as the wage does not vary much over the business cycle in the U.S.

The UI system provides a replacement rate of $b = 0.35$ for earnings up to the median wage and a zero replacement rate thereafter. The minimum consumption floor is set to $\bar{c} = 0.005$. UI benefits have an median duration of 6 months during normal times and, to mimic Federal emergency benefits, do not expire in recessions. This low value is intended to capture food stamp programs that equal less than half a percent of GDP and are the most common welfare used by temporarily unemployed workers.

The shocks governing labor market frictions in the model need to be estimated. These include the job finding rates $\lambda_s(Z)$ and exogenous job separation rates $\delta(y)$. The p shock is normalized to arrive with probability $\lambda_p(G) = 0.2$ in good times and the cost value p and arrival rates in bad times are estimated. The participation shock process is set so that the average time in non-participation is 2 years and the steady state share of the population with a constrained participation status is 10%. These values are meant to capture the second mode in duration estimates of job quitters to non-participation that we estimate in the PSID.

Finally, there are three remaining parameters affecting the relative flow values of each market state: utility cost of work, utility cost of search in unemployment, and home production. The utility cost of search is set to 0.25α, roughly in line with time spent on search relative to work. The other two parameters are estimated.

The ten estimated parameter values are:

p	$\lambda_p(B)$	$\delta(G)$	$\delta(B)$	$\lambda(G)_u$	$\lambda(B)_u$	$\lambda(G)_n$	$\lambda(B)_n$	δ	h
3.5	0.3	0.002	0.006	0.26	0.05	0.09	0.08	1.0	0.12

Table 13: Estimated Parameter Values

The estimated p-shock value is not too large. It is equal to 3.5 times the normal flow value of work. The value of home production is also low. It is equal to about 10% of the median wage. Both of these values hint at a substantial role for selection conditional on a p shock.

The model's fit to the target statistics is:

	Model		Data	
Statistic	**Overall**	**Recession**	**Overall**	**Recession**
Emp Rate	0.7949	0.7723	0.7900	0.7650
Unemp Rate	0.04837	0.0901	0.0500400	0.080550
NILF Rate	0.1567	0.157	0.1700	0.175800
Flow EU	0.0036	0.0057	0.0025	0.0375
Flow EN	0.0039	0.0043	0.0038	0.0035
Flow UE	0.083	0.0437	0.0700	0.0425
Flow UN	0.0139	0.013	0.0058	0.0050
Flow NE	0.0137	0.0140	0.0125	0.0113
Flow NU	0.0125	0.015	0.0058	0.0088
Share Layoffs To N	0.3667	0.304	0.3600	0.3000
Layoff Rate	0.0056	0.0082	0.0028	0.0040
Quit Rate	0.0016	0.0013	0.0020	0.0010
Av Duration short term N	37.7	33.4	34.0	

Table 14: Model Fit

	Model	
Statistic	**Overall**	**Recession**
Avg Assets	4.7428	4.7232
Avg Assets E	5.4135	5.4428
Avg Assets U	4.1961	4.2433
Avg Assets N	1.6762	1.6814
Avg Z E	2.1812	2.1885
Avg Z U	1.9420	1.9525
Avg Z N	1.3203	1.3358
Share Layoffs- Selective	0.3683	0.272
Share E To N- Exogenous	0.1952	0.1775

Table 15: Employment Statistics: Model Results

4.9 Validation on Selection- PSID

The specific order of selection in separation of employment by type of flow and destination predicted by our model is validated in PSID data. Workers who quit to non-participation are the least productive and those who are laid-off and select unemployment are the most productive. The workers who are laid-off and select non-participation are between the two. They are the marginal workers who would not have chosen to quit to non-participation but who had low enough productivity that it is not worth it for them to search in unemployment after a layoff.

Figure 8 shows this predicted ordering is validated in PSID data. The left panel shows the kernel density of residuals from a regression of earnings on dummies for college, high school, and no degree interacted with a cubic on age-25.[10] QN workers have the lowest residual wage upon separation, LN are next, then LU are the highest. The right panel shows the selection carries through to non-employment duration as the model predicts. For workers with some attachment, those who return to work within 4 years, the QN workers take the longest to return, the LN workers are next, and the LU workers have the shortest non-employment duration.

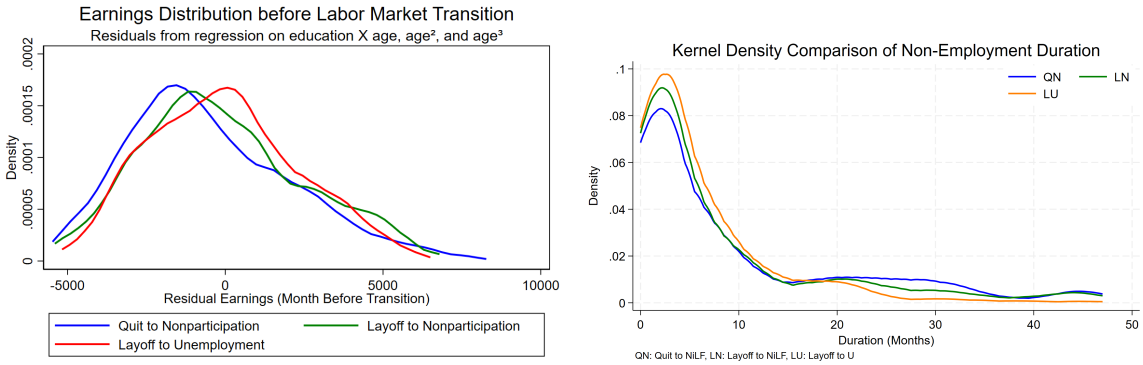


Figure 8: Evidence on Selection- Panel Study of Income Dynamics.)

5 Labor Supply Elasticities in the Steady State

We now use our calibrated model that accurately captures the marginal workforce to explore the reaction of labor market aggregates to changes in labor supply.

Changes in Wealth. We explore a pure wealth effect by introducing an unfunded lump-sum transfer in each period to all agents. Figure 9 summarizes the key results. First, a pure wealth effect lowers labor supply. A transfer equal to one-percent of the steady-state asset holdings (about 5% of the median earnings), lowers the share of workers in the labor force 2 percentage points, from 85.2% to 83.2%. Employment falls by a larger amount, 2.5 percentage points. The difference between these changes manifests in a higher unemployment rate rising from 4.7% to 6.0%.

[10] The sample includes only prime-age workers.

The first of these results is standard: a positive wealth effect lowers labor supply and employment. The second is, perhaps, less intuitive: a positive wealth effect lowers labor supply and increases unemployment. If one views unemployment as a measure of labor market slack, then this would seem puzzling. In fact, this result is due to an increase in frictional unemployment. The bottom panels in 9 show that positive wealth effects are associated with more quits (left) that are shorter duration (right). Wealth is acting as an insurance to transitory negative productivity shocks. Higher wealth allows agents to sit out of the labor market and not pay the utility cost of employment in periods they're not very productive. Labor market frictions lead them to then transit to unemployment when their productivity recovers where they remain for a spell while searching for a job. This higher churn is the driver of higher unemployment.

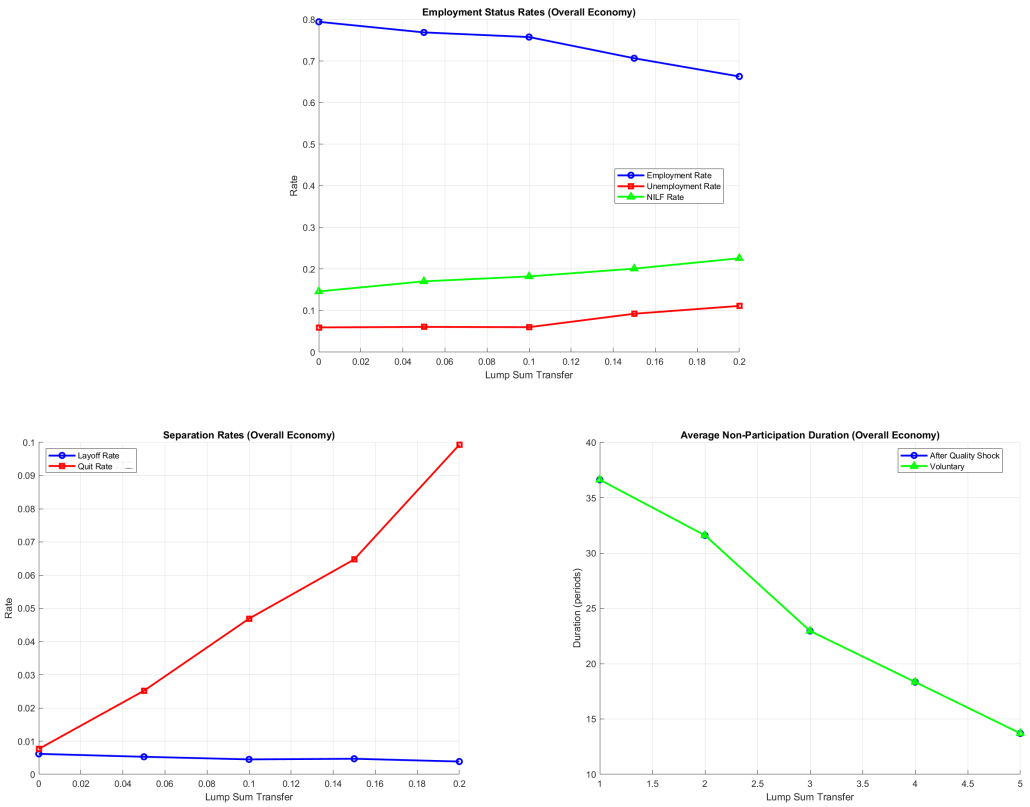


Figure 9: Wealth Elasticity: Reaction of Aggregate Variables to a Lump sum Transfer

