Quits, Layoffs, and Labor Supply

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Abstract

We analyze quits and layoffs leading to unemployment or non-participation using real-time Current Population Survey data. Standard employment to unemployment (EU) and employment to non-participation (EN) flows substantially mischaracterize the nature of job separations and their cyclical properties. Layoffs are 20% more common than EU flows, while quits are 45% less common than EN flows. Over the business cycle, layoffs contribute 15% more to unemployment fluctuations than EU and are the main driver of employment fluctuations. The negative correlation of quits and layoffs reduces the volatility of total separations, but laid off workers are more likely to stay in the labor force during downturns, amplifying unemployment volatility by 25%. These data are useful to understand slack and improve labor market forecasting.

JEL Classification: E24, E32, J63, J64 **Keywords:** Labor market flows, unemployment, business cycles, job separations, forecasting

1 Introduction

The flows of workers between employment, unemployment, and non-participation are fundamental to understanding labor market dynamics and business cycles. Since Blanchard and Diamond (1990), economists have relied on gross worker flows to analyze unemployment fluctuations, with Shimer (2012) concluding that job finding rates dominate separation rates in driving cyclical unemployment variation. However, this literature has been constrained by a critical limitation: the inability to distinguish voluntary quits from involuntary layoffs in large timely surveys, leading to the conventional assumption that flows from employment to unemployment represent layoffs while flows to non-participation represent quits.

This paper analyzes a comprehensive time series that tracks both the reason for job separation to non-employment (quit versus layoff) and the worker's subsequent labor force participation decision using Current Population Survey (CPS) data from 1978 to 2024. Our approach

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follows Flaim (1973) but extends their work by creating monthly, seasonally-adjusted series of quits and layoffs closely following the methodology used to produce the Integrated Public Use Microdata Series (IPUMS). The data are available in near real-time, monthly, and cover nearly five decades of labor market history.

Our findings challenge conventional wisdom about worker flows and reveal new insights about business cycle dynamics. We find that standard measures of flows between labor market states significantly mischaracterize the composition of job separations. Layoffs to non-employment occur 20% more frequently than employment to unemployment (EU) flows. The reason is that over one-third of laid-off workers choose non-participation rather than active job search, which implies that these workers would be counted in the employment to non-participation (EN) flows instead of EU. Consequently, quits are 45% less common than EN flows indicate, because nearly 40% of EN transitions actually result from involuntary layoffs.

The reasons for job separations (quit or layoff) have important implications for understanding how labor supply decisions relate to cyclical patterns in the labor market. Although EU and EN flows are uncorrelated, we document a strong negative correlation (-0.46) between quits and layoffs that creates a stabilizing force in the labor market. When layoffs surge during recessions, quits fall sharply, causing total separations to be less volatile than layoffs on their own. This off-setting relationship means that focusing either on total separation rates or EU alone would understate the underlying volatility in labor demand conditions captured by layoffs.

Using the Shimer (2012) decomposition methodology, we find that properly measured layoffs to non-employment contribute 45% more to unemployment fluctuations than EU flows. Moreover, rises in layoffs drive increases in unemployment at the start of most recessions, a few months before job finding (UE) rates contribute. This makes tracking layoffs particularly useful for identifying the onset of a recession. A key mechanism amplifies the role of layoffs in the cyclical volatility of unemployment: laid-off workers are more likely to remain in the labor force during recessions rather than exiting to non-participation. We show that holding constant the propensity of laid-off workers to remain in the labor force would reduce unemployment volatility by 25% with large variance across recessions. Changes in participation decisions reduced the increase in unemployment by a third in the 1991 recession but by only 1.5% in the 2020 COVID spike. This countercyclical attachment of laid-off workers to the labor force represents an important but mostly unstudied factor in the volatility of unemployment.

More strikingly, layoffs have a more than double the impact (144% larger) on fluctuations in the share of the population employed than EU flows have. It turns out that layoffs are actually the dominant driver of employment-population fluctuations with a 24% larger impact than job finding rates (UE). The finding of Shimer (2012) that declines in job-finding rates drive the increase in unemployment in recessions does not carry over to declines in employment. This is a subtle but important distinction for policymakers who should consider layoffs as the most important factor in determining growth and decline in employment rates.

Our decomposition also highlights how much offsetting movements in quits dampen the volatility of both unemployment and employment in fundamentally different ways than would be inferred from employment to non-participation (EN) flows. That is because although EN flows are nearly uncorrelated with the unemployment rate, quits are notably procyclical and negatively correlated with the unemployment rate. The procyclicality of quits is large enough to reduce unemployment fluctuations by 60% more than the relatively acyclical EN flows. This is because many EN flows actually contain many layoffs. Isolating just the role of quits is useful for tracking movements in labor supply over the cycle since workers who quit to non-employment are those who had a job and likely could have continued working.

The quit and layoff data provide superior real-time forecasting performance compared to other flow measures. CPS layoffs best predict unemployment one quarter ahead, while CPS quits excel at longer horizons of two or more quarters. This forecasting advantage stems from quits' strong correlation with workers' expectations about future job availability, making them a valuable leading indicator of labor market conditions. The CPS series also outperform JOLTS measures, particularly because CPS data are virtually unrevised while JOLTS undergoes substantial revisions that reduce real-time forecasting accuracy. In fact, CPS quits and layoffs can be used to predict JOLTS quit and layoff revisions.

Our empirical patterns hold remarkably consistently across all six NBER recessions in our sample, including the 2020 pandemic recession. While the pandemic involved an unprecedented increase in layoffs, the fundamental relationships between quits, layoffs, and labor force attachment followed historical patterns when conditioning on economic fundamentals like labor market tightness.

We think the statistics in this paper will be useful for both macroeconomists who simply need a calibration target that is a better analogy of a quit or layoff in their model; and those trying to better understand labor demand, supply, and markets in general. The data are freely available online and are updated monthly.[1] The remainder of the paper proceeds as follows. Section II reviews related literature. Section III describes our data construction methodology and validation. Section IV presents key statistics for macroeconomists, including business cycle correlations and the importance of labor supply decisions after job loss. Section V applies the Shimer decomposition to evaluate the contribution of quits and layoffs to cyclical unemployment and employment dynamics. Section VI analyzes similarities and differences across recessions. Section VII examines forecasting performance. Section VIII compares our measures to JOLTS. Section IX concludes.

2 Literature Review

Beginning with Abowd and Zellner (1985) and Blanchard and Diamond (1990), researchers have used the flow approach to better understand the evolution of labor market flows across time, cross-sections, and business cycles. Rogerson and Shimer (2011) summarize key papers in this

[1] Data can be accessed through our website sites.google.com/qlmonthly.com/home, or from Federal Reserve Bank of St Louis' FRED as series 738: fred.stlouisfed.org/release?rid=738.

literature and describe how the flow approach has been used to advance macroeconomic theory.[2] More recently, Fujita et al. (Forthcoming) introduce facts on direct job-to-job changes in the CPS; Ferraro (2018) studies the skewness of flows; and Barnichon and Figura (2015), Coglianese (2018), Hall and Kudlyak (2020), and Ellieroth (2023), among others, study heterogeneity in flows across worker types. We contribute by documenting how separations vary by both reason (quit vs. layoff) and destination (unemployment vs. non-participation).

Few other papers document facts on job separations over the cycle separately for quits and layoffs. Flaim (1973) and Akerlof et al. (1988) both established that quits tend to be procyclical and layoffs countercyclical. We use a quit/layoff classification for the CPS similar to that introduced in Flaim (1973) to add facts on labor supply decisions after each type of separation.[3]

Second, we contribute to the literature providing statistical decompositions of the contribution of job separation and finding to cyclical fluctuations in unemployment following Shimer (2012).[4] Shimer (2012) uses data on transitions between employment, unemployment, and non-participation to assess the relative contribution of cyclical changes in each flow to unemployment rate fluctuations. Elsby et al. (2015) and Elsby et al. (2019) apply a similar methodology to analyze the contribution of each flow to the fluctuations of the labor force participation rate. Simmons (2023) uses SIPP data and finds that the contribution of job separations to fluctuations in the unemployment rate is larger when parsing by reason for separation. Our contribution to the Shimer-style decomposition literature is to parse separations by both reason and destination (unemployment or non-participation) using the CPS. We also provide results showing movements in job separation rates are even more important for employment to population dynamics than for unemployment.

Third, we contribute to the emerging literature studying the use of labor market flows to forecast labor market variables such as the unemployment rate. Barnichon et al. (2012) showed that the addition of labor market flows to standard forecasting variables improves the performance of VAR predictions of unemployment and labor force participation, especially two to three quarters in the future. Ahn and Hamilton (2021) add worker heterogeneity and Chodorow-Reich and Coglianese (2021) add unemployment duration to further improve forecasting ability with worker flows. Krolikowski and Lunsford (2024) add advanced layoff notice data to JOLTS data to improve forecasting of the unemployment rate. We contribute by taking a machine learning approach to evaluate the potential of CPS quit and layoff data to improve real-time unemployment forecasting in addition to standard flows from the CPS and JOLTS.

[2] A complementary literature focuses on jobs. For example, Davis et al. (2011) use the Job Openings and Labor Turnover Survey (JOLTS) to provide statistics on establishments' contributions to job destruction and creation.

[3] A non-exhaustive list of other papers using a CPS quit/layoff classification following Flaim (1973) include: Flaim (1969), Schwab (1974), Deutermann Jr (1977), Bednarzik and Klein (1977) , Job (1979) Freeman (1980), Gellner (1975), Ellieroth (2023), Graves et al. (2023), and Michaels (2024).

[4] This relates to the unemployment volatility puzzle (Shimer (2005),Chodorow-Reich and Karabarbounis (2016), Hagedorn and Manovskii (2008), Ljungqvist and Sargent (2017), and Mitman and Rabinovich (2019))

3 Data and Methodology

3.1 Data source

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

3.2 Methodology

We classify flows out of employment by reason for separation (quit or layoff) following the methodology explained in Ellieroth and Michaud (2024b) and following Flaim (1973). We further divide both quits and layoffs by workers' participation choices after employment separation. An individual is considered unemployed if they do not have a job but report they are actively searching for a job, and considered a non-participant (or out of the labor force) if they do not have a job and are not seeking one. We study four distinct flows:[5]

- 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)

Flows to Unemployment. Surveyors ask all unemployed individuals for the reason they became unemployed. Response options distinguish individuals 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 to 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`

This classification is readily available in the harmonized data in CPS IPUMS (Flood et al. (2023)) and constructed series of layoffs and quits to unemployment are provided by the Bureau of Labor Statistics (BLS). We do not use these series directly. Instead, we check that our series nearly replicate the series provided by the BLS as a check that our classification and harmonization procedures replicate the methods used by IPUMS. This ensures our newly constructed variables come as close as possible in methodology to the popular IPUMS variables researchers have historically studied.

[5] For a glossary of the naming convention of flows please see the appendix A

Flows to Non-participation. The variable coding reason for leaving the last job is not available on CPS IPUMS for non-participants, nor are the constructed flow series of quits and layoffs to non-participation released by BLS. We instead work directly with a question asked to individuals to inquire their reason of non-participation. It has slightly changed over the years, but is a close variant of:

`Why did ... leave that job?`

We restrict our sample to anyone who has worked in the past 12 months to provide consistent measurement across time.[6] Prior to 1994, surveyors asked this question 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.

The possible answer choices to the question have changed over time and we harmonize them as in Ellieroth and Michaud (2024b). 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.

