Reassessing Labor Market Flows: The Role of Marginal Workers and the Composition of Quits and Layoffs

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Abstract

We develop a framework in which the circumstances of an employment separation (quit or layoff) and destination (unemployment or non-participation) inform estimates of the marginal workforce and their impact on the labor market throughout the business cycle. Quits and the participation choices of laid off workers critically inform our analysis. In the model, laid off workers who exit the labor force are those closest to the margin of participation and have the highest extensive margin labor supply elasticity. Using monthly CPS data, we document that over a third of laid off workers exit the labor force and this share is procyclical. Combining data and theory we find that 48% of layoffs selectively target workers near the margin of participation but this falls to 24% in recessions. Modelling the employment surplus distribution and marginal workforce allows us to analyze the role of labor supply in shaping the business cycle.

1 Introduction

Understanding the business cycle dynamics of the labor market remains is a key question in research and policy. Traditional aggregate metrics often mask the complex transitions between employment, unemployment, and non-participation that drive fluctuations in the labor force. We argue that these dynamics are fundamentally shaped by the distribution of the employment surplus—the net value individuals place on working versus not working. Workers with low but positive employment surplus constitute a "marginal workforce" whose labor supply decisions are highly responsive to economic conditions. Knowing participation decisions of these

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marginal workers is critical to understanding the cyclical volatility of labor market stocks, such as employment and unemployment, as well as the response of the labor market to policy.

Our key insight is that labor supply choices following job loss offer a unique window into the composition of this marginal workforce. Standard approaches typically interpret flows into unemployment as layoffs and flows into non-participation as quits. However, using monthly CPS data from 1978 to 2024, we document a striking fact: over one-third of laid-off prime-age workers exit the labor force immediately rather than searching for new employment. The fact that these laid-off workers exit the labor force rather than search for new employment suggests that these workers were near the margin of participation. Their subsequent choices—whether to search in unemployment or exit to non-participation—reveal valuable information about the employment surplus distribution as well as labor supply elasticities.

The distribution of employment surplus is not the end of the story in understanding the extensive margin of labor supply. We must also understand what factors would impact net value of working versus not working, particularly for marginal workers. The wage elasticity is only one of many factors. Responses to changes in non-employment income, the difficulty of finding a job, or unemployment benefits; and how these all move over the cycle; is also critical. And more so for marginal workers since individuals firmly attached, or detached, from the labor force are less responsive to these changes. This emphasizes the desire for a structural model of labor supply since a single parameter cannot capture all of these effects. We use the structural model to identify the marginal workers and selection in labor market transitions and stocks.

We develop a framework that incorporates both selective and random quits and layoffs to explain these patterns. The degree of selection in the model depends on the employment surplus distribution. We replicate stocks as well as flows over the business cycle by chosen destination and reason. We find that around 48% of layoffs selectively target these marginal workers during normal times but only 24% in recessions. This selection is critical for understanding aggregate labor supply over the business cycle: in recessions, the pool of unemployed shifts away from these marginal workers toward more "attached" workers with higher employment surplus. Our model demonstrates that accounting for these marginal participation choices is essential for interpreting movements in the labor market.

Ex-ante it is not obvious whether the pool of unemployed shifts towards or away from marginal workers. Factors affecting labor supply choices of marginal workers work in opposite directions: extension of UI benefits increase the value of working and pulls marginal workers into unemployment; higher job loss and lower job finding probabilities lowers the value of working and makes unemployment less desirable. We decompose the effects of the different factors and find that, everything else equal, labor supply increases for marginal workers in recessions. While this seems contradicting the results in the previous paragraph, the explanation is simple. While more marginal workers choose to remain in unemployment after a layoff in recessions compared to normal times, relatively more attached workers get laid off, which skews the pool of unemployed towards high productivity workers. These findings are link with Mueller (2017).

We show that the effect of marginal workers on the cyclicality of the labor market is a mix of composition and changes in labor supply choices. In a counterfactual exercise, we find that when shutting off cyclical selection, the rise in unemployment during recessions is lower than in the benchmark, since more marginal workers exit the labor force after a layoff. These results highlight the importance of getting the distribution of employment surplus as well as the marginal workforce correct to understand changes in unemployment.

Lastly, we use the model which captures the employment distribution correctly to analyze two policy experiments: an increase in UI benefits and a lump-sum wealth transfer. We find that both policies increase the value of working as more marginal workers choose unemployment over non-participation.

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

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

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

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

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

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

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

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

2 Data and Methodology

2.1 Data source

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

2.2 Methodology

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

- Employment to unemployment due to a quit (EUQ)

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

Table 1: Standard approach of flow rates in the CPS

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

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

The standard approach often interprets flows between employment and unemployment as layoffs and flows between employment and non-participation as quits. We show this convention is not accurate. Flows into both unemployment and non-participation consist of both layoffs and quits.

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

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

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

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

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

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

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

Table 2: Our contribution to the standard approach

2.3 Decomposition into Layoffs and Quits

2.3.1 Unemployment

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

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

2.3.2 Non-participation

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

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

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

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

`Why did ... leave that job?`

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

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

There are additional separations where the question asking the reason why the last job ended is not asked. These include, for example, retirements. We label these separations as other, but the reader should think of them as "unknown" since these separations such as retirements can certainly be preceded by an involuntary layoff as well as a planned quit.

2.4 Linking over Time & Variable Construction

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

We follow Madrian and Lefgren (1999) when linking individuals across two consecutive months and verify match quality based on sex and age.[3] This method ensures that when we aggregate our flows to broad E-N and E-U rates, we recover the same transition probabilities that would be computed from IPUMS harmonized CPS data. In the CPS, the unique household and person identifier corresponds to the physical address of the individuals and therefore being able

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

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

to match an individual does not necessarily imply matching the same individual but rather two individuals living at the same physical address in subsequent months. Personal characteristics, such as age and sex, which do not change over two subsequent months (or by not more than one in the case of age) and help to reduce false matches. Once we matched individuals across two subsequent months based on the above criteria, we use the matched data to compute the numbers of individuals in each labor market state in a given month.

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

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

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

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

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

2.5 Prime-age vs. Working-age population

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

3 Motivation

Figure 1 plots the full time series of the monthly quit and layoff rates to non-employment from 1978 - 2025 as a percent of total employment for the prime-age population in the United States. On average, 40% of all separations into non-employment are quits, and the remaining 60% are

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

layoffs. This implies that in any given month, about 0.9% of all employed workers decide to leave their job. The majority of these quits are into non-participation, about 86% on average.[5]

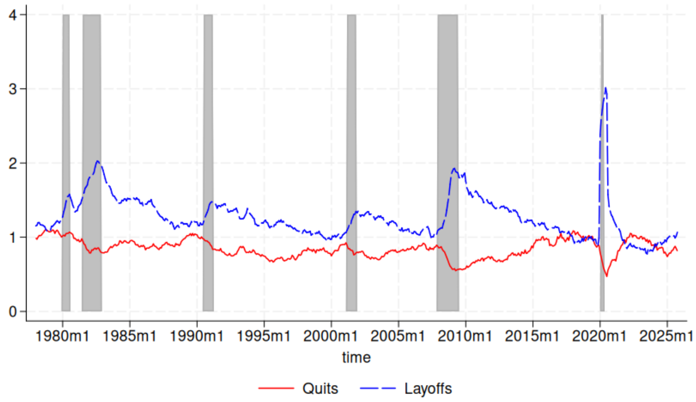


Figure 1: Monthly Quits and Layoff rates (as a percent of employment) (Monthly seasonally-adjusted data and 6-month centered moving average)

Since our data allows to classify all flows into non-participation as a layoff or quit, we can analyze the destination of all layoffs. Generally, the literature has assumed that an EU transition is due to a layoff, whereas an EN transition is due to a quit. We can see in figure 2 that 40% of all layoffs end in non-participation. Clearly, not all movements to non-participation are due to a quit decision as was previously assumed. This implies that about 40% of workers choose to leave the labor force after being laid-off.

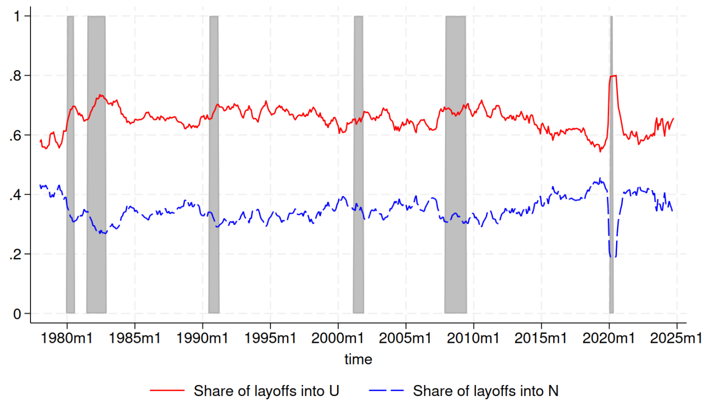


Figure 2: Share of layoffs by destination (Unemployment or non-participation)

In total, about 65% of all separations in a given month end in non-participation and are a result of labor supply decisions. Both types of labor supply decisions, quits and leaving the labor force after a layoff, tell us about the workers' value of employment compared to non-participation and help to inform labor supply elasticities.

The 40% of workers who quit in a given month are likely to have a negative employment

[5]See appendix for figure.

surplus, or equivalently, the value of non-participation exceeds their value of employment. One interpretation of the large number of quits is that many individuals are on the margin of participation, i.e. the difference between their value of employment and non-participation is small. Additionally, we also observe large transition rates between non-participation and the labor force, about 10% of all individuals in non-participation join the labor force in the average month. These facts suggests that these workers are near the margin of participation. However, it is unlikely that all quits in the US are due to marginal workers. Some individuals who quit are likely to not join the labor force anytime soon and remain out of the labor force for a long time. The model will allow us to distinguish between the two types of quits. Understanding the distinction is important for estimating elasticities of labor supply. More importantly, the model will allow us to study the extensive labor supply decisions of these marginal workers, in particular, the factors that drive these decisions.

Similarly, 40% of all layoffs end in non-participation, which implies that these workers likely had a small but positive employment surplus, since they were working. However, the choice of non-participation after a layoff implies that these workers were very close to the margin. Our data, which allows for observing the reason and destination of a separation, is crucial to identify these marginal workers in a model. Laid-off workers and their decision to either stay in unemployment or leave the labor force is central to estimating labor supply elasticities in the model.

We can see in figure 2 that the share of layoffs into non-participation and unemployment display cyclical patterns. Table 3 shows how the destination of quits and layoffs vary over the business cycle. In times when the unemployment rate is high, the share of layoffs and quits into non-participation decline. The share of layoffs into non-participation is strongly negatively correlated with the unemployment rate. One interpretation of this finding is that laid off work-

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

Table 3: Business Cycle correlation of the share of layoffs and quits into N with the unemployment rate

ers become more attached to the labor force in recessions as more workers choose to remain unemployed after losing their job, for example, due to an increase in the value of unemployment benefits. Alternatively, this suggests that there is potential selection in the pool of laid-off workers in recessions. In normal times, when the share of laid-off workers exiting the labor force is larger, layoffs might be more targeted towards these small employment surplus marginal workers. In recessions, however, layoffs are less targeted and, therefore, the share of layoffs into non-participation declines. The model will help us to identify how much of the decline in the share of layoffs into non-participation is due to unemployment benefits versus a change in the composition of laid-off workers.