Changes in Wages. We now consider a change in the wage rate per efficiency unit with results shown in 10. A 20% change in the wage increases employment to population by 1.1 ppt, from 80.7 to 81.8. As employment rises, the non-participation rate falls by a similar amount and the unemployment rate creeps down a small amount from 4.79 to 4.71.

Qualitatively, these results are more aligned with conventional labor market mechanics. Wages increase labor supply which results in higher employment, lower non-participation, and lower unemployment. Yet, the magnitudes are interesting. Employment rises by a full percentage point but unemployment hardly moves. This is because the marginal workers become more

attached and churn more within the labor force through employment and unemployment than out of the labor force. This can be seen in the bottom panels of 10. The left shows that more marginal workers remain in the labor force if they are laid off. This increases unemployment. It also results in a shift in composition of non-participants to the exogenous quits, or less marginal workers.

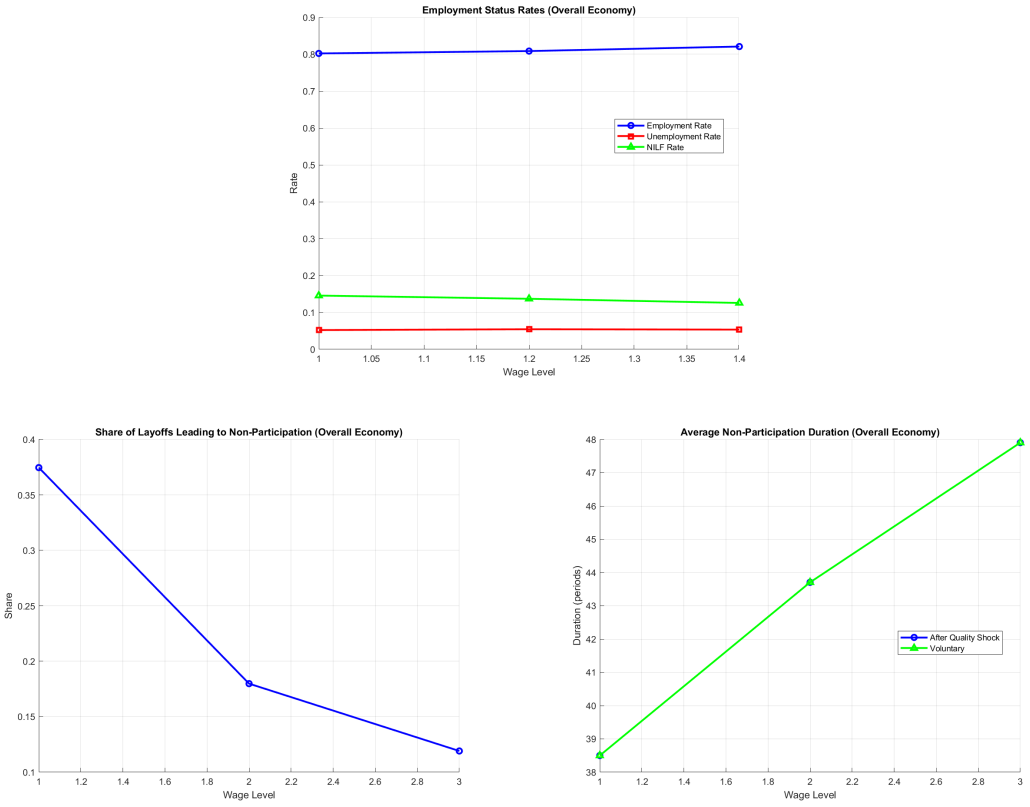


Figure 10: Total Wage Elasticity: Reaction of Aggregate Variables to Wage Rates

Changes in UI Benefits. We now consider a change in the replacement rate of UI benefits while maintaining the same maximum benefit. This change would most impact low productivity workers who are the main marginal workers in the model. Our results are shown in 11. A change in the replacement rate from 40 to 50% leaves employment barely changed but lowers non-participation and increases the unemployment rate by 0.9 ppt. The right panel of 11 shows that this is partially due to higher inflows of marginal laid-off workers to unemployment. It is also partially due to the fact that marginal workers have a longer unemployment duration because they are more likely to remain in unemployment until their benefits run out.

The result that more generous unemployment benefits raise the unemployment rate is common in the literature and often attributed to moral hazard. In our model, the increase in unemployment is partially due to increased moral hazard but is also due to an increased labor supply of marginal workers. These two effects compound upon each other because the marginal workers have a higher degree of moral hazard.

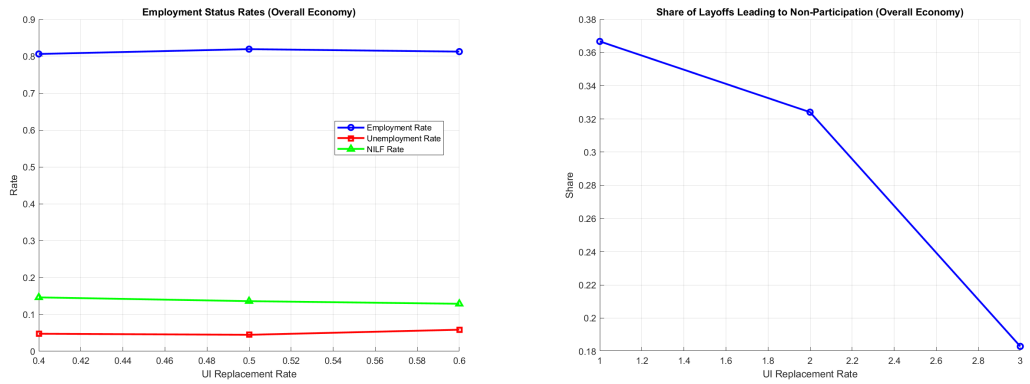


Figure 11: Effect of UI Benefits: Reaction of Aggregate Variables to UI Replacement Rates

6 The Business Cycle

6.1 What drives cyclical dynamics in the baseline?

The cyclical dynamics of the labor market are generated by several empirically relevant changes. Our model features two mechanisms. First, labor market frictions change: the job loss rate increases, and the job finding rate falls. Second, UI benefits are extended.

We have a third, less standard mechanism of cyclical selection of layoffs. In our model, the incidence of layoffs in recessions mores towards less marginal workers who have a higher employment surplus. Specifically, the share of selective layoffs reduces from 37% to 27% of all layoffs from expansion to recession. This is inferred by our estimation largely due to the introduction of the target of the cyclicality of the share of layoffs to N. As less marginal workers are less likely to exit the labor force after layoff, all else equal, this leads to a higher increase in unemployment caused by the increase in the layoff rate alone.

The presence of marginal workers in our model also interacts with the standard drivers of recessions. Marginal workers are more reactive to features that lower labor supply, like lower job finding rates; but they also are more reactive to features that increase labor supply, like longer unemployment benefits.

In Figure 12, we show impulse responses of the labor market to a 50 period recession. Specifically, we feed in a series of a convex combination of the cyclical parameters with a linear transition from a weight of 1 on recession to a weight of 0. The exception is unemployment benefits. They do not expire during the recession.

The "baseline" line in Figure 12 represents the results from the baseline calibration. A recession is characterized by a decline in employment. Most of the non-employed end up in unemployment but non-participation also rises. Although the share of layoff targeting the marginal workers falls during a recession and within the marginal workers, they are more likely to go to and stay in unemployment, the total amount of layoffs increases and this increases flows of marginal workers to non-participation despite these off-setting effects. This effect dominates as the flows from N to E do not fall much in a recession in our model.