Linking over Time & Flow Series Construction We follow standard methods to compute gross flows and transition rates that have been developed in a long literature for a more coarse classification of flows that omit reason for an employment separation and just look at transitions from employment (E) to unemployment (U) or non-participation (N) (Abowd and Zellner (1985), Shimer (2012), Elsby et al. (2015), and many others). We employ established harmonizing and linking methods used by IPUMS in order to come as close as possible to the variables available in IPUMS that are heavily used by researchers in Economics and other fields.

[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.

We specifically follow Madrian and Lefgren (1999) when linking individuals across two consecutive months and verify the quality of the matches based on sex and age.[7] This method ensures that when we aggregate our flows to broad EN and EU rates, we recover the same transition probabilities that would be computed from IPUMS harmonized CPS data.

To compute aggregate flow rates, or probabilities, we simply divide the number of transitions by how many individuals are in each labor market state.[8] An exception is layoffs and quits into non-participation because only individuals in the outgoing-rotation groups are asked about their reason for non-participation. This means there are only 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 EN transition rate to compute the number of layoffs for all other individuals making an employment to non-participation transition.

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

3.3 Validity and Robustness

Validity. Is the quit/layoff distinction meaningful for non-participants and is the participation decision distinct for those who have been laid-off? These are two common questions. Past research has argued that the answers to these questions on the reasons nonparticipants left the labor force are informative about future labor supply. Using the same questions in the CPS that we do, 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.[9]

Another indication that reason for separation to non-participation provides additional information about labor supply comes from a question that asks individuals about their primary activity in non-participation.[10] The possible answers are disabled, ill, in school, taking care of house or family, and other. We group disabled and ill together and add a category of "unknown" for all individuals for whom the answer was missing.

Table 1 shows some meaningful differences in primary activity during non-participation by reason for job separation which could be indicative of future labor supply. For example, twice as many quits than layoffs (30% versus 14%) to non-participation are due to disability/illness or school, two activities that are often associated with prolonged periods of non-employment. This table also provides evidence that the state of non-participation itself is meaningful. The majority of both groups report specific, valid reasons they are not looking for a job. For example,

[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.

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

[10] 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.

	Reason for Non-participation	
Activity	Layoff	Quit
Disabled/Ill	6%	12%
School	8%	18%
Family	49%	52%
Other	33%	15%
Unknown	4%	3%

Table 1: **Primary Activity by Reason for Non-Participation**

a similar share of non-participants report that their main activity is family care regardless of whether they quit or were laid off.

Ellieroth and Michaud (2024b) provide additional validation of the measurement in the CPS by comparing the four core flow rates (EUQ, EUL, ENQ, and ENL) to their analogous counterparts in the Panel Study of Income Dynamics (PSID) and Survey of Income Program and Participation (SIPP). These surveys have longer and/or more continuous panels of individuals and families but have much smaller and less representative sample sizes making them of ill-use for business cycle analysis.[11] None-the-less the average flow rates are remarkably similar between the PSID and CPS. The share of quits and layoffs comprising each employment to unemployment and employment to non-participation flows all differ by less than 4 percentage points across the two surveys.[12]

Robustness. Ellieroth and Michaud (2024b) show the data are largely robust to several concerns. First, the data are robust to “DeNUNification”: the removal of individuals who make one of the following labor market transitions: non-participation to unemployment to non-participation, or unemployment to non-participation to unemployment. The average flow levels are identical in the raw and de-NUNified data and the cyclical volatility of the flows show only small differences. Second, the business cycle properties of the total layoff series are fairly robust to the inclusion or omission of layoffs from temporary jobs. Layoffs from temporary jobs account for 20-30% of all layoffs but the layoff rate from temporary jobs display surprisingly little cyclical volatility compared to the layoff rate from permanent jobs.

4 Key Statistics for Macroeconomists

In this section we provide statistics on the incidence and cyclical variability of employment separations by reason and destination. We focus on statistics that we think would be of use to Macroeconomists. In particular, we provide statistics about total quits and layoffs resulting

[11]Publishers release these series with a lag while the quit and layoff series we construct are available a month after the survey is collected.

[12]The SIPP shows a larger departure, particularly for quits. The substantial difference in coarse labor market flow rates between the SIPP and CPS is known and discussed in Simmons (2023).

in non-employment. This is importantly distinct from prior work that established business cycle facts to validate a theory or calibrate/estimate a model using data on employment to unemployment flows only, or assuming employment to non-participation flows were all voluntary quits. We will show that the actual layoff and quit time series are quite different and should hold different implications both for quantitative analysis and economic theories.

All statistics and analyses in the main text are for the prime-age population, those between 25 and 55 years old, only. We replicate statistics and analyses for the working-age population, those 16 years and older, in the appendix. We focus on the prime-age population because retirees are not asked the reason for non-participation question. Retirements make up a sizable share of EN flows and we do not want to impute these flows as quits or layoffs because our analysis of PSID data shows flows into retirement include both quits and layoffs and the share of each moves over the business cycle.

The series span January 1978 to December 2024 and are smoothed using a 6-month centered moving average smoother.[13] This is a typical filtering choice for CPS data and Ellieroth and Michaud (2024b) show alternative 3 or 4 month, centered or lagging, smoothing windows affect the series little except for the layoff series in times around extreme spikes such as COVID-19. During those times, shorter windows provide more volatile swings in layoffs as would be expected.

4.1 An Overview of Quits and Layoffs to Non-Employment

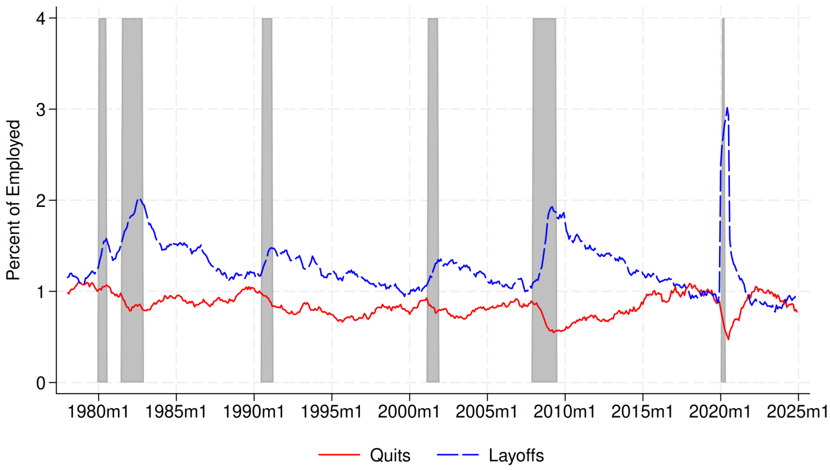


Figure 1: **Monthly Quit and Layoff Rates to Non-Employment** Prime Age. Shown as a percent of employment. Monthly seasonally-adjusted data and 6-month centered moving average.

Figure 1 plots the time series of total 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

[13] In order to avoid any problems at the end of the time series due to smoothing using a centered moving average, we smooth the time series using data until mid-2025 and then restrict to end at 12/2024.

the United States. Table 2 provides averages for these series and their correlation. These quits and layoffs series combine separations to both unemployment and non-participation.

	Total	Quits	Layoffs	Corr(Q,L)
1978-2024	2.12	0.85	1.27	-0.46
1978-1990	2.35	0.94	1.41	-0.65
1991-2019,2021-2024	2.05	0.81	1.24	-0.41

Table 2: **Statistics on Monthly Quit and Layoff Rates to Non-Employment** Prime Age. Shown as a percent of employment. Monthly seasonally-adjusted data and 6-month centered moving average.

In most months, layoffs exceed quits as a share of separations to non-employment. On average, 40% of all separations to non-employment are quits and 60% are layoffs as an average of 1.27% of workers leave employment via layoff each month and 0.85% via a quit. There are some exceptions to this regularity. Notably, the quit rate exceeded the layoff rate during the tighter labor markets of the late 2010s and 2022-2023. Both types of separations became rarer after 1990. Although the extreme year of 2020 is excluded, it is not clear whether this decline is a feature of long cyclical dynamics over this period or of a more fundamental structural change.

The rates of quits and layoffs to non-employment are negatively correlated. When layoffs rise, quits fall. The correlation is -0.46 for the whole time series, and -0.65 during the pre-1990's period and -0.41 post-1990. The drop in the correlation is even stronger for the working age population as shown in Appendix Table 20.

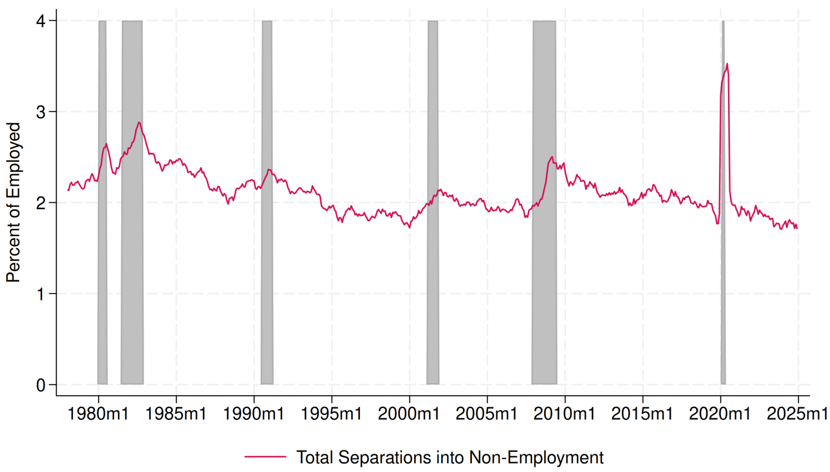


Figure 2: **Total Separations into Non-employment** Prime age. Total = Quits + Layoffs. Shown as a percent of employment. Monthly seasonally-adjusted 6-month centered moving average data.

Figure 2 shows the sum of the two series, 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. Although Figure 1 showed that both quits and layoffs vary with the business cycle, total separations move much less. The reason for that is that the decline in quits during recessions works to offset the rise in layoffs.

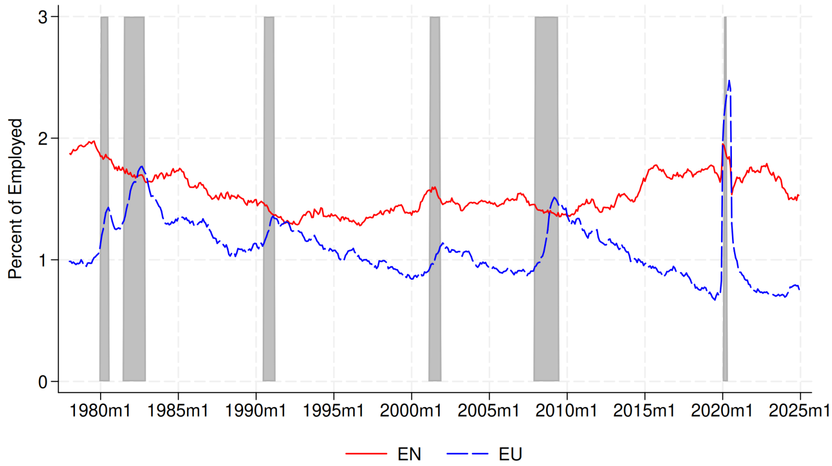


Figure 3: **Flow Rates from Employment to Non-Participation (EN) and to Unemployment (EU)** Prime Age. Shown as a percent of employment. Monthly seasonally-adjusted data and 6-month centered moving average.

Figure 3 plots flows from employment to non-employment by destination: unemployment or non-participation. These are standard flows considered in prior research on the cyclical properties of the labor market, and yet they can be misleading if one assumes employment to non-participation flows to be voluntary and employment to unemployment flows to be involuntary. 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.