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

Table 4: Second rows: range of hypothetical unemployment rate if the share of laid-off workers is time invariant. Percent difference: how much of the increase in unemployment is from more laid off workers going to unemployment

We test for composition effects based on observable characteristics in the following section and find that compositional changes only have a small impact on the declining share of layoffs into non-participation. However, the data only allows us to check for selection on certain demographic characteristics, such as gender, race, age, and we will use the model to estimate how many layoffs are selectively target workers with a small employment surplus.

The increase in the propensity of laid off workers to remain in the labor force during a recession works to increase the cyclical volatility of unemployment. The magnitude of this effect can be understood by computing an alternative series of unemployment where the share of laid-off workers leaving the labor force is fixed and constant over time.[6] We will do this in two ways to create a range. The first we will call a lower bound and assumes that the newly classified unemployed workers have the same job finding rate as actual unemployed workers. The second we will call an upper bound and assumes that the newly classified unemployed workers have the same job finding rate as the non-participants. The following formalizes the first series for concreteness, and the second is constructed analogously. Let the constructed series be denoted as $\hat{u}$, the fixed share of laid off workers entering unemployment as $\bar{s}$, the actual series without hats, and the actual flow rates by $\lambda^{source,destination}$ and $\lambda^{source,reason,destination}$ for quits and layoffs. The series is then constructed as:

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

The correlation between the two constructed series and the actual unemployment series are high at 0.980 and 0.914 for the lower and upper bounds, respectively, but the cyclical variances over the entire time period are 39-43% lower and closer to 30% lower when excluding the pandemic recession. Table 4 displays this calculation for all the recessions in our data. To illustrate this point: the unemployment rate increased 4.63 percentage points in the Great Recession but would have increased only 3.4-3.6 percentage points if the share of laid off workers exiting the labor force would have been held constant. That's a decrease of roughly 25%.

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

3.1 The Role of Composition Effects

We showed in the previous section that the share of individuals who leave the labor force after job loss declines during recessions. This section will investigate how much of this is due to a change in the composition of laid-off individuals in recessions or changes within different groups of laid-off workers. We do this by computing the counterfactual share of layoffs that flow into non-participation during each of the previous five recessions. Thus, we perform a shift-share analysis similar to Elsby et al. (2015) and share_{it}^{eln} is the weighted average of the fraction of laid-off workers exiting the labor force for different groups of laid-off workers:

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

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

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

We calculate three different counterfactual analyses; by gender, race, and education, such that $i = \{\text{men}, \text{women}\}$, $i = \{\text{white}, \text{black}\}$, or $i = \{\text{high school at most}, \text{college and more}\}$,

Table 5 compares the actual change in the share of individuals who leave the labor force after job loss to the counterfactual change for each recession. We can see that in general the composition of the laid-off workers during recessions contributed little to the observed change in the share of laid-off leaving the labor force. Table 6 shows that while the importance of

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

Table 5: Actual and counterfactual change (in pp) in the share of layoffs into non-participation

changes in the composition varies across the different groups and recessions, changes within groups contributes at least 75% to the decline in the share of layoffs into non-participation. Thus, the changes in labor supply decisions during recessionary periods is not a simple story of different people in the laid-off pool but rather a story about changes in people's labor supply decisions over the business cycle. It is worthwhile noting that our results differ from previous research[7] which has found that the pool of unemployed differs substantially in recessionary

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

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

Table 6: Actual and counterfactual change (in percentage) in the share of layoffs into non-participation

times from normal times. However, in our analysis we focus on everyone who is laid-off, i.e. we include individuals in unemployment *non-participation*.

4 Model

4.1 Overview

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

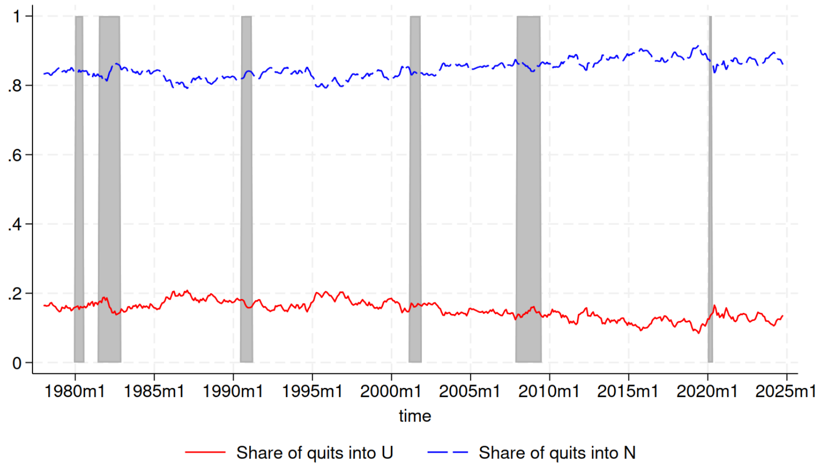
4.2 Environment

Time is discrete and the economy is populated by a unit measure of heterogeneous workers. The aggregate state is summarized by a vector $\mathcal{S}$ which includes prices (w, r) and a business cycle indicator (Z). Prices are equilibrium objects. The business cycle indictor can be high (normal times) or low (recession) and follows a standard Markov process. Labor market frictions including shocks related to job loss and job finding as well as some government programs will depend on the business cycle indicator.

Preferences. Individuals have preferences represented by

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

where $c_t \geq 0$ is consumption in period t, $e_t \in \{0, 1\}$ is employment status, and $s_t \in \{0, 1\}$ is a discrete variable reflecting whether the individual engages in active job search. The parameters $\alpha > 0$ and $\theta > 0$ represent the disutilities of work and active search, respectively, while $0 < \beta < 1$ is the discount factor.



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

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

Flow earnings, denoted by y_t, depend on the individual's labor market status. An employed worker's labor earnings are the product of her idiosyncratic labor productivity z and the market wage per efficiency unit of labor services $w(Z)$, net of labor income tax $\tau(Z)$:

$$y = (1 - \tau(Z))w(Z) \cdot z \tag{9}$$

As is typical, an individual's idiosyncratic productivity z_t is stochastic and follows an AR(1) process in logs:

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

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

Non-participants produce home production h , which is constant across all individuals and so their flow income is: $y = h$.

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

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

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

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

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

Production. The production function is Neoclassical. Output is produced by capital services K and effective labor L according to the function $AK^{\alpha_y}L^{1-\alpha_y}$. The capital stock in production is equal to the total savings across households (i) $K = \int_i a_i$, and labor services are equal to the total efficiency units of labor supplied by the employed. Let $\mathcal{I}_e(i) = 1$ if agent i is employed, then this is $L = \int_i \mathcal{I}_e(i)z_i$. We assume capital and efficiency units of labor are rented at their respective marginal products: $r = A(\frac{L}{K})^{1-\alpha_y}$ and $w = A(\frac{K}{L})^{\alpha_y}$.

Government Budget. We assume that the government budget clears period by period. In any given period, total revenues equal the labor tax revenue from the employed $TR = \int_i \tau\mathcal{I}_e(i)z_i$, and total expenditures equal total spending on the consumption floor and unemployment benefits $TE = \int_i \mathcal{I}_{ub}(i)b_i + \int_i \mathcal{I}_c(i)c_min$ where $\mathcal{I}_{ub}(i) = 1$ for an unemployed individual eligible for unemployment insurance and $\mathcal{I}_c(i)c_min = 1$ for an individual receiving the consumption floor.

4.3 Labor Market Transitions and Employment Dynamics

Job Loss: Quits and Layoffs. Employed workers can lose their job each period in four different ways. Some we will classify as quits and others as layoffs. A portion of each of the quit and layoff hazards are totally exogenous and common to all workers. Another portion of each of the quit and layoff hazards are selective: the hazard rates are higher for workers with a lower surplus from employment. There is no on the job search and so any job loss results in a transition to non-employment.

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

Alternatively, the worker may be laid-off. As is standard in search models, there is a probability $\delta(Z)$ that a worker is laid-off exogenously, and this probability is common across all workers but varies with the aggregate state (Z). We call these types of lay-offs "non-selective" or "random". The other type of lay-off is called "selective" and is generated by a shock x.

This shock has a random arrival rate of $\lambda_x(Z)$ and upon arrival requires the worker to pay a utility cost x in order to remain employed. This is a simple way to capture selective firings of low-surplus workers within the firm. While both a selective lay-off and an endogenous quit target low-surplus workers, the layoff is completely transitory to the worker. It is meant to represent pressures idiosyncratic to the firm causing it to cut its' least productive workers even though those workers could have positive surplus elsewhere, similar to a match quality shock. An endogenous quit, by contrast, is a separation initiated by a worker who does not have a positive employment surplus at *any* job. While all separated workers have the choice of whether to pay the search cost and enter unemployment or exit to non-participation, it is easy to show that since endogenous quits are due to a persistent decline in a worker's employment surplus, all selective quits will result in a transition to non-participation. By contrast, since endogenous selective layoffs are driven by transitory (one-period) changes in the employment surplus, they can result in the worker choosing either unemployment or employment.

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

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

2. **Random Quits**: With probability $\pi^p(1, 0)$, a worker is forced to quit into non-participation where they remain until the shock is removed. These are the quits of non-marginal workers who are far from participating despite changes in policy or their circumstances.

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

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

Finally, a measure R_d of agents die each period and are replaced by an equal measure of newborn agents. The newborn agents begin non-employed and are endowed with assets equal to the average holdings in the economy. Deaths are not counted in labor market flows in the model (and they are not counted in the flows in the data). The newborn agents are counted as originating from non-participation. If they choose unemployment in their first period, then that will be counted as a flow from non-participation to unemployment.

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

4.4 Value Functions

The state variable of an individual is $(a, z, p; \mathcal{S})$, where a are assets, z is their idiosyncratic productivity, p is whether they are exogenously constrained from participation and $\mathcal{S}$ is the aggregate state which includes the recession indicator Z. An unemployed worker will have an additional state for their UI eligibility, e.

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

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

For the unemployed:

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

For the non-participants:

$$\begin{aligned} N(a,z,p;\mathcal{S}) = \max_{c\geq 0, a'\geq 0} & \log(c) + \beta E_{z',p';\mathcal{S}'}\Big[\lambda_n(Z)J(a',z',p',0;\mathcal{S}') \\ & + (1-\lambda_n(Z))V(a',z',p',0;\mathcal{S}')\Big] \\ \text{st} \quad & c + a' = (1+r(\mathcal{S}))a + h + I_c\underline{c} \\ & I_c = 1 \quad \text{if} \quad (1+r(\mathcal{S}))a + h < \underline{c}; \quad = 0 \end{aligned}$$

The value for an individual without an employment opportunity depends on whether he or she is constrained to non-participation ($p = 0$) or not ($p = 1$):

$$V(a,z,p,e;\mathcal{S}) = \begin{cases} \max\{U(a,z,p,e;\mathcal{S}), N(a,z,p;\mathcal{S})\} & \text{if } p = 1 \\ N(a,z,0;\mathcal{S}) & \text{if } p = 0 \end{cases}$$

And the value for an individual with an employment opportunity is the following where the first line features the arrival of a match continuation shock x:

$$\begin{aligned} J(a,z,p,e;Z) = & \lambda_x(Z)[(1-p)\max\{W(a,z,p;\mathcal{S}) - x, V(a,z,p,0;\mathcal{S})\} + pN(a,z,p;\mathcal{S})] \\ & + (1-\lambda_x(Z))[(1-p)\max\{W(a,z,q;\mathcal{S}), V(a,z,p,0;\mathcal{S})\} + pN(a,z,p;\mathcal{S})] \end{aligned}$$

4.5 Aggregate Shocks and Business Cycle Dynamics

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

In good times, job-finding rates are higher and the job-separation rate is lower:

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

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

where λ_s^* and σ^* are the steady-state values, and ε_s and ε_δ control the cyclicality of these parameters. The finding rates are specific to whether the individual's labor market state s: searching in unemployment or from not in the labor force.