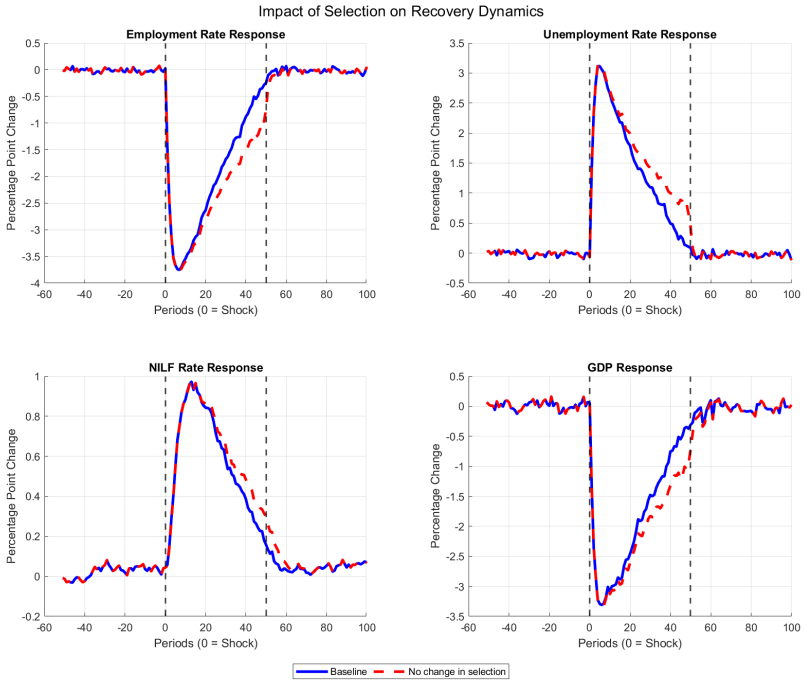


Figure 12: Impact of the Counter-cyclicality of Selective Share of Layoffs.

The "no change in selection" red dashed line in Figure 12 represents the following experiment in which we try to eliminate the cyclical component of selection. We chose the arrival rate of the employment continuation shock p and the exogenous layoff rate such that we match the initial increase in unemployment in this impulse response but maintain the same share of selective layoffs over the cycle: 37% instead of falling to 27% as it does in the baseline. We re-solve the entire model in this experiment and so the agents' policy functions reflect this change in risks. The difference between the red dashed line and blue baseline line shows that the movement of layoffs towards non-marginal high employment surplus individuals speeds-up the labor market recovery. Employment recovers more quickly; and unemployment and non-participation also fall more quickly.

The more rapid recovery at the end of the recession (period 50) is when the unemployment benefit extension ends. There you can see the interaction between selection and UI benefits. The lower surplus, more marginal workers are more numerous in the pool of non-employed in the "no change in section" case and their labor supply is more elastic to UI changes. Yet, UI is not the whole story as the dynamics of non particpation are also prolonged when there are more marginal types in the non-employed pool and these non-participants are note eligible for UI.

6.2 How do changes in labor supply affect cyclical dynamics?

In the prior section we learned that factors that change aggregate labor supply change labor market aggregates in interesting ways. For example, gross churn can increase as labor supply

decreases leading to a rise in unemployment that is entirely frictional and unrelated to slack. These sort of changes arise because factors that change aggregate labor supply also change the distribution of marginal agents. There can be more or fewer marginal workers with low employment surplus relative to non-employment, and the relative value of unemployment and non-participation can also change, particularly for the marginal workers.

These changes suggest that factors driving trends in labor supply can also impact cyclical dynamics of the labor market. This is both because marginal workers are a significant share of laid-off workers throughout the cycle and also because they are more responsive than other workers to the disincentives provided by UI.

To understand and quantify the affect of lower frequency labor supply trends to higher frequency business cycles, we analyze how the cyclicality and volatility of labor market aggregates changes if labor supply changes due to either an 1% increase in wages, wealth, or UI. Volatility of the labor market stocks is calculated as the standard deviation and the cyclicality is calculated as the correlation with GDP. In our model, GDP is the integral over idiosyncratic productivities of the employed. The results are shown in 16.

Metrics	Baseline	10% Δ in Wage	10% Δ in Wealth	10% Δ in UI Rate
σE	0.0011	0.0011	0.0012	0.0011
σU	0.110	0.116	0.120	0.117
σN	0.0026	0.0021	0.0029	0.0028
corr(ΔE,ΔY)	0.76	0.73	0.79	0.764
corr(ΔU,ΔY)	-0.75	-0.72	-0.77	-0.762
corr(ΔN,ΔY)	0.02	0.08	0.06	-0.01

Table 16: Cyclicality of Labor Market Status for Different sources of changes in labor supply.

An increase in the wage increases labor supply. It has little change on the volatility of employment or unemployment but decreases the volatility of non-participation rates. Employment and unemployment become a little less correlated with output and non-participation becomes more correlated. This is consistent with the idea that increases in wages lead to fewer marginal workers. The employment surplus of the employed moves further from zero, but also does the employment surplus of non-participants (but towards more negative values).

An increase in wealth lowers labor supply and increases the volatility of all of the aggregate stocks, particularly unemployment. All stocks also become more correlated with output. This is because the increase in wealth raises the share of marginal workers. In both employment and non-employment there are more individuals with near zero employment surplus. This leads to stronger disincentives to return to work in recessions and makes the cycle more volatile.

An increase in the UI replacement rate has an ambiguous impact on labor supply as jobs become higher valued because a layoff from a job is the only path to UI. Higher UI benefits, however, create a disincentive for an unemployed worker to move to employment. All in all the changes in benefits have relatively small effects but notably make non-participation a bit counter-cyclical. This is because more workers laid-off who would have otherwise exited the

labor force remain in unemploymen to collect more generous UI during recessions and then exit as output recovers and UI extensions expire.

7 A practical path to track slack in real time.

Unemployment dynamics are partially shaped by labor demand and partially shaped by labor supply. In this paper, we argued that they are also shaped by labor force participation decisions of marginal workers for whom the difference between unemployment and non-participation is small and a choice of unemployment over non-participation reflects a very minor increase in their labor supply, if any.

The dynamics of selection in layoffs and the participation decisions of marginal workers muddy the signal that the unemployment rate provides about dynamics of labor market slack. We now provide a simple, alternative unemployment rate that economists may track to get a sense of how these factors are affecting unemployment. It is not a perfect measure but instead meant to provide a signal for when changes (or lack thereof) in unemployment are primarily due to changes in participation decisions and/or selection in layoffs.

We proceed to construct "participation neutral" series of unemployment as follows. We take the entirety of flows for prime age workers from the data: quits from E to NE; layoffs from E to NE; other from E to NE; UE finding rate; NE finding rate; NU; UN; and the shares of all separations that end up in N. We then construct a series of employment-pop, unemployment-pop, and non-participation-pop with the share of layoffs to N, NU, and UN fixed each at a constant rate. We solve for these shares to maximize the correlation between our participation neutral series of unemployment and the actual series of unemployment.

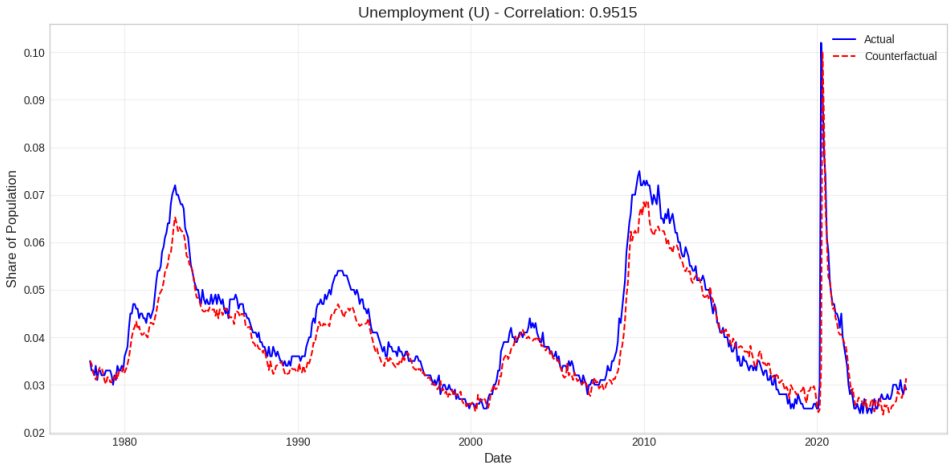


Figure 13: Counterfactual: Impact of Participation Flows on the dynamics of unemployment.