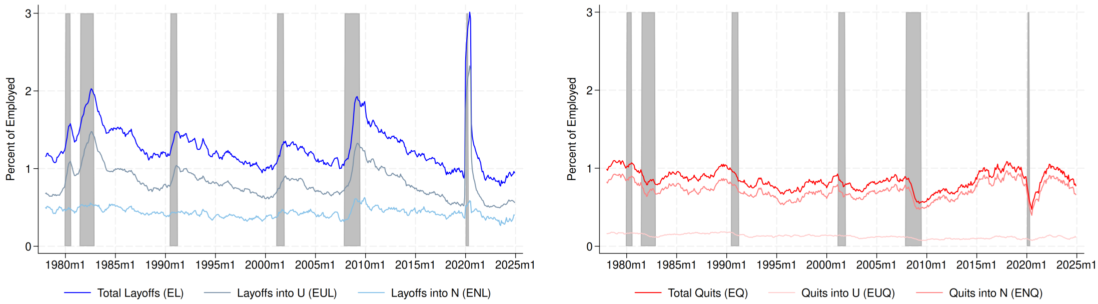
	Total	EN	EU	Corr(EN,EU)
1978-2024	2.64	1.55	1.09	0.01
1978-1990	2.92	1.67	1.25	-0.13
1991-2019,2021-2024	2.53	1.51	1.03	-0.09

Table 3: **Separation Rate by Destination.** (Prime Age. Total = EN + EU. Shown as a percent of Employment. Monthly seasonally-adjusted 6-month centered moving average data)

Table 3 shows how the EU and EN flows differ from quits and layoffs from employment shown in Table 2.[14] Total EN flows are 1.8 times larger than quits to non-employment and layoffs are 1.2 times more common than EU flows. Furthermore, the negative correlation between quits and layoffs to non-employment is more stark. EN and EU flows show no correlation over 1978-2024 but quits and layoffs to non employment have a -0.46 correlation.

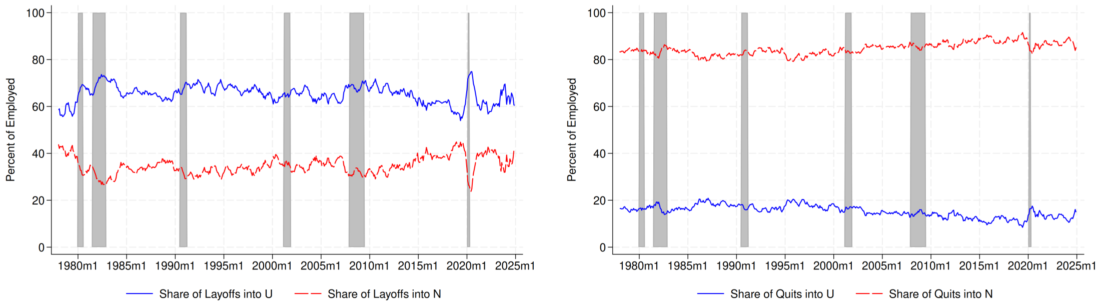
[14]Total flows, the sum of EU and EN, are higher in Table 3 than total flows, the sum of quits and layoffs, in 2 because some EN and EU flows cannot be classified as quit or layoff or are misclassified. A nontrivial number of individuals who makes an EU transition reports (wrongly) being a re-entrant or new entrant into the labor force.

Comparing Figure 4 and Figure 1, it is obvious that quits are related to total flows to N and layoffs to total flows to U, but they are not the same. Notably, the rate of EN flows is around 70% higher at a 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 and generates less volatile EN flows.



(a) Layoffs (b) Quits

Figure 4: **Quit and Layoff Rates by Destination: Unemployment (U) or Non-participation (N).** (Prime Age. Shown as a percent of Employment. Monthly seasonally-adjusted 6-month centered moving average data)



(a) Layoffs (b) Quits

Figure 5: **Share of Each Separation to Unemployment or Non-Participation.** (Prime Age. Monthly seasonally-adjusted 6-month centered moving average data)

Table 4 shows an average of 34.8% of prime-age workers move to non-participation if they are laid off to non-employment. That means that they had a job last month, lost it, and decide not to look for a job this month. For workers who quit, the share who move to non-participation is much higher at 84.7%. This makes it clear that it should not be assumed that all movements to non-participation are due to a quit decision. Indeed, 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.

	% Quits to		% Layoffs to		
	U	N	U	N	Corr(sQN,sLN)
1978-2024	15.3	84.7	65.2	34.8	0.38
1978-1990	17.2	82.8	65.9	34.1	-0.10
1991-2019,2021-2024	14.6	85.4	65.1	34.9	0.39

Table 4: **Percent of Quits and Layoffs to Non-Employment by Destination.** (sQN (sLN) = share of quits (layoffs) to non-participation. Prime Age. Monthly seasonally-adjusted 6-month centered moving average data)

Table 4 also shows that the share of workers choosing to look for a job after a layoff is stable across the early and late period of the sample. The share looking after a quit has decreased by 2.6 ppt from 17.2% to 14.6%. This does appear to be a secular decline despite business cycle fluctuations. The correlation between the share of quit workers who exit the labor force and share of laid off workers who exit is positive on average but flips signs from the early to the late period. In the early period the relationship was negative and in the later it is positive. This finding is even stronger for the working age population as shown in Appendix Figure 22.

4.2 Business Cycle Statistics

Flow rates determine the business cycle properties of labor market stocks, such as unemployment and employment-population ratios. Understanding their properties helps researchers understand how labor supply choices and frictions interact with each other and form over the business cycle.

We start by illustrating how quits and layoffs evolve over the business cycle. The first row of Table 5 shows the correlation of each flow rate (x) with the aggregate unemployment rate (y).[15] Here we present results using the aggregate unemployment rate, defined as the number of unemployed divided by the total labor force, as the indicator of the cyclical state of the labor market (Foote et al. (2025)). In the appendix, we repeat this exercise using an alternative indicator of tight labor markets.

Statistic	Quits			Layoffs			Total sep.
	to U	to N	Total	to U	to N	Total	to (U+N)
Corr(x, y)	-0.16	-0.48	-0.46	0.82	0.75	0.83	0.72
SD(x)/SD(y)	0.02	0.06	0.07	0.14	0.04	0.17	0.15

Table 5: **Business Cycle Correlations: Quits and Layoffs.** (Prime age. Monthly. Correlations of each flow (x) with the unemployment rate (y))

Table 5 confirms that quits and layoffs move in opposite directions over the business cycle as shown graphically in Figure 1. Quits into both unemployment (U) and non-participation

[15]None of the flow rate series show strong lower frequency trends, nor does the series of unemployment, and so we do not filter to remove trends.

(N) decrease in recessions when unemployment is rising but quits into N decline much more strongly over the cycle than quits into U. The layoff column shows that layoffs respond much more to the business cycle as they rise during recessions when unemployment is rising. Layoffs into unemployment respond more than layoffs into non-participation during a recession. This difference is partially due to the finding that the share of laid-off workers who leave the labor force decreases in recessions.

Statistic	
Corr(Quits, Layoffs)	-0.46
SD(Quits)/SD(Layoffs)	0.41

Table 6: **Business Cycle Relation of Quits and Layoffs** (Prime age. Monthly and seasonally adjusted.)

Table 6 shows that the correlation between quits and layoffs is -0.46 over the entire sample period. This is starkly different from the correlation between EU and EN flows which is 0.01. Quits decrease in times when unemployment increases, and thus are procyclical. Layoffs move in the opposite direction, they are countercyclical and increase when the unemployment rate is high.

Statistic	Layoffs	EU	Quits	EN
Corr(x, y)	0.83	0.82	-0.46	-0.06
SD(x)/SD(y)	0.17	0.14	0.09	0.07

Table 7: **Business Cycle: Relationships with the Unemployment Rate (y)** (Prime age. Monthly and seasonally adjusted. Correlations of each flow (x) with the unemployment rate (y))

Table 7 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 5. The first two columns compare EU flow rates (those typically assumed to comprise all layoffs) with our layoff series. Both series are countercyclical with similar cyclical volatility. This is a lucky coincidence. When we compare the standard deviations of our layoff series with the standard deviations of the EU rate, we see that our layoff rate exceeds the EU rate in terms of volatility relative to the unemployment rate by over 20%. The researcher who considers layoffs to unemployment (a variable available in IPUMS) to comprise all layoffs would fare worse and find a cyclicality which is too low compared to the true cyclicality of total layoffs to both unemployment and non-participation.

The second two columns of Table 7 show starker differences between quits and EN rates. While our quit series is strongly procyclical, i.e. quits decline in recessions, the EN rate is only mildly procyclical. This means that the prior work on quits over the business cycle that considered all EN flows to be voluntary had the cyclical nature of voluntary quits wrong. An explanation for this difference is that around 40% of all EN transitions are actually precipitated by layoffs. We have seen in Table 5 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 employment and unemployment over the business cycle.

Statistic	Layoffs	EU	Quits	EN
Corr(x, y)	0.91	0.91	-0.05	0.36
SD(x)/SD(y)	1.13	0.98	0.46	0.63

Table 8: **Business Cycle: Relationships with the Total Separation Rate (y)** (Prime age. Monthly and seasonally adjusted. Correlations of each flow (x) with the total separation rate (y))

Table 8 repeats the exercise from the previous table but looks at the relationship with the total separation rate. Again, we see that both layoffs and the EU transition rate are similarly correlated with total separations. However, our layoff series shows a significantly higher volatility relative to the total separation rate than the EU rate. While the standard deviation of the EU rate is less or similar to that of the total separation rate, the standard deviation of our layoff series is significantly larger. Looking at Table 9, which shows the absolute and relative increase of layoffs and EU transitions in recessions, confirms the previous findings. Layoffs consistently fluctuate by more, i.e. increase by more during recessions, than total separations because of the dampening effect of quits. [16] Our layoff series is comprised of layoffs into unemployment and non-participation, which both increase in recessions. The EU rate, however, only includes about 60% of all layoffs, those into unemployment, and in addition quits into unemployment which decline in recessions. Therefore, the EU rate significantly understates the volatility of layoffs in the economy.

[16] Table 8 shows that quits are negatively correlated with total separations.

Recession	Total Separations	Layoffs		EU	
	in pp	in pp	Relative	in pp	Relative
1980	0.41	0.35	0.85	0.37	0.90
1981	0.57	0.67	1.18	0.51	0.89
1990	0.21	0.27	1.59	0.19	0.90
2001	0.27	0.37	1.37	0.27	1.00
2007	0.67	0.92	1.37	0.62	0.93
2020	1.76	2.13	1.21	1.76	1.00

Table 9: **Recessionary increase in total separations, layoffs, and EU rate** Prime age, monthly. Peak-to-trough-change in percentage points (pp) and relative to total separations

4.3 Importance of Labor Supply Decisions

Table 10 shows how labor supply decisions after quits and layoffs vary over the business cycle. The main finding is that the labor supply of workers who separate from employment increases during recessions. In times when the unemployment rate is high, the share of each layoffs and quits into non-participation decline. This is similar to employed workers who too become more attached and less likely to quit their job to non-employment, as shown in Table 6.

Statistic	Share of Layoffs into N	Share of Quits into N
Corr(x, y)	-0.64	-0.15
SD(x)/SD(y)	0.02	0.02

Table 10: **Business Cycle: Relationship between Labor Force Exits (x) and the Unemployment Rate (y)** (Prime age. Monthly and seasonally adjusted.)

The share of quits that flow into N decreases in recessions when the unemployment rate increases. We have seen the reason for that in Table 5: 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.