Selective quits may also vary over the business cycle. The arrival of a job continuation cost shock x is $\lambda_x(Z)$, and may be higher or lower in good times than in bad. We will see later that cyclicality of this parameter determines how much recessions change the composition of layoffs towards higher or lower productivity workers.

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

4.6 Computation

We follow a modified version of Boppart et al. (2018) to define agents' expectations when computing the model. The steady state of the model is defined by the simulation of the model over many periods with the cyclical state set to Z =G. In the steady state, agents still have rational expectations that the state will switch to Z =B according to the true Markov process for Z. The value functions defining the continuation value for agents if the switch were to occur is chosen to match the actual value for a shock away from the steady state following Boppart et al. (2018).[8] The impulse of a recession (Z =B) of the average length defined by the Markov process followed by a series of non-recession states is simulated as a series of MIT shocks. This means that agents are aware of equilibrium prices when they make savings and labor supply choices within a period but expect those same prices to prevail next period. This approximation technique is well-suited for our model because prices do not move much over the business cycle due to our focus on shocks to labor market frictions instead of shocks to aggregate TFP which would move prices more.

4.7 Calibration

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

[8]This is an iterative process where the continuation functions are guessed and then updated according to the actual solutions of the deterministic paths.

$1/(1+r)$ in the steady state.

The log productivity process is set to match an annual persistence of $\rho_z = 0.96$ and an annualized standard deviation of $\sigma_z = 0.20$, values within the typical range of the literature. The labor-share in production is set to $(1-\alpha_y) = 0.67$ and aggregate total factor productivity is set so that the average output is equal to one, a normalization.

The UI system provides a replacement rate of $b = 0.5$ for earnings up to the median wage and a zero replacement rate thereafter. UI benefits have a median duration of 6 months during normal times and, to mimic Federal emergency benefits, do not expire in recessions. The minimum consumption floor is set to $\bar{c} = 0.005$. This low value is intended to capture food stamp programs that equal less than half a percent of GDP and are the most common welfare used by temporarily unemployed workers.

The shocks governing labor market frictions in the model need to be estimated. These include the job finding rates $\lambda_s(Z)$ and random job separation rates $\delta(Z)$. Selective layoffs are most affected by the match continuation cost shock, x. The value of this shock is set to 1.0, the median flow wage in the economy and the arrival rates in each aggregate state $\lambda_x(Z)$ are estimated.

The participation shock process is constant over the business cycle and is set so that the average time in non-participation is 20 months and the steady state share of the population with a constrained participation status is 6.5%. These values are meant to capture the second mode in duration estimates of job quitters to non-participation that we estimate in the PSID for prime-age individuals who have some work experience in the past five years.

A birth/death rate of agents is included in the quantitative model to better align observed stocks and flows. This is because (1) in the data we do not see flows out of employment when an individual leaves the survey but that does affect the employment stock; and (2) new entrants are in the data and affect particularly NU, UE, and NE rates and so we also need them in the model. We choose this parameter to equal half a percent per month and hold it constant over the business cycle.[9]

Finally, there are three remaining parameters affecting the relative flow values of each market state: utility cost of work, utility cost of active search in unemployment (versus free passive search in non-participation), and home production in non-participation. These parameters are jointly estimated.

[9] This parameter does improve the model fit of UN and NU flows. With it, we have an UN flow of 6.5% and NU flow of 4.0% versus 18% and 3.5% in the data, respectively. If we set birth/death to zero, we have an UN flow of 6.3% and NU flow of 1.1%.

Full Model													
Selective Layoffs		Random Layoffs		Random Quits		Job Offer Arrival				Others			
$\delta_s(G)$	$\delta_s(B)$	$\delta(G)$	$\delta(B)$	$\pi(0,1)$	$\pi(1,0)$	$\lambda(G)_u$	$\lambda(B)_u$	$\lambda(G)_n$	$\lambda(B)_n$	α	θ	h	ρ
0.050	0.082	0.006	0.0152	0.9965	0.950	0.230	0.110	0.152	0.088	0.204	0.102	0.285	0.96
Standard Targets Only- No Selective Layoffs													
Selective Layoffs		Random Layoffs		Random Quits		Job Offer Arrival				Others			
$\delta_s(G)$	$\delta_s(B)$	$\delta(G)$	$\delta(B)$	$\pi(0,1)$	$\pi(1,0)$	$\lambda(G)_u$	$\lambda(B)_u$	$\lambda(G)_n$	$\lambda(B)_n$	α	θ	h	ρ
0	0	0.008	0.014	0.986	0.910	0.255	0.165	0.240	0.192	0.205	0.580	0.170	0.96

Table 7: Key Parameter Values

Key parameter values are listed in Table 7. The top row lists parameters for the full benchmark model. The arrival rate of the selective layoff shock exceeds that of the random layoff shock but only 13.5% of the employed have a small enough surplus from employment that they would be laid off if they draw a selective layoff cost. Job offer arrival rates to the non-participants exceed NE flows in the data because most are rejected by non-participants who are either participation constrained or have negative employment surplus. The value of home production is 0.285 for non-participants. For context, the median wage for the employed is 1.17 and the shadow wages for the unemployed and non-participants are 1.16 and 0.95, respectively.

The "No Selective Layoffs" calibration serves to illustrate how targeting quits and layoffs changes the inference about the forces driving the economy through the lens of the model. This version omits the quit, layoffs, and share of layoffs to non-participation as target moments. We also remove the three moments governing selective layoffs from the model because there are no longer empirical targets to discipline these parameters. The best fit parameters show an AR(1) process that is more persistent because more quits to non-participation are necessary without the selective layoffs that flow to non-participation. The value of home production (h) is lower than the full model while the cost of search in unemployment and job arrival rates to non-participants are both higher. This shows that without endogenous layoffs the pool of laid-off workers have higher value of working. The estimation then needs to choose a higher cost of being in unemployment and a higher benefit of being in non-participation to get enough flows from employment to non-participation. The important economic meaning is that the extensive margin elastiticities of the non-employed are lower when not including selective layoffs– they are further from the margin of participation.

The model's fit to targeted and non-targeted moments is listed in Table 8. The empirical moments in the "Target" column are our calculations from the CPS except for the "Duration Short N" which is the first mean of the bimodal duration distribution for non-participation calculated in the PSID 2003-2019 sample. The "Full Model" column records statistics from the full model with the benchmark calibration.

The model has 18 targeted parameters which the estimation attempts to match. The model's structure is key to generating a close fit to the data since there are only 12 free parameters in the estimation. The model does not target flows between unemployment and non-participation

Moment	Target		Full Model	
	Normal	Recession	Normal	Recession
Epop	0.794	0.751	0.803	0.748
Upop	0.034	0.069	0.027	0.055
EU	0.009	0.014	0.008	0.014
EN	0.015	0.014	0.012	0.011
UE	0.250	0.160	0.228	0.110
NE	0.070	0.060	0.073	0.053
sN	0.355	0.312	0.357	0.307
Layoff	0.012	0.020	0.012	0.020
Quit	0.008	0.005	0.007	0.005
Non-targeted Statistics				
UN	0.180	0.150	0.065	0.037
NU	0.035	0.056	0.040	0.034
Duration Short N	3.00	—	3.14	—

Table 8: Model Fit to Targeted Moments

Notes: Data is prime age. E/pop = employment-to-population ratio; U/pop = unemployment-to-population ratio; Flow rates: EU = employment to unemployment; EN = employment to non-participation; UE = unemployment to employment; NE = non-participation to employment; Layoff = layoff rate; Quit = quit rate; UN = unemployment to non-participation; NU = non-participation to unemployment. sN = share of layoffs to non-participation. Duration Short N is the first mode in the data and the duration of those entering N for all reasons other than the exogenous participation shock in the model.

and subsequently provides too little of these types of flows.[10] The targeted stocks and flows are also not internally consistent. We subjectively choose to emphasize getting the stocks as well as the new statistics of quits, layoffs, and the share of layoffs to nonparticipation correct by assigning weights to these moments that are six times larger than the weights on the EU, EN, UE, and NE flows. Consequently, the model performs better on fitting these statistics.

5 The Role of Marginal Workers

5.1 How Many are There?

Labor supply choices, specifically quits and the decision of whether or not to stay in the labor force after a layoff, discipline the quantitative influence of marginal workers in our calibrated model. These targets are key to pin down the distribution of the population near zero surplus in each of the employment, unemployment, and non-participant pools. Knowing this distribution is key to predict the change in employment in response to policy or changes in fundamentals like the business cycle, but also expands our understanding of the potential workforce beyond the unemployed.

[10] The model also generates a good fit to NU flows in normal times but does not have mechanisms necessary for these flows to rise in recessions. Such mechanisms would include cyclical wealth effects on labor supply such as counter-cyclical declines in asset values or counter-cyclical partner job loss risk in dual earner couples.

Selection into quits and layoffs. Individuals with a high net value of employment are less likely to selectively quit or be selectively laid-off if a job continuation shock arrives. The net value of employment increases in productivity and decreases in assets. Unemployment benefits and home production replace less of high productivity individuals' labor income. This pushes the net flow value of employment higher and is more likely to compensate for the utility cost of searching for a job or the flow utility cost of employment. The same logic is true for low asset individuals. All else equal, they have a greater increase in flow consumption when employed.

Layoffs to Non-participation. A layoff, whether random or selective, is more likely to result in an exit from the labor force for workers with low, but positive net-values of employment. A worker who was happy to continue working until a layoff chooses to exit all together because searching for a job in unemployment is costly due to lost home production and the utility cost of search. It is more likely that a low productivity worker exits after a layoff because these costs are higher than can be rationalized by their low value of employment.

Normal Times				
Category	Total	Employed	Unemp	NILF
1. Constrained by Non-participation Shock ($p = 0$)	6.5%	0.0%	0.0%	39.5%
2. Negative work surplus $W < V$	4.3%	0.0%	0.0%	22.7%
3. Negative work surplus only if layoff cost $V < W < V + x$	13.5%	11.1%	39.6%	18.7%
4. Positive work surplus even if layoff cost $W > V + x$	76.8%	88.9%	60.4%	19.1%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Recessions				
Category	Total	Employed	Unemp	NILF
1. Constrained by Non-participation Shock ($p = 0$)	6.5%	0.0%	0.0%	33.8%
2. Negative work surplus $W < V$	3.7%	0.0%	0.0%	19.0%
3. Negative work surplus only if layoff cost $V < W < V + x$	8.7%	6.0%	21.0%	12.5%
4. Positive work surplus even if layoff cost $W > V + x$	81.1%	94.0%	79.0%	34.7%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Table 9: Employment surplus characteristics of the population

Contribution to Stocks Table 9 shows the distribution of employment surpluses in the economy. The numbers are at the beginning of the period after shocks are realized but before quits and layoffs occur. We can break them down into four groups. First, those constrained by the non-participation shock have the lowest employment surplus in the sense that they simply cannot work. These individuals make up around 40% of the non-participating individuals. Second, are the workers who have a negative employment surplus ($W < V$). Absent any shocks, these workers would still choose to quit their job due to the drift in their idiosyncratic productivity towards low values. All workers who quit transition to non-participation but some individuals in this category show up in unemployment. They are the ones whose idiosyncratic productivity has drifted after a layoff but, since they were laid off and are eligible for UI, they stay in unemployment instead of exiting to non-participation. Third are the workers who only have positive surplus if the job continuation cost does not arrive. They are not in the negative surplus group because $W > V$ but they would not pay the job continuation cost $W - q < V$. Fourth are the majority of the population who has positive surplus from work even if the job continuation cost arrives, meaning they are not at risk of a selective layoff or quit.