The results are shown in Figure 13. Moving from the red-dashed "counterfactual" line to the blue "actual" line is interpreted as the impact of marginal participation flows on aggregate unemployment dynamics. The main feature, one emphasized in our model, is that marginal participation decisions amplify the cyclical volatility of unemployment. Interestingly, this is not

true for all recessions. The 2000 and COVID recessions show little difference between the two series. Furthermore, the height of the 2000 recession unemployment rate becomes close to the early 1990s one suggesting more similar dynamics in labor demand (layoff rates and job finding rates).

Another interesting features is that the actual unemployment series often leads our counterfactual series. This suggests that either marginal participants become more attached before a recession or layoffs select more highly attached workers before a recession. The very recent movements from 2023-current show a more stark example of this lagged relationship. The actual rise in unemployment is first driven by a rise in labor force participation and then, a year later, demand factors start to slow down and contribute to lower slack and higher unemployment.

8 Focus on an Episode: The Pandemic Recession and Recovery

The empirical patterns we have established are strikingly similar across recessions.[11] No single episode proves this point better than the recession and recovery following the COVID-19 pandemic. Although the pandemic recession stood out compared to other recessions in many aspects, our time series of quits and layoffs shows that the business cycle patterns of quits, layoffs, and labor supply decisions are mostly unremarkable. They are consistent with historic patterns given economic fundamentals.

The pandemic recession was characterized by an unprecedented increase in layoffs. Our data show that the increase in layoffs is accompanied by a decrease in quits. Thus, like all other recessions, quits fall as layoffs increase. However, compared to the prior recessions, we see an increase in total separations into non-employment during the pandemic recession (see Figure 14). Unlike prior recessions, quits did not, and arithmetically could not, fall enough to offset the huge rise in layoffs. While looking at total separations might lead someone to conclude that the pandemic recession was different, observing layoffs and quits separately shows that the business cycle pattern is consistent with our findings about procyclical quits and countercyclical layoffs.

We emphasized that the share of laid off workers who exit the labor force falls during a recession and the pandemic recession is no different. However, the magnitude of that fall is striking as layoffs into non-participation made up almost 50% of all layoffs prior in late 2019, but then dropped to under 20% in early and mid-2020.[12] Being able to decompose transitions into non-participation into quits and layoffs, allows to us to make this observation which potentially has important implications for policy makers, e.g. were the unemployment insurance benefits extensions during that time period an important contributor for this finding?

Lastly, let us focus on the recovery after the pandemic recession, a period which has been frequently called the "great resignation". The pandemic recession has been referred to as such

[11] See Appendix C for a detailed comparison across all recessions covered by our timeseries between 1978 and 2024.

[12] In April 2024, the share of layoffs into non-participation was only 14% which is the lowest share between 1978 and 2024.

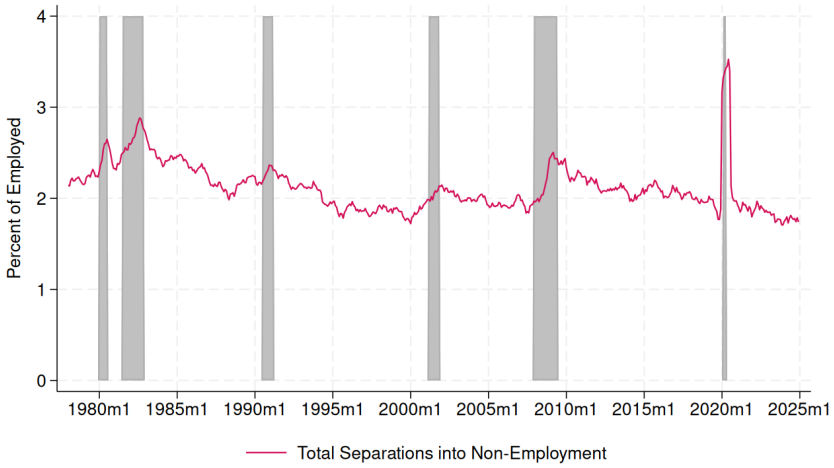


Figure 14: Total Separations (Quits+Layoffs) into Non-employment (as a percent of employment) (Monthly seasonally-adjusted 6-month centered moving average data)

because of the "high level of worker separations in the form of quits" (Şahin and Tasci (2022)) Most studies researching this phenomenon have been using quits data from JOLTS.[13] However, contrary to JOLTS data, our time series of quits does not display an increase in the Covid recovery higher than in previous recessions.[14] Figure 15 shows the peak-to-peak change for the 2001, 2007, and 2020 recessions, and it is clear from the figure that the recovery after the pandemic recession follows a very similar pattern as the recovery after the 2007 recession, albeit on a seemingly faster timeline.

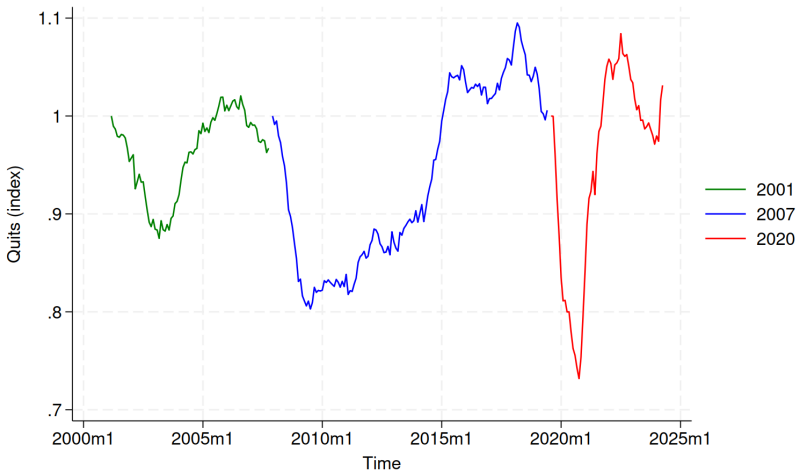


Figure 15: Peak-to-peak change in quits for the 3 most recent recessions (Note: Each peak is normalized to 1)

[13] Appendix section B of this paper speaks more of the difference between the CPS and JOLTS.

[14] Our data can be combined with the CPS series of employer-to-employer flows assembled by Fujita et al. (Forthcoming) but their series does not identify an employer to employer move as a quit or layoff. These figures are in the final section of the paper.

The similarity to other episodes of quits, layoffs, and labor force participation in the pandemic recession is best seen by comparing flows to economic fundamentals. For an "apples to apples" comparison, we consider correlations with market tightness. Market tightness is defined as the number of unemployed over the number of vacancies.

Figure 16 displays the correlation of quits with labor market tightness using peak-to-peak data for the same three recessions, and similarly, we do not find evidence of a great resignation. All three recessions show a positive correlation of quits and labor market tightness with a very similar magnitude of correlation. The only apparent deviation is the negative correlation between quits and labor market tightness in the first few months of the pandemic. The subsequent recovery has displayed similar correlations as past cycles.

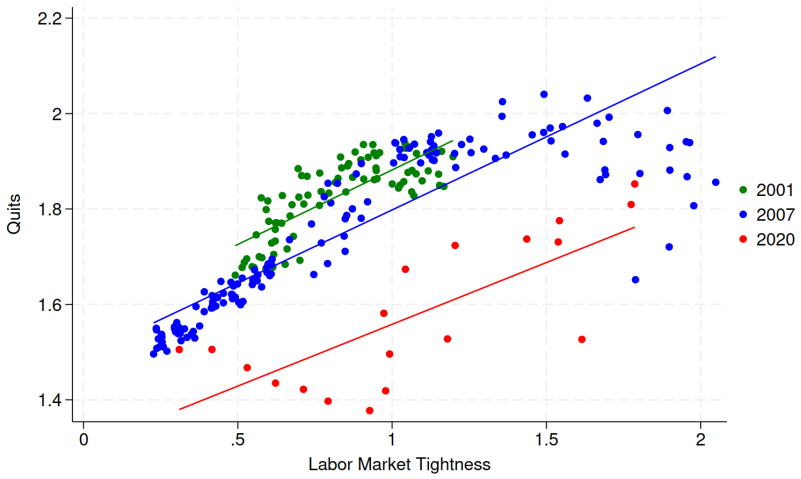


Figure 16: Correlation of quits with labor market tightness for the 3 most recent recessions

9 Conclusion

In this paper, we develop a framework in which labor supply choices by individuals help to estimate labor supply elasticities. We use monthly data from the Current Population Survey (CPS) to construct labor market transition rates by destination, employment, unemployment, or non-participation, and importantly, reason, quit or layoff. We show that the ability to distinguish whether a worker entered non-employment due to a quit or layoff is key in understanding individuals' labor supply decisions. In particular, the decisions of laid-off workers to remain in unemployment or leave the labor force provides unique insight into the distribution of employment surplus.

