Quits, Layoffs, and Labor Supply

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Abstract

We provide fresh evidence that labor supply is broadly counter-cyclical. Employed and laid-off workers both increase labor market attachment when unemployment is high. A workhorse search model is used to frame how these facts add nuance to our understanding of business cycles and of labor supply fundamentals: how many workers are near the margin of participation and what drives their choices? Additional results explore regularities of these patterns across cyclical episodes and in the cross section of workers. Additional microeconomic data that suggest income effects contribute to increased labor supply in recessions but are unlikely to be the complete story.

1 Introduction

What drives labor markets over the business cycle? While movements in labor demand are the primary driver, this paper provides fresh evidence that labor supply provides an important countervailing force. Indeed, we find labor supply is more broadly counter-cyclical than perhaps previously appreciated. This finding stands in contrast to neoclassical theory and can change views of labor markets in three ways. First, rising labor supply counters falls in labor demand during recessions, and implies the fundamental shocks driving employment fluctuations are larger when the supply channel is considered. Second, rising labor supply amplifies increases in unemployment more during recessions as laid-off workers stay more attached to the labor force. Third, the broad scope of movements in labor supply over the business cycle illuminate and refine our theories of labor supply. It appears many workers are on the margin of the labor force and understanding what drives them to work is fundamental to understanding labor markets.

We show that workers increase their labor supply in recessions by focusing on three labor supply decisions distinctly: whether an employed person quits out of the labor force, whether

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a laid-off worker exits the labor force after they lose their job, and whether a person currently not in the labor force chooses to enter. We find that individuals in all three scenarios are more likely to increase their labor supply when unemployment is high. The cyclical dynamics of labor supply on each of these three margins carry distinct information about the nature of the business cycle as well as aggregate labor supply elasticities.

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 reason, quit or layoff, and find that 40% of all layoffs lead to a labor force exit, not unemployment.[1] Labor supply decisions of laid-off workers provide particularly useful insights into the elasticity of the extensive margin of labor supply. A worker who separates due to a layoff is one who would likely have stayed on and kept working at their old job. Exiting after a layoff indicates that the worker had been near the margin of labor force exit and seeing such a large share of workers exiting after a layoff suggests there are many workers for whom the surplus from work is relatively small.

We not only find that there is a sizable share of workers who exit the labor force after a layoff, it is also the case that the choices of these marginal workers help shape cyclical dynamics of the labor market, and particularly unemployment. Their labor supply follows a distinct countercyclical pattern as the share of workers who leave the labor force after a layoff markedly decreases during recessions. This finding is consistent across all recessions since the 1980s. Through a counterfactual exercise in which we keep the share of workers exiting after layoff constant over the business cycle, we show that around 25-30% of the increase in the unemployment rate in recessions is due to the decrease of laid-off workers exits during recessions.

Our empirical analysis also reveals that voluntary quits from employment to non-participation are procyclical, that is these quits decrease during recessions implying the labor supply of employed workers is also countercyclical. Separating flows from employment into quits and layoffs is essential for this result because flows from employment to non-participation are not equivalent to quits out of employment. For instance, around 1.5% of workers exit the labor force from employment each month but only 1% of workers voluntarily quit to non-employment. This difference is largely attributed to workers who choose non-participation after a layoff. While the employment to non-participation (EN) transition rate is acyclical to mildly countercyclical, we find that quits are procyclical, decreasing when unemployment rises during recessions.[2]

The procyclicality of quits and countercyclicality of layoffs paint a unique picture of how

[1] All statistics and findings in the main text are for the prime-age population, i.e. those between 25 and 55 years of age. We provide the same information for the entire working-age population in the appendix.

[2] Cyclicality in this paper is defined with respect to the unemployment rate. We find that quits are also more procyclical than EN with respect to the cyclical component of GDP as in Krusell et al. (2017), Graves et al. (2023), Qiu (2022), and others.

business cycles unfold. During recessions, quits decline as layoffs increase. This is not news. What is new and striking is the magnitudes. The fall in quits almost completely offsets the rise in layoffs leading total separations to be almost acyclical. This indicates that while the total separation rate from employment may appear irrelevant for rises in unemployment during recessions, we now see the composition of separations critically changes. Layoffs are a leading indicator of a recession even if total separations are not.

We synthesize the impact of our empirical findings on our understanding of business cycles by highlighting the challenges standard search theory faces in replicating facts on labor supply. Taking stock, we believe there are three salient facts characterizing recessions: (i) labor supply increases, on the margin, via quits to non-employment fall and the share of laid-off workers who exit the labor force falls; (ii) total separations from unemployment are virtually acyclical, (iii) market tightness falls (aka vacancies per unemployed worker fall). The first fact is that labor supply increases for everybody during a recession, and the second fact emphasizes the quantitative importance that the decrease in voluntary quits almost completely offsets the increase in layoffs. The third fact is well-established and shows that the reduction in employment must mostly come from reductions in vacancies and hiring. Increased labor supply, however, causes market tightness to move more than the drop in vacancies and is quantitatively non-trivial since we have shown that 25-30% of the cyclicality of unemployment is due to labor supply of laid-off workers. We find that, qualitatively it is challenging to identify a single shock which can decrease market tightness, increase labor supply, and simultaneously increase layoffs, as we have observed in the data. We posit a collection of shocks that can do the job and use the model to explore how large those shocks would have to be.

The remainder of our paper explores ancillary evidence related to theories of counter-cyclical labor supply. First, we focus on a couple of demographics with many marginal participants who drive overall quits and labor force exits and their declines during recessions. Marginal participants, compared to highly attached participants, experience a 2 to 3 times larger decline in quits during recessions. Additionally, the share of marginal participants exiting the labor force after a layoff falls more during recessions than for the average US worker. These facts indicate that studying marginal participants is useful for understanding the increased labor supply in recessions and identifying necessary features for a complete theory of labor markets over the business cycle.

Second, we examine recovery after the COVID-19 pandemic recession and show that our time series offer an informative alternative for researchers and policymakers interested in quits and layoffs. Despite the pandemic recession differing in many aspects from other recessions, it is no different in the business cycle patterns of quits and layoffs. Both quits and layoffs into non-participation decrease, but the decline in quits is dominated by the unprecedented rise in layoffs. Interestingly, we find no evidence of a "great resignation" and instead a recovery pattern that is very similar to earlier recessions.

Our data present new opportunities to research quits and layoffs and connect them to worker characteristics and their subsequent labor supply decisions. Prudent researchers will view these data alongside other data on layoffs and quits to form the most accurate view of labor markets. The main complementary data, updated monthly, come from the Job Openings and Labor Turnover Survey (JOLTS), a survey of employers. We conclude by comparing and contrasting our data with JOLTS. Notably, the quits series track each other well across the two surveys until the late 2010s. Even when combined with direct employer to employer flows computed by Fujita et al. (Forthcoming), the CPS data and JOLTS data diverge after the pandemic. Regarding layoffs, our series shows a more pronounced increase during the 2007 recession compared to JOLTS data, but both series display similar business cycle patterns.

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

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. While our paper focuses on employment to non-employment separations, as only these can be decomposed into quits and layoffs using the Current Population Survey (CPS), Fujita et al. (Forthcoming) have used the CPS to study job-to-job transitions. However, the CPS does not have information to be able to distinguish whether a direct job-to-job transition is due to a quit, layoff, or other reason.

The majority of these studies, including ours, rely on CPS data. However, some researchers, such as Davis et al. (2011) have employed alternative data sources like the Job Openings and Labor Turnover Survey (JOLTS) to study labor market fluctuations. We provide a comparison of our CPS-derived series with JOLTS separations data in Section 8 of this paper.

A few other papers include non-participants in their time series on quits and layoffs. Perhaps the most related paper to our study is Akerlof et al. (1988). They establish similar empirical regularities of quits and layoffs over the cycle that we do and develop an unified theory of procyclical quits and countercyclical layoffs that includes job hording. We add insight from labor supply decisions after layoff and argue additional ingredients are required. Other studies of business cycles have used methodology similar to what we do in this paper to study quits and layoffs inclusive of non-participants in the CPS.[3] Flaim (1973) used the CPS to show that quits/layoffs are negatively/positively correlated with the unemployment rate and Bednarzik

[3]This review is non-exhaustive. A few other examples are: Clark and Summers (1978) and Freeman (1980).

and Klein (1977) delineates these results by gender.[4] Gellner (1975) uses these questions to explore the concept of a labor reserve similar to our notion of a marginal participant. He shows around 40% of laid off workers who transition to non-participation stay out of the labor force to go to school or tend to home responsibilities.

More recent revivals of the quit/layoff distinction in the CPS include Michaels (2024) who focuses on the great resignation and Graves et al. (2023) who examine the relationship with monetary policy. Graves et al. (2023) find that monetary contractions stimulate a large labor supply response by reducing quits and increasing job search among people not in the labor force. This complements our theoretical argument that recessions feature large labor supply increases, on the margin, to be consistent with our findings of lower quits to non-employment and a higher share of laid off workers choosing to seek when unemployment is high. Simmons (2023) uses data from the Survey of Income and Program Participation (SIPP) and UK survey data to classify all separations as layoffs, quits, or other. While this SIPP-based approach allows for the classification of all separations, including direct job-to-job, it lacks some advantages of CPS data which is more frequent (monthly) and longer (uninterrupted since 1978). None-the-less, Simmons (2023) provides external validity of our CPS classifications and we add to this by replicating similar results for all quits and layoffs in a third dataset, the PSID.

Recent studies have also employed dis-aggregated CPS data on flows and transition rates to examine how demographic factors influence business cycles and trends in various labor market stocks (e.g. Ellieroth (2023), Hegarty (2023), Ellieroth and Michaud (2024))

The unique dynamics of quits and layoffs following the COVID-19 pandemic have sparked renewed interest in the distinct implications of the reason for a separation. Qiu (2022), Graves et al. (2023), Moscarini and Postel-Vinay (2023), and Bagga et al. (2023) investigate cyclical dynamics, including the "Great Resignation" phenomenon. Cai and Heathcote (2023) and Blanco et al. (2023) explore the quit versus layoff distinction in other contexts.

Our work also relates to the literature on the unemployment volatility puzzle, as discussed by Shimer (2005) and further explored by Chodorow-Reich and Karabarbounis (2016), Hagedorn and Manovskii (2008), Ljungqvist and Sargent (2017), and Mitman and Rabinovich (2019). We contribute to this discourse by demonstrating that layoffs are more frequent and less cyclically volatile than flows from employment to unemployment; and also that labor supply appears to be countercyclical, on the margin.

2 Data and Methodology

2.1 Data source

We use monthly data from the Current Population Survey (CPS) from January 1978 to July 2024. The CPS is a rotating panel survey of approximately 60,000 households, conducted by the

[4] Flaim (1969), Schwab (1974), Deutermann Jr (1977), Job (1979) Freeman (1980), and others study characteristics of CPS non-participants based on whether they report a quit or layoff including demographics and whether they want a job.

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

U.S. Bureau of Labor Statistics. 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. Our primary sample includes all individuals aged 15 and above, with a supplementary analysis focusing on the prime-age population (25-55 years old).

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.

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

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

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

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.[5]

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 CPS data. The next paragraphs will outline the process to distinguish separations into non-participation by reason of separations.

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.[6] 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 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.

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

[6]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.

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.[7] 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.[8] 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.

2.5 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

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

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

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 An Overview of Quits and Layoffs

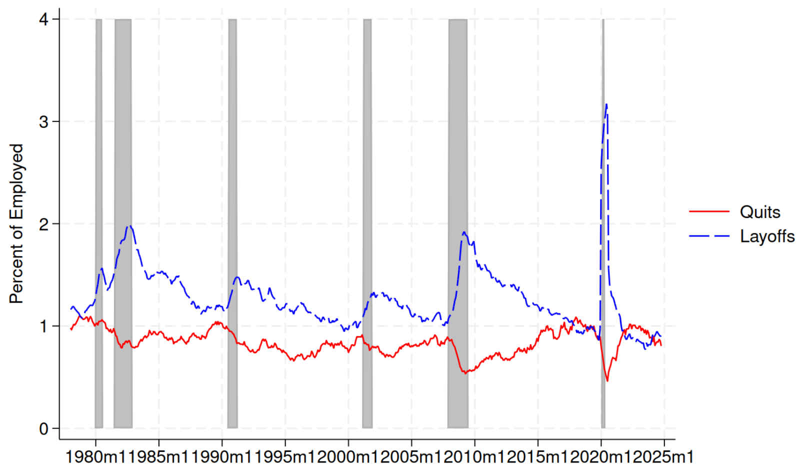

Figure 1: Monthly Quits and Layoff rates (as a percent of employment) (Monthly seasonally-adjusted data and 6-month centered moving average)

Figure 1 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 quit rate generally exceeds the layoff rate but the two converge 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 the following section.

Figure 2 shows the two series together, i.e. total separations into non-employment. In the average month, 2.1% of workers leave their job to non-employment either as a result of a quit or a layoff. While we saw in the previous figure that both quits and layoffs vary with the business cycle, total separations do not move much over the business cycle. The reason for that is that the decline in quits during recessions mostly off-sets the rise in layoffs.