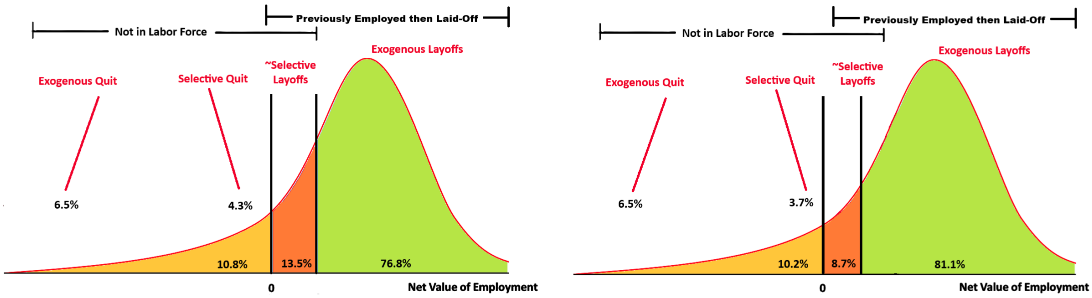


Figure 3: Distribution by Employment Surplus. Left: Normal Times. Right: Recessions.

Figure 3 is a stylized depiction of the distribution of the population but with the actual numbers from Table 9. We define marginal individuals as those with idiosyncratic productivity that would result in selective quit or layoff. In normal times, marginal workers make up 17.2% of all prime-age individuals. Another 6.5% are non-participants that we would not expect to react to small changes to labor market conditions. The remaining 77.4% are strongly attached participants that we would expect to also not react to small changes in labor market conditions. Marginal workers make up 11.1% the employed, 39.6% of the unemployed, and 18.7% of the non-participants. The impact of changes in policy or labor market conditions on labor supply elasticities is then understood by how much they change the participation surplus for this sizable minority of individuals.

5.2 Labor Supply Elasticities.

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

Table 10 shows how the stocks and flows change as a result of a change in wealth and a change in the wage (Marshallian Elasticity).

Changes in Wealth. We explore a pure wealth effect by introducing an unfunded lump-sum transfer equal to 10% of the median wage to all agents in every period. This is a pure wealth effect that lowers labor supply. The share of workers in the labor force is reduced by 0.81 percentage points, from 83.0% to 82.2%. Employment falls by even more, 1.13 percentage points, as unemployment rises by 0.32 percentage points. The result is due to labor market frictions. The wealth effect induces workers to set a higher threshold on their own idiosyncratic productivity to participate. Since this productivity is transitory, this results in more layoffs and selective quits and then more churning through unemployment.

Figure 4 shows that the effects of an increase in wealth are not linear across different levels of the transfer. The reason for that relates precisely to the key message of the paper, it is the marginal workers who are most likely to respond to small changes in policy or economic conditions. The relatively small increase in wealth is enough to affect the labor supply and search choice of the marginal workers as they were very close to the participation margin in the baseline. Thus, we see a large decline in both the employment population ratio as well as the unemployment rate. Further increases in the asset subsidy are going to lower both employment and unemployment but by lesser magnitudes since most marginal workers already respond to small changes.

Table 10: Labor Market Outcomes Under Policy Experiments (Normal Times)

	Stocks			Flow Rates					
Scenario	E/pop	U/pop	LFP	EU	EN	UE	NE	Layoff	Quit
Baseline	80.3	2.7	83.0	0.9	1.5	2.5	0.7	1.1	0.8
Changes relative to baseline (percentage points):									
Wealth +10%	−1.13	+0.32	−0.81	0.31	0.45	−0.01	+0.19	+0.31	+0.46
Wage +10%	+1.23	+0.22	+1.45	0.03	−0.11	+0.03	−0.29	0.02	−0.05
Standard Model									
Changes relative to baseline (percentage points):									
Wealth +10%	−0.25	−4.66	−4.91	0.00	0.01	−0.13	−6.11	0.00	0.00
Wage +10%	*Negligible*								

Notes: E/pop = employment-to-population ratio; U/pop = unemployment-to-population ratio; LFP = labor force participation (E+U). Flow rates shown as percentages: EU = employment to unemployment; EN = employment to non-participation; UE = unemployment to employment; NE = non-participation to employment; Layoff = layoff rate; Quit = quit rate.

Changes in Wages. As a second policy experiment, we explore Marshallian elasticities by varying the wage rate per efficiency unit. Table 10 shows that a 10% increase in the wage increases the share of workers in the labor force by 1.45 percentage points. Employment increases by 1.23 percentage points and unemployment by 0.22 percentage points. As wages rise, we see a decline in quits as well as an increase in the flows from non-employment to employment as the value of employment increased. Similarly, we see an increase in the number of unemployed as more laid-off workers choose unemployed and non-participating workers start to search. These results are aligned with conventional labor market mechanics. Wages increase labor supply which results in higher employment, lower non-participation, and higher unemployment. This is because the marginal workers become more attached and when they do separate from employment they are more likely to stay within the labor force through unemployment than to exit to nonparticipation.

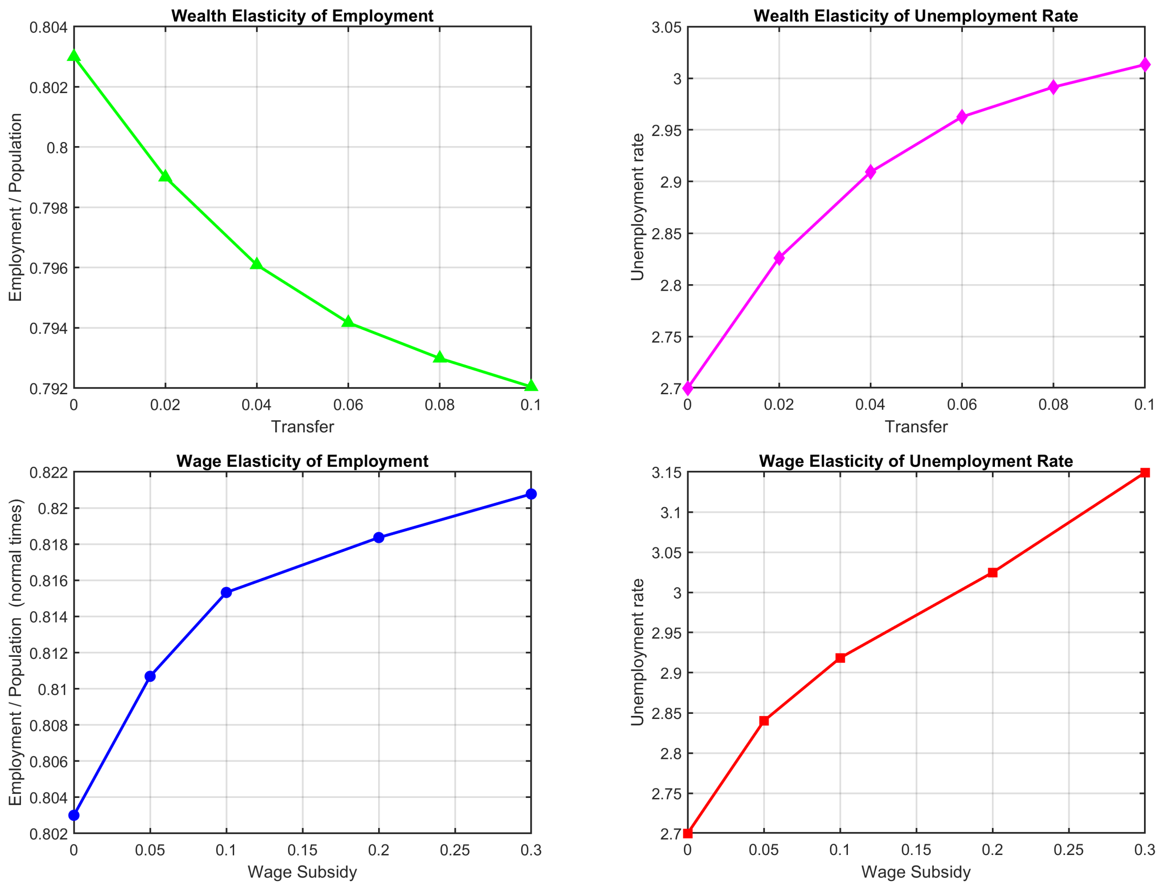


Figure 4: Elasticity of Employment and Unemployment across Wealth Transfers and Wage Subsidy Rates

Figure 4 confirms that marginal workers are at the center of quantifying labor supply elasticities. Similar to the change in wealth, we see that the elasticities are non-linear across the level of the wage subsidy. Relatively small increases in wages are associated with a relatively large change in employment and unemployment as it targets primarily workers who are close to the participation margin, the marginal workers.

6 The Business Cycle

6.1 Cyclicality of Flows and Stocks.

The cyclical dynamics of the labor market are generated by several empirically relevant changes. Our model features two standard mechanisms: First, labor market frictions change: the job loss rate increases, and the job finding rate falls; Second, UI benefits are extended. In addition, we have a third, less standard mechanism: Cyclical selection of layoffs. In our model, the incidence of layoffs in recessions moves towards less marginal workers who have a higher employment surplus. Specifically, the share of selective layoffs reduces from 47.9% to 24.4% of all layoffs from expansion to recession as can be seen in table 11. This is inferred by our estimation largely due to the introduction of the target of the cyclicality of the share of layoffs to N.

Whether selective layoffs increase or decrease in recessions compared to normal times would not be clear without the use of a quantitative model. The different cyclical forces have opposing effects on workers' choice to leave the labor force after a layoff in recessions. An extension of UI benefits incentivizes laid-off workers to remain in the labor force after a layoff instead of leaving. A decline in the job finding rate, all else equal, however, would make remaining in unemployment less attractive after a layoff as it is more difficult to find a job, so workers would choose to not pay the search cost and leave the labor force instead. The effect of an increase in the job separation rate on laid-off workers leaving the labor force is ambiguous. On one hand, it lowers the value of employment, but on the other hand, it makes it more likely for workers to be laid-off which would make them eligible for UI benefits which they would not qualify if they quit instead. Lastly, it is also important to consider composition effects as all workers, marginal and highly attached, are more likely to get laid off in recessions compared to normal times.