The share of layoffs into non-participation is negatively correlated with the unemployment rate. This suggests that laid-off workers become more attached to the labor force in recessions as more workers choose to remain unemployed after losing their job. When layoffs increase by a certain amount in a recession, flows into unemployment rise even more due to the increased propensity of laid-off workers to stay in the labor force. This is important for understanding cyclical volatility in the labor market because 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.

Implications for Tracking Components of Slack. The cyclical changes in the labor supply of laid-off workers increases the cyclical variability of unemployment in a statistical sense. If the decision to report being unemployed versus a non-participant is superficial or has little meaning for actual job search efforts, then unemployment will be more volatile than actual slack. After all, the majority of hires from non-employment come from non-participation and so unemployment is hardly fully encompassing of the pool of potential workers. In this case, one might want to track an unemployment rate that holds fixed the labor supply decisions of laid-off workers. This is useful because labor supply choice after layoff is a major contributor to the cyclical component of labor supply, so holding it fixed is one way to isolate the contribution of fluctuating labor demand (layoffs and lower job finding rates) to fluctuations in the unemployment rate.[17]

We construct a counterfactual unemployment series that holds labor force participation patterns constant while allowing all other labor market flows to vary with the business cycle.

[17] Cajner et al. (2021) provide an alternative method of estimating the cyclical component of labor supply that exploits cross-state variation in labor demand shocks.

The labor market consists of three stocks: employment (E_t), unemployment (U_t), and not in the labor force (N_t), that sum to the total population (normalized to one). These stocks evolve according to gross flows between them. Unemployment dynamics are given by

$$\Delta U_t = (EU_t + NU_t) - (UE_t + UN_t) \tag{1}$$

where EU_t denotes the flow from employment to unemployment, NU_t the flow from not in the labor force to unemployment, and so forth.

Gross flows are the product of hazard rates and source stocks. The EU flow depends on both quits and layoffs:

$$EU_t = \lambda_{eq,t}E_t + (1 - s_t)\lambda_{el,t}E_t \tag{2}$$

where $\lambda_{eq,t}$ is the quit rate to unemployment, $\lambda_{el,t}$ is the total layoff rate, and s_t is the share of layoffs flowing to not in the labor force rather than unemployment. Similarly, the employment to non-participation flow is $EN_t = \lambda_{en,t}E_t + s_t\lambda_{el,t}E_t$, where $\lambda_{en,t}$ captures quits to non-participation. Other flows follow analogously: $UE_t = \lambda_{ue,t}U_t$, $UN_t = \lambda_{un,t}U_t$, $NE_t = \lambda_{ne,t}N_t$, and $NU_t = \lambda_{nu,t}N_t$.

We consider a "participation neutral" series of unemployment that holds constant the flow rates between unemployment and non-participation as well as the share of workers laid off from employment who exit the labor force.[18] To construct the participation neutral series, we hold three parameters constant at their optimal values $(s^*, \lambda^*_{nu}, \lambda^*_{un})$ while allowing all other flow rates to vary over time. These optimal values are chosen to maximize the correlation between actual unemployment U_t and counterfactual unemployment U^{cf}_t, subject to the constraint that all parameters lie in $[0, 1]$. The counterfactual unemployment stock evolves according to

$$U^{cf}_t = U^{cf}_{t-1} + \left[\lambda_{eq,t}E^{cf}_{t-1} + (1 - s^*)\lambda_{el,t}E^{cf}_{t-1} + \lambda^*_{nu}N^{cf}_{t-1}\right] - \left[\lambda_{ue,t}U^{cf}_{t-1} + \lambda^*_{un}U^{cf}_{t-1}\right], \tag{3}$$

with initial condition $U^{cf}_0 = U_0$. By fixing the labor force participation margins (s^*, λ^*_{nu}, λ^*_{un}) while allowing cyclical flows to vary, this counterfactual isolates unemployment fluctuations that would occur if participation patterns remained constant throughout the business cycle.

The results are plotted in Figure 6. The blue line is the actual series and the red-dashed line is the participation neutral series. The correlation between the two series is high at 0.95, but the actual series is more volatile than the participation neutral series. The actual series has a standard deviation of 0.0127, while the participation neutral series has a standard deviation of 0.0108. The higher volatility of the actual series implies that participation decisions amplify the volatility of unemployment by about 25%. When they are removed, we get the less volatile red-dashed line.

The contribution of participation decisions to unemployment volatility varies across recessions. Table 11 presents the change in actual unemployment-to-population and in our constructed participation-neutral unemployment-to-population from min to max for each relevant

[18] This is because UN and NU flows can be fickle as movements in them can capture both changes in real labor force participation decisions and misclassifications of participation status month-to-month.

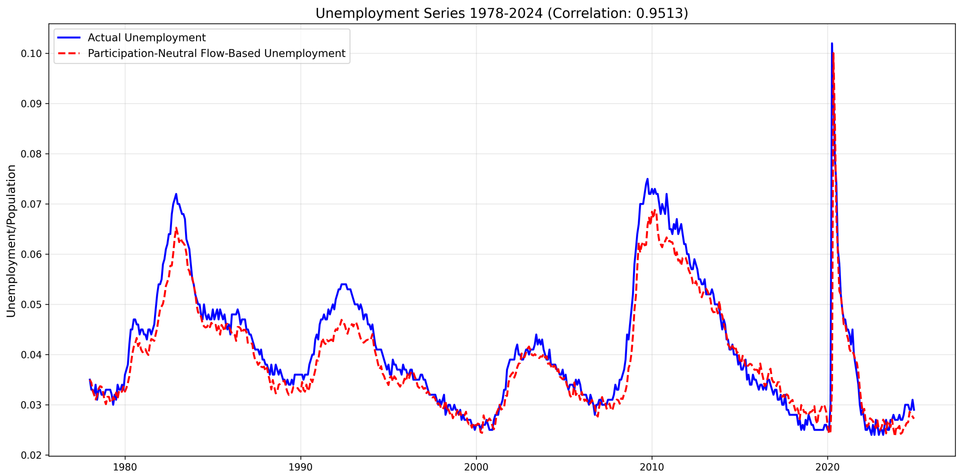


Figure 6: **Impact of participation flows on the dynamics of unemployment.** neutral unemployment holds fixed each share of layoffs to nonparticipation, UN, and NU at values to maximize the correlation of the series.

Period	Actual U	Participation-Neutral U	Relative Difference (%)
1979-1982	4.20	3.48	20.8
1990-1992	1.90	1.43	32.8
2000-2003	1.90	1.72	10.5
2007-2009	4.50	3.84	17.3
2019-2020	7.70	7.58	1.5

Table 11: **Unemployment Rate Changes During Recessions** First two columns: percentage point change from period min to max. Last column: difference between column one and two as a percent of column two.

period. The periods are chosen to capture the low of the unemployment rate preceding each recession and the maximum of the unemployment rate during the recession. The final column shows how much larger the increase in the actual series is relative to the increase in the participation neutral series, in percent terms.

The 1990's recession stands out as having the largest difference between the actual unemployment and participation neutral unemployment. This is both because an unusually large amount of laid-off workers remained in the labor force and unemployed workers were less likely to exit to non-participation. These changes in labor supply caused unemployment to rise by almost a third more than it otherwise would have. The COVID recession is also an extreme outlier. While the share of laid-off workers leaving the labor force plummeted to record lows, this was mitigated by a record spike in the UN rate possibly due to misclassifications of workers awaiting recall (Hall and Kudlyak (2022)). The 2001 recession is another example where changes in participation decisions did relatively little to exacerbate the rise in unemployment, adding only an additional 10.5% to the percentage point increase.

This colors how we compare volatility across recessions. For example, the rise in actual unemployment-to-population is identical in the 1990's and 2001 recessions but the participation neutral rise is 20% higher in the 2001 recession. This suggests more different dynamics in labor demand (layoff rates and job finding rates) across the two recessions than can be seen once we hold dynamics of labor supply to be fixed.

A separate but interesting feature seen in Figure 6 is that the actual unemployment series often leads our counterfactual series. This suggests that participation decisions shift in anticipation of the cycle. The very recent movements from 2023-current show a more stark example of this lagged relationship. The actual rise in unemployment is first driven by a rise in labor force participation and then, a year later, demand factors start to slow down and contribute to lower slack and higher unemployment. Section 7 explores how this feature makes the quits and layoffs time series useful when forecasting unemployment.

5 Shimer Decomposition

In this section, we follow the methodology of Shimer (2012) to evaluate the quantitative contributions of layoffs and quits to the dynamics of unemployment and employment rates over the business cycle. As in Shimer (2012), we start by computing (discrete) monthly flow rates as described in Section 3. We follow Shimer (2012) as closely as possible, with the only difference being that we split transitions into unemployment and non-participation by reason. The flows we study are illustrated in Table 12.

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 12: **Flow rates by source (left column) to destination (top row)**

Next, we compute instantaneous transition rates based on the above flow rates to correct for time aggregation bias generated by individuals making multiple labor market transitions in a month. Lastly, we take quarterly averages of the monthly time series and smooth the data. We will start by explaining how we change the time aggregation method by Shimer (2012) to account for the addition of reason for movement into non-employment from employment.

Time Aggregation Bias We construct instantaneous transition rates λ^{AB} which denote a movement from state $A \in \{E, U, N\}$ to state $B \neq A$ following the methodology of Shimer (2012). This gives us six transition rates for each month: EU, EN, UE, UN, NE, NU. We use the two rates from employment to non-employment, λ^{EU} and λ^{EN}, to calculate the four rates from employment to non-employment by reason. In order to do that, we multiply the instantaneous transition rate λ^{EU} and λ^{EN} by the fraction of workers who quit or were laid off for every month in the observed time period to construct the four flow rates by reason and destination: λ^{EUQ}, λ^{EUL}, λ^{ENQ}, and λ^{ENL}.[19]

Decomposition We start by assuming the economy is in steady state which requires the flows in and out of employment and in and out of unemployment to be equal. Mathematically, this is:

$$\underbrace{(\lambda^{EUQ} + \lambda^{EUL} + \lambda^{ENQ} + \lambda^{ENL})e}_{\text{flows out of employment}} = \underbrace{\lambda^{UE}u + \lambda^{NE}n}_{\text{flows into employment}} \tag{4}$$

$$\underbrace{(\lambda^{UE} + \lambda^{UN})u}_{\text{flows out of unemployment}} = \underbrace{(\lambda^{EUQ} + \lambda^{EUL})e + \lambda^{NU}n}_{\text{flows into unemployment}} \tag{5}$$

where λ^{AB} indicates the instantaneous transition rates from A to B. We also assume that all individuals can be classified as either employed (e), unemployed (u) or not in the labor force (n):

$$e + u + n = 1 \tag{6}$$

Equation 4 is modified to include our quit and layoff series. Instead of looking at outflows by destination, we use our quit and layoff series to group outflows of employment by reason and destination. Again, we try to remain as similar as possible to the original approach in that the only modification we make is to replace λ^{EU} with $\lambda^{EUQ} + \lambda^{EUL}$ and λ^{EN} with $\lambda^{ENQ} + \lambda^{ENL}$.

Solving equations 4, 5, and 6 for e, u, and n, we get

$$e = k\left(\lambda^{UE}\lambda^{NU} + \lambda^{NE}\lambda^{UE} + \lambda^{NE}\lambda^{UN}\right) \tag{7}$$

$$u = k\left((\lambda^{EUQ} + \lambda^{EUL})\lambda^{NE} + (\lambda^{EUQ} + \lambda^{EUL} + \lambda^{ENQ} + \lambda^{ENL})\lambda^{NU}\right) \tag{8}$$

$$n = k\left(\lambda^{UE}(\lambda^{ENQ} + \lambda^{ENL}) + \lambda^{UN}(\lambda^{EUQ} + \lambda^{EUL} + \lambda^{ENQ} + \lambda^{ENL})\right) \tag{9}$$

where k is a constant.