Figure 3 plots flows from employment to non-employment by destination: unemployment or non-participation. These were the standard flows considered in prior research on the cyclical properties of the labor market. 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. Comparing Figure 4 and Figure 1, it is obvious that these flows are related but not the same. Notably, the rate of EN flows is around 70% higher at a

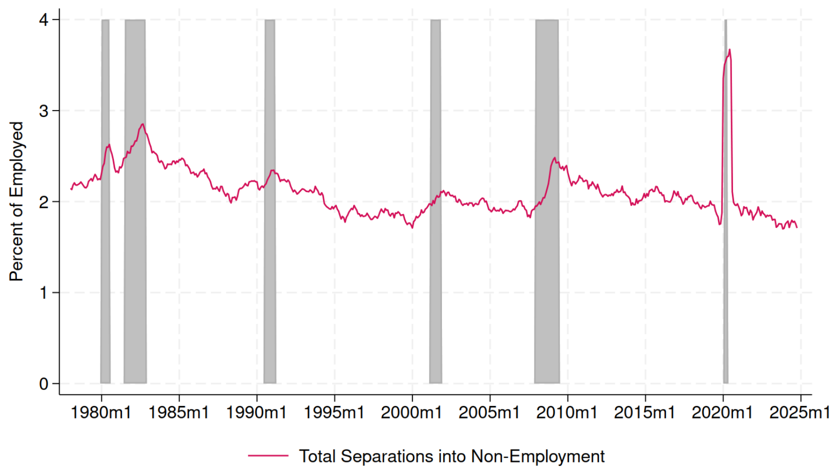

Figure 2: Total Separations (Quits+Layoffs) into Non-employment (as a percent of employment) (Monthly seasonally-adjusted 6-month centered moving average data)

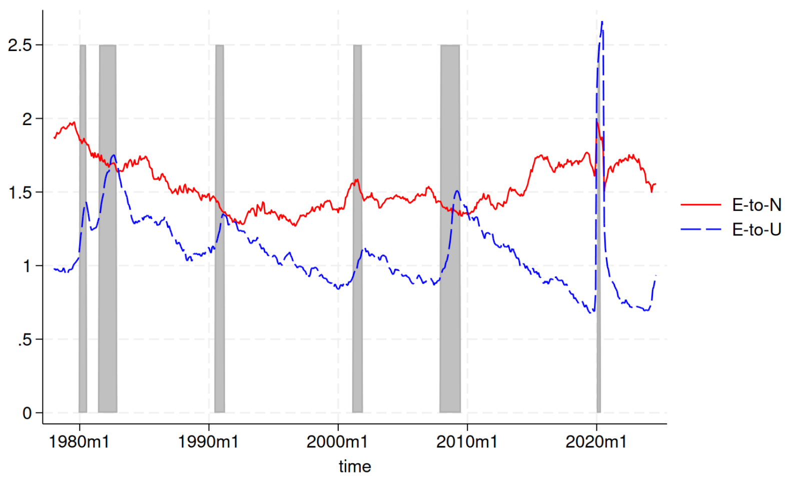

Figure 3: Flow Rates from Employment to Non-Participation (EN) and to Unemployment (EU) (as a percent of employment) (Monthly seasonally-adjusted 6-month centered moving average data)

monthly frequency than the quit rate. There are also clear cyclical differences with the quits and layoffs each more volatile than EN and EU, respectively. Figures 4 and 5 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 rest.

Specifically, 40% of laid of workers move to non-participation. For workers who quit, the share who move to non-participation is much higher at over 86%. 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 40%, which will be especially important considering business cycle fluctuations.

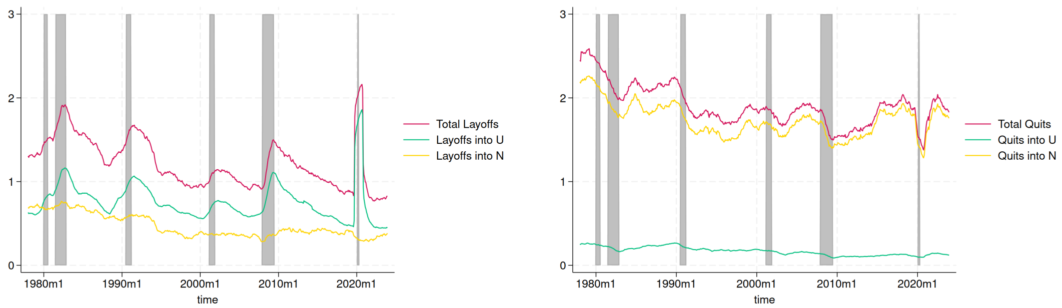

Figure 4: Monthly Quits and Layoffs by Destination

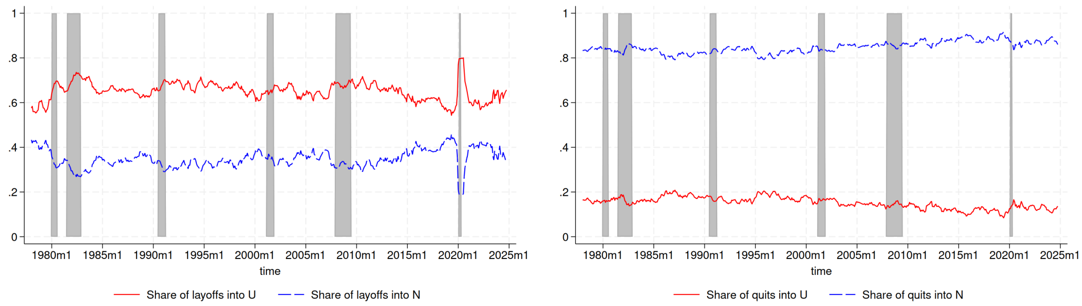

Figure 5: Share of Quits and Layoffs by Destination

3.1 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 recent job.[9]

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 3 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

[9]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.

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

Table 3: Activity in non-participation by reason for non-participation

non-participation and the major activity after leaving employment into non-participation.

4 Business Cycle: How Quits and Layoffs Shape Labor Market Fluctuations

4.1 Basic 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 and frictions interact and vary over the business cycle.

We start by illustrating how quits and layoffs evolve over the business cycle in Table 4. The first row of Table 4 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 1. Table 5 shows that the correlation between quits and layoffs over the entire observation period is -0.3019. (For comparison, the correlation between E-to-U and E-to-N flows is strongly positive, 0.05). Quits decrease in times when unemployment increases, and thus, are procyclical. Layoffs, on the other hand, are countercyclical and increase when 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, on the other hand, display a similar cyclicality regardless of the destination of the layoff. 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.

Statistic	Quits			Layoffs			Total sep.
	to U	to N	Total	to U	to N	Total	to (U+N)
Corr(x, y)	-0.1478	-0.3897	-0.3929	0.6013	0.4885	0.6117	0.7062
SD(x)/SD(y)	0.0191	0.0844	0.0910	0.2499	0.0639	0.2989	

Table 4: Business cycle correlations of each flow (x) with the unemployment rate (y)

Table 6 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 4. The first two columns compare

Statistic	
Corr(EQ, EL)	-0.3019
SD(EQ)/SD(EL)	0.3044

Table 5: Business cycle correlations of quits and layoffs

EU flow rates (those the standard method often assumed to be layoffs) 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 ture cyclicality of the layoffs.[10]

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 procyclical, they decrease in recessions, the EN transition rate is actually (midly) countercyclical, increasing during recessions. An explanation for this difference is that around 40% of all EN transitions are actually precipitated by layoffs. We have seen in Table 4 that layoffs are strongly countercyclical and work to offset the procyclicality of quits into non-participation. We therefore strongly recommend using the quits series rather than the EN transition rate in order to analyze how labor supply choices, e.g. whether to quit from employment, shape job destruction over the business cycle.

Statistic	Layoffs	EU	Quits	EN
Corr(x, y)	0.6117	0.6210	-0.3929	0.0122
SD(x)/SD(y)	0.2989	0.2531	0.0910	0.1175

Table 6: Business Cycle correlation of EU and EN flow rate with Unemployment Rate

4.2 Shimer Decomposition

In order to evaluate the quantitative importance of our new measures of layoffs and quits, we follow Shimer (2012) and compute how each of the flow rates contribute to the fluctuations in the unemployment rate. Since individuals can make multiple labor market transitions in a given month, we start by computing instantaneous transition rates based on the monthly CPS transition rates.

Time Aggregation Bias Time aggregation bias is an understood shortcoming of using CPS data to analyze labor market flows. It refers to the under count of quits and layoffs that result in quick reemployment or a job-to-job transition. This bias is due to the nature of the CPS questionnaire. It asks only about an individual's current labor market status and, if that status is different from last month, asks questions about why his or her status changed. It does not

[10]Compare 0.5083 in Table 4 with 0.5775 in Table 6

capture status changes that occurred between monthly interviews. For example, an individual who is employed in the March survey and then gets laid off but finds a job before the April survey will not be counted in our tabulation of layoffs.

The time aggregation bias implies that our method of tracking quits and layoffs would under count during expansions when it is easy to find another job and non-employment duration is short and get closer to the true count of separations during recessions when it takes longer to find a job. This would overstate the cyclical volatility of each type of separation.

We provide a correction for the time aggregation bias by adapting the methodology from Shimer (2012). This methodology is used to convert discrete monthly Markov transition matrices to continuous time, typically for three labor market states: (E)mployment, (U)nemployment, and (N)ot in the Labor Force. Since we are interested whether a flow out of employment was predicated by a quit or a layoff we must expand the set of states. We refer to the two new states as "employed at risk of layoff" (EL) , "employed at risk of quit" (EQ), "employed at risk of unknown separation" (EO). This is critical because we have shown that quits and layoffs are fundamentally different types of transitions out of E due to the fact that they have different destination probabilities between U and N. This expansion introduces a challenge because we do not observe the share of employed in these states, the flow rates between these two states, or the flow rates back into these states from unemployment or non-participation (see Table 7). As a result, we must make additional assumptions.

t/t+1	EQ	EL	EO	U	N
EQ				X	X
EL				X	X
EO				X	X
U				X	X
N				X	X

Table 7: Schema of observed flows. All X's are observed in CPS. Flows into EQ or EL are not observed separately. The red box shows E to E flows are observed in aggregation, not separately for EQ, EL, and EO. Similarly, the blue bars represent the aggregation of U to E and N to E flows.

We fill in the missing components of the Markov matrix with four assumptions. First, we normalize the share of the employed across EQ, EL, and EO to time-invariant and arbitrary values summing to one: say a third in each.[11] Second, we assume that flows between EQ, EL, and EO are zero in all months. Third. we assume that the share of flows from U to E that end up in EQ is the same as the share of flows from N to E that end up in EQ. Fourth, as in Shimer (2012) we assume the US data is in steady state every month. With these four assumptions in place, we use identities of a stationary distribution to complete the missing entries. In other words, then solve for the value of the share of the total inflows to employment that end up

[11]The share is completely inconsequential. We adjust the flow rates from each EQ, EL, and EO to be consistent with observed quit, layoff, and unknown separation rates from the totality of employment. We also always analyze the sum of flows back into the totality of employment (EQ + EL + EO), never decomposing the flows back to each EQ, EL, and EO separately, as they the disaggregation is a meaningless normalization.

in EQ to match the 50% share of employment in EQ in steady state and the remaining flows should exactly provide 50% of the share of employment in EL in steady state. to EQ or EL are each proportional to the share of flows from employment to unemployment that are quits and layoffs that month, respectively. We extend these assumptions to include "other" separations to non-participation where the reason for the last job ending is unknown and include only prime age workers.[12] Under this procedure we have found the eigenvalues of the Markov matrices satisfy the requirements of Shimer (2012).

Decomposition We start by assuming that in steady state the flows in and out of employment and unemployment are equal, such that, including our quits and layoffs series, we have:

$$(\lambda^{EQ} + \lambda^{EL} + \lambda^{EO})e = \lambda^{UE}u + \lambda^{NE}n \tag{6}$$

$$(\lambda^{UE} + \lambda^{UN})u = \lambda^{EU}e + \lambda^{NU}n \tag{7}$$

where λ^{IJ} indicates the instantaneous transition rates.

Equation 6 is modified to include our quit and layoff series. Instead of looking at outflows by destination, we use our quit and layoff series which group outflows of employment by reason (and destination). Note that the flow rates by reason, EQ, EL, and EO, include flows to both unemployment and non-participation. Similarly, EU includes both quits and layoffs.[13]

Solving the above equations for e, u, and n, we get

$$e = k(\lambda^{UE}\lambda^{NU} + \lambda^{NE}\lambda^{UE} + \lambda^{NE}\lambda^{UN}) \tag{8}$$

$$u = k(\lambda^{NE}\lambda^{EU} + \lambda^{NU}\lambda^{EL} + \lambda^{NU}\lambda^{EQ}) \tag{9}$$

$$n = k(\lambda^{UE}\lambda^{EL} + \lambda^{UE}\lambda^{EQ} + \lambda^{UE}\lambda^{EO} + \lambda^{UN}\lambda^{EL} + \lambda^{UN}\lambda^{EQ} + \lambda^{UN}\lambda^{EO} - \lambda^{EU}\lambda^{UE}) \tag{10}$$

so that the unemployment rate in steady state is

$$\frac{\lambda^{NE}\lambda^{EU} + \lambda^{NU}\lambda^{EL} + \lambda^{NU}\lambda^{EQ}}{\lambda^{NE}\lambda^{EU} + \lambda^{NU}\lambda^{EL} + \lambda^{NU}\lambda^{EQ} + \lambda^{UE}\lambda^{NU} + \lambda^{NE}\lambda^{UE} + \lambda^{NE}\lambda^{UN}} \tag{11}$$

In the following we will compute the quantitative importance of each instantaneous flow rate to the fluctuations of the unemployment rate. To do that we start by computing the alternative unemployment rate using equation 11 by setting all flow rates to their average and only letting the flow rate of interest vary over time. In order to compute the quantitative importance of the flow rate of interest, we regress the alternative unemployment rate on the unemployment rate constructed in equation 11.