Share of Flows due to Selection				
	Baseline		**Standard**	
	normal	recession	normal	recession
layoffs	47.9	24.4	6.4	6.4
quits	70.6	68.8	100.0	100.0
Share of Stock Entering by Selection				
	Baseline		**Standard**	
	normal	recession	normal	recession
unemployment	28.8	16.9	0.0	0.0
non-participation	50.1	42.8	9.6	9.6

Table 11: Contribution of Selection to Flows and Stocks

From Table 11, we see that selection in both layoffs and quits declines in recessions. This finding is due to a combination of changes in labor supply choices *and* composition effects. While the finding that selective layoffs decline in recessions lead to the conclusion that the effect from the extension of the UI benefits dominates the decline in the job finding and increase in the job separation rate for marginal workers, it only shows half of the picture. We also find that the selection among workers entering unemployment in recession declines. The two findings together show that composition is important as well. Higher job loss rates imply that more marginal workers get laid off and they are more likely to choose unemployment but higher job loss rates also imply that relatively more attached worker than marginal workers lose their job which results in the decline in selection in unemployment. Thus, the pool of workers entering unemployment in recessions shifts towards more attached workers.

The decline of selection among workers entering non-participation during recessions is explained by the decline in selective quits. Quits decline in recessions due to workers' job hoarding motive: Workers know that once they quit, it is now more difficult to find a job since job finding rates declined. In addition, workers who quit are not eligible to receive the extended UI benefits, thus, it is better for them to stay employed and hope to get laid off instead.

6.2 Selection Among Unemployed.

The results in the previous showed that the pool of workers entering unemployment in recessions contains relatively less marginal workers in recessions which implies that the stock entering shifts towards more attached workers. This finding suggests the possibility that the pool of unemployed shifts towards highly attached workers in recessions. In order to test this hypothesis, we follow the approach by Mueller (2017) and Table 12 shows that similar to Mueller (2017) in recessions the pool of unemployed shifts towards workers with high wages (productivity). Panel A shows that the productivity (z) of layoffs increases in recessions. Coincidentally this increase matches exactly the results by Mueller (2017) who finds a coefficient of 2.77.

Table 12: OLS Regression Coefficients on Unemployment Rate

Variable	Coefficient	Mueller-2017	Coefficient
Panel A: Individual Productivity			
z (unemployed)	2.77	EU	2.77
z (layoff)	3.29		
z (quit)	1.63		
Panel B: Transition Rates by High vs Low Productivity			
EU (above median)	0.140	separations: w_{high}	0.74
EU (below median)	0.011	separations: w_{low}	0.32
EN (above median)	−0.009		
EN (below median)	0.056		
UE (above median)	−0.844	job finding: w_{high}	-0.62
UE (below median)	−0.624	job finding: w_{low}	-0.55
NE (above median)	0.096		
NE (below median)	-0.322		

Note: All coefficients are from OLS regressions of the dependent variable on the unemployment rate $U/(E+U)$ and a constant. Panel A shows individual-level regressions pooling all agents across time periods. Panel B shows time-series regressions of aggregate transition rates.

Mueller (2017) argues that the shift towards high-wage workers among the unemployed in recessions is due to the high cyclicality of separations for high-wage workers which can be seen in Panel B. Again, we qualitatively match the finding as we also find that EU transitions increase more for high-productivity workers in recessions than low-productivity workers. Interestingly, we find that also among quit productivity increases in recessions. This result is primarily driven by the job hoarding effect of marginal workers, who quit less in recessions. High-productivity workers never quit unless they are forced to quit due to the random shock π^p. Thus, quits in recessions are increasingly due to forced quits and less selective quits.

Lastly, we match the findings on the differences in the cyclicality of job finding rates for low and high-productivity qualitatively and quantitatively.

6.3 How Important Are Marginal Workers?

The previous sections showed that changes in marginal workers' labor supply choices as well as the ratio of marginal workers to highly attached workers are important to understand business cycle dynamics of labor market aggregates. In this section, we analyze the role of selection and marginal workers' labor supply over the business cycle. We do this by considering two counterfactuals that allow us to analyze the importance of selection over the business cycle. First, we turn off cyclical selection, i.e. we still have selective layoffs but they do not vary over the business cycle. Second, we keep policy functions fixed at normal times to turn off the cyclicality of labor supply. Note that we match layoff rates in the baseline model as well as both counterfactuals, so that layoffs are the same in all three model specifications.

Panel A shows how the different stocks and flows vary over the business cycle in the baseline model. We consider three measures of cyclicality: Averages in normal times and recessions, standard deviations of stocks, and correlations of stocks with a measure of output. Panel A is our baseline model and shows commonly known facts about the business cycle dynamics of flows and stocks: quits and employment decrease in recessions, layoffs, unemployment, and non-participation increase in recessions.

Panel B solves for the arrival rates of the random and selective layoff shocks in recessions such that we match the increased layoff rate in recessions but keep constant the share of selective layoffs as it is in normal times. The interpretation is that this isolates what the world would look like if selection into layoffs was constant over the business cycle. We find the unemployment to population ratio would increase significantly less in recessions by 2.2 percentage points versus 2.8 in the baseline. This result can also be seen in a lower standard deviation of unemployment and a lower correlation with output. This result is because exercise lays off more marginal workers in recessions who are more likely leave the labor force after a layoff thus keeping unemployment lower in recessions but non-participation rises more. In addition, quits drop by more than in the baseline model as higher overall job loss rates increase the motive for job hoarding and thus, reduces the quits in the economy.

Panel C analyzes the role of marginal workers differently by not allowing labor supply choices to vary with the business cycle. Specifically, we fix the policy functions at their "normal times" values but allow the changes to all cyclical shocks to vary when simulating the model. We find that labor supply choices serve as a stabilization mechanism for both employment and unemployment over the business cycle. Without labor supply of the employed increasing due to job hoarding motives, both quits and layoffs would increase more during recessions leading to even higher unemployment. This result is interesting because it shows that labor supply actually mitigates the forces of fluctuations in labor demand resulting in a relatively more stable business cycle.

Table 13: Role of Selection and Labor Supply in the Business Cycle

	Model Version		**Data**
	Full Model	Standard Model	**(2000-2019)**
Panel A: Baseline Model			
Stocks and Flows (Normal, Recession)			
Epop	(0.803, 0.748)		(0.794, 0.751)
Upop	(0.027, 0.055)		(0.034, 0.069)
Quits	(0.0072, 0.0054)		(0.0084, 0.0061)
Layoffs	(0.0123, 0.0201)		(0.0110, 0.0189)
Standard Deviations			
Employment	0.0271	0.0177	*0.0190*
Unemployment	0.0143	0.0161	*0.0141*
Non-participation	0.0124	0.0064	*0.0094*
Output	1.85		
Correlations of changes with changes in Output			
Employment	0.6656	0.7753	*0.6845*
Unemployment	−0.6350	−0.7308	*-0.5999*
Non-participation	−0.4905	−0.2617	*-0.3541*
Panel B: No Cyclical Selection			
Stocks and Flows (Normal, Recession)			
Epop	(0.803, 0.755)		
Upop	(0.025, 0.047)		
Quits	(0.0072, 0.0075)		
Layoffs	(0.0125, 0.0203)		
Standard Deviations			
Employment	0.0242		
Unemployment	0.0110		
Non-participation	0.0145		
Output	1.66		
Correlations of changes with changes in Output			
Employment	0.5934		
Unemployment	−0.5415		
Non-participation	−0.4571		
Panel C: No Cyclical Labor Supply			
Stocks and Flows (Normal, Recession)			
Epop	(0.803, 0.727)		
Upop	(0.026, 0.066)		
Quits	(0.0072, 0.0079)		
Layoffs	(0.0130, 0.0208)		
Standard Deviations			
Employment	0.0359		
Unemployment	0.0184		
Non-participation	0.0187		
Output	2.06		
Correlations of changes with changes in Output			
Employment	0.7209		
Unemployment	−0.6944		
Non-participation	−0.5933		

Note: Employment, unemployment, and non-participation are as shares of population. In the data these are for prime age. Output in the model is the sum of the wages paid. Output in the data is the labor share times real gross domestic product. No Cyclical Selection: match layoff rates but keep share entering selectively fixed. No Cyclical Labor Supply: fix policy functions at normal aggregate state.

6.4 The Role of Frictions.

As we have learned in the previous sections, there are important interactions between marginal workers' labor supply choices and the cyclicality of labor frictions. This sections analyzes the role of job finding and job loss rates in the business cycle dynamics of the labor market. In Panel A we have the results for the baseline model and for panels B and C we set the job loss and job finding probability to its value in normal times.

Turning off the cyclicality of job loss impacts the cyclicality of all three stocks as well as quits, and unsurprisingly, layoffs. Panel B shows that employment drops by less and unemployment and non-participation increase by less in recessions compared to the baseline model. Employment drops by only 1.5 pp compared to 5.5 pp in the baseline model. The reason for that is straightforward, less layoffs imply that more workers remain employed in recessions. Unemployment still increases but by much less than in the baseline model. The first reason is obvious: the job loss rate is lower which means fewer workers leaving employment. But this is not the end of the story, there two additional reasons which relate to marginal workers : First, UI benefits are extended in recessions, which means although the layoff rate has not changed, more marginal workers are now going to choose unemployment over non-participation. In addition, lower job loss rates in recessions increase the value of working which again makes more marginal workers choose unemployment over non-participation. These two forces explain why we see an increase in unemployment which we would not see in a model without selective layoffs when job loss rates are held constant over the business cycle. We also see an increase in non-participation in recessions but smaller than in the baseline model since the probability finding a job is lower which means workers remain longer in non-participation and some workers will leave unemployment and choose non-participation.

In panel C we show how the cyclicality of the stocks and flows change when we keep the job finding rate fixed at its normal times value. Again, turning off this job friction means that employment decreases by less and unemployment and non-participation rise by less in recessions as compared to the baseline model. Comparing to Panel B shows that variation in job finding has a smaller impact on cyclical variance in the labor market than variation in job loss rates.[11] Employment drops less than in the baseline model since the high job finding rate is going to set off the effect of the higher job loss rate. Unemployment increases because some marginal workers will choose unemployment over non-participation since the value of unemployment increased: UI benefits are extended and it is easy to find a job. These two improvements will offset the search cost for workers that are very close to the margin between labor force and non-participation.

Overall, this section shows that the interaction between frictions and people on the margin is important to understand the business cycle dynamics of the labor market. Without correctly accounting for the marginal workers, we would attribute changes in frictions almost entirely to

[11] Another way to think about it is that Panel B shows the impact of changes in job finding only (by shutting off changes in job loss) and Panel C shows the impact of changes in job loss only (by shutting off changes in job finding).

exogenous changes whereas in this model frictions also change labor supply in important ways.

7 Policy Experiments.

Now that we have quantified the marginal workforce and gained better understanding about their quantitative important to business cycle dynamics of the labor market, we conduct two policy experiments to understand how they change the flows and stocks over the business cycle.

Table 16 shows how changes in the UI replacement rate impact stocks, flows, and consumption volatility. As a reminder, the UI replacement rate in the baseline model is 0.5. An increase in the UI replacement rate unambiguously increases labor supply but creates a disincentive for an unemployed worker to move to employment which makes the impact on employment ambiguous. We can see both effects in Panel B of Table 16. An increase in the replacement rate to 0.6 reduces employment in normal times by 0.7 percentage points and increases unemployment by 0.9 percentage points indicating a rise in labor force participation.