The model finds that between 25 to 30 percent of layoffs target workers with a low employment surplus, i.e. those who are near the margin of participation. Identifying these workers is important in understanding the evolution of joblessness over time. Traditional analysis which focused only on the destination of workers transitions and interprets EU flows as layoffs and EN flows as quits underestimates the layoff rate by about 35%. We argue that this group of

workers, however, is key to understanding how labor market aggregates evolve due to policy or aggregate shocks as these are close to the participation margin and changes might alter their valuation of employment versus non-employment.

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A Working-Age Population

This section provides the same figures and statistics as in the main text but for the working-age population, i.e. everyone in the United States who is 16 years or older and not currently institutionalized or an active member of the armed forces.

A.1 An Overview of Quits and Layoffs

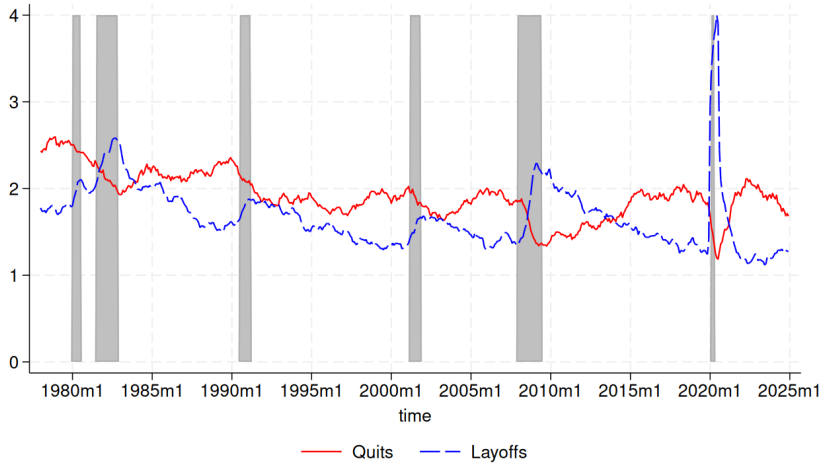


Figure 17: Monthly Quit and Layoff Rates (as a percent of employment)

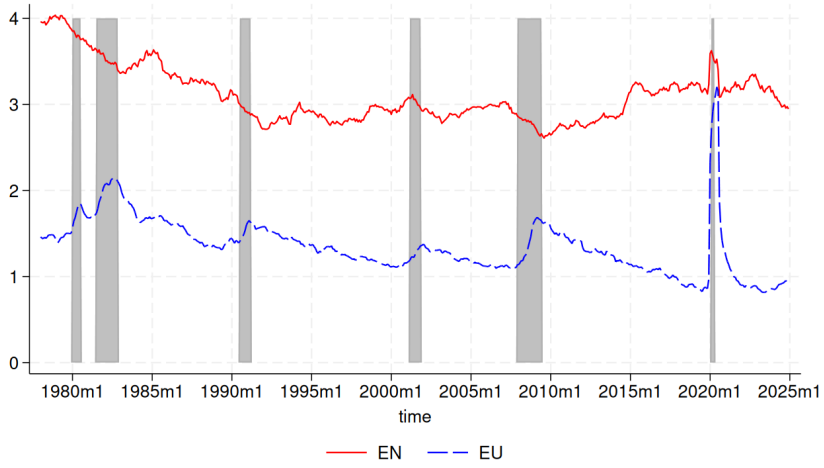


Figure 18: Flow Rates from Employment to Non-Participation (EN) and to Unemployment (EU) (as a percent of employment)

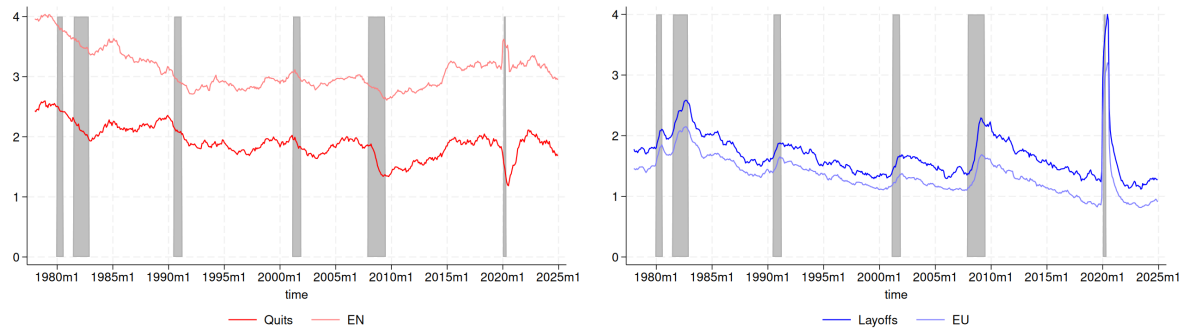


Figure 19: Comparison of Quits and EN flows (left) and Layoffs and EU flows (right)

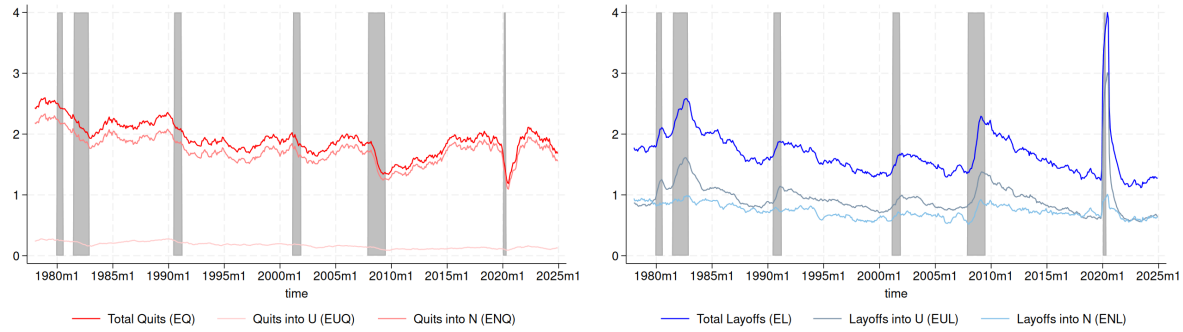


Figure 20: Monthly Quits (left) and Layoffs (right) by Destination

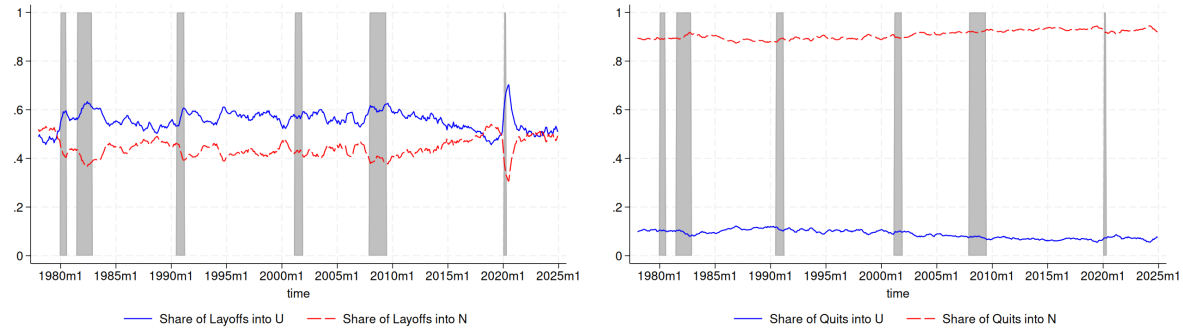


Figure 21: Share of Quits (left) and Layoffs (right) by Destination

A.2 Business Cycle Statistics

Statistic	Quits			Layoffs			Total sep.
to connect	to U	to N	Total	to U	to N	Total	to (U+N)
Corr(x, y)	-0.0278	-0.2708	-0.2356	0.7629	0.7526	0.8170	0.5595
SD(x)/SD(y)	0.0303	0.1514	0.1721	0.2569	0.0862	0.2429	

Table 17: Business cycle correlations of each flow (x) with the unemployment rate (y)

Statistic	
Corr(EQ, EL)	-0.1225
SD(EQ)/SD(EL)	0.5458

Table 18: Business cycle correlations of quits and layoffs

Statistic	Layoffs	EU	Quits	EN
Corr(x, y)	0.8170	0.7726	-0.2356	0.0292
SD(x)/SD(y)	0.2429	0.2750	0.1721	0.2013

Table 19: Business Cycle correlation of EU and EN flow rate with Unemployment Rate

A.3 Importance of Labor Supply Decisions

Statistic	Share of Layoffs into N	Share of Quits into N
Corr(x, y)	-0.5859	-0.1015
SD(x)/SD(y)	0.0217	0.0101

Table 20: Business Cycle correlation of the share of layoffs and quits into N with the unemployment rate

B Comparison to Jolts

The Job Openings and Labor Turnover Survey (JOLTS) has been the primary source used to analyze quits and layoffs in the United States.[15] It is a monthly employer survey run by the Bureau of Labor Statistics (BLS). In this section, we compare our CPS quits and layoffs series with the corresponding JOLTS series.