Table 8 shows the quantitative importance of each instantaneous flow rate to the fluctuation of the unemployment rate.

The first column shows the decomposition for the entire pre-pandemic period using our flow rates constructed from CPS. Column 3 chooses the same time period as Shimer (2012)

[12] Other separations to unemployment are noisy and near zero, and so we set those transitions to zero.

[13] All the other flows from employment to unemployment are misclassification and close to zero, so we ignore them here.

Rate	This paper 1978-2019	Shimer (2012)	This paper 1987-2010
λ^{EQ}	-0.05	-	-0.05
λ^{EL}	0.19	-	0.17
λ^{EU}	0.15	0.17	0.12
λ^{UE}	0.38	0.51	0.43
λ^{UN}	-0.03	0.16	-0.03
λ^{NU}	0.08	0.13	0.08

Table 8: Decomposition of the unemployment rate

to compare our results with his. Similar to Shimer (2012) we find that fluctuations in the job finding rate from unemployment, UE, contribute the most to fluctuations in the unemployment rate (regression coefficient 0.38 for the full 1978-2019 sample). However, we find the contribution of job finding UE to be lower when including quits and layoffs in the decomposition (regression coefficient 0.43 vs 0.51 for the Shimer period of 1987-2010). The importance of EU is similar to Shimer (2012) but we can now see that the layoff rate, EL, contributes even more than the EU rate but is offset by declines in quits EQ.

4.3 Importance of Labor Supply Decisions

Table 9 shows how the destination of quits and layoffs vary over the business cycle. In times when the unemployment rate is high, the share of each layoffs and quits into non-participation decline. The share of layoffs into non-participation is negatively correlated with the unemployment rate. This indicates that while both layoffs into U and N increase in recessions, the increase is larger for layoffs into U. The share of quits that flow into N decreases when the unemployment rate increases. We have seen the reason for that in Table 4: 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 9 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.

Statistic	Share of Layoffs into N	Share of Quits into N
Corr(x, y)	-0.6222	-0.1253
SD(x)/SD(y)	0.0231	0.01543

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

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-

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

off workers leaving the labor force is fixed and constant over time.[14] 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%.

4.4 Robustness

Permanent vs. Temporary Layoffs 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 6 shows that the business cycle pattern of layoffs is driven by permanent layoffs and the majority of layoffs are from permanent jobs. Interestingly, layoffs from temporary are mildly

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

procyclical, i.e. decline during periods when unemployment is high. Because permanent layoffs

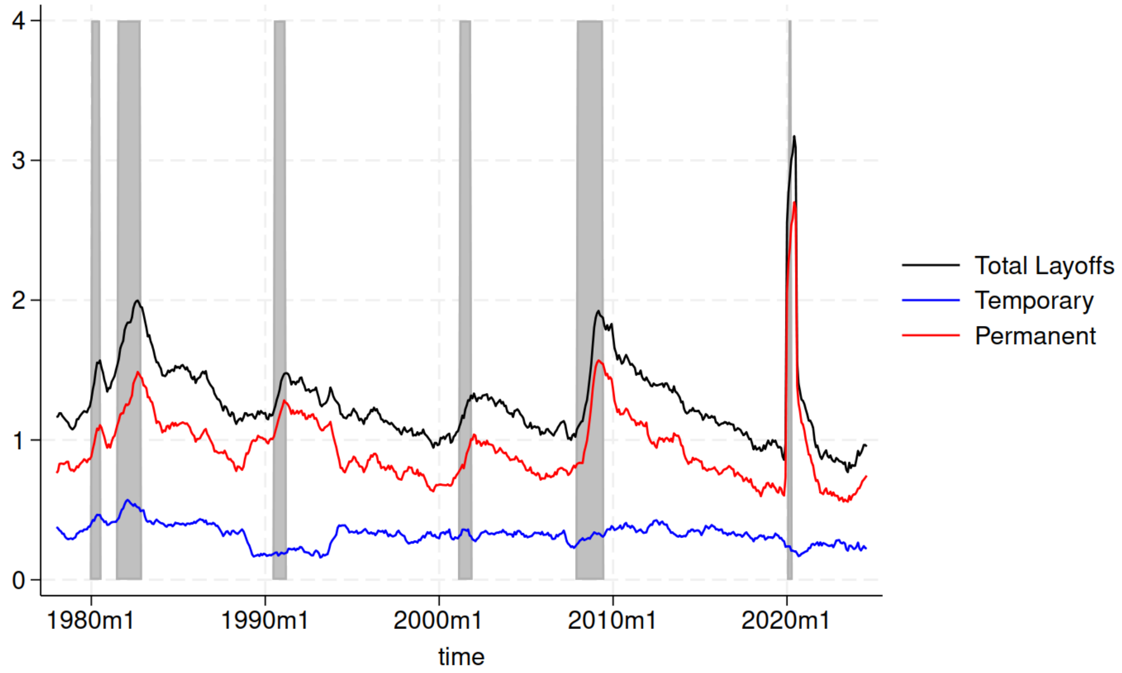

Figure 6: Layoffs from temporary vs permanent jobs

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

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 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. 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.[15] Figure 7 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.

Figure 8 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

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

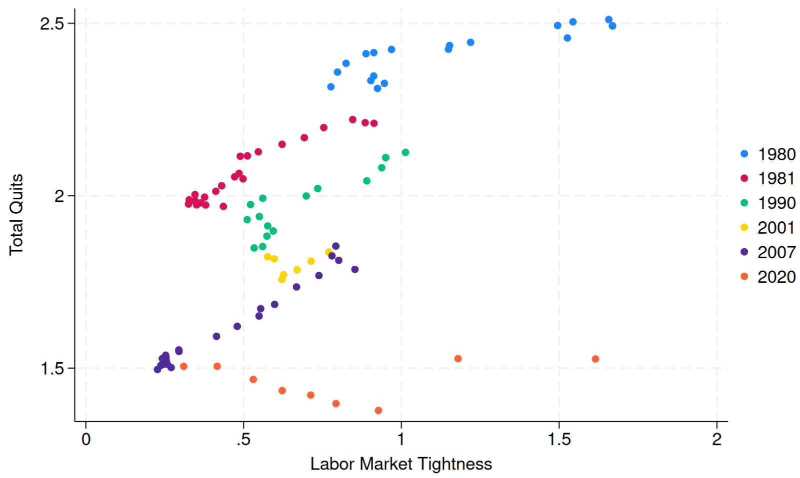

Figure 7: Total quits into non-employment is positively correlated with labor market tightness

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.

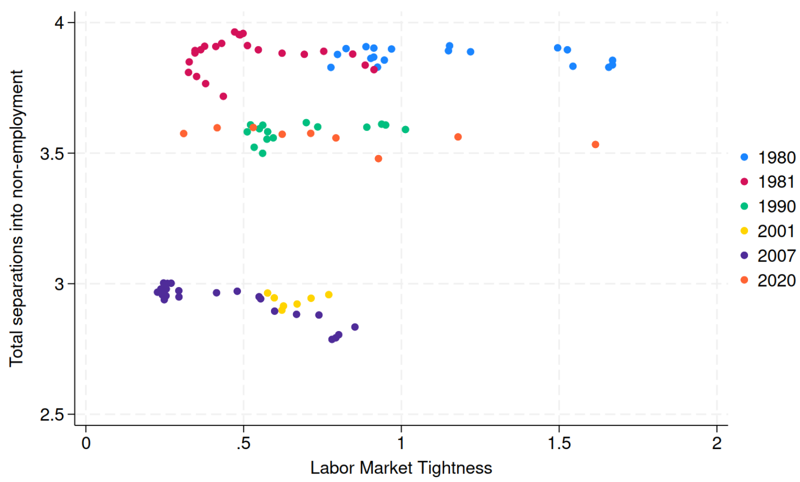

Figure 8: Total separations into non-employment is not correlated with labor market tightness

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..[16] Table 11 shows correlations 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 4 which uses the unemployment rate as an indicator.

We see that tight labor markets (expansions) are characterized by higher quits, both into

[16]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.

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

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 9 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.[17] 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.

5 Theory: Implications for Models of the Labor Market.

Most theories of the labor market view recessions as a time where the net value of employment declines relative to non-employment. Existing jobs are destroyed as firms and workers cannot find terms under which they benefit from continuing their relationship. Vacancies fall as new hires become less profitable.

In this section, we analyze a workhorse model of labor markets to argue that our empirical findings present a refinement, or even a challenge, to this conventional wisdom. In the data, recessions are a time when quits and the share of laid off workers who exit the labor force both fall. In the general theory we present, this is indicative of labor supply increasing, at least on the

[17] If we were to plot all recessions in the same figure, they would be not all laying on top of each other, see figure 32 in the appendix.

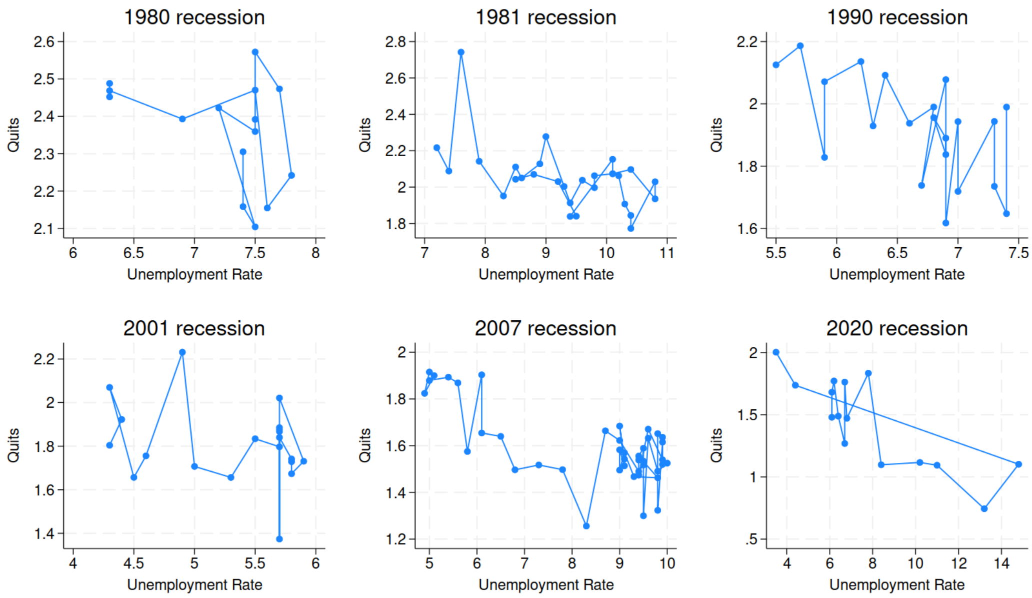

Figure 9: Alternative Beveridge Curves for each recession

margin. We will show this is at odds with some theories of recessions: the shocks that generate recessions also generate a decline in labor supply. Extending models to replicate this behavior is important for understanding drivers of business cycles and how labor supply decisions serve to dampen business cycle fluctuations.

The model follows Garibaldi and Wasmer (2005) who augment the Mortensen Pissarides model with shocks to the value of non-participation to generate quits distinct from layoffs and significant gross flows across labor force participation.

5.1 Model Set Up

Time is continuous. The model has two types of agents: firms and unit measure individuals. Both types are risk neutral and discount the future at rate $r > 0$.

Individuals may either be employed (e), unemployed (u), or are a non-participant (n). Individuals differ in their value of home production, b.[18] A non-participant collects the full value of their home production b. An unemployed worker collects a share of their home production that is net of search costs and unemployment benefits $(1-\alpha)b$. It is assumed that $0 \leq \alpha \leq 1$. An employed individual collects labor income $w(b)$, a Nash-bargained wage that will depend on the worker's individual outside option b.

An individual's value of home production (b), realized or latent, follows a stochastic process. The initial value is drawn from a continuous distribution with c.d.f $F(b)$. New draws occur at Poisson rate ρ.

[18]We call b home production for convince but the quantitative interpretation of b is any idiosyncratic time-varying wedge in the flow net benefit of a job. Real reasons for this could be related to child care needs, health, return to school, etc.

Individuals make labor supply choices. Non-employed individuals choose whether to search for a job in unemployment or do not search and are a non-participant. Unemployed individuals receive job offers at rate $\lambda(\theta)$ and non-participants receive no offers. Employed workers choose whether to quit to non-employment. Jobs can also end exogenously at rate δ.