We will use these flow-based equations to calculate the contribution of each of the ten flow rates to the unemployment rate $\frac{u}{e+u}$ and the employment-to-population ratio $\frac{e}{e+u+n}$ each month.

Contribution of each Flow to the Unemployment Rate. We start by taking quarterly averages of the monthly data and smooth the time series using a 2-quarter-centered moving average. In order to quantify the effect of each flow rate, we compute alternative unemployment rates. We construct the time series of each alternative unemployment rate by setting all flow rates to their average value and only letting the flow rate of interest vary over time. We then regress the alternative unemployment rate on the unemployment rate constructed using the flow-based stocks.

[19]This approach relies on the assumption that quits and layoffs into U and N have a similar time bias in each month. While we cannot directly test for it, this approach allows us to calculate the instantaneous transition rates similar to the original paper by Shimer (2012) with minimal additional assumptions or restrictions.

Rate	Shimer (2012)	This paper	This paper
	1987-2010		1978-2024
	(1)	(2)	(3)
λ^{EUQ}	-	-0.04	-0.02
λ^{EUL}	-	0.28	0.41
λ^{ENQ}	-	-0.04	-0.05
λ^{ENL}	-	0.04	0.04
λ^{EU}	0.22	-	-
λ^{EN}	-0.05	-	-
λ^{UE}	0.51	0.54	0.42
λ^{UN}	0.16	0.11	0.11
λ^{NE}	0.08	0.05	0.06
λ^{NU}	0.13	0.09	0.10

Table 13: **Decomposition of fluctuations in the unemployment rate: All Flows**

Rate	Shimer (2012)	This paper	This paper
	1987-2010		1978-2024
	(1)	(2)	(3)
λ^{EU}	0.22	0.24	0.39
λ^{EN}	-0.05	0.00	-0.01
λ^{EL}	-	0.32	0.45
λ^{EQ}	-	-0.08	-0.07

Table 14: **Decomposition of fluctuations in the unemployment rate: Quits and Layoffs vs. EU and EN**

Table 13 shows the quantitative importance of each instantaneous flow rate to the fluctuation of the unemployment rate, and Table 14 summarizes the differences between our total quits and layoffs series compared to the standard EU and EN transition rates.

Columns (1) and (2) show the results when we restrict our data to cover the same time period as in Shimer (2012). 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 0.54 our data vs. 0.51 original data). To support our methodology, Table 14 shows the contribution of λ^{EU} computed by adding up λ^{EUQ} and λ^{EUL} is similar to what Shimer (2012) finds.[20] Additionally controlling for the reason of separation, however, reveals that the contribution of the layoff rate, EL, is about 35% larger than the EU rate.[21] Thus, we show that the layoff rate, EL, contributes significantly more than would be assumed by only looking at the EU rate. The reason is that the rise in the unemployment rate due to the rise in the layoff rate is partially offset by the decline in quits EQ.[22]

[20]The difference is due to EU and EN flows that we cannot classify as quit or layoff and subsequently drop from this analysis.

[21]The total contribution of layoffs is $\lambda^{EUL} + \lambda^{ENL} = 0.28 + 0.04 = 0.32$ vs 0.24

[22]This result is of similar spirit to Simmons (2023). He finds the contribution of separation rates to cyclical

Another result is that movements within non-employment, those between unemployment and non-participation, account for about one third less of the cyclical changes in unemployment once we include our quit and layoff distinction. This reinforces our claim that the reason for a separation carries additional information above the destination that is important for understanding fluctuations in the unemployment rate.

Results for the entire 1978-2024 time period (Column (3)) show that UE rates have not been the dominant source of movements in unemployment outside of the 1987-2010 period. Instead, layoffs become the largest contributor to the fluctuations in the unemployment rate when we expand the sample to include the early 1980s recession, more of the 2010's recovery, and the pandemic. However, most of this finding is driven by the pandemic recession, where layoffs experienced historically high levels.

Figure 7 shows the actual unemployment rate (UR); the flow-based unemployment rate if only our layoff series varies (Counterfactual UR: Layoffs); and the flow-based unemployment rate if only the UE rate varies (Counterfactual UR: UE). Although layoffs and UE are the main contributors to the fluctuations in the unemployment rate from our Shimer decomposition, we can see from the figure that the importance of each of the two flow rates differs at different points in the business cycle. Fluctuations in our layoff series are more important to fluctuations in the unemployment rate at the beginning of a recession whereas fluctuations in the UE transition rate contribute more towards the end of a recession and during expansionary periods. It appears that layoffs are more important at turning points, whereas the job finding rate from unemployment contributes more to the persistence of fluctuations in the unemployment rate.

In addition, the figure helps to understand why layoffs are the most important contributor to the volatility of the unemployment rate over the entire time period; the pandemic recession was characterized by an increase in layoffs which outweighed the contribution of the UE transition rate.

Contribution of each Flow to the Employment-Population Ratio. We decompose the drivers of fluctuations in the employment-population ratio in an analogous fashion as we did for the unemployment rate. Tables 15 and 16 show our findings, the importance of different transition rates to fluctuations in the employment-population ratio.

The contribution of layoffs to fluctuations in the employment-population ratio is more than twice as large than just looking at the EU transition rate would suggest, as shown in Table 16. The reason is twofold. First, quits into unemployment fall in recessions and offset some of the effect of increased layoffs into unemployment. Second, and more importantly, layoffs into non-participation, λ^{ENL}, have a significant impact on the fluctuations in the employment-population ratio, but are not captured when just examining flows from E to U. Two-thirds of the importance of layoffs to the employment-population ratio stems from fluctuations in layoffs

unemployment fluctuations to be over five times as large when accounting for reason for quit using SIPP data. We find the overall contribution of separations to be larger in the CPS data at 32% versus his finding of 25.4%, and we show the contribution is even larger for Employment-Population at 49%.

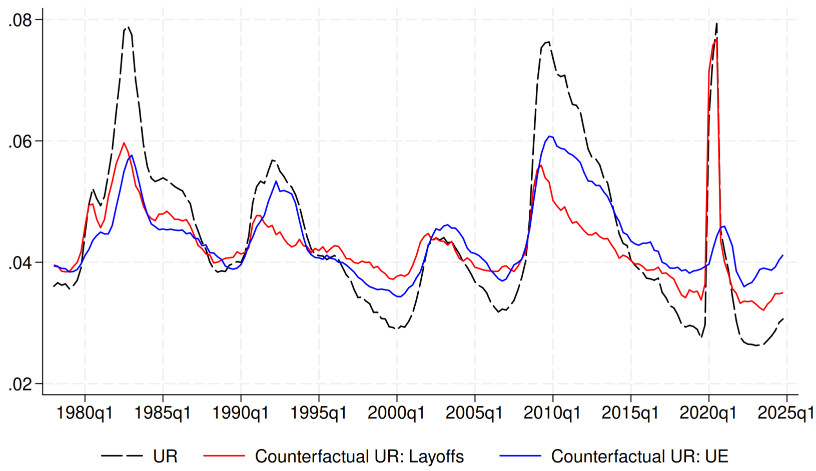


Figure 7: **Unemployment Rate and Counterfactual Unemployment Rate based on contribution of layoffs and UE transition rate** UR = Unemployment Rate. We construct the time series of each counterfactual unemployment rate by setting all flow rates to their average value and only let the the flow rate of interest (here: layoffs or EU) vary over time.

Rate	Shimer (2012)	This paper 1987-2010	This paper 1978-2024
λ^{EUQ}	-	-0.04	-0.01
λ^{EUL}	-	0.43	0.44
λ^{ENQ}	-	-0.14	-0.01
λ^{ENL}	-	0.24	0.18
λ^{EU}	0.30	-	-
λ^{EN}	-0.40	-	-
λ^{UE}	1.16	0.93	0.50
λ^{UN}	-0.50	-0.24	-0.14
λ^{NE}	0.73	0.26	0.27
λ^{NU}	-0.42	-0.18	-0.05

Table 15: **Decomposition of fluctuations in the employment-to-population ratio: All Flows.**

Rate	Shimer (2012)	This paper 1987-2010	This paper 1978-2024
λ^{EU}	0.30	0.39	0.43
λ^{EN}	-0.40	0.10	0.17
λ^{EL}	-	0.67	0.62
λ^{EQ}	-	-0.18	-0.02

Table 16: **Decomposition of fluctuations in the employment-to-population ratio: Quits and Layoffs vs. EU and EN**

into unemployment and the other third is due to fluctuations in layoffs in non-participation. This is why fluctuations in layoffs account for a larger portion of the decline of the employment-population ratio in recessions than the rise in unemployment.

Table 16 also shows that quits, λ^{EQ}, had a dampening effect on employment volatility for the 1987-2010 period. This is because quits are negatively correlated with the unemployment rate, a fact explored in recent research on the importance of quits to business cycle fluctuations.[23] A comparison with Table 14 shows that quits have a larger dampening effect on fluctuations in the employment-population ratio than they do on fluctuations different expansions in the unemployment rate. This is because quits account for a much larger share of flows to nonparticipation than to unemployment.

6 Differences and Similarities Across Recessions and Expansions

In the previous section we analyzed the different flow rates' contributions to overall business cycle fluctuations in the labor market. This section shows that most findings are robust to the different economic downturns and expansionary periods in our time frame.

6.1 Recessions

Our sample covers six NBER dated recessions starting with the 1980 recession up until the pandemic recession of 2020. Although recessions differ in their causes, lengths, and impacts on the labor market, we will show in this section that they are remarkably similar with regards to dynamics of quits, layoffs, and total separations into non-employment. Thus, we do not think that our empirical findings are the result of specific recessions having a dominating effect on the overall time-series.

Recession	UR	EPR	Quits	Layoffs	Total Separations
1980	1.90	-1.20	0.04	0.36	0.40
1981	3.60	-1.80	-0.16	0.41	0.26
1990	2.60	-1.40	-0.20	0.17	-0.03
2001	2.40	-2.10	-0.20	0.23	0.03
2007	5.30	-4.40	-0.33	0.77	0.44
2020	9.70	-8.40	-0.18	0.30	0.12

Table 17: **Comparing Recessions.** Peak-to-trough change in percentage points. UR = Unemployment Rate. EPR = Employment-to-Population Ratio. Prime-age population

Table 17 shows that all recessions are associated with an increase in layoffs and, with the exception of the 1980s recessions, all downturns feature a decline in quits. The resulting change

[23] See e.g. Ellieroth and Michaud (2024a)

in total separations varies in size and depends on whether the decline in quits or the increase in layoffs dominated. The recessions listed in the table vary in length and in intensity, as can been seen by the differing increases in the unemployment rate.

We use labor market tightness as a measure of the state of the economy to better compare flows across recessions of different magnitudes. Labor market tightness is defined as the vacancy rate in the economy divided by the share of the working-age population that is unemployed.[24] Analyzing our time-series in relation to market tightness allows for a more equal comparison among very different recessions.