JOLTS defines layoffs as "Involuntary separations initiated by the employer" and quits "Employees who left voluntarily. Exception: retirements or transfers to other locations are reported with Other Separations". Lastly, the JOLTS category "Other Separations" includes "retirements; transfers to other locations; deaths; or separations due to employee disability". Therefore, a quit in JOLTS is any voluntary separation with the exception of retirement, disability, death, or transfers to other locations; and a layoff is any involuntary separation. It is important to note that JOLTS includes job-to-job quits and layoffs, whereas we can only observe the quits and layoff distinction for separations to non-employment[16] The JOLTS are also known to under count separations even when sampling weights are applied because they do not measure separations due to firm exit (Faberman (2005)). To remedy this, the disseminated JOLTS

[15] Other complementary and timely data sources include the Survey of Consumer Finance (SCF) as for example in Koşar and Van der Klaauw (2023).

[16] Fujita et al. (Forthcoming) provide a series of employer to employer flows that does not distinguish quits and layoffs.

data are adjusted via a Monthly Alignment Method to produce stocks that are consistent with employment measured in the Current Employment Statistics (CES) (Cheng et al. (2009)).

In order to compare our data to JOLTS, we will restrict it accordingly. Layoffs are straightforward since we, similar to JOLTS, only consider individuals as laid off if they lost their job involuntarily. With regards to quits, we exclude all individuals who are retired[17] and disabled individuals are automatically excluded because they are not in the universe of individuals being asked the question of reason for non-participation. Death is also automatically excluded due to our linking strategy, because a dead person would not show up in the current month. Lastly, since we only consider separations into non-employment we do not have to worry about transfers to other locations. The earliest available from JOLTS is for January 2001, so restrict our series to start at the same date. Both series are seasonally-adjusted.

Figure 22 compares the JOLTS layoffs series with our layoffs series constructed using the CPS, including and excluding the pandemic recession. For every month in the sample, with the exception of the pandemic recession, the layoff rate computed using JOLTS data exceeds our layoff rate based on the CPS data.

The correlation between the two series for the entire time period is 0.63. Notably, our layoffs series is significantly more responsive to fluctuations in the unemployment rate. The correlation of the CPS layoffs series with the unemployment rate is 0.50, whereas it is only 0.27 for the JOLTS layoffs series.

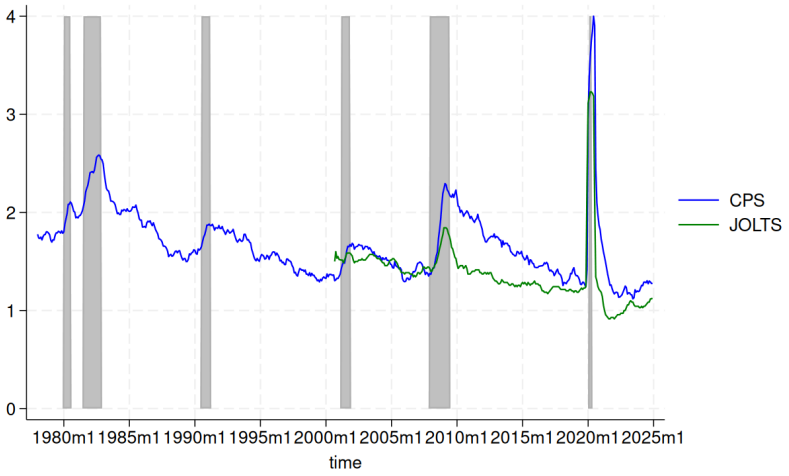


Figure 22: Comparison Layoffs CPS and JOLTS

C Additional Business Cycle Statistics

Comparing Recessions Our time series covers six recessions starting with the one in 1980 up until the pandemic recession of 2020. Obviously, recessions differ in their cause, length, and

[17] By definition, they should not be asked the question in the CPS, but yet, there is a very small number in some months, which respond with retirement, and we exclude those

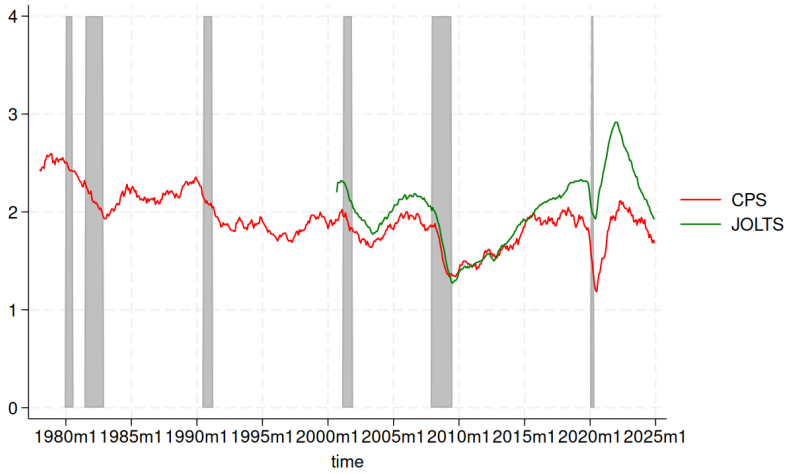


Figure 23: Comparison Quits CPS and JOLTS

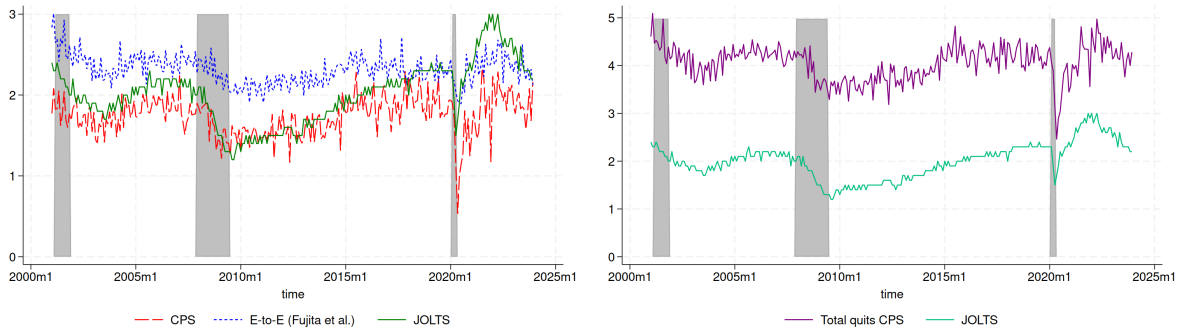


Figure 24: Quits: adjusted CPS quits to nonemployment, E-to-E flows Fujita et al. (Forthcoming), and JOLTS (Left); combined CPS quits plus E-to-E and JOLTS (right)

severity, as well as their impact on the labor market. However, the following two figures show that recessions are remarkably similar with regards to quits, layoffs, and total separations into non-employment. Thus, we do not think that our empirical findings are the result of specific recessions having a dominating effect on the overall timeseries.

Rather than looking at a measure of the business cycle that depends on time, we consider labor market tightness as a measure of the state of the economy.[18] Analyzing our timeseries in relation to market tightness allows for a more equal comparison among very different recessionary periods. Figure 25 shows the relationship between labor market tightness and our quit series for each recession plus six months of recovery. Each set of colored dots represents one of the six recessions. We see that quits are low if labor market tightness is low and increase when the labor market becomes tighter. This observation is true for all recessions. While we see a long-run trend decline in quits, there does not seem to be large differences across business cycles as the positive correlation between quits and labor market tightness is similar in magnitude across all recessions.

[18]Labor market tightness is defined as the vacancies relative to unemployed.

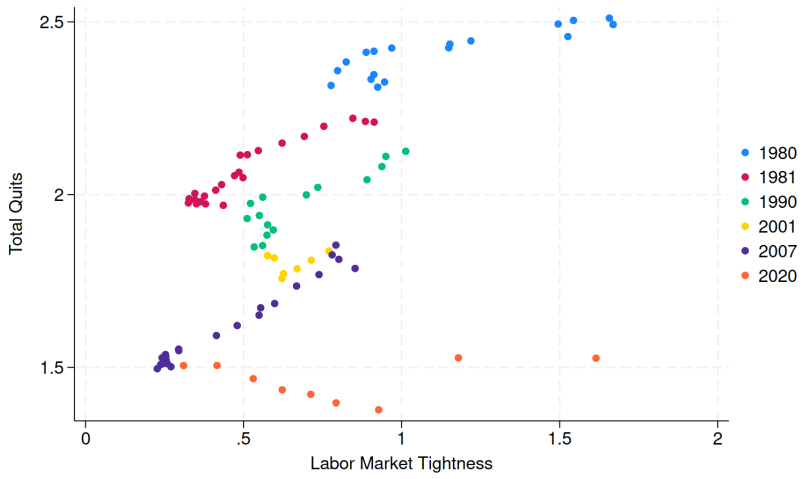


Figure 25: Total quits into non-employment is positively correlated with labor market tightness

Figure 26 shows the relationship between total separations into non-employment and labor market tightness for the same time frame as the previous figure. We see that total separations are completely unrelated to labor market tightness for all recessions. As mentioned previously, the reason is that the decline in quits during loose labor markets almost perfectly offsets the increase in layoffs during these periods. Again, we can observe level differences across the different recessions, primarily due to the severity of job loss and the level of layoffs, but business cycle patterns are the same across all recessions.