Let $W(b)$, $U(b)$, and $N(b)$ be the values of employment, unemployment, and non-participation (respectively) to an individual with home productivity b. These can be defined recursively as:

$$\begin{aligned}
(r+\rho)W(b) &= w(b) + \rho\int_{b'} max\{W(b'), U(b'), N(b')\}dF(b') \\
&\quad +\delta[max\{U(b), N(b)\} - W(b)] \\
(r+\rho)U(b) &= (1-\alpha)b + \rho\int_{b'} max\{U(b'), N(b')\}dF(b') \\
&\quad +\lambda(\theta)[max\{W(b), U(b)\} - U(b)] \\
(r+\rho)N(b) &= b + \rho\int_{b'} max\{U(b'), N(b')\}dF(b')
\end{aligned}$$

Firms choose whether to pay a cost κ to maintain an open vacancy. A vacancy yields a match with an unemployed individual at rate $\lambda^f(\theta)$. All employed matches produce output y and so the flow profit to a firm with worker with home production b is $y - w(b)$. Firms enter freely until their matching probability reaches the value where the expected profit from posting an additional vacancy net of the posting cost equals zero. Let $J(b)$ denote the value of a match given the worker's current draw b.

$$(r+\rho)J(b) = y - w(b) + \rho\int_{b'} max\{J(b'), 0\}dF(b') - \delta J(b)$$

Wages are determined by Nash bargaining in the standard way. Let $J(b)$ be the value of the match to the firm and β be the worker's bargaining power. Then,

$$w(b) = argmax_w[W(b) - max\{U(b), N(b)\}]^{\beta} J(b)^{1-\beta}$$

The meeting probabilities $\lambda(\theta)$ and $\lambda^f(\theta)$ are determined by market tightness $\theta = \frac{v}{u}$ where v is the measure of vacancies and u is the measure of unemployed individuals. The flow of total matches is given by a matching function $m(u, v)$. The function $m()$ is assumed to have constant returns to scale so then an unemployed individual meets a firm at rate $\lambda(\theta) = \frac{m(u,v)}{u} = m(1, \theta)$ and a vacancy meets an unemployed worker at rate $\lambda^f(\theta) = m(\theta^{-1}, 1)$.

An equilibrium is a pair of policy functions: quits $g^q(b)$ and entry to unemployment from non-employment $g^e(b)$; a measure of vacancies v; the distribution of unemployed workers across states denoted with cdf $F^u(b)$.[19] These objects determine an equilibrium market tightness θ which all agents take as given. We will focus on comparative statics of stationary equilibria, those where the joint distribution of workers across states and types is constant but there are still gross flows of individuals.

[19] The distribution is necessary so that firms can calculate the expected profits from whom then meet when posting a vacancy.

As shown in Garibaldi and Wasmer (2005), the policy functions each satisfy a cut-off rule. The quit cut-off is b^q such that $W(b^q) = N(b^q)$. For any $b > b^q$, a worker will quit and quit specifically to non-participation since $\alpha > 0$. The entry/exit cut-off is b^e such that $U(b^e) = N(b^e)$. For any b larger than/smaller than or equal to b^e a non-employed worker will exit/enter the labor force.[20]

We will call a labor force exit from employment due to $b > b^q$ a "quit" and a labor force exit following the arrival of destruction shock δ due to $b > b^e$ a "layoff". Costly search ($\alpha > 0$) implies $U(b) < W(b)$ for all $b \leq b^q$ and so the quit threshold must be higher than the exit threshold: $b^q > b^e$. Workers who exit after layoff span $(b^e, b^q]$. These workers would be happy to keep working while employed but decide to exit and not look for work if they are laid off. It makes sense to call these workers "marginal". The appear in center (blue) in Figure 10.

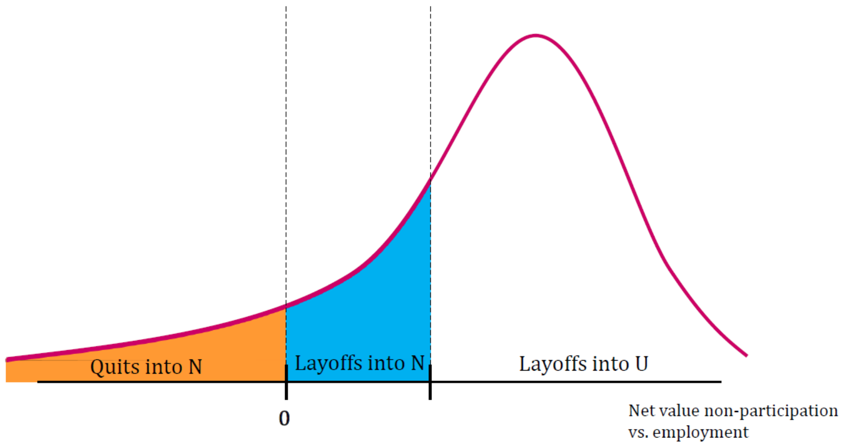

Figure 10: Cut-off rules and the distribution of workers.

Figure 10 provides a qualitative depiction of workers' quit and exit cut-offs ranked on a hypothetical distribution over net values of employment provided by variation in home production b. The x-axis depicts $W(b) - N(b)$. The quit threshold b^q is where $W(b^q) = N(b^q)$. The participation threshold is to the right, indicating that a greater net value of employment is necessary to enter to compensate for paying search costs in unemployment. The blue shaded area between the two is the mass of marginally attached workers.

Characterizing a recession in the model that looks like the data. Empirically, recession are characterized by declines in market tightness and subsequent job finding rates. We will define recessions in the model similarly. In the model, vacancies are determined by the zero profit condition. It is,

$$0 = -\kappa + \lambda^f(\theta) \int_{\underline{b}}^{b^q} J(b')dF(b')$$

[20]If there is no b^q such that $W(b^q) = N(b^q)$, then the worker always quits or always not quit depending on $W(b) > N(b)$ or $W(b) < N(b)$ for all b. Similar logic holds for b^e. These are not empirically relevant cases and so we consider only the parameter space where b^q and b^e are determinate.

Substituting the expected value of a match, in equilibrium, we have:

$$\kappa = \lambda^f(\theta)(1-\beta)\frac{b^q - b^e}{r+\rho+\delta}$$

A recession that is consistent with the data is depicted in Figure 11. To simultaneously have market tightness fall, quits fall, and the share of layoffs that go to N fall it must be that both b^q and b^e rise, but b^e rises more than b^q. The quit threshold b^q is where the worker is paid the total surplus of the current match. The entry threshold b^e is where the value of searching for a new match, net of the search cost, offsets the outside option of home production. The difference between b^q and b^e therefore reflects that having a job is more valuable than searching for one. This gap is entirely due to search costs and frictions and gives rise to a "job hoarding" motive. It takes a higher draw of outside option b to induce a worker to quit than it does to induce a worker to exit the labor force because re-entry into unemployment is costless but re-entry into employment is not. A recession must then be a time when job hoarding motives decrease, curiously alongside a decrease in quits and a decline in workers' job finding rates. This is the dynamic that is hard to capture: job hoarding decreases when non-employment becomes less nasty relative to employment but (1) lower job finding rates make non-employment more nasty, and (2) if non-employment is less nasty then exits after layoff should increase, counter to the data.

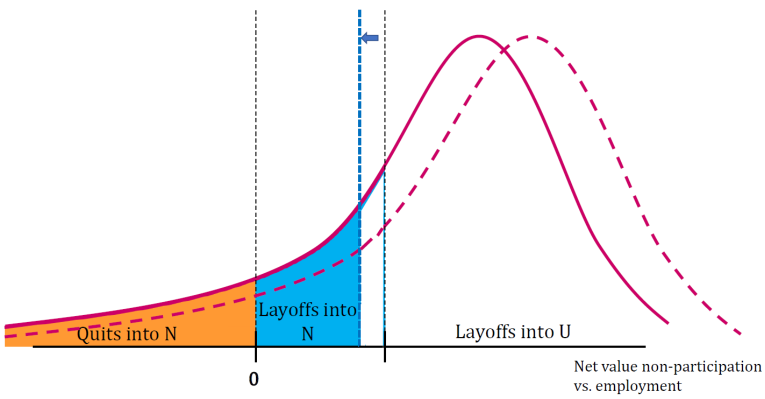

Figure 11: A recession that features procyclical quits, exit rates after layoff, and market tightness.

Why could exits after layoff fall in a recession? The threshold to exit after layoff is where the loss of home production due to search costs is equal to the gain from searching for a job: $\alpha b^e = \lambda(\theta)(W(b^e) - U(b^e))$. All else equal, exits after layoff decrease (b^e becomes larger) when α decreases, $\lambda(\theta)$ increases, or when the net benefit of search increases.

It is well established that the job finding rate $\lambda(\theta)$ is procyclical. This must be a feature of any theory of labor markets over the cycle and must be undone by other features to deliver procyclical exits after lay-off.

What about the net benefit of search? Using the definitions of W and U we have:

$$\beta \frac{b^q - b^e}{r + \rho + \delta} = \frac{\alpha b^e}{\lambda}$$

We showed that $b^q - b^e$ must fall to generate a decline in vacancies, as in the data. It is also the case that job finding rates λ fall during recessions in the data. To get exits after layoffs to decrease, a decline in b^e, we must offset these two forces. There are two remaining margins: either the search cost α or lay-off rate δ must fall. Lay-off rates move in the opposite direction, rising or at least not falling during recessions. That leave search costs. Search cost α has a broad interpretation. A rise in unemployment benefits during recessions would be captured as a fall in α: the net benefit of unemployment and claiming benefits rises relative to non-participation and not claiming benefits. This is one plausible mechanism for exits after layoffs to fall in a recession.

Why could quits fall in a recession? The threshold to quit from employment is where the value of home production is equal to the total expected joint-surplus of the match. This is:

$$b^q = y - \rho \int_{\underline{b}}^{b^q} [J(b') + W(b') - N(b')] dF(b')$$

The expression includes the result that Nash bargaining dictates provision of the entire flow value of production to the worker on the margin of quitting. Workers quit less often (b^q increases) when current productivity y increases or the net surplus of employment relative to non-employment increases. Productivity is generally acyclical or procyclical and so the recessionary decline in quits ought to come from the increase in the net surplus of employment. Yet because productivity does not move much, the change in the net value likely comes from a fall in the value of non-employment. There is one force in the model working in this direction: a decline in the job finding rate. Whether this is a quantitatively important force is a delicate balance. Declines in the job finding rate would push towards more exits after layoff, a movement opposite to our empirical findings that would have to be undone by another force. Further, it would have to be "undone" by another force significantly enough to have the gap between b^q and b^e increase substantially enough to maintain the decline in vacancies found in the data.

Taking Stock. In this section we analyzed what is required from a conventional search model to deliver three key empirical characteristics of labor markets: (i) there are large gross participation flows; (ii) quits and exits after layoff fall in recessions; (iii) market tightness falls in recessions. The model required a decrease in the job hoarding motive, decrease in the value of non-participation relative to employment, and a decrease in the value of unemployment relative to non-participation. Neither a productivity shock nor a shock to the job destruction rate, alone, could provide all three. It may be possible to manufacture an empirically consistent recession by decreasing search costs α, perhaps interpreted as a rise in unemployment benefits. The decline in job finding rates may be enough to decrease the quit rate through a decline in the value of non-participation with the modification that quitting workers are not eligible for unemployment benefits. Altogether, it is a quantitative question because a decline in vacancies is also necessary. One thing is clear: productivity shocks work in the wrong way on labor supply in all dimensions.

Perhaps it is better then to focus on ingredients that the model does not have that could put it into better shape. The first is risk aversion and non-labor income. If there are wealth effects on labor supply then countercyclical declines in non-labor income, such as asset income, would raise labor supply during recession and reduce quits. Countercyclically elevated risk would do the same. The second is heterogeneity. It could be that the workers laid off in a recession are selected to be those most likely to remain in the labor force or the workers surviving in employment are the most attached. We will explore these ideas in the following sections but it is a non-exhaustive list. Our point is to assess other theories and models of the labor markets over the business cycle by considering whether they also replicate the counter-cyclicality of labor supply, on the margin, that is salient in our empirical analysis.

6 Focus on Marginal Participants

This section uses the unique ability to break down the data by different demographics in the CPS to better inform margins on which benchmark theories could be enriched to better capture labor supply dynamics. While there are many interesting ways to slice the data, this section focuses on married women and Blacks. In sum, married women and Blacks make up about 35% of both the labor force and employed workers in the U.S. over the last 30 years. While married women and Blacks are different in many aspects of their labor market patterns, both are characterized by frequently crossing the participation margin, a defining characteristic of "marginal participants" critical to the theory of Section 5. The monthly flow rates from the labor force to non-participation for married women and Blacks are 28% and 26%, respectively. These flows are about twice as high as the flow rates for prime-age white men, a group that is commonly studied when analyzing the U.S. labor market and considered highly attached.