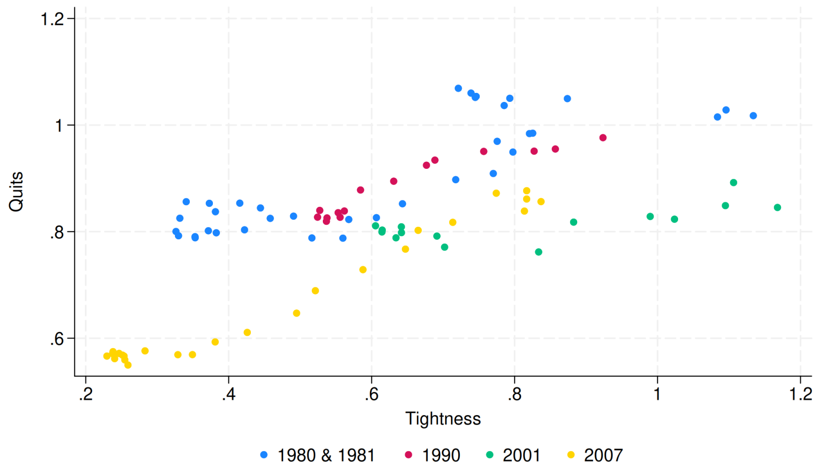


Figure 8: **Comparing Recessions: Quits versus Labor Market Tightness** Quits are the total quit rate from employed to non-employment. Market tightness is vacancies divided by the share of the working age population that is unemployed. Each recession includes the NBER recession months plus six months into the recovery. Data is for the working-age population.

Figure 8 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 a recession. We grouped the two recessions in the early 1980s because of the small gap between them. The slopes of the lines are generally positive. A positive slope means that quits are low if labor market tightness is low and quits increase when the labor market becomes tighter. This observation is true for all recessions except the 2001 recession. The slopes of the relationship between quits and market tightness differ across some recessions. The correlation coefficient between our quit series and tightness is high for all recessions and varies from 0.7 to 0.95.

Figure 8 shows another interesting feature beyond the business cycle: quits seem to be lower relative to labor market tightness in the 2000s recessions than in the 1980s and 1990s recessions. Fewer quits out of employment for a given market tightness over time could be related to decreased dynamism in the labor market (Davis and Haltiwanger (1999)) or due to

[24]We use data on the vacancy rate in the U.S. economy from Petrosky-Nadeau and Zhang (2021). They combine vacancy data from different sources and provide a series that spans most of the time frame of our data (1/1978-12/2017)

higher labor force attachment (Ellieroth and Michaud (2024a)).

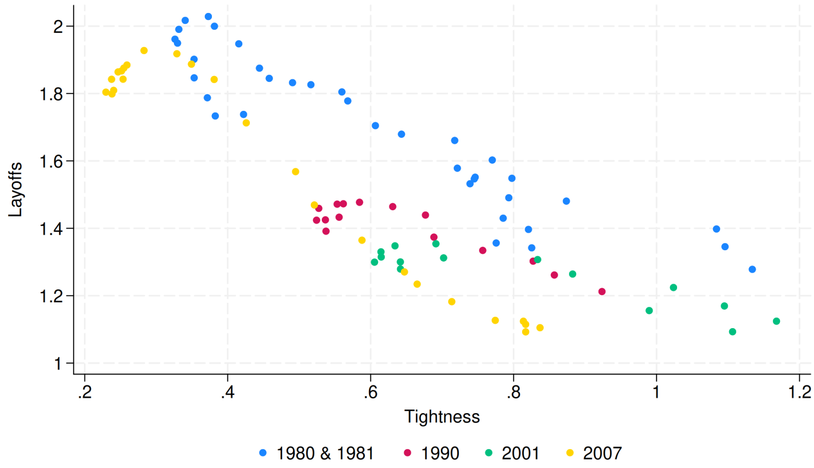


Figure 9: **Comparing Recessions: Layoffs versus Labor Market Tightness** Total layoffs are the total layoff rate from employed to non-employment. Market tightness is vacancies divided by unemployed. Each recession includes the NBER recession months plus six months into the recovery. Data is for the working-age population

Figure 9 shows the relationship between layoffs into non-employment and labor market tightness for the same time period as the previous figure. The figure shows a strong negative correlation between layoffs and labor market tightness for each recession. Thus, layoffs are high if labor market tightness is low and vice versa. All recessions are characterized by a very similar slope. The correlation coefficient between layoffs and tightness is high and within the narrow range of 0.9 to 0.94. There are some level differences since the recessions that were more severe, those in the 1980s and 2007, show a higher average level of layoffs.

6.2 Focus on an Episode: The Pandemic Recession and Recovery

The empirical patterns of quits and layoffs are strikingly similar across recessions. No single episode better proves this point than the recession and recovery following the COVID-19 pandemic. Although the pandemic recession stood out compared to other recessions in many aspects, our series of quits and layoffs show that the business cycle patterns of quits, layoffs, and labor supply decisions during that time were mostly unremarkable. They are consistent with historic patterns but scaled by the size of the shocks hitting the economy except with a couple of important exceptions.

The pandemic recession was characterized by an unprecedented increase in layoffs. Like all other recessions in our sample, this increase in layoffs was accompanied by a smaller decrease in quits summing to an increase in total separations into non-employment (see Figure 2).

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. The magnitude of that fall, however, is striking. Layoffs into non-participation made up almost 50% of all layoffs prior in late 2019, a record high, and 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, e.g. were the unemployment insurance benefits extensions during that time period an important contributor to 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 but Afrouzi et al. (2024) cite our quits series to offer a different view.[25] Contrary to JOLTS data, our time series of quits does not display an increase in the Covid recovery higher than in previous recessions.[26] Figure 10 shows the peak-to-peak change for the 2001, 2007, and 2020 recessions, and it is clear from the figure that the recovery after the pandemic recession follows a very similar pattern as the recovery after the 2007 recession, albeit on a faster timeline.

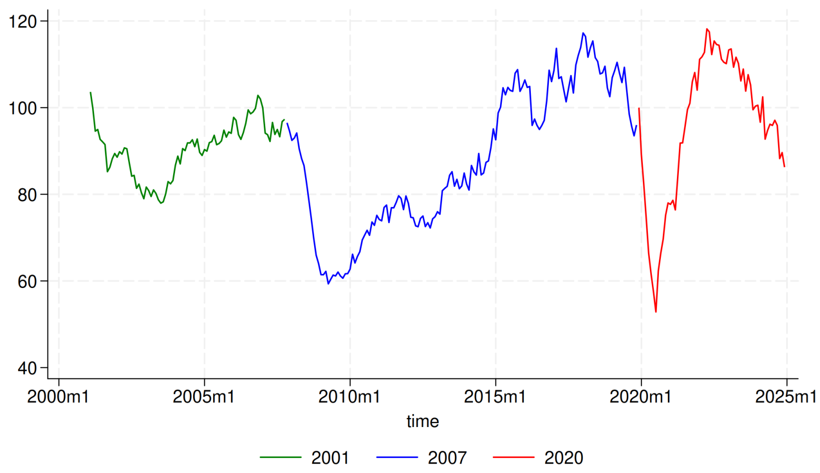


Figure 10: **Dynamics of Quits in Three Recessions.** Peak-to-peak change in quits with each peak normalized to 100

The similarity of the dynamics of quits, layoffs, and labor force participation in the pandemic recession with other episodes 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.[27]

Figure 11 displays the correlation of quits with labor market tightness using peak-to-peak data for three business cycles. We do not find evidence of a "great resignation" after COVID. All three cycles show a positive correlation between quits and labor market tightness with a very similar magnitude of correlation. The only apparent deviation is the negative correlation between

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

[26]Our data can be combined with the CPS series of employer-to-employer flows assembled by Fujita et al. (Forthcoming) but these flows cannot be classified into quits and layoffs.

[27]Here we use JOLTS data on vacancies because we need data on vacancies which includes the pandemic recession time period.

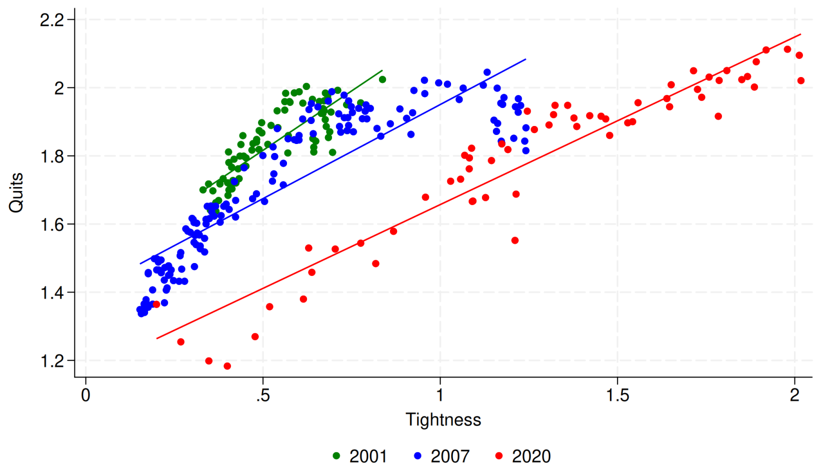


Figure 11: **Correlation of Quits and Market Tightness over Three Cycles.** Each recession include months from beginning of that recession to the start of the next.

quits and labor market tightness in the first few months of the pandemic. The subsequent recovery has displayed similar correlations as past cycles.

7 Forecasting

We now evaluate the ability of various flow series to predict a key labor market indicator: the unemployment rate.[28] We focus on forecasting the unemployment rate on horizons of 1, 3, and 6 months ahead. We give each indicator its "best shot" by using LASSO and elastic nets to allow a different regression specification for each indicator. The elastic net framework addresses two key econometric challenges: multicollinearity among flow indicators and the curse of dimensionality arising from multiple lag structures. For each labor flow indicator, we feed the algorithm six monthly lags as potential controls to capture the temporal dynamics of labor market adjustments. Additionally, we feed six lags of the unemployment rate itself, recognizing the strong autoregressive properties in unemployment dynamics. This specification results in a regression with 42 flow-related covariates plus 6 unemployment lags, totaling 48 potential predictors.

The elastic net estimator combines LASSO and Ridge penalties through the objective function:

$$\hat{\beta} = \arg\min_{\beta} \left\{ \frac{1}{2n} \|u_{t+h} - X\beta_2\|^2 + \lambda \left[\alpha \|\beta_1\| + (1-\alpha)\frac{1}{2}\|\beta_2\|^2 \right] \right\} \tag{10}$$

where X contains all lagged flow indicators and unemployment lags, λ controls the overall regularization strength, and $\alpha = 0.5$ is chosen to balance between LASSO ($\alpha = 1$) and Ridge ($\alpha = 0$) penalties. The elastic net's advantage lies in its ability to perform variable selection while maintaining correlated predictors, which is crucial given the potential correlation structure

[28] See Foote et al. (2025) for a discussion of indicators used to assess maximum employment.

among different measures of labor market flows. Finally, we implement 5-fold cross-validation to select the optimal λ parameter.[29]

We consider three different time periods to acknowledge the shorter time-series of JOLTS versus CPS. The full samples available are each monthly and span 1978-2024 for CPS and 2001-2024 for JOLTS. The training sample for the "Full Sample" specification uses all available data. The training sample for the "Real-Time" specification uses all available real-time data at the time. That is, the revision vintage of the time series *prior* to the date the forward forecast is made. This specification uses only post-2011 data in order to use the correct real-time revision vintage of JOLTS available from ALFRED.[30] The training sample for the post-2001 specification uses final revisions of all data starting in 2000, and restricts the prediction set to 2001-2024. This gives JOLTS its best shot by removing both the long-time series advantage of CPS and the revision disadvantage of JOLTS.[31]

For each time period, we consider two different methods to evaluate the forecasting power of each indicator. The first is a univariate specification that considers how much the prediction improves when the indicator we are evaluating is provided to the LASSO algorithm compared to using lags of unemployment alone. This is labeled as "Individual $\mathbf{R^2}$". The second is a "leave-one-out" specification that considers how much the prediction worsens when the indicator we are evaluating is removed from the LASSO algorithm compared to using *all* labor market flows we have plus unemployment.