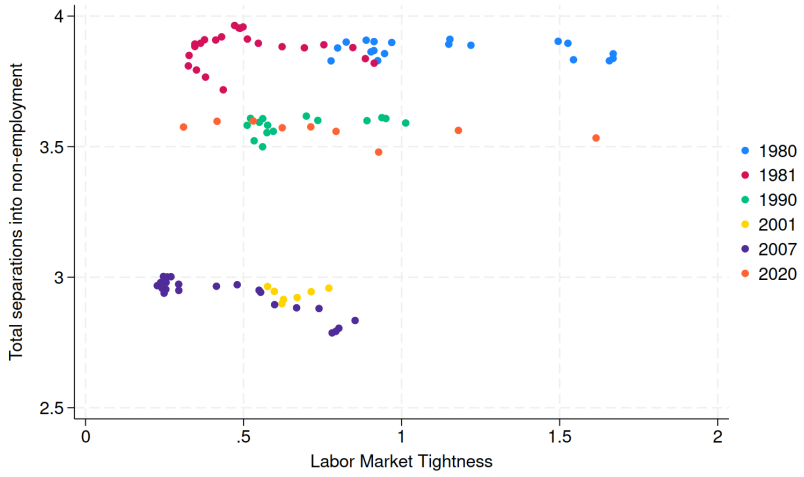


Figure 26: Total separations into non-employment is not correlated with labor market tightness

Tight Labor Markets To focus on expansions we construct a measure of a tight labor markets. We follow Aaronson et al. (2019) and use an indicator of whether the unemployment rate in a given quarter is below the noncyclical rate of unemployment..[19] Table 21 shows correlations

[19]Since data for the noncyclical rate of unemployment is only available at the quarterly frequency, we transform our monthly data into quarterly by averaging over each quarter.

of the different flow rates with this measure of tight labor markets. They capture the movement of flows in exceptionally good times for comparison with Table 6 which uses the unemployment rate as an indicator.

Statistic	Quits			Layoffs			Total sep.
	to U	to N	Total	to U	to N	Total	to (U+N)
Corr(x, y)	0.1828	0.2967	0.2664	-0.3491	-0.2291	-0.3880	-0.1945

Table 21: Correlations of each flow (x) with the measure for a tight labor market (y)

We see that tight labor markets (expansions) are characterized by higher quits, both into unemployment and non-participation. In other words, workers become more likely to quit when vacancies are high, the unemployment rate is low, and jobs are easy to find. Layoffs show the opposite pattern. Layoffs decline in tight labor markets, which is not surprising.

Total separations, quits plus layoffs, decline during tight labor markets. Although quits increase, the fall in layoffs during these periods dominates the rise in quits and leads to an overall fall in separations into non-employment.

Alternative Beveridge Curve Figure 27 uses our quits series to produce an alternative Beveridge curve. Instead of graphing the unemployment rate against a measure of vacancies, we graph the unemployment rate against our quits series. We do this for each recession, starting at the peak and ending 12 months after the trough. The resulting figures show a downward sloping curve similar to the standard Beveridge curve. The downward shape shows that the number of quits decreases as unemployment in the economy increases. One interpretation is that quits are higher in tighter labor markets. This is not surprising based on the theory of "job hoarding". Workers are less likely to quit a job during times when it is difficult to find a new job, which would explain the shape of the alternative Beveridge curve.

Notably, the relationship between quits and unemployment does not vary much from recession to recession, whereas the relationship between vacancies and unemployment does.[20] Thus, we do not observe any shifts of the alternative Beveridge curve as one commonly does with the standard Beveridge curve. The most likely explanation is that quits to non-employment are not (as) informative about matching efficiency as the rate of vacancies.

D Additional Statistics

D.1 Quits and Layoffs for Different Demographic Groups

We observe substantial heterogeneity and highlight here the most commonly used distinctions: gender, race, education, and family structure. However, the data allows for studying many more

[20] If we were to plot all recessions in the same figure, they would be not all laying on top of each other, see figure 28 in the appendix.

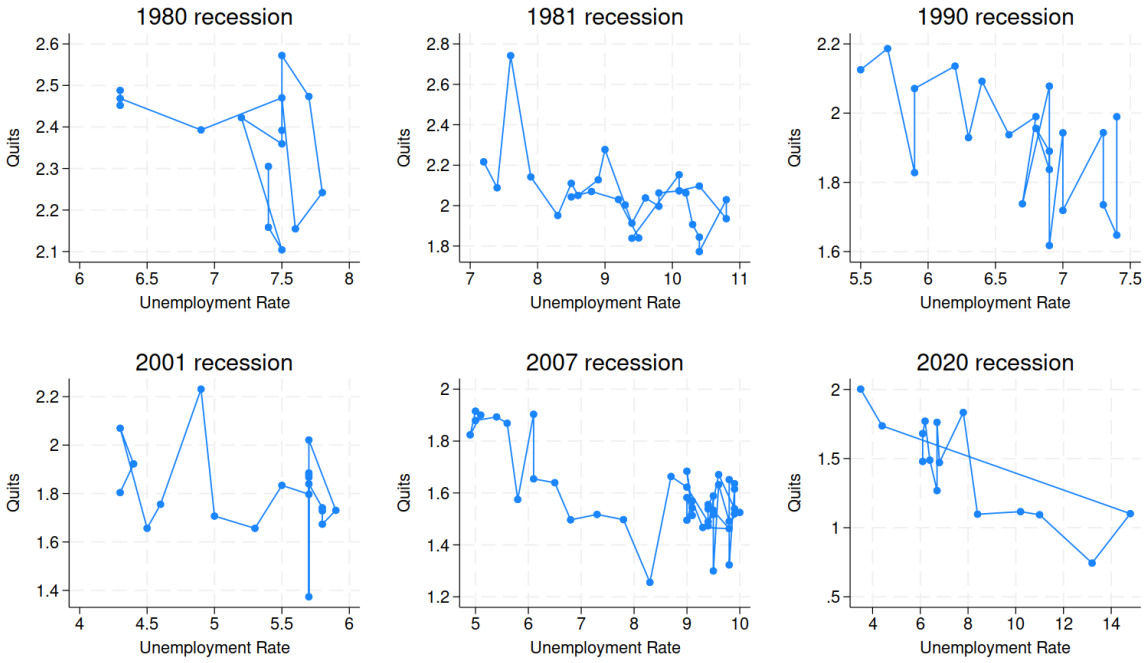


Figure 27: Alternative Beveridge Curves for each recession

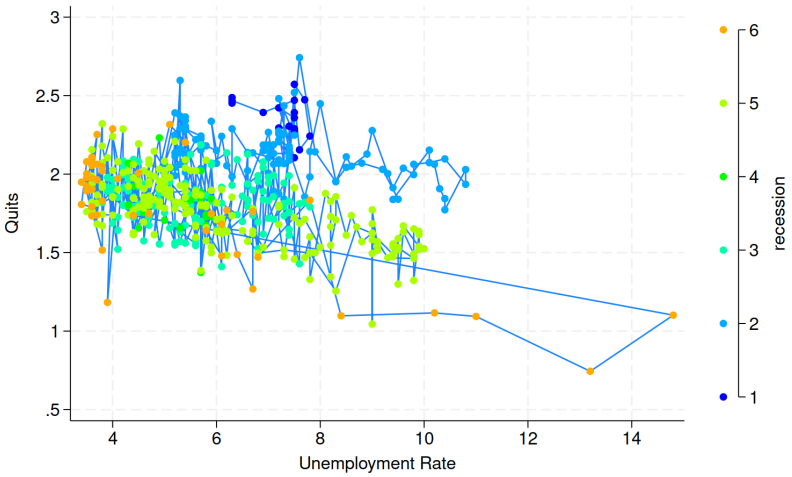


Figure 28: Beveridge Curves for the entire time period

dimensions of heterogeneity.