Although Panel B posits an increase in the replacement rate in all periods, we end up with an increase in the cyclical volatility of the labor market. Again, the key to understanding this result are marginal workers. They are more likely to show up in unemployment as more of them are choosing unemployment over non-participation after a layoff and this is even more true in recessions when eligibility for benefits is extended for additional weeks. Panel C shows that increasing the replacement rate during recessions only would result in higher employment throughout the cycle than the unconditional increase of Panel B, and this would deliver greater less volatility in consumption relative to GDP.

The second policy experiment we consider is a lump-sum transfer of 10% of the median earnings. This transfer only goes to workers in the lowest 20% of productivity. The idea is a similar concept to Universal Basic Income. While we concede that this productivity is likely to be unobservable, we still think it is useful to ask what impacts this would have on labor supply even in the best case scenario of perfect observability. Panel B shows the unconditional transfer and Panel C shows the transfer in recessions only. In both cases employment decreases considerably with little impact on unemployment. This is different than other experiments we have done as it moves workers away from the margin and towards non participation. The volatility of all stocks and output fall since workers are less likely to churn between different labor market states and become more persistently disattached from participation.

8 Conclusion

In this paper, we develop a new framework for understanding aggregate labor supply by re-examining the circumstances and destinations of employment separations. By distinguishing between quits and layoffs into both unemployment and non-participation, we uncover a more nuanced picture of the ”marginal workforce” that drives labor market dynamics.

Table 14: Role of Job Loss and Job Finding in the Business Cycle

	Model Version		**Data**
	Full Model	Standard Model	**(2000-2019)**
Panel A: Baseline Model			
Stocks and Flows (Normal, Recession)			
Epop	(0.803, 0.748)		(0.794, 0.751)
Upop	(0.027, 0.055)		(0.034, 0.069)
Quits	(0.0072, 0.0054)		(0.0084, 0.0061)
Layoffs	(0.0123, 0.0201)		(0.0110, 0.0189)
Standard Deviations			
Employment	0.0271	0.0177	*0.0190*
Unemployment	0.0143	0.0161	*0.0141*
Non-participation	0.0124	0.0064	*0.0094*
Output	1.85		
Correlations of changes with changes in Output			
Employment	0.6656	0.7753	*0.6845*
Unemployment	−0.6350	−0.7308	*-0.5999*
Non-participation	−0.4905	−0.2617	*-0.3541*
Panel B: No Cyclical Job Loss			
Stocks and Flows (Normal, Recession)			
Epop	(0.807, 0.792)		
Upop	(0.024, 0.028)		
Quits	(0.0071, 0.0070)		
Layoffs	(0.0114, 0.0115)		
Standard Deviations			
Employment	0.0129		
Unemployment	0.0041		
Non-participation	0.0107		
Output	1.23		
Correlations of changes with changes in Output			
Employment	0.3860		
Unemployment	−0.2737		
Non-participation	−0.2886		
Panel C: No Cyclical Job Finding			
Stocks and Flows (Normal, Recession)			
Epop	(0.801, 0.768)		
Upop	(0.026, 0.051)		
Quits	(0.0074, 0.0077)		
Layoffs	(0.0119, 0.0130)		
Standard Deviations			
Employment	0.0168		
Unemployment	0.0116		
Non-participation	0.0087		
Output	1.32		
Correlations of changes with changes in Output			
Employment	0.4774		
Unemployment	−0.4452		
Non-participation	−0.2454		

Note: Employment, unemployment, and non-participation are as shares of population. In the data these are for prime age. Output in the model is the sum of the wages paid. Output in the data is the labor share times real gross domestic product. No Cyclical Job Loss: δ's set at normal times rates. No Cyclical Job Finding: λ's set at normal times rates.

Our analysis of monthly CPS data from 1978 to 2024 reveals a critical empirical fact: approximately 35% to 40% of laid-off prime-age workers exit the labor force immediately rather than searching for new employment. Because these individuals would likely have continued working if not for the layoff, their immediate exit identifies them as being at the margin of participation. Furthermore, we document that this share of exits is procyclical, declining during recessions as workers become more attached to the labor force—a pattern that is not explained by changes in demographic composition.

Quantitatively, our model demonstrates that 48% of layoffs selectively target these marginal workers during normal times but only 24% in recessions. This selection is essential for interpreting business cycle fluctuations. That change in layoffs towards more attached workers in recessions increases the unemployment rate roughly 25% more than if the composition was constant over the cycle. None-the-less marginal workers make up 29% of the unemployed in good times and 17% in recessions, and they have higher labor supply elasticities than the average. We show that they increase their labor supply in recessions in response to job hording and unemployment insurance extensions. This serves a non-trivial employment stabilizer but also amplifies the cyclical volatility of unemployment. Finally, the disproportionate presence of marginal workers in the pool of non-employed also amplifies the impact of policies targeting the low income or non-employed such as Unemployment Insurance programs.

By providing a more precise classification of worker flows—now available as a monthly series—we offer a resource to better track the evolving distribution of employment surplus and its impact on aggregate labor supply.

Table 15: UI Policy Experiments: Changes from Baseline

	Full Model
Panel A: Baseline with UI replacement rate = 0.5	
Standard Deviations	
Employment	0.0271
Unemployment	0.0143
Non-participation	0.0124
Output	1.85
Correlations of changes with changes in Output	
Employment	0.6656
Unemployment	−0.6350
Non-participation	−0.4905
Consumption Volatility (std(C)/std(Y))	
Aggregate	0.99
Bottom 20%	1.50
Stocks and Flows (Normal, Recession)	
Epop	(0.803, 0.748)
Upop	(0.027, 0.055)
Quits	(0.0072, 0.0054)
Layoffs	(0.0123, 0.0201)
Panel B: UI replacement rate = 0.6	
Standard Deviations	
Employment	0.0278
Unemployment	0.0166
Non-participation	0.0129
Output	1.87
Correlations of changes with changes in Output	
Employment	0.6776
Unemployment	−0.6459
Non-participation	−0.4564
Consumption Volatility (std(C)/std(Y))	
Aggregate	0.98
Bottom 20%	1.44
Stocks and Flows (Normal, Recession)	
Epop	(0.796, 0.739)
Upop	(0.0363, 0.0707)
Quits	(0.0069, 0.0072)
Layoffs	(0.0155, 0.0231)
Panel C: UI = 0.5 in normal, 0.6 in recessions	
Standard Deviations	
Employment	0.0290
Unemployment	0.0182
Non-participation	0.0127
Output	1.92
Correlations of changes with changes in Output	
Employment	0.6859
Unemployment	−0.6620
Non-participation	−0.4528
Consumption Volatility (std(C)/std(Y))	
Aggregate	0.95
Bottom 20%	1.43
Stocks and Flows (Normal, Recession)	
Epop	(0.803, 0.743)
Upop	(0.027, 0.065)
Quits	(0.0071, 0.0075)
Layoffs	(0.0129, 0.0204)

Note: Consumption volatility is measured as std(C)/std(Y) which includes home production. UI replacement rate experiment increases both the replacement rate to 60% but retains the same cap as the baseline.

Table 16: UI Policy Experiments: Changes from Baseline

	Full Model
Panel A: Baseline (No transfers)	
Standard Deviations	
Employment	0.0271
Unemployment	0.0143
Non-participation	0.0124
Output	1.85
Correlations of changes with changes in Output	
Employment	0.6656
Unemployment	−0.6350
Non-participation	−0.4905
Consumption Volatility (std(C)/std(Y))	
Aggregate	0.99
Bottom 20%	1.50
Stocks and Flows (Normal, Recession)	
Epop	(0.803, 0.748)
Upop	(0.027, 0.055)
Quits	(0.0072, 0.0054)
Layoffs	(0.0123, 0.0201)
Panel B: Transfer = 10% of median wage to bottom 20%	
Standard Deviations	
Employment	0.0160
Unemployment	0.0143
Non-participation	0.0083
Output	1.74
Correlations of changes with changes in Output	
Employment	0.5491
Unemployment	−0.6105
Non-participation	−0.0618
Consumption Volatility (std(C)/std(Y))	
Aggregate	1.06
Bottom 20%	2.12
Stocks and Flows (Normal, Recession)	
Epop	(0.7524, 0.7257)
Upop	(0.0260, 0.0554)
Quits	(0.0129, 0.0130)
Layoffs	(0.0117, 0.0187)
Panel C: Transfer = 10% of median wage to bottom 20% in recessions only	
Standard Deviations	
Employment	0.0177
Unemployment	0.0144
Non-participation	0.0083
Output	1.76
Correlations of changes with changes in Output	
Employment	0.7841
Unemployment	−0.6158
Non-participation	−0.1313
Consumption Volatility (std(C)/std(Y))	
Aggregate	1.02
Bottom 20%	2.56
Stocks and Flows (Normal, Recession)	
Epop	(0.7603, 0.7291)
Upop	(0.026, 0.055)
Quits	(0.0124, 0.0126)
Layoffs	(0.0113, 0.0184)

Note: Consumption volatility is measured as std(C)/std(Y). UI replacement rate experiment increases both the replacement rate to 60% but retains the same cap as the baseline.

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A Data Robustness

A.1 Choice of moving average filter

In the main text, all timeseries were smoothed using a 6-month centered moving average smoother. We will show in the following that the choice of the smoothing parameter as well as whether it is centered or not does not change the data in any significant way. The following figures plot our layoff series, quit series, and total separations for four different smoothing techniques. 6-month centered is the standard we use in the main text, which means we include the previous 3 months, the current month, and three forward terms. 3-month, 4-month, and 6-month only include the previous 3, 4, and 6 months respectively, as well as the current month.

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

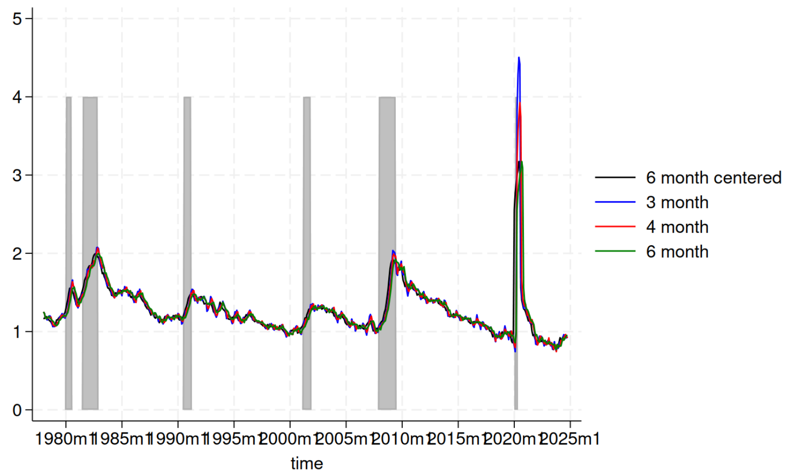

Figure 5: Comparison of moving-average filter for layoff series

A.2 DeNUNifying the Data

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

Table 17 shows that excluding these potentially misclassified transitions has no effect on the main statistics in this paper.