Overview. Figure 12 shows that quits account for a significantly higher share of total separations for married women and Blacks than for prime-age white men and the average US worker. About 40% of total separations are quits but 50-60+% of separations of marginal participants are quits. This implies that marginal participants are an important contributor to the aggregate quit rate. It also reinforces the meaning of the term "marginal participant" since these two groups have high labor force participation rates but also high quit rates implying frequent moves between employment and non-participation.

A higher share of each Black and married women workers choose to exit the labor force if they are laid-off than compared to other workers. Figure 13 shows 28% of laid off Black workers exit the labor force. For married women this number is 53%. For comparison, only 14% of all prime-age white men leave into non-participation after experiencing a layoff. Thus, married women and Blacks are about 2 to 3 times more likely to exit the labor force after layoff than the

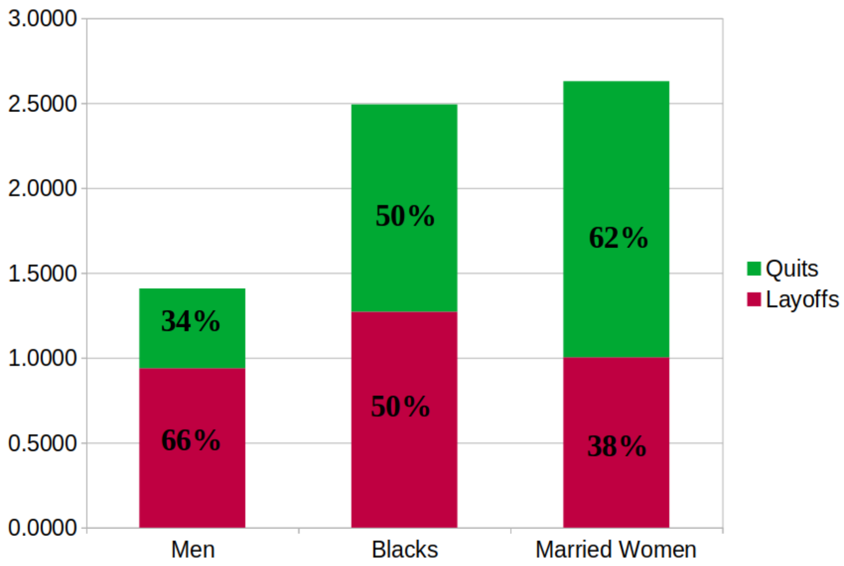

Figure 12: Share of quits and layoffs

group of highly attached prime-aged men. As discussed in Section 5, the participation decision after a layoff is an important part of labor supply. Such workers are assumed to have wanted to continue working while employed but decide to exit and not look for work if they are laid off. This means that, all else equal, changes in layoff rates would have a greater impact on the labor supply of these groups. The next section uses the business cycle to evaluate the "all else equal" caveat and see whether the labor supply of laid off marginal workers changes in recession.

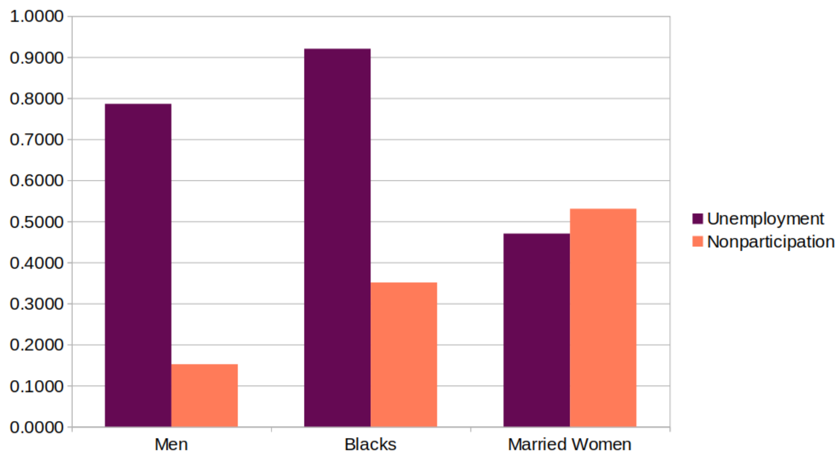

Figure 13: Destination after layoff

Business Cycle Married women and Blacks experience a significantly larger decline in quits during a recession, defined by NBER dates, than the average worker. Figure 14 compares them to men. Notably, the decline in quits for Blacks and married women is almost entirely a result of a decline in quits into non-participation. By contrast, the highly attached group (men) show almost no change in quits into N.

Another way to show Blacks and married women have more pro-cyclical quits is by assessing

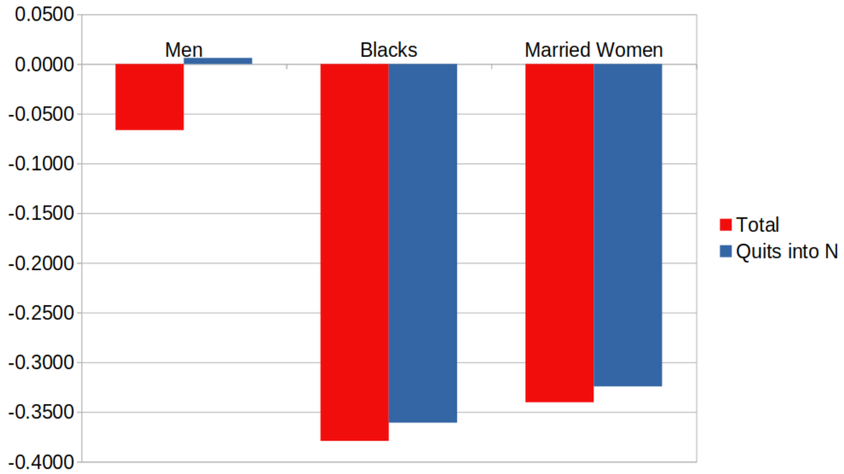

Figure 14: Recession change in quits

their correlation with the unemployment rate. Table 12 shows that the correlation of quits with the unemployment rate is 2 to 4 times higher for Blacks and married women, respectively, than for the average US worker studied in Section 3. The correlation of layoffs with the unemployment rate for both groups, however, is more comparable to the average in the US economy (0.5775). Blacks display a slightly higher volatility, indicating a larger increase in layoffs during recessions, and married women experience a lower volatility.

Married women become much less likely to exit the labor force after a layoff if that layoff occurs during a recession. Column 3 of Table 12 shows the correlation of the share of laid off workers that exit the labor force for each group with the unemployment rate. The comparable statistic for the whole population is -0.2569 suggesting the elasticity of quit behavior to the unemployment rate is almost twice as high for married women than for the average worker.

For Blacks, on the other hand, the state of the economy does not seem to be correlated with the likelihood of exiting the labor force after a layoff. While employed Black workers quit less during recessions signaling higher attachment to the labor force, this increased attachment is not present after they experience a layoff. While providing an explanation of this differing behavior is beyond the scope of this paper, it highlights the importance of studying labor supply decisions of different demographic groups on the extensive margin to understand overall business cycle patterns.

Demographic group	Quits	Layoffs	Share of layoffs into N
Blacks	-0.3852	0.5952	0.0041
Married Women	-0.7623	0.5133	-0.4920

Table 12: Correlations with the unemployment rate

Taking stock, marginal participants refine our theories in two ways. First, since they are the ones moving across the participation margin, the magnitudes of their experiences may be more in-line with magnitudes in the model. For example, when thinking about how much labor hoarding reduces quits in the aggregate, it may still be more accurate to look at the recessionary fall in job finding rates for these groups since they drive both the level and cyclicality of overall quits in the economy. Second, they may hold clues to specific mechanisms outside the basic model. For example, Ellieroth and Michaud (2024) develop a theory of a counter-cyclical "non-subtracted worker" effect that can account for married women's procyclical quits. The mechanism is that higher risk to spousal job loss during recessions serves as an increased risk of a wealth effect that raises labor supply out of a precautionary motive. Such wealth effects may be present for other workers through countercyclical risk to financial assets.

7 Focus on an Episode: The Pandemic Recession and Recovery

The empirical patterns we've established are strikingly similar across recessions. No single episode better proves this point than the recession and recovery following the COVID-19 pandemic. While the pandemic recession stood out compared to other recessions in many aspects, our new time series of quits and layoffs show 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 2). 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. 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 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.[21] However, contrary to JOLTS data, our time series of quits does not display an increase in the Covid recovery higher than in previous recessions.[22] Figure 15 shows the peak-to-peak change for

[21]The final section of this paper speaks more of the difference between the CPS and JOLTS.

[22]Our data can be combined with the CPS series of employer-to-employer flows assembled by Fujita et al.

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.

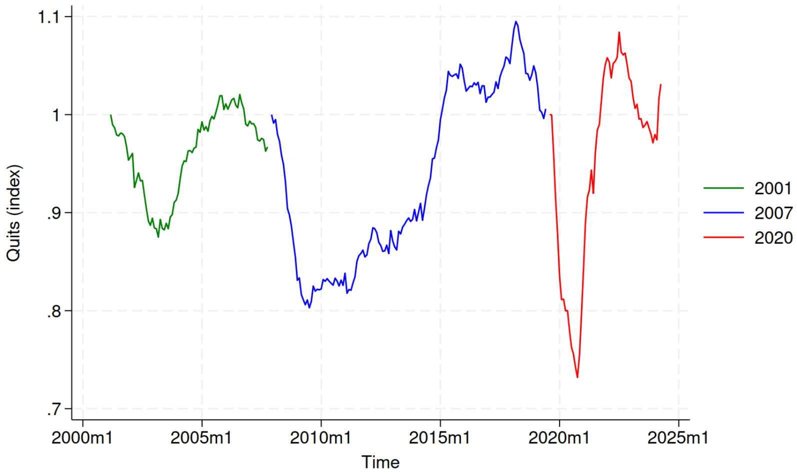

Figure 15: Peak-to-peak change in quits for the 3 most recent recessions (Note: Each peak is normalized to 1)

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.

8 Comparison to Jolts and Other Data

The Job Openings and Labor Turnover Survey (JOLTS) has been the primary source used to analyze quits and layoffs in the United States.[23] 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

(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.

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

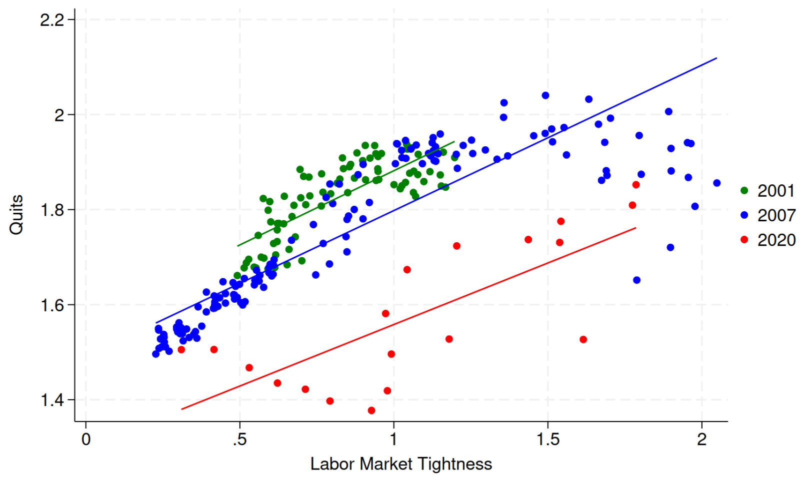

Figure 16: Correlation of quits with labor market tightness for the 3 most recent recessions

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[24] 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 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[25] 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 17 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

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

[25]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

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.

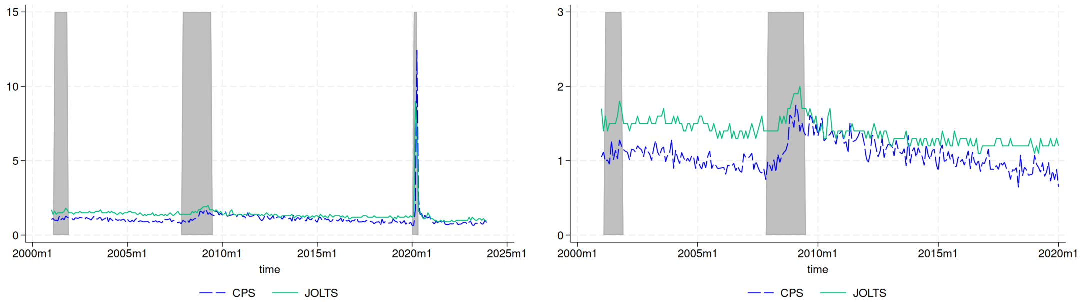

Figure 17: Layoffs, full series (left) and with the removal of 2020 + (right).

