The Cyclical Behavior of Unemployment Claims*

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Abstract

The insured unemployment rate (IUR)—the percentage of covered workers who are seeking unemployment benefits in a given week—is a key barometer of US labor market conditions. I develop a framework for decomposing cyclical changes in the IUR into contributions from initial claims, claim denials, job finding, and benefit exhaustions. Using event studies around the onset of state-level recessions, I show that about two thirds of the recessionary increase in the IUR reflects elevated initial claims, due to increased flows into unemployment, a larger share of job losers among the unemployed, and an increase in claims filed per job loser. Reduced job finding also contributes to the higher IUR, while increased exhaustions have a small negative effect on the IUR.

Keywords: unemployment insurance, initial claims, continued claims, layoffs, job finding, business cycle fluctuations

JEL codes: J64, J65

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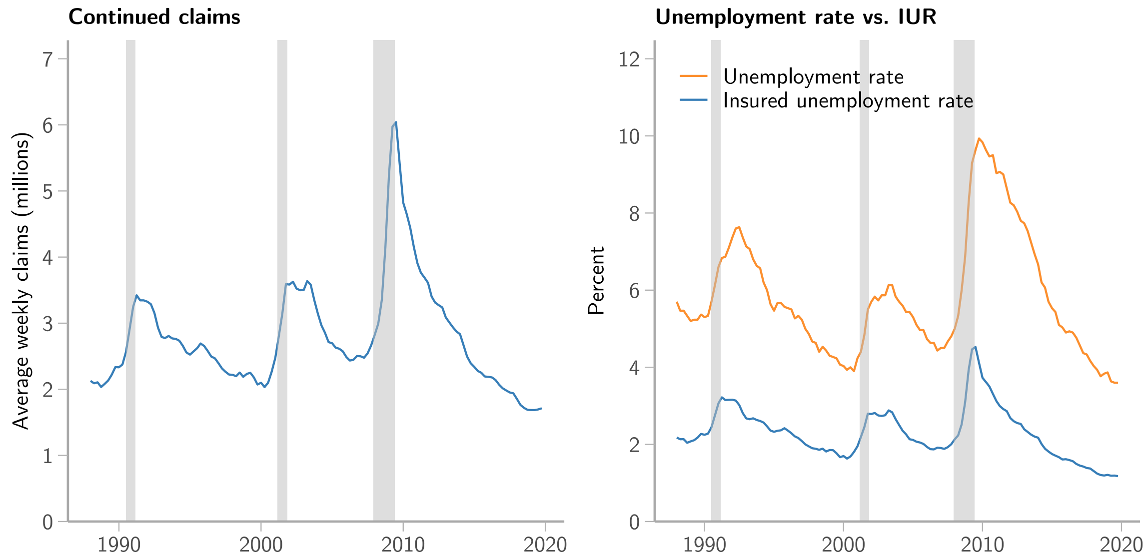
1 Introduction

In the US unemployment insurance (UI) system, continued claims represent the stock of unemployed workers seeking benefits in a given week. Because they are reported in near–real time, observed at weekly frequency, and strongly countercyclical, both initial and continued claims are widely followed barometers of labor market conditions. Indeed, the insured unemployment rate (IUR)—defined as the ratio of continued claims to UI-covered employment—closely tracks the unemployment rate over the business cycle (Figure 1). In principle, the IUR is informative about changes in unemployment along both job-losing and job-finding margins. In practice, however, interpretation of the IUR is clouded by institutional factors and measurement challenges that influence flows into and out of the UI system.

In this paper, I develop a novel framework for tracking UI inflows and outflows. Using Department of Labor data spanning 1988–2019, I decompose state- and national-level changes in the IUR into contributions from initial claims, claim denials, job finding, and benefit exhaustions. To understand the cyclical behavior of UI claims, I estimate event studies around the onset of state-level recessions. During recessions, (i) initial claims rise, (ii) more claims are denied due to insufficient earnings, (iii) fewer claims are denied due to invalid reasons for separation, (iv) claimants are slower to find jobs, and (v) more claims reach the point of benefit exhaustion. Using my decomposition framework, I show that the glut of initial claims accounts for about two thirds of the recessionary increase in the IUR, with reduced job finding accounting for the remainder. Initial claims rise not only because more workers are entering unemployment, but also because a larger share of these workers are job losers who are potentially eligible for benefits, and because a larger share of job losers file claims. Increased exhaustions have a slight negative effect on the IUR in the latter stages of a recession, while changes in denial rates have a negligible effect on net.