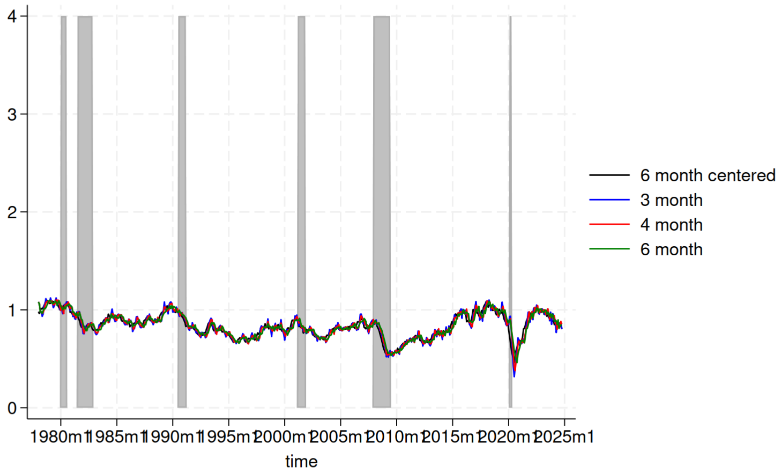

Figure 6: Comparison of moving-average filter for quit series

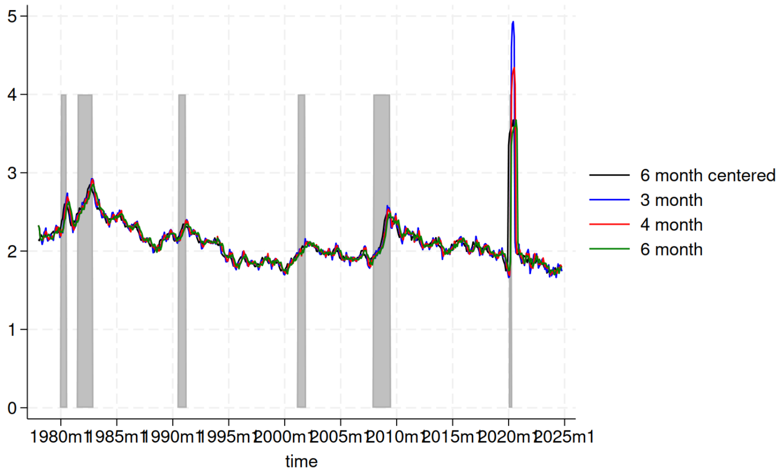

Figure 7: Comparison of moving-average filter for total separations

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

Figure 8 shows that the business cycle pattern of layoffs is driven by permanent layoffs and the majority of layoffs are from permanent jobs. Interestingly, layoffs from temporary are mildly procyclical, i.e. decline during periods when unemployment is high. Because permanent layoffs are strongly countercyclical and temporary layoffs mildly procyclical, recessionary periods are characterized by an increase in the share of layoffs from a permanent job.

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

Table 17: Comparison with deNUNified data

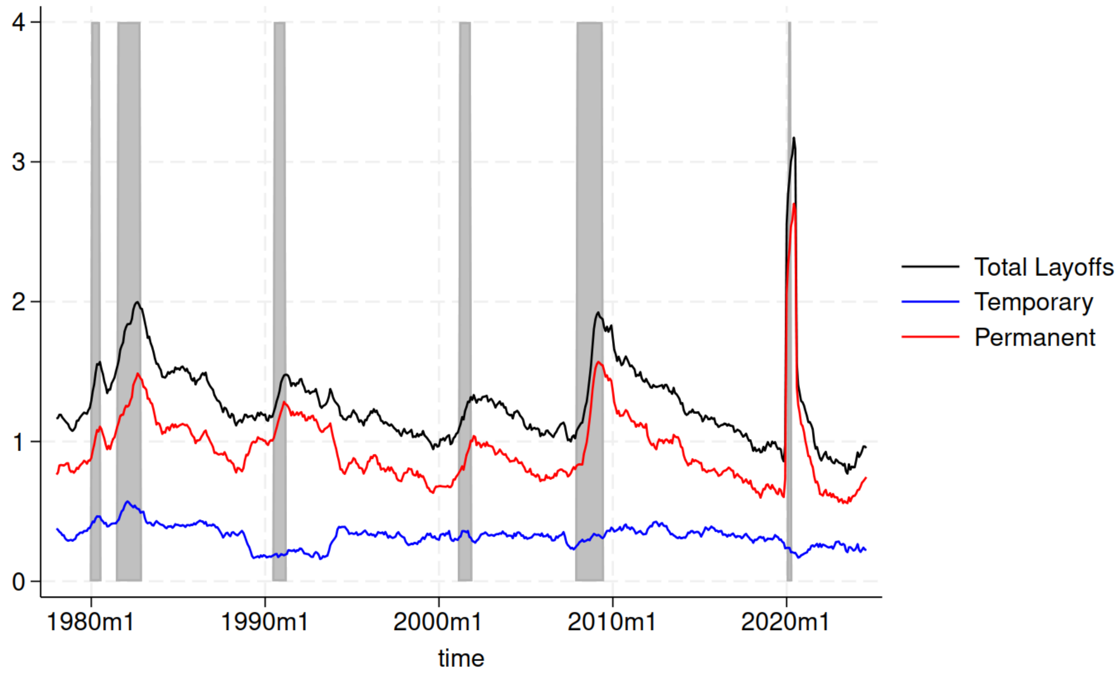

Figure 8: Layoffs from temporary vs permanent jobs

B Working-Age Population

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

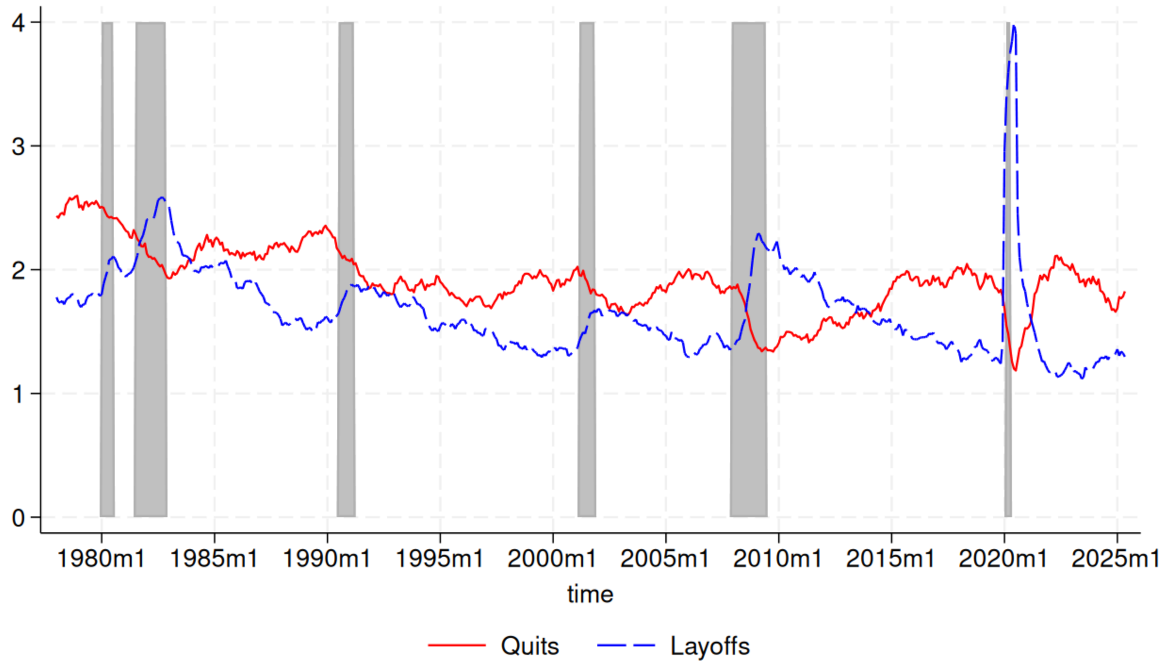

Figure 9: Quits and layoff

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

Table 18: Business cycle correlations of each flow (x) with the unemployment rate (y)