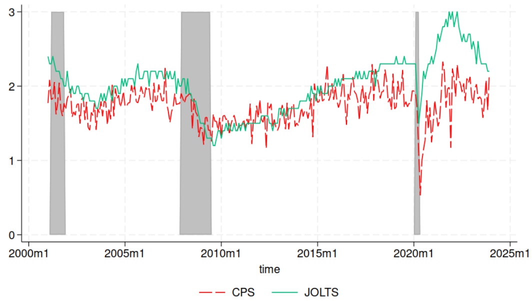

Figure 18: JOLTS total Quits and our adjusted CPS quit to nonemployment series

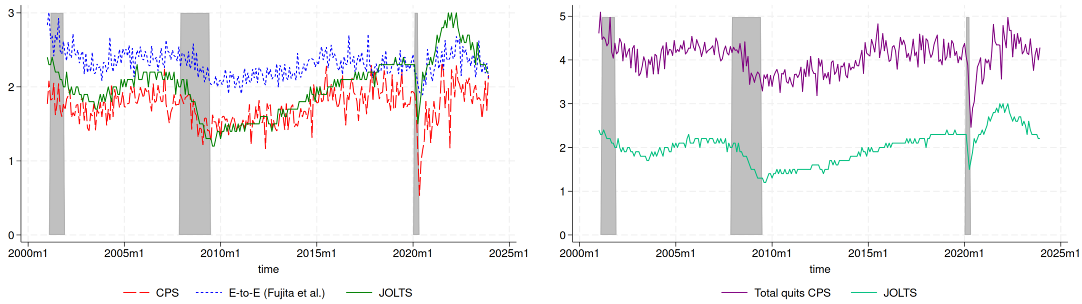

Figure 19: Quits: adjusted CPS quits to nonemployment, E-to-E flows Fujita et al. (Forthcoming), and JOLTS (Left); combined CPS quits plus E-to-E and JOLTS (right)

Comparison to Panel Study of Income Dynamics (PSID) The PSID is a long-running panel survey that has grown to over 9,000 families. While the smaller sample size limits the accuracy of business cycle analysis in the PSID relative to CPS or JOLTS, the comprehensiveness of the survey surpasses the other two sources. Using data from 2003-2019 we can study the reason each *job* an individual has ended (similar to JOLTS) and the labor market status of the

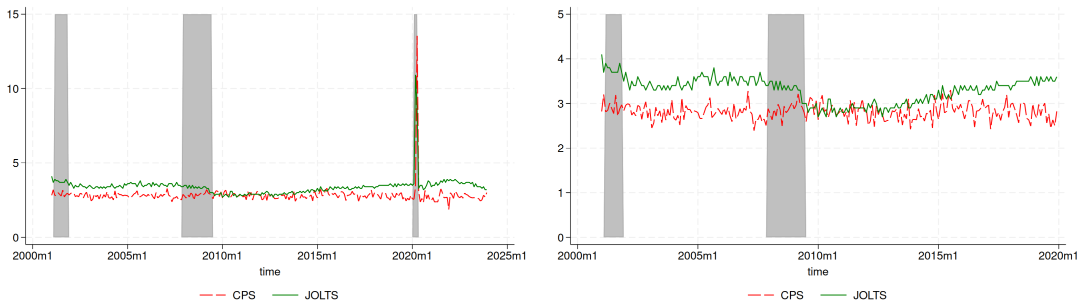

Figure 20: Total separations, full series (left) and with the removal of 2020 + (right).

Table 13: Panel Study of Income Dynamics 2003-2019

Share of Separations by Destination	All Workers		Prime Age	
Quits	All	to N or U	All	to N or U
Non Participation	0.540	0.912	0.452	0.882
Unemployment	0.052	0.088	0.060	0.118
Employment	0.425	n/a	0.507	n/a
Layoffs	All	to N or U	All	to N or U
Non Participation	0.273	0.349	0.248	0.320
Unemployment	0.509	0.651	0.527	0.680
Employment	0.279	n/a	0.291	n/a

individual after a job ends (as in CPS). The PSID is, for these reasons, an excellent check on the accuracy of our CPS classification and can reconcile some differences with JOLTS.

Table 13 shows that the split between quits and layoffs to non-employment that end up in non-participation is similar in the PSID as it is in our CPS sample. Over the same same period, 12.9% of prime age quits to non-employment are classified as unemployment in the CPS compared to 11.8% in the PSID sample; and 64.8% of prime age layoffs to non-employment are to unemployment compared to 68.0% in the CPS sample.[26] This provides confidence that our classification of quits and layoffs is consistent with how workers describe the reason for a job ending in other popular surveys.

Table 13 also includes the separations we miss in the CPS. Separations directly to another employer or the termination of a single job held by a multiple job holder are included in quits and layoffs with a destination of "Employment". These types of separations make up 42.5% or 50.7% of all quits and 27.9% or 29.1% of all layoffs for all workers or prime age, respectively. During the recessionary years of 2008-10, the share of quits directly to a new employer falls to 30.1%; and the share of layoffs directly to a new employer falls to 21.6%. This backs our hypothesis that the CPS layoffs rise more during recession because layoffs to non-employment

[26]Quits to unemployment with an unemployment duration of over one year are dropped.

rise more than total layoffs, in part because the share of layoffs to non-employment increases. The analogous argument is supported for quits.

9 Conclusion

We developed and analyzed a new data product for macroeconomists: quits, layoffs, and their subsequent labor participation status. These data were developed by harmonizing raw data in the CPS household survey. The standout results of our analysis are as follows. First, over 40% of layoffs lead to a labor force exit. This means that assuming all moves out of the labor force are quits, as has been frequent in the literature, has vastly overstated quits and understated layoffs. Quantitative macroeconomists should take note and reconsider their model targets. Second, both quits and the share of laid off workers exiting the labor force are procyclical. This means that labor supply, on the margin, increases in recessions which serves as a mitigating force against employment declines. Models of the labor market, particularly quantitative ones, should capture this feature. We walked through some ideas of what is necessary for this to occur in a simple search model.

The new data opens the door for many areas of future research and motivates many research questions. The most obvious question of interest is: why do such a high share of laid off workers exit the labor force after being laid off and why is this number decreasing in recessions? The CPS data provide opportunities to examine household and worker correlates with these patterns that could bring us closer to answering this and other questions. Another important question is what drives the procyclicality of quits? Understanding this behavior is important since they play a critical role in smoothing employment separations over the business cycle by almost completely offsetting movements in layoffs.

A main motivation for this project was to provide additional information about the functioning of labor markets to help guide policy.[27] Two things need to happen to increase the impact of these data. First, the gaps between our CPS series and JOLTS need to be better understood. The two series are some of the only high frequency data on quits and lay offs but, as we stand today, it is difficult to know how much to weight each series in our understanding. Second, macroeconometricians need to formally evaluate the predictive power and correlates of each series. Nonetheless, the research as it stands has an important take away for policy makers. Labor supply decisions matter and they matter more than we previously thought. Flows from employment to unemployment understate the true extent of job loss in the economy because job loss can lead workers to exit the labor force entirely. We hope future research will guide our understanding of whether there is a role for public policy to intervene in these exits or if they are simply a feature of individuals choosing what's best for themselves in a well functioning labor market.

[27] Our series of quits and layoffs will be available at https://sites.google.com/qlmonthly.com/home and will be updated monthly.

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A Data Robustness

A.1 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 series, quit series, and total separations 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. 3-month, 4-month, and 6-month only include the previous 3, 4, and 6 months respectively, as well as the current month.

We see that the different lengths really only affects 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 is 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.

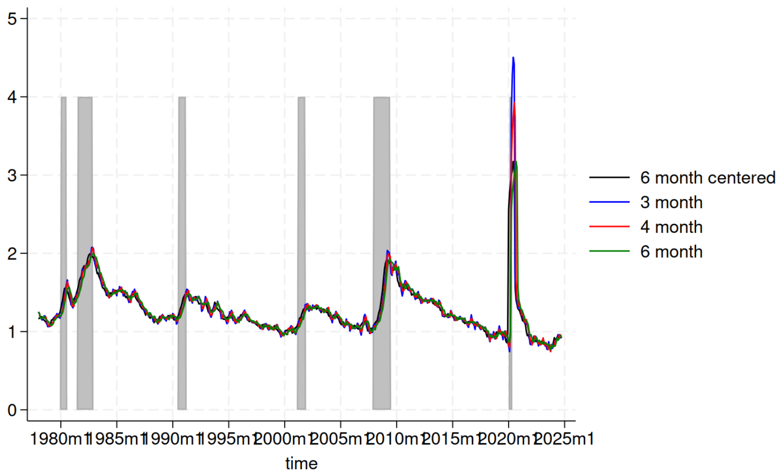

Figure 21: Comparison of moving-average filter for layoff series

A.2 DeNUNifying the Data

One common concern when linking individuals or household in the CPS data is that unemployment and non-participation are misclassified. In the following we will provide the main statistics for our data in the main text and deNUNified data. For the deNUNified data we remove all individuals which make one of the following labor market transitions: non-participation to unemployment to non-participation, or unemployment to non-participation to unemployment.

Table 14 shows that excluding these potentially misclassified transitions has no effect on the main statistics in this paper.

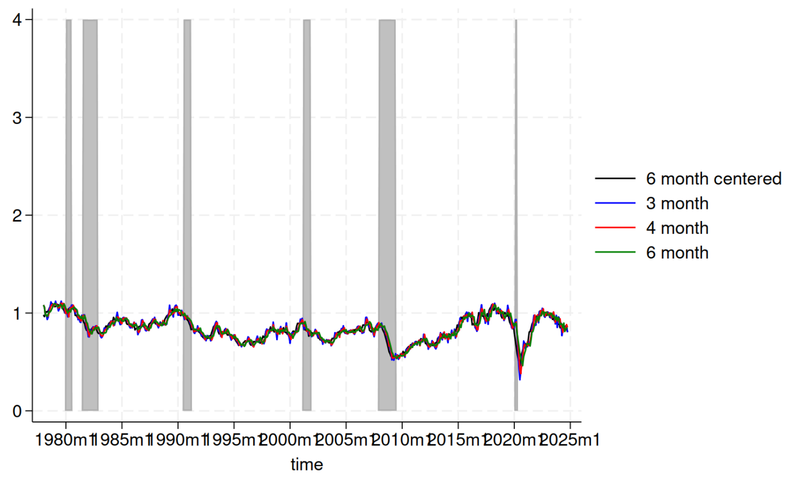

Figure 22: Comparison of moving-average filter for quit series

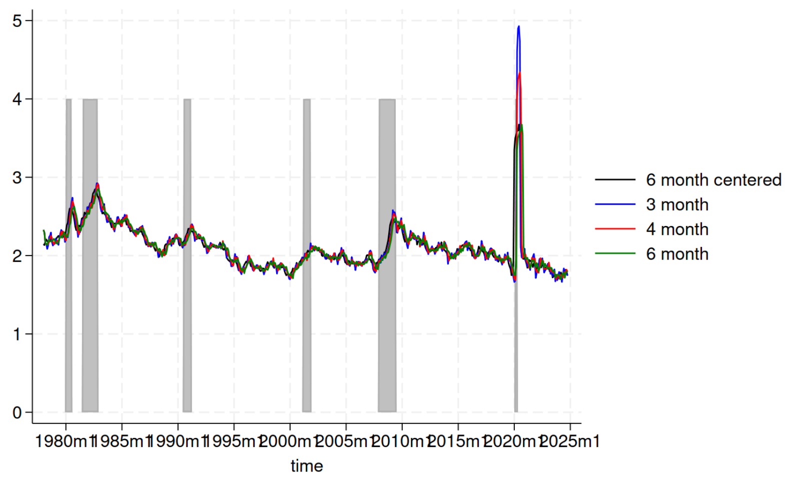

Figure 23: Comparison of moving-average filter for total separations

B 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.

C Additional Statistics

C.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 dimensions of heterogeneity.