Gender We observe very clear level differences between men and women in their quit series. For women, quits are twice as large in the 1980s than for men, and this difference slowly decreases as the monthly quits for women decline. Actually, it appears that both quits and layoffs are trending downwards over time for women, whereas there is no apparent trend for men in either of the two series. For men, quits and layoffs are on average about the same magnitude, but for women monthly quits are always larger than monthly layoffs, with the exception of the three pandemic months. For both men and women, quits are procyclical and layoffs are countercyclical.

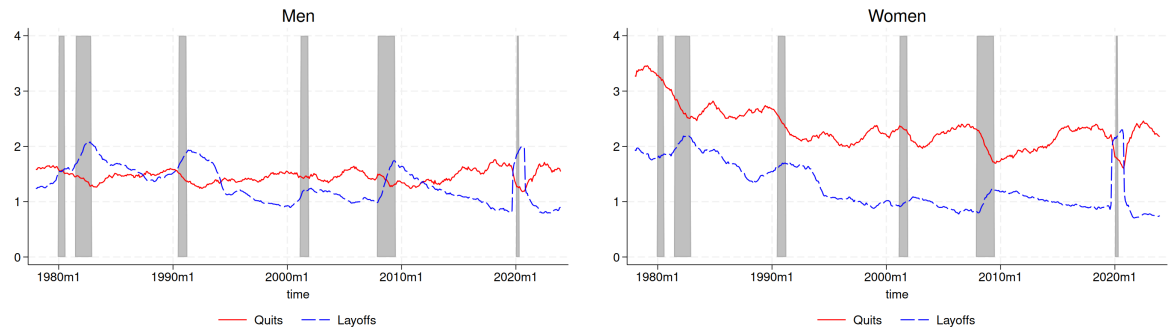


Figure 29: Quits and Layoffs by Gender

Race We also observe substantial level differences when distinguishing between Blacks and white individuals. Both quits and layoffs are larger for Blacks than Whites. Interestingly though, the co-movement of quits and layoffs are similar for both groups, it just looks as if the two series are shifted upwards for Blacks. For both groups, quits are larger than layoffs, with the notable exception of the 1980s for the Blacks, where layoffs were significantly larger than quits. It appears that Blacks and whites experienced a decline in their layoffs between the late 1970s and mid-2000s. Quits, however, are procyclical but without a clear trend.

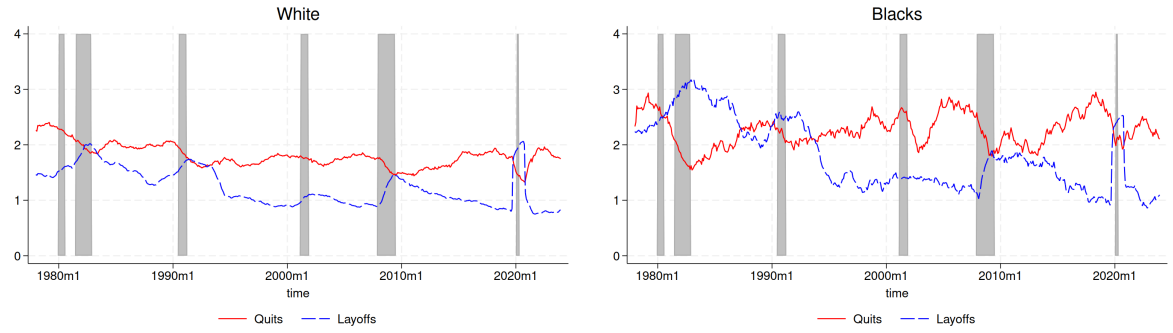


Figure 30: Quits and Layoffs by Race

Education Again, when we split the sample by education, we observe level differences. High school (at most) educated workers' quits and layoffs are higher than for College (at least) educated workers for the entire observation period. For both groups, quits are procyclical and layoffs are countercyclical. Although quits appear to fall more and layoffs increase more for high school educated workers, the relative changes (relative to their level) in recessions for the two groups are similar. Layoffs have been falling for the high school group from the 1980s until right before the pandemic, but we do not see a similar trend in the college group.

Family Structure Lastly, we split the data into three groups: Married without kids, single without kids, and households with kids, such that there are no overlaps between the three groups. Maybe not too surprising, but households with kids have the highest quit rates, which

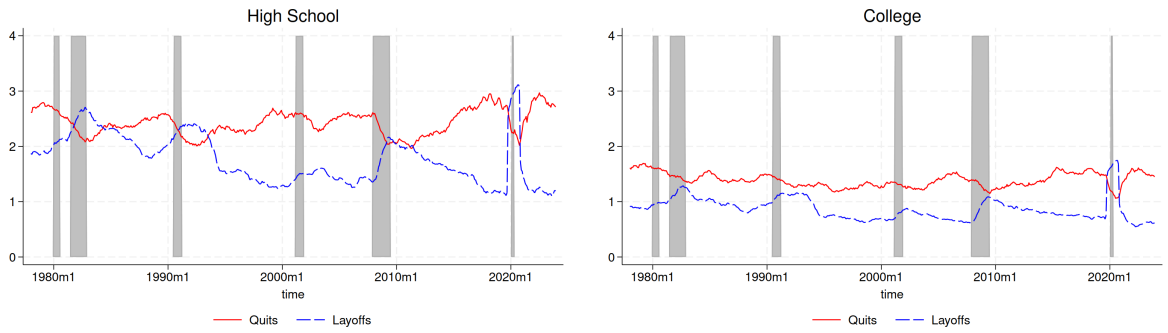


Figure 31: Quits and Layoffs by Education

are higher than for any of the other types we analyzed in this section. Furthermore, this group also has the layoff rates compared to married households and single households; however, this rate displays a clear downward trend from the early 1980s until the beginning of 2020.

Married and single households are more similar in their level of quits and layoffs. The quit rates for married households are slightly higher as married women have the highest quit rates (see Ellieroth and Michaud (2024)) and married men have the lowest and singles fall between the two. The quits and layoffs series for all three types of family structure display the procyclical quit pattern and countercyclical layoff pattern.

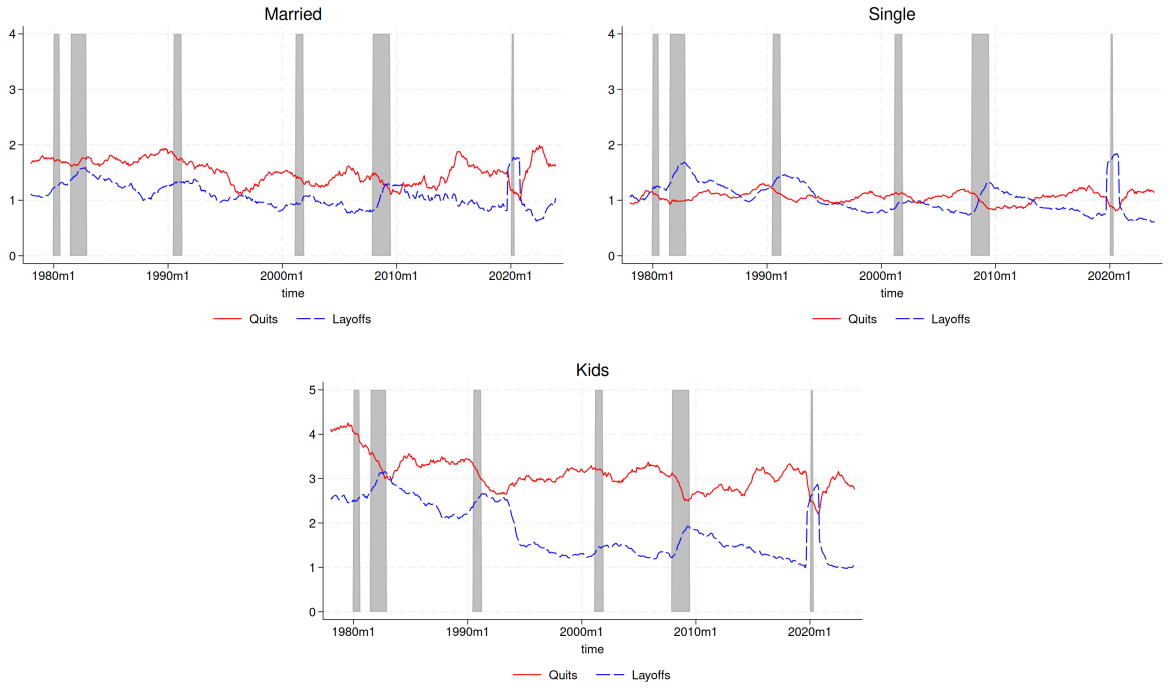


Figure 32: Quits and Layoffs by Family Structure