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

Table 19: Business cycle correlations of quits and layoffs

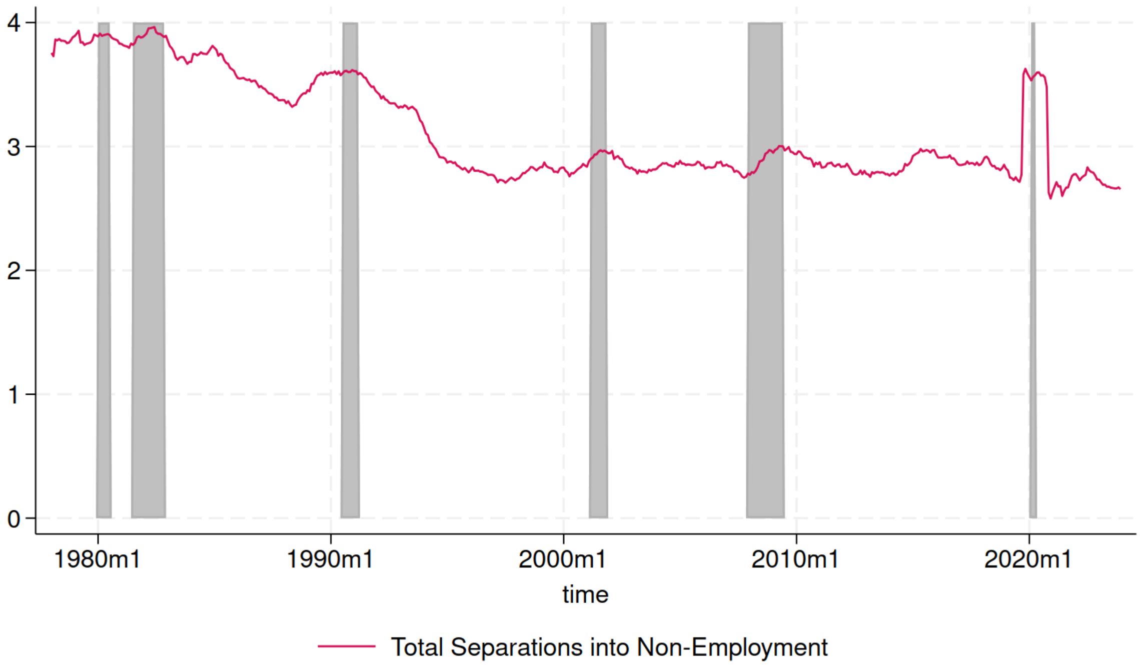

Figure 10: Total separations

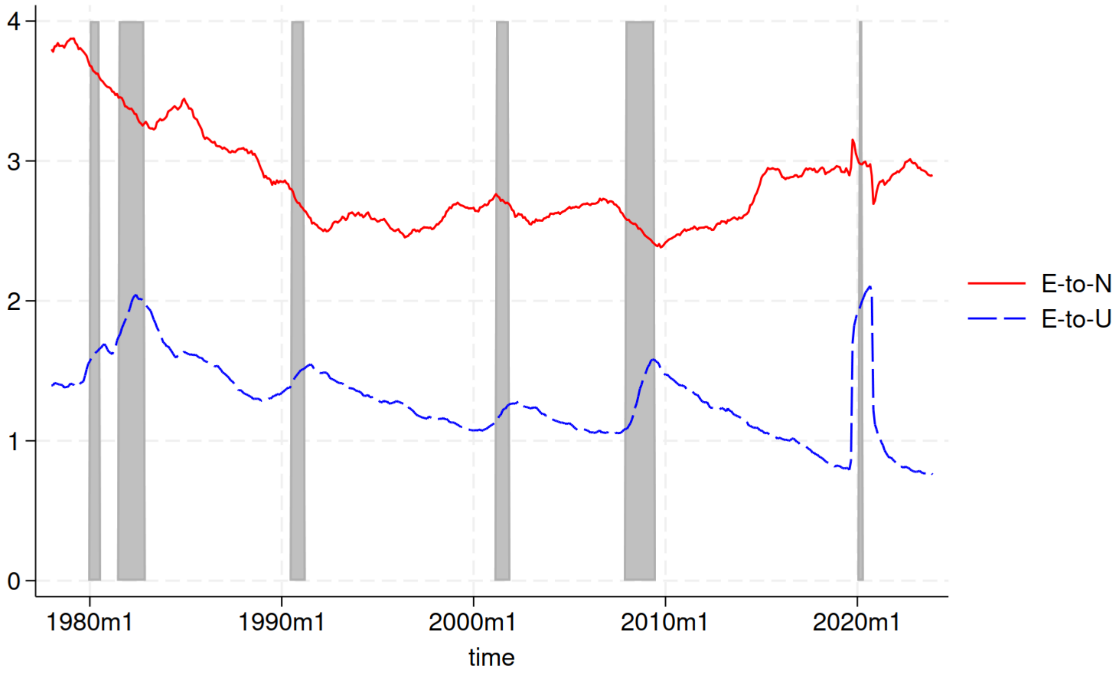

Figure 11: EN and EU flow rates

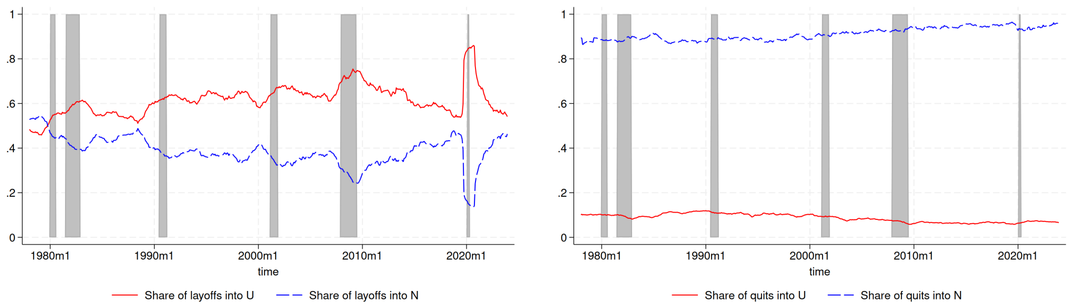

Figure 12: Share of quits and layoffs by destination

C Comparison to Jolts and Other Data

The Job Openings and Labor Turnover Survey (JOLTS) has been the primary source used to analyze quits and layoffs in the United States.[12] It is a monthly employer survey run by the Bureau of Labor Statistics (BLS). In this section, we compare our CPS quits and layoffs series with the corresponding JOLTS series.

JOLTS defines layoffs as "Involuntary separations initiated by the employer" and quits "Employees who left voluntarily. Exception: retirements or transfers to other locations are reported with Other Separations". Lastly, the JOLTS category "Other Separations" includes "retirements; transfers to other locations; deaths; or separations due to employee disability". Therefore, a quit in JOLTS is any voluntary separation with the exception of retirement, disability, death, or transfers to other locations; and a layoff is any involuntary separation. It is important to note that JOLTS includes job-to-job quits and layoffs, whereas we can only observe the quits and layoff distinction for separations to non-employment[13] The JOLTS are also known to under count separations even when sampling weights are applied because they do not measure separations due to firm exit (Faberman (2005)). To remedy this, the disseminated JOLTS data are adjusted via a Monthly Alignment Method to produce stocks that are consistent with employment measured in the Current Employment Statistics (CES) (Cheng et al. (2009)).

In order to compare our data to JOLTS, we will restrict it accordingly. Layoffs are straightforward since we, similar to JOLTS, only consider individuals as laid off if they lost their job involuntarily. With regards to quits, we exclude all individuals who are retired[14] and disabled individuals are automatically excluded because they are not in the universe of individuals being asked the question of reason for non-participation. Death is also automatically excluded due to our linking strategy, because a dead person would not show up in the current month. Lastly, since we only consider separations into non-employment we do not have to worry about transfers

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

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

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

to other locations. The earliest available from JOLTS is for January 2001, so restrict our series to start at the same date. Both series are seasonally-adjusted.

Figure 13 compares the JOLTS layoffs series with our layoffs series constructed using the CPS, including and excluding the pandemic recession. For every month in the sample, with the exception of the pandemic recession, the layoff rate computed using JOLTS data exceeds our layoff rate based on the CPS data. The correlation between the two series for the entire time period is 0.63. Notably, our layoffs series is significantly more responsive to fluctuations in the unemployment rate. The correlation of the CPS layoffs series with the unemployment rate is 0.50, whereas it is only 0.27 for the JOLTS layoffs series.

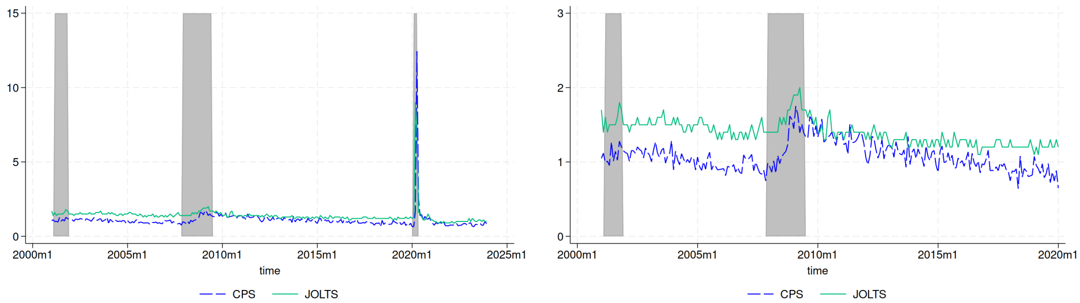

Figure 13: Layoffs, full series (left) and with the removal of 2020 + (right).

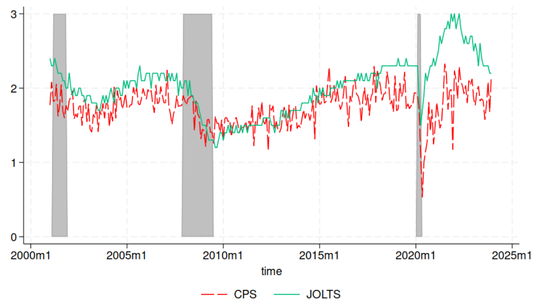

Figure 14: JOLTS total Quits and our adjusted CPS quit to nonemployment series

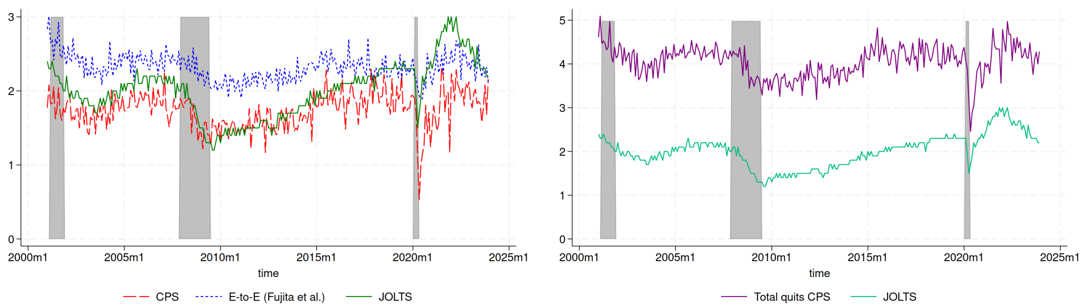

Figure 15: Quits: adjusted CPS quits to nonemployment, E-to-E flows Fujita et al. (Forthcoming), and JOLTS (Left); combined CPS quits plus E-to-E and JOLTS (right)

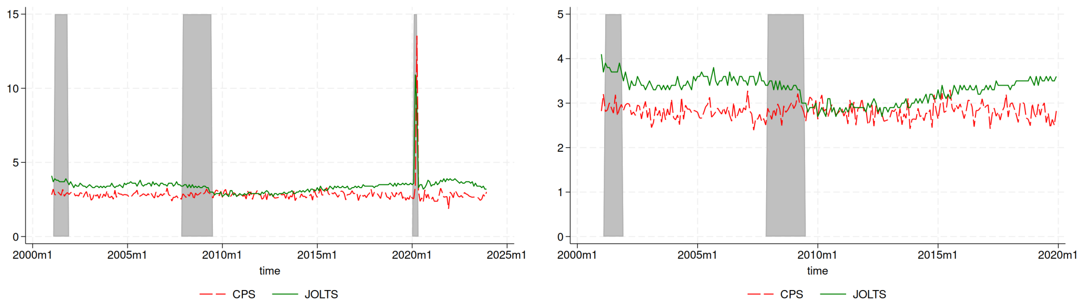

Figure 16: Total separations, full series (left) and with the removal of 2020 + (right).

Table 20: Panel Study of Income Dynamics 2003-2019

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

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

Table 20 shows that the split between quits and layoffs to non-employment that end up in non-participation is similar in the PSID as it is in our CPS sample. Over the same same period, 12.9% of prime age quits to non-employment are classified as unemployment in the CPS compared to 11.8% in the PSID sample; and 64.8% of prime age layoffs to non-employment are to unemployment compared to 68.0% in the CPS sample.[15] This provides confidence that our classification of quits and layoffs is consistent with how workers describe the reason for a job ending in other popular surveys.

Table 20 also includes the separations we miss in the CPS. Separations directly to another employer or the termination of a single job held by a multiple job holder are included in quits

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

and layoffs with a destination of "Employment". These types of separations make up 42.5% or 50.7% of all quits and 27.9% or 29.1% of all layoffs for all workers or prime age, respectively. During the recessionary years of 2008-10, the share of quits directly to a new employer falls to 30.1%; and the share of layoffs directly to a new employer falls to 21.6%. This backs our hypothesis that the CPS layoffs rise more during recession because layoffs to non-employment rise more than total layoffs, in part because the share of layoffs to non-employment increases. The analogous argument is supported for quits.

D Additional Model Results

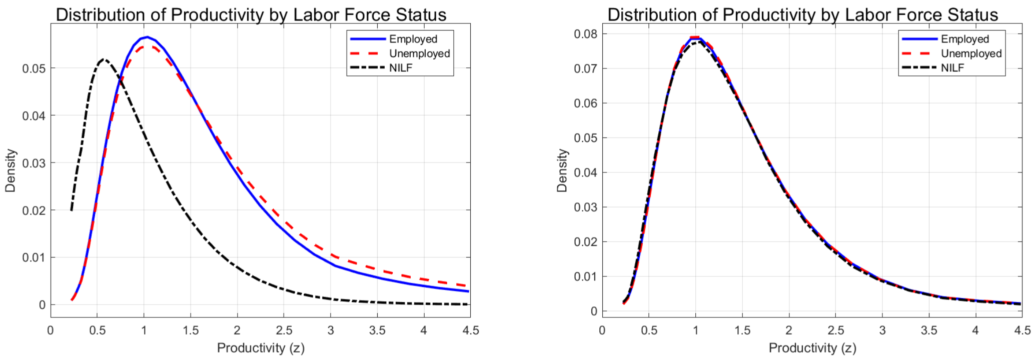

Figure 17: Distribution of Individuals' Idiosyncratic Productivity by Labor Market Status. Left: Full Model. Right: Best Calibration without Selection.

Figure 17 again emphasizes how selection is intertwined with the participation surplus, and hence labor supply elasticities, for individuals in different labor force statuses.