Statistic	Main Data	DeNUNified Data
	Averages	
Quits	0.84	0.84
Layoffs	1.27	1.27
Total Separations	2.11	2.11
Layoffs share N	0.40	0.40
Quit share N	0.85	0.85
EN	1.54	1.54
EU	1.08	1.08
	Correlation with Unemployment Rate	
EUQ	-0.1478	-0.1464
ENQ	-0.3897	-0.3904
EQ	-0.3929	-0.3917
EUL	0.6013	0.6011
ENL	0.4885	0.4872
EL	0.6117	0.6119
EN	0.0122	0.0119
EU	0.6210	0.6213
Layoff share N	-0.6222	-0.6239
Quit share N	-0.1253	-0.1302
Corr(EQ,EL)	-0.3019	-0.3007

Table 14: Comparison with deNUNified data

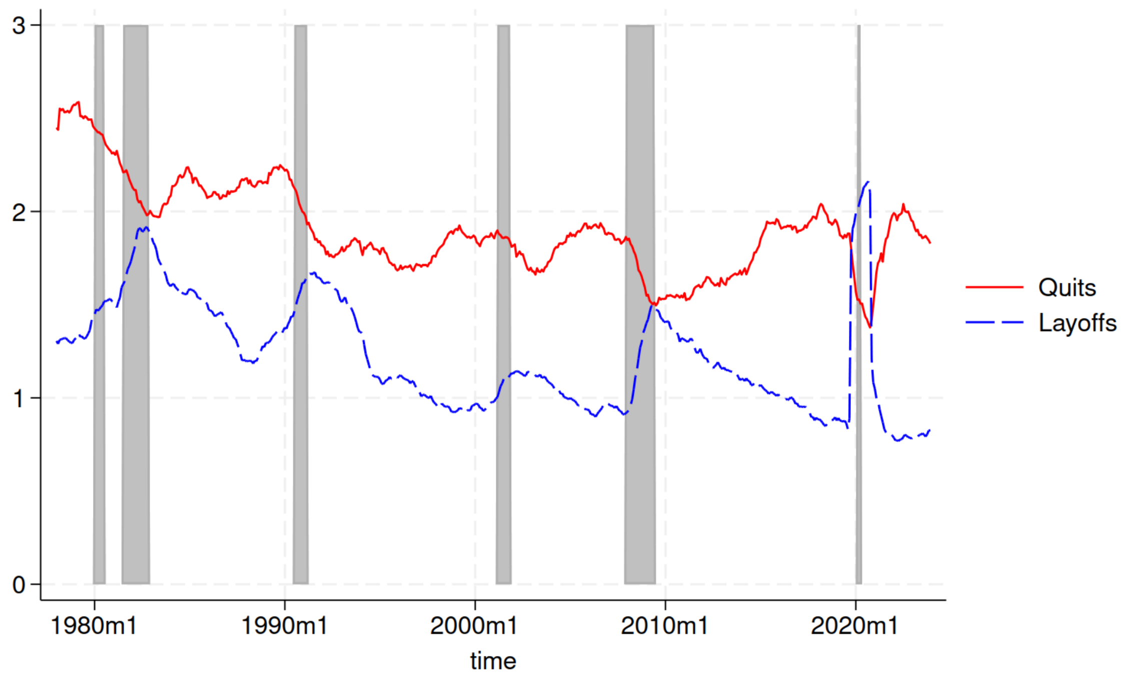

Figure 24: Quits and layoff

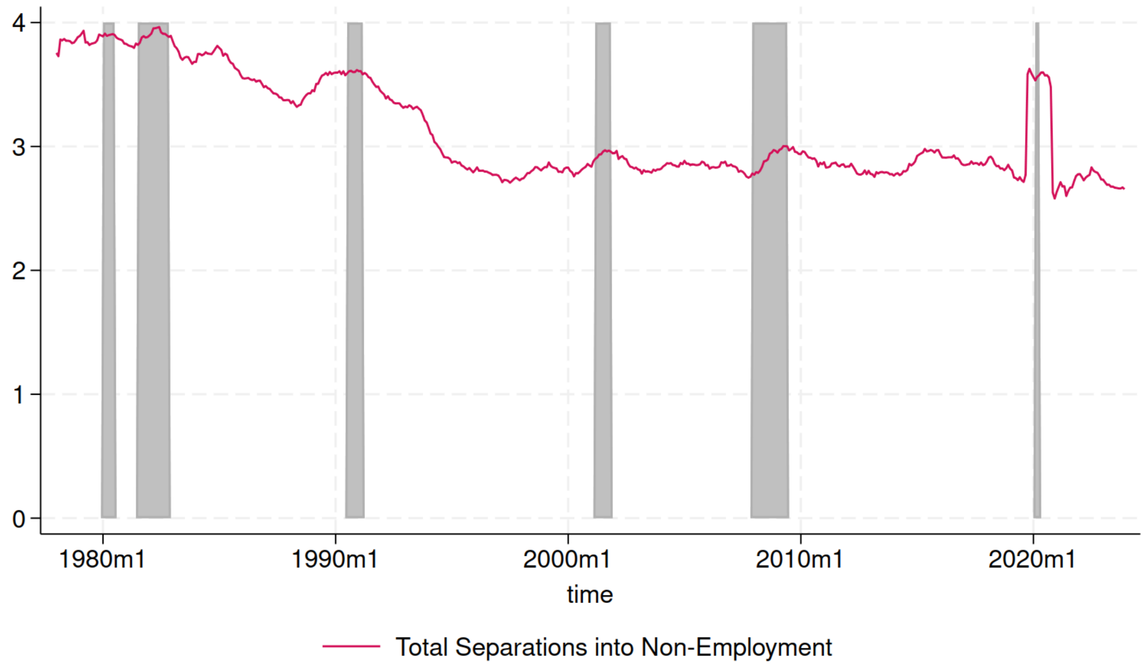

Figure 25: Total separations

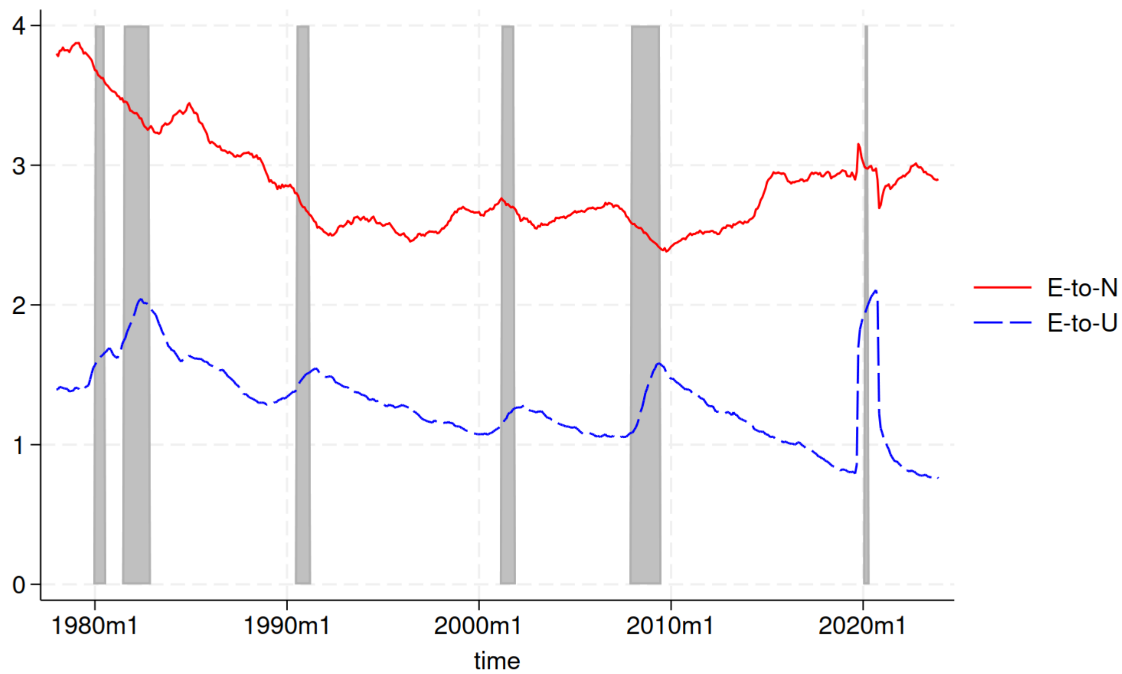

Figure 26: EN and EU flow rates

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

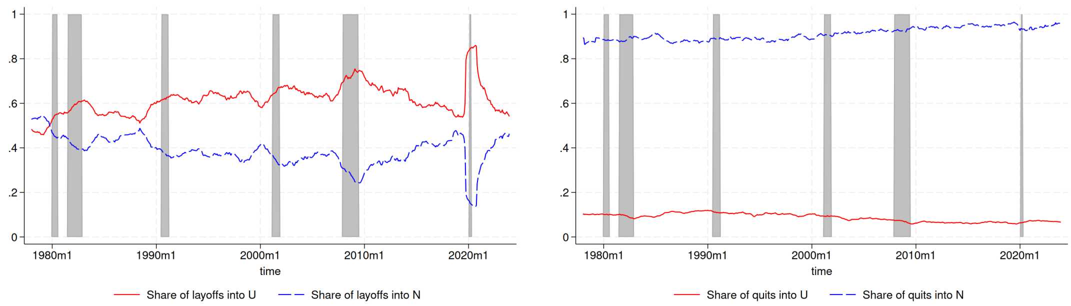

Figure 27: Share of quits and layoffs by destination

Statistic	Quits			Layoffs			Total sep.
	to U	to N	Total	to U	to N	Total	to (U+N)
Corr(x, y)	-0.0626	-0.2469	-0.1906	0.5083	0.3982	0.5775	0.4499
SD(x)/SD(y)	0.0300	0.1451	0.1648	0.2909	0.0894	0.3200	

Table 15: Business cycle correlations of each flow (x) with the unemployment rate (y)

Statistic	
Corr(EQ, EL)	-0.0255
SD(EQ)/SD(EL)	0.5149

Table 16: Business cycle correlations of quits and layoffs

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.

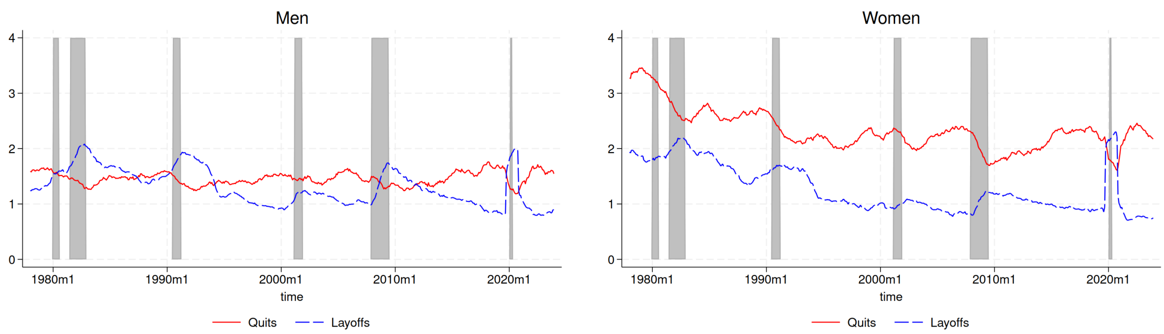

Figure 28: Quits and Layoffs by Gender

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.

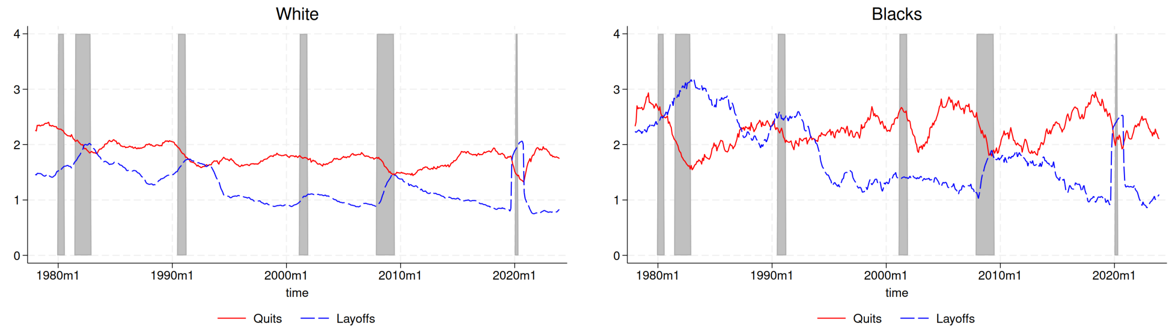

Figure 29: Quits and Layoffs by Race

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.

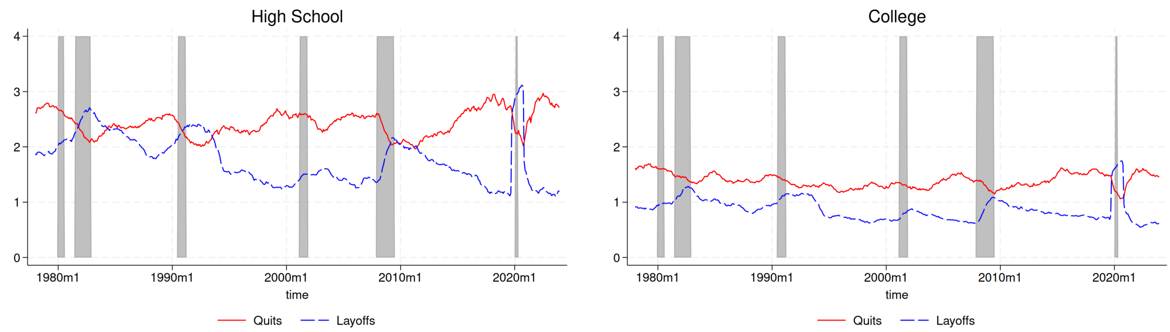

Figure 30: Quits and Layoffs by Education

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 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.