The top section of Table 18 provides the gain in R^2 when adding just the indicator to lags of unemployment, and the bottom section provides the reduction in R^2 when removing the indicator from the full specification including all indicators. The larger the absolute value, the more the indicator aids in predicting unemployment.

A first result is that quits and layoffs measures outperform the forecasting ability of the standard CPS employment to unemployment (EU) flow rate at all time horizons greater than one month. This is somewhat surprising because the EU rate directly and mechanically feeds additional persons into unemployment whereas the quits and layoff rates feed to both unemployment and non-participation. Our CPS layoffs series is the best indicator for forecasting unemployment at the one-quarter horizon, and is so by a wide-margin. This is true in both univariate and leave-one-out specifications and across all time periods we consider. Interestingly, quits measures become more important for forecasting unemployment at longer horizons such as two quarters. This is likely because individuals' quitting behavior is forward looking and anticipatory of future layoffs.

[29] A low λ eliminates fewer variables ($\lambda = 0$ is OLS). The five-fold method involves breaking the training sample into five segments, leaving one out, and evaluating the fit of it's prediction. We do this five times, for each segment, and find the λ that provides the best fit.

[30] ALFRED from the Federal Reserve of St Louis has real-time data for JOLTS only from August 2010 on.

[31] The JOLTS series is subject to sizeable revision over the course of many months and sometimes more than a year while the CPS flows are mostly unrevised. We return to this point below.

Table 18: R^2 of Labor Flow Indicators for Predicting Unemployment Rate Changes

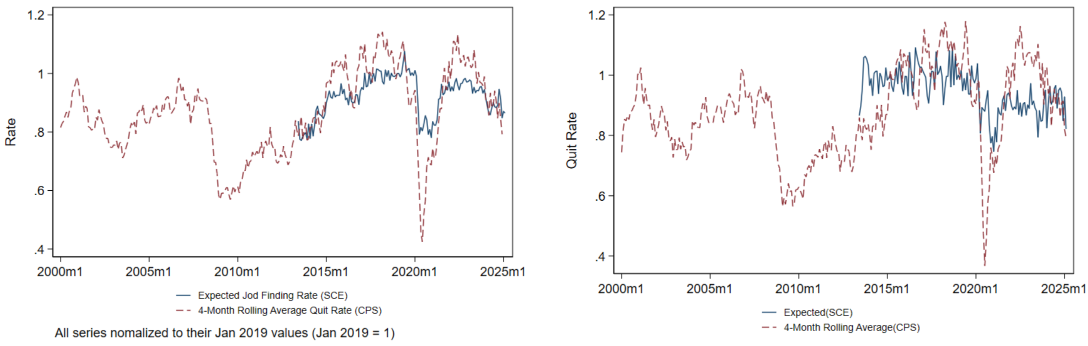
	Full Sample			**Real-time**			**Post-2001**		
Indicator	1 Mo	3 Mo	6 Mo	1 Mo	3 Mo	6 Mo	1 Mo	3 Mo	6 Mo
Panel A: Individual R^2									
CPS Quits	0.055	0.241	0.176	0.055	0.241	0.176	0.081	0.348	0.244
CPS Layoffs	0.091	0.696	0.113	0.091	0.696	0.113	0.094	0.760	0.121
Jolts Quits	0.134	0.296	0.171	0.134	0.284	0.121	0.143	0.319	0.195
Jolts Layoffs	0.140	0.102	0.030	0.137	0.098	0.033	0.149	0.110	0.034
CPS EU	0.285	0.400	0.027	0.285	0.400	0.027	0.291	0.406	0.020
CPS EN	0.073	0.016	0.089	0.073	0.016	0.089	0.102	0.026	0.107
Panel B: Leave-One-Out R^2 Contribution									
CPS Quits	-0.000	-0.008	-0.009	-0.000	-0.011	-0.010	-0.000	-0.006	-0.009
CPS Layoffs	-0.006	-0.227	-0.000	-0.010	-0.309	0.000	-0.016	-0.202	-0.000
Jolts Quits	-0.001	-0.020	-0.084	-0.000	-0.012	-0.079	-0.002	-0.015	-0.072
Jolts Layoffs	-0.012	-0.002	-0.113	-0.018	-0.001	-0.142	-0.031	-0.002	-0.103
CPS EU	-0.037	-0.004	-0.049	-0.051	-0.002	-0.067	-0.092	-0.004	-0.045
CPS EN	-0.000	-0.003	-0.017	-0.001	-0.001	-0.019	-0.001	-0.002	-0.017

Notes: R^2 values for predicting changes in the unemployment rate using labor flow indicators. Panel A reports individual R^2 values from univariate regressions. Panel B reports the contribution of each variable in a leave-one-out analysis from the full multivariate model. Full Sample trains on all data and shows R^2 from 1978-2024 (CPS) and 2001-2025 (JOLTS); Real-time trains on real time data 2011- and predicts 2011-; and Post-2001 restricts the training and predictions samples to 2001-2024.

Why are quits a good leading indicator of unemployment? Quits are the best indicator of unemployment two and more quarters out due to their strong relationship with future changes in job finding rates. The contemporaneous correlation of quits and UE flows is 0.38 and the correlation with future UE flows remains high: over 0.35 two-quarters out and 0.30 one year out. This is important because UE flows are the dominant driver of unemployment fluctuations over the business cycle (Section 5). Layoffs, on the other hand, are less useful both because they have a lower correlation with future EU rates, below 0.2 two-quarters out, and the contribution of EU rates to unemployment fluctuations is less than half as much as UE rates.

The positive correlation of quits with future job finding rates is interesting because it suggests that quits capture some grassroots information workers have about the labor market that may not appear directly in official statistics. Evidence that anticipatory information about job finding rates affects quits can be found by comparing our series to the Survey of Consumer Expectations conducted by the Federal Reserve Bank of New York. Figure 12 plots our quit series against job finding expectations (left) and quit expectations (right).[32] It shows that quits co-move strongly with workers' expectations about job availability, and even more strongly than their expectations over their own future quit behavior. In contrast, Figure 13 shows that actual layoff

[32]The SCE question we use for job finding is: "What is the percent chance you will find a job in the next three months if you lost your job today?"; and for quits is: "What is the probability that you will quit your job in the next year?".



(a) Quits vs. Job Finding Expectations (b) Quits vs. Quit Expectations

Figure 12: **Quits and Expectations.** SCE is the Survey of Consumer Expectations.

rates are less correlated with the expectations of the SCE respondents about layoff rates and in times when they are correlated, actual layoffs lag.[33]

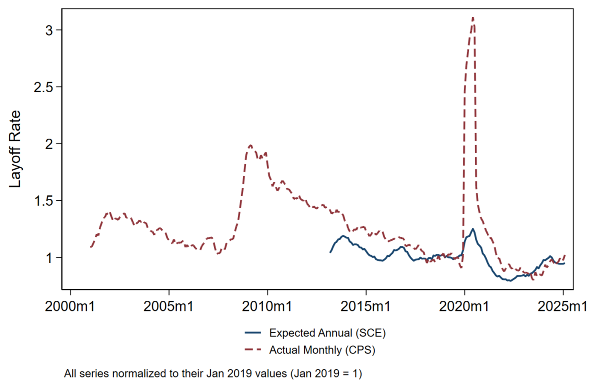


Figure 13: **Layoffs and Expectations.** SCE is the Survey of Consumer Expectations.

CPS quits and layoffs predict JOLTS revisions. The final result is that the real-time JOLTS data have less predictive power than the revised JOLTS data. JOLTS revisions occur for many months after initial release, and the revisions have been larger around turning points in the cycle and after 2020. An advantage of the CPS flows we construct is that they are virtually unaffected by revisions. Simple linear regressions show that the CPS layoff series aids in predicting future final JOLTS revisions. It is statistically significant at the 99% level, even when controlling for the first JOLTS release. The same is true for CPS quits as a predictor of JOLTS quits revisions.

[33] The SCE question we use for job loss expectation is: "What is the percent chance that you will lose your job in the next year?".

Independent Variable	**JOLTS- Final Revision**	
	Quits	**Layoffs**
	(1)	(2)
CPS	-0.0938***	0.0321***
	(0.0276)	(0.0110)
JOLTS 1st Release	0.9982***	1.1492***
	(0.0144)	(0.0138)
Constant	0.0869**	-0.1351***
	(0.0299)	(0.0112)
Observations	144	144
R-squared	0.9761	0.9935
Adj. R-squared	0.9758	0.9934

Table 19: **Regression Results for JOLTS Revisions** Final release is the dependent variable.

8 Comparison to JOLTS.

The Job Openings and Labor Turnover Survey (JOLTS) has been the primary source used to analyze quits and layoffs in the United States in near real-time.[34] 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.

The JOLTS provide a broader measure of quits and layoffs than we do with the CPS but they also contain imputed data, particularly around turning points in the business cycle. The JOLTS are broader because they include job-to-job quits and layoffs, whereas we can only observe the quits and layoff distinction for separations to non-employment[35] The JOLTS, however, are also known to underestimate separations even when sampling weights are applied because they do not measure separations due to firm exit (Faberman (2005)). This problem is particularly acute when the economy is entering a recession. 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)). The adjustments require some assumptions about the composition of quits versus layoffs in the missing data to be made.

The definition of a layoff in the JOLTS is similar to the CPS but the definition of a quit has important differences. JOLTS defines layoffs as “Involuntary separations initiated by the employer”, and quits as “Employees who left voluntarily. Exception: retirements or transfers to other locations are reported with Other Separations”. Lastly, the JOLTS category “Other Separations” includes “retirements; transfers to other locations; deaths; or separations due to

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

[35] Fujita et al. (Forthcoming) provide a timeseries of employer-to-employer flows using CPS data. Note that these flows do not distinguish quits and layoffs.

employee disability".

In order to compare our data with JOLTS, we will restrict it to be as similar in concept as possible. Layoffs are straightforward since, as in JOLTS, we only consider an individual as being laid off if they lost their job involuntarily. With regard to quits, we exclude all individuals who are retired. Disabled individuals are automatically excluded because they are not in the universe of individuals being asked the question of reason for non-participation.[36] 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 data from JOLTS is for January 2001, so we restrict our series to start at the same date. Both series are seasonally-adjusted.[37]

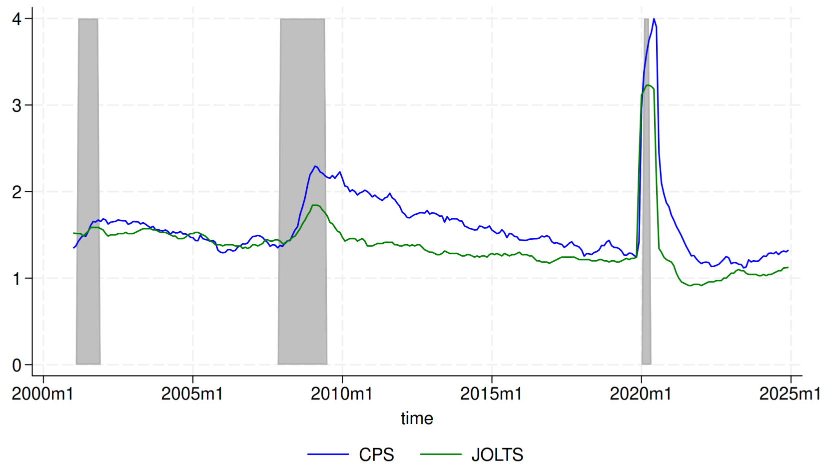


Figure 14: **Layoffs: CPS versus JOLTS**

Figure 14 compares the JOLTS layoffs series with our layoffs series constructed using the CPS. The correlation between the two series for the entire time period is 0.60, a significant departure from 1.00. Notably, our layoffs series is much more related to fluctuations in the unemployment rate. The correlation of the CPS layoffs series with the unemployment rate is 0.82, whereas it is only 0.29 for the JOLTS layoffs series.