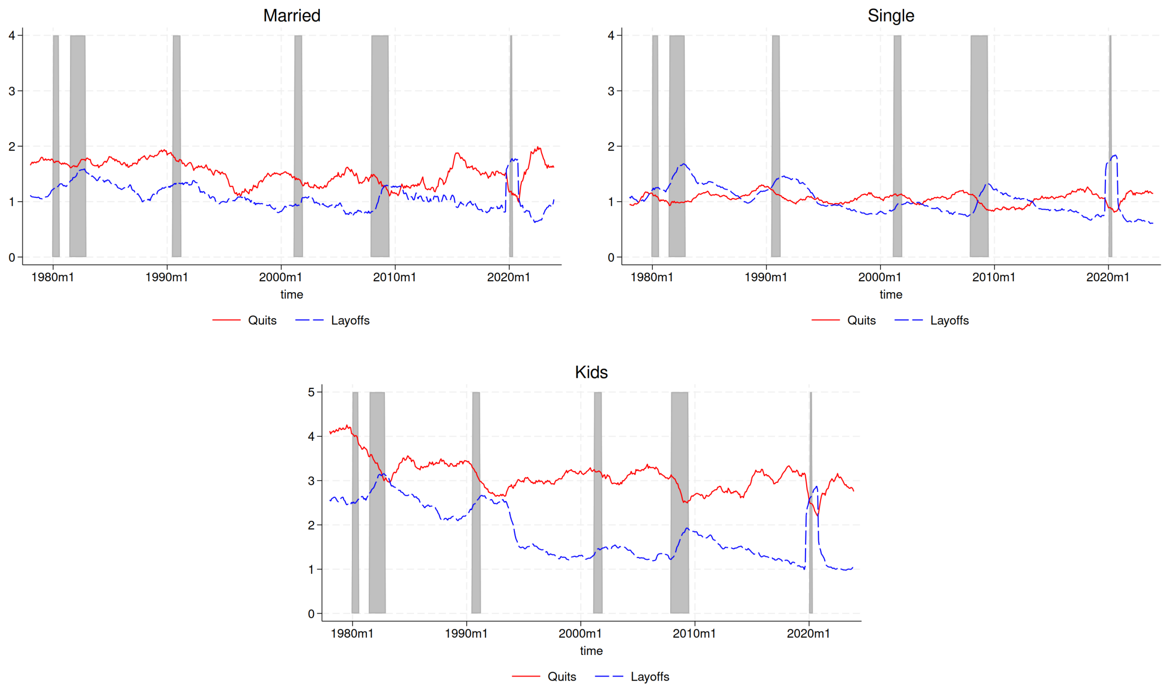

Figure 31: Quits and Layoffs by Family Structure

C.2 Complete Shapley Decomposition

	QN	QU	LN	LU	UE	NE	UN	NU
				Expansion				
Employment	17.5	3.3	52.8	12.8	11.7	9.4	-6.6	-11.0
Unemployment	-8.5	1.3	-8.1	63.7	7.1	9.0	19.7	15.8
				Recession				
Employment	-102.5	-1.2	+25.2	+91.6	+133.7	79.4	-45.6	-86.0
Unemployment	-1.3	11.6	5.2	27.7	33.0	7.4	12.7	16.4

Table 17: Shapley values of flows measured as percent contribution to change in employment/population and the unemployment rate.

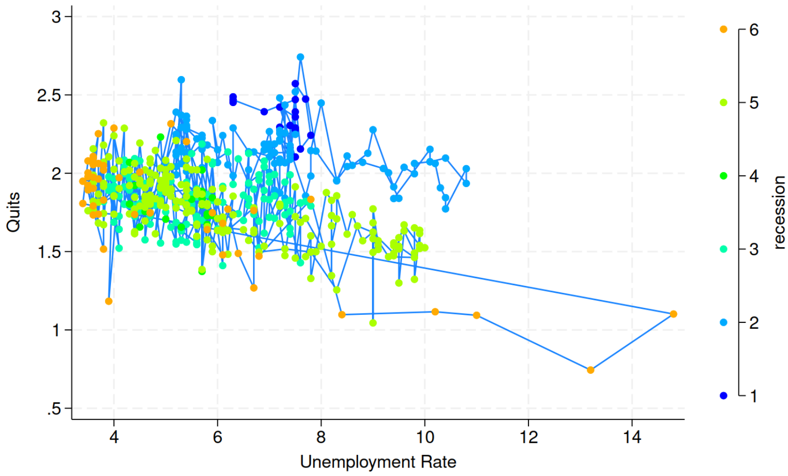

Figure 32: Beveridge Curves for the entire time period

C.3 Alternative Beveridge Curve

C.4 Which flows drive the cycle? A Shapley value decomposition.

In this section we compute the contribution of each type of labor market flow to employment and unemployment changes through recessions peak-to-trough and expansions trough-to-peak. We do this both decomposing flows by destination (employment to/from unemployment to/from non-participation) and by reason (quit versus layoff). The idea is to understand the decline in employment during a recession as the culmination of increased outflows to non-employment a decreased inflows from non-employment. The same can be said for employment increases during expansions and for the dynamics of unemployment: how much do each of inflows and outflows matter?

The marginal contribution of a flow is defined by it's Shapley value: the appropriately weighted sum of its marginal contribution to every permutation of the set of other flows. The concept of marginal contribution takes into consideration that all other flows change as well. Take for example the contribution of changes in labor force exits after unemployment to changes in unemployment during a recession. The marginal contribution considers that layoffs also increase during a recession and job finding rates from unemployment fall, both of which magnify the contribution of the fall in exits after layoff. This is particularly important because we have emphasized that labor supply of employed and laid off workers increases, on the margin, during a recession. This does not mean the labor force participation rate is counter-cyclical since many other forces, such as higher layoff rates, affect aggregate participation more strongly.

We have eight flows: quits resulting in non-participation (QN); quits resulting in unemployment (QU); lay-offs resulting in non-participation (LN); lay-offs resulting in unemployment (LU); flows to employment from unemployment (UE); flows to employment from non-participation (NE); flows to non-participation from unemployment (UN); and flows to unemployment from non-participation (NU). Each decomposition begins with the shares of employed, unemployed, and non-participants equal to their values in the month prior to the start of the expansion/recession and then calculates the cumulative change in each to the end date. Expansions begin when unemployment peaks and end when recessions begin. Recessions begin according to the Sahm rule.[28] The average contribution of each flow across business cycles weights each business cycle by its relative change in employment to population or unemployment rate.[29]

Table 18 sums the Shapley values in terms of a few themes. The complete values are in Appendix Table 17. "Quits" and "Layoffs" are all quit or layoff separations from employment to non-employment regardless of destination. "Exits" and "Entry" are flows in/out of the labor force regardless of origin or reason (e.g., exits include quits and layoffs to non-participation plus flows from unemployment to non-participation). "Job loss/finding" is the sum of the contribution of layoffs and job finding from unemployment.

	Quits	Layoffs	Exit	Entry	Job Loss/Finding
			Recession		
Employment	-103.7	116.8	-122.9	-6.5	224.1
Unemployment	-1.2	32.9	16.6	23.9	60.9
			Expansion		
Employment	30.9	65.6	73.7	-1.6	27.9
Unemployment	-7.2	55.7	3.1	24.9	72.1

Table 18: Shapley values of flows measured as percent contribution to change in employment/population and the unemployment rate.

Job loss and job finding rates are the dominant forces driving employment and unemployment in recessions, but in the case of employment this is only because changes in quits and labor force participation offset changes the layoff rate. The fall in quits boosts employment during a recession by almost completely offsetting the contribution of layoffs to reducing it. The same is not true for unemployment. The contribution of the reduction to quits to unemployment is swamped by the increase in layoffs because most quits are to non-participation. Reductions in labor force exit work in a similar way to boost employment during a recession but both higher entry and lower exits after layoff work to increase unemployment.

Most flows work together to shape expansions. Falling layoffs and labor force exits drive employment growth. Falling layoffs and rising job finding rates drive unemployment declines. Results for employment must be taken with the caveat that there is trend growth pre-2000.

These patterns can also be shown graphically. Figures 33 and 34 show the Shapley value contribution of each flow to the cumulative change in the respective employment or unemploy-

[28]We begin with the first full cycle we have: the 1980s recessions which we group into one. The recession start dates (expansion end dates) are: Jan 1980, Sep 1990, May 2001, Dec 2006, May 2020, and we compute the final expansion until May 2024. The Expansion start dates (recession end dates) are Dec 1982, July 1992, July 2003, March 2010, and March 2020.

[29]The contributions do not add up to 100% within recession but not when we take the average across recessions because of this weighting scheme.

ment series. The decomposition treats the employment-to-population growth period (1978-1999) and period of stabilization/decline (2000-2019) separately. The graphs better capture long run trends but offer glimpses at higher order moments and variation (or lack thereof) across specific episodes.

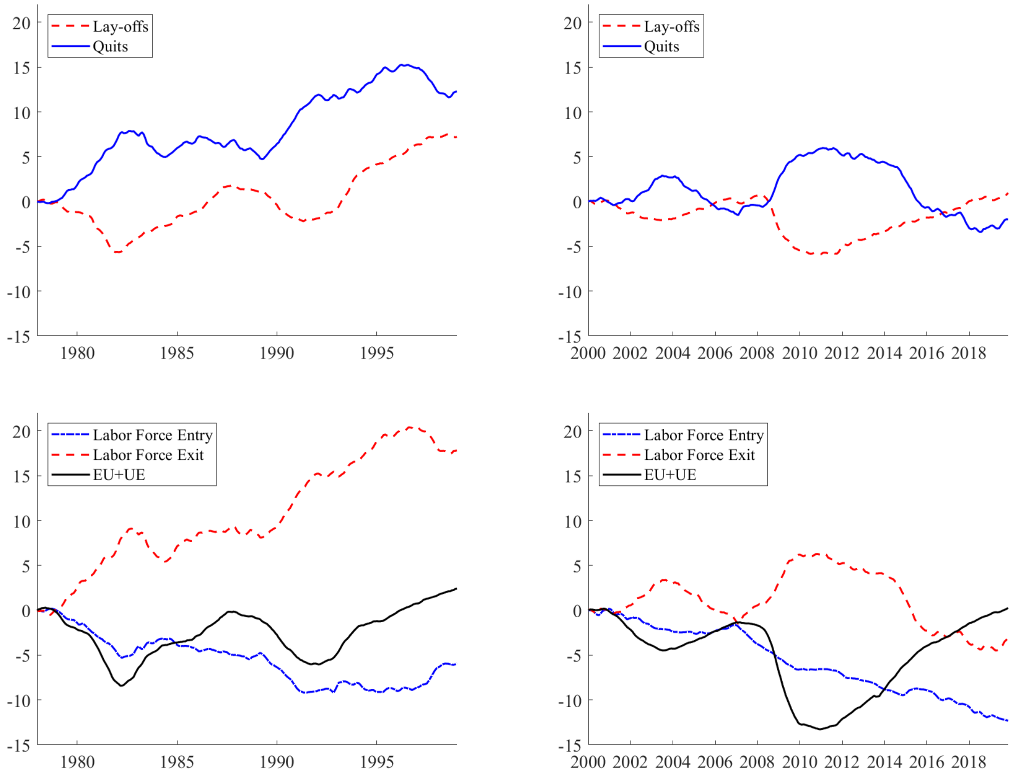

Figure 33: Shapley-Owen decomposition of flow contribution to employment-population trends.

Taking stock, the Shapley value decomposition emphasizes that quits and layoffs have different behavior, often moving in opposite directions, which emphasizes the importance of treating them as distinct. Labor force participation decisions are quantitatively important as well.

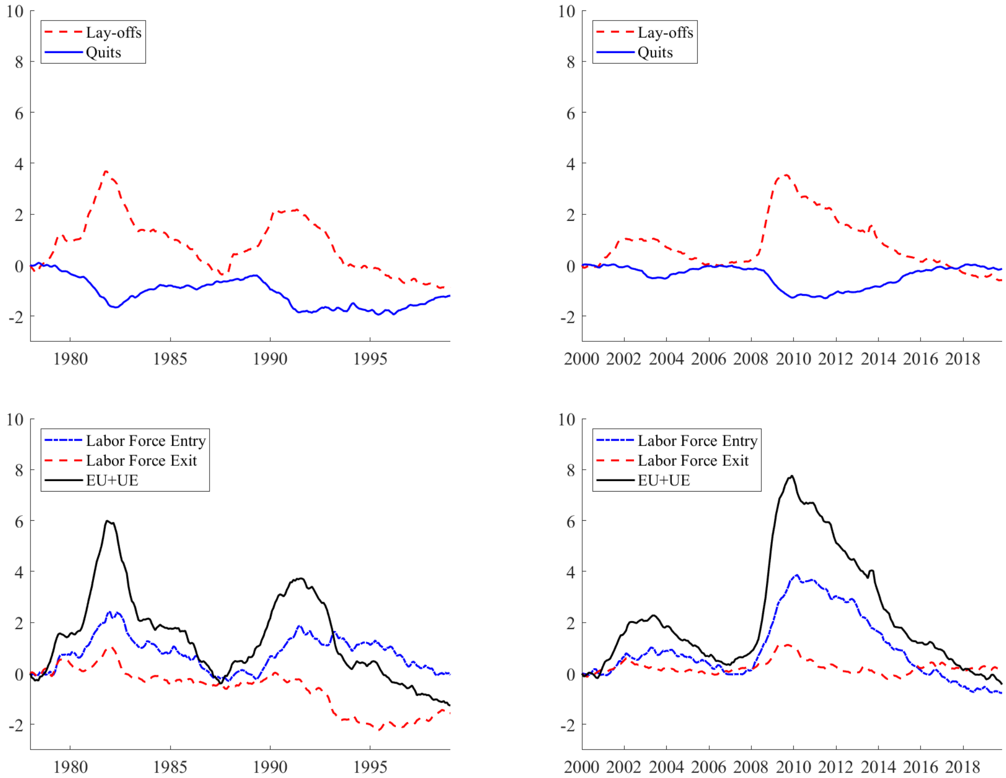

Figure 34: Shapley-Owen decomposition of flow contribution to the unemployment rate.