The business cycle dynamics of the two series give some clues as to how the series differ. The two series track each other closely until the 2007 recession. At that point, our layoff series exceeds the JOLTS layoff series and they slowly converge over the 2012-2019 period. The two series deviate again during the pandemic recession but converge more quickly. We speculate that the departures around the GFC and COVID recessions and subsequent convergences are due to the fact that the CPS series only counts layoffs resulting in non-employment. In this sense, the CPS series is a product of both layoff and job finding rates and this amplifies its

[36] Although retirees should not be asked the question in the CPS, there is a very small number in some months reporting a quit or layoff.

[37] We seasonally-adjust the data as described in the Section 3 and compare with the seasonally-adjusted JOLTS, thus, there might be differences in the seasonal adjustment procedure.

cyclical volatility. This would explain why the CPS series is a better indicator of turning points and better tracks unemployment. We do not know why the series so closely tracked each other prior to 2008 and then never become nearly as close to tracking each other again.

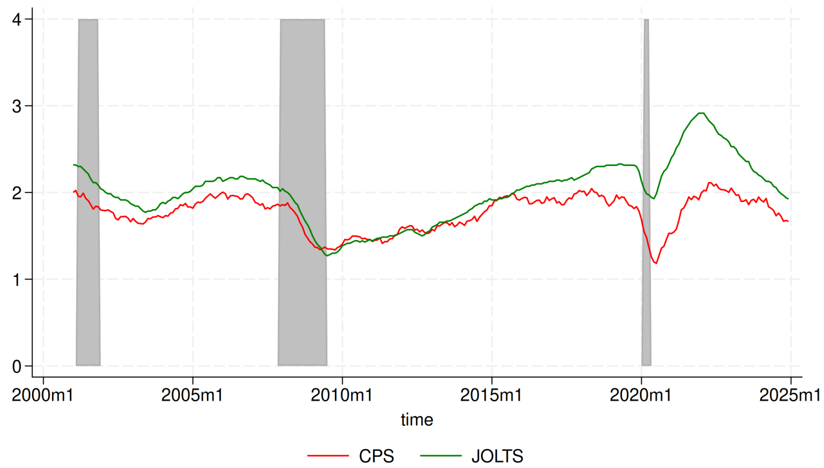


Figure 15: **Quits: CPS versus JOLTS**

Figure 15 similarly compares the JOLTS quits series with our quits series. The levels of the series are similar up until 2015. Between 2001 and 2015, the average quit rate in our CPS data is 1.70 which is just a bit lower than the 1.82 quit rate in JOLTS. The two series begin a steady divergence as labor markets tightened deeper into the post-GFC recovery. This divergence grows even larger in tight labor markets after 2021 before converging again as labor markets cooled.

The correlation between the two quit series is 0.74, and is higher than for the layoff series. It is also clear from the figure that the two quit series are more similar. The series seem to diverge in tighter labor markets. This difference is likely explained by the fact that our data only captures quits into non-employment, whereas JOLTS captures all quits, including those directly to another job. It is natural that quits directly to another job would rise during times when vacancies are rising. The gap between our series and the JOLTS after the pandemic recession, however, is large. JOLTS show an unprecedented increase in quits but our series shows a rise in quits that is in line with previous expansions following downturns. We cannot be sure this difference is entirely accounted for by direct employer-to-employer quits. Other explanations are quits of multiple job holders (only counted in JOLTS) and mismeasurement given the strong decline in survey response rates during this time, particularly for JOLTS.

9 Conclusion

This paper demonstrates that distinguishing quits from layoffs fundamentally changes our understanding of labor market dynamics and business cycles. By analyzing a comprehensive time series that tracks both the reasons for employment separations and subsequent labor force participation decisions, we reveal that standard flow measures substantially mischaracterize the nature of job separations and their cyclical properties. Layoffs contribute more to unemployment than previously thought and are the main driver of employment fluctuations. Additionally, the negative correlation between quits and layoffs creates an important stabilizing mechanism that is absent from coarser EU and EN flows. On the other hand, the procyclical attachment of laid-off workers— their increased tendency to remain in the labor force during downturns— is a significant amplification mechanism for unemployment volatility. For all of these reasons, we strongly recommend that economists use these direct quits and layoff series rather than employment-to-unemployment (EU) or employment-to-nonparticipation (EN) flows to study labor market churn and labor supply and demand over the business cycle.

Beyond these insights, these data present avenues for future research that could deepen our understanding of labor market heterogeneity and structural change. The data could aid in research of longer-run trends in job stability and worker mobility, such as the secular decline in quits relative to labor market tightness that we document. Disaggregating by demographics, industries, occupation, or job tenure could reveal how concentrated quits and layoffs are across different worker groups, and whether certain segments drive aggregate patterns. Such analysis could inform theories about firm-worker matching, the role of specific human capital, and how technological change affects different types of jobs. Understanding which workers are most likely to exit the labor force after a lay-off, and how this varies across business cycles, could provide crucial insights for designing social insurance and retraining programs.

The real-time availability and forecasting power of these series also suggest practical applications for policymakers and analysts. Quit rates could be incorporated as forward-looking indicators of labor market slack, and the superior predictive performance of CPS measures relative to heavily-revised JOLTS data makes them particularly valuable for real-time decisions. More broadly, our findings underscore that measuring labor market slack requires looking beyond unemployment rates to capture the full impact of demand-driven layoffs on employment. For central banks whose mandate is to achieve maximum employment rather than just low unemployment, understanding the complete picture of worker flows becomes essential for effective macroeconomic stabilization.

During the preparation of this work the author(s) used Claude in order to aid the formatting of graphs. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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A Glossary

This section gives an overview of the different transition rates and the commonly used abbreviations.

For flow rates that follow the pattern origin-destination, each rate is abbreviated with two letters where the first one indicates the origin and the second indicates the destination:

- Employment-to-Unemployment (EU)
- Employment-to-Nonparticipation (EN)
- Unemployment-to-Employment (UE)
- Unemployment-to-Nonparticipation (UN)
- Nonparticipation-to-Employment (NE)
- Nonparticipation-to-Unemployment (NU)

For the transition rates which in addition to destination also specify the reason, each rate is abbreviated with three letters in the order origin, destination, reason:

- Employment-to-Unemployment due to a Layoff (EUL)
- Employment-to-Unemployment due to a Quit (EUQ)
- Employment-to-Nonparticipation due to a Layoff (ENL)
- Employment-to-Nonparticipation due to a Quit (ENQ)

B Statistics for Working Age Population.

In this section we replicate key statistics for the working age population. We continue to caution the reader that we cannot distinguish the reason for separation for people who flow from employment to non-participation and report that they are retired. These individuals are not asked why they left their prior job.

	Total	Quits	Layoffs	Corr(Q,L)
1978-2024	3.66	1.92	-0.15	-0.1222
1978-1990	4.16	2.24	1.92	-0.47
1990-2019,2021-2024	3.41	1.79	1.62	0.04

Table 20: Working Age: Monthly average percent of employed workers separating to non-employment by reason.

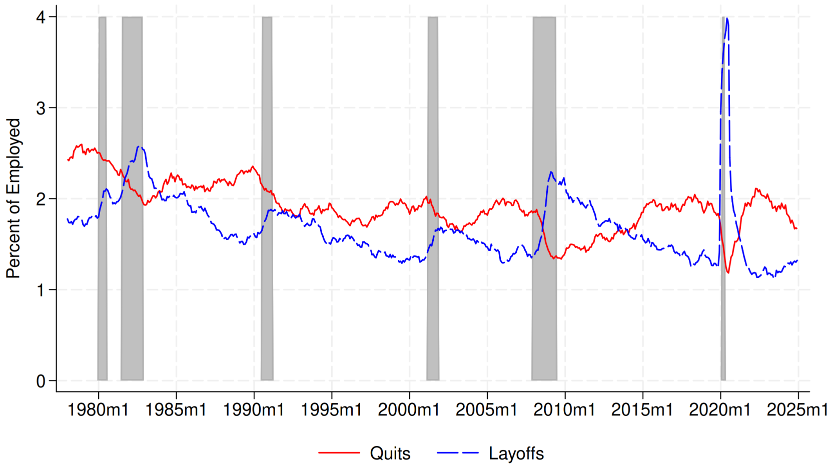

Figure 16: **Monthly Quits and Layoff rates to Non-Employment** (Shown as a percent of employment. Monthly seasonally-adjusted data and 6-month centered moving average)

	Total	EN	EU	Corr(EN,EU)
1978-2024	4.45	3.11	1.35	0.31
1978-1990	5.10	3.48	1.63	0.10
1991-2019,2021-2024	4.21	2.96	1.24	0.31

Table 21: Working Age: Monthly average percent of employed workers separating to non-employment by destination.

	% Quits to		% Layoffs to		
	U	N	U	N	Corr(sQN,sLN)
1978-2024	9.1	90.9	55.6	44.4	0.14
1978-1990	10.8	89.2	55.0	45.0	-0.49
1991-2019,2021-2024	8.5	91.5	56.0	44.0	0.17

Table 22: Working Age: Monthly average share of quits and layoffs to non-employment by destination.

Recession	UR	EPR	Quits	Layoffs	Total Separations
1980	32.20%	-2.00%	4.23%	29.58%	18.00%
1981	50.00	-3.05	-15.71	26.66	10.56
1990	50.00	-2.22	-20.45	14.33	-1.53
2001	61.54	-3.26	-22.02	21.70	1.40
2007	112.77	-6.99	-37.17	74.14	22.77
2020	277.14	-13.48	-25.11	11.60	3.52

Table 23: **Comparing Recessions.** Percentage peak-to-trough change

Recession	Quits	Layoffs	Quits	Layoffs
	Percentage points		Percentage change	
1980	-0.04	0.38	-4.32%	32.23%
1981	-0.19	0.67	-19.53%	49.39%
1990	-0.23	0.31	-23.28%	26.38%
2001	-0.16	0.36	-17.77%	36.83%
2007	-0.34	0.93	-38.51%	92.98%
2020	-0.42	2.13	-47.16%	242.99%

C Additional Statistics

C.1 Tight Labor Markets

We construct an indicator of tight labor markets to compare the dynamics of quits and layoffs in expansionary periods of the economy, i.e tight labor markets. We follow Aaronson et al. (2019) and use an indicator that equals one if the unemployment rate in a given quarter is below the noncyclical rate of unemployment and zero otherwise.[38]

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 24: **Business Cycle Correlations.** Correlations of each flow (x) with the indicator for a tight labor market (y)

Table 24 shows the correlations of the different flow rates with the indicator of a tight labor market. They capture the movement of flows in exceptionally good times for comparison with Table 5 which uses the unemployment rate as an indicator. We see that tight labor markets (expansions) are characterized by higher quits, both into unemployment and non-participation. In other words, workers become more likely to quit when vacancies are high, the unemployment rate is low, and jobs are easy to find. Layoffs show the opposite pattern. Layoffs decline in tight labor markets, which is not surprising.

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

[38]Specifically, we use the Noncyclical Rate of Unemployment released by the U.S. Congressional Budget Office, and retrieved from FRED (NROU). These data are at the quarterly frequency and so we transform our monthly data into quarterly by averaging over each quarter.