This paper makes three contributions. First, I shed new light on the cyclical behavior of UI claims. At the individual level, UI benefits are a major source of income support

Figure 1: Continued claims and the insured unemployment rate



Notes: Source data are from the Bureau of Labor Statistics via FRED. Left panel shows quarterly averages of weekly continued claims. Right panel shows quarterly averages of the US unemployment rate and insured unemployment rate (the ratio of weekly continued claims to UI-covered employment). Here and in subsequent figures, UI series are seasonally adjusted using the Census Bureau's X13-ARIMA package.

for displaced workers (East and Simon, 2024). At the macro level, countercyclical increases in benefit receipt are a major automatic stabilizer (Chodorow-Reich and Coglianese, 2019). Moving beyond heuristic interpretations of why the IUR rises during recessions, I provide a quantitative breakdown that distinguishes the roles of economic and institutional factors in driving this increase. Because my framework can be implemented at both the state and national levels over a long period of time, it could be used to answer other questions about UI, such as how changes in benefit generosity affect UI inflows and outflows, or why the share of unemployed workers receiving UI benefits fell sharply in the 2010s (Vroman, 2018).

Second, I derive a novel proxy for the job-finding rate, a key indicator for understanding and modeling labor market dynamics (Barnichon and Nekarda, 2012; Elsby, Michaels, and Ratner, 2015; Ahn and Hamilton, 2019). My framework yields an estimate of withdrawals from UI net of claim denials and benefit exhaustions. While these withdrawals partly reflect labor force exit and other lapses in filing, I show that changes in the withdrawal rate closely track changes in job finding among unemployed job losers in the Current Population Survey

(CPS). The UI withdrawal rate is a useful complement to the CPS because it is (i) based on administrative data and thus immune to declining response rates to government surveys, (ii) measurable over a long time period, and (iii) available at both state and national levels.

Third, I complement a longstanding literature that decomposes changes in the US unemployment rate into contributions from inflows and outflows (Darby, Haltiwanger, and Plant, 1986; Shimer, 2005; Hall, 2005; Elsby, Michaels, and Solon, 2009; Fujita and Ramey, 2009; Shimer, 2012). In contrast to movements in the unemployment rate—which recent research has tended to find occur mostly along the outflow margin (job finding)—I show that increased inflows drive most of the recessionary increase in the IUR. Alongside contributions from increased flows into unemployment, the IUR rises for two additional reasons: a larger share of unemployed workers are job losers—as opposed to quitters or labor market entrants, who are generally ineligible for UI—and a larger share of job losers file claims. Because these additional channels affect continued claims but not overall unemployment, the IUR is more strongly countercyclical than the unemployment rate, and the share of unemployed workers seeking UI benefits rises durng recessions.

Section 2 gives a brief overview of the UI system and UI data. Section 3 develops an accounting framework for decomposing changes in the IUR into inflows and outflows. Section 4 uses this framework to derive a proxy for the job-finding rate and to establish basic facts about UI flows. Section 5 analyzes the cyclical behavior of the IUR and UI flows. Section 6 examines the excess countercyclicality of the IUR. Section 7 concludes.

2 The UI system and UI data

Unemployment insurance (UI) is a joint state-federal program that provides weekly benefits to eligible workers who lose employment through no fault of their own. In this section, I provide a brief overview of the process through which workers apply for benefits, establish eligibility, receive benefits, and exit the system through job finding or other channels. Given the complexity of the UI system, the rules for which differ across states, I abstract from many institutional details to focus on the key points needed to understand claim volumes.[1] I then describe the Department of Labor (DOL) data used throughout the paper.

2.1 The life cycle of a UI claim

Upon losing a job, a worker may file an *initial claim* for benefits with their state employment office. To establish eligibility, claimants must document their recent employment and earnings history, as well as the reason they separated from their last job. Initial claims fall into two main categories. *New claims* are filed by workers who have not received benefits in the recent past. *Reopened claims* are filed by workers who seek to resume benefit receipt after an earlier, unexhausted claim.[2] Reopened claims accounted for an average of 37.3 percent of initial claims during my analysis period, which runs from 1988 through 2019.

New claimants first undergo a *monetary determination* that checks whether they earned enough during a pre-claim base period to establish eligibility.[3] A successful monetary determination stipulates the claimant's weekly benefit amount (indexed to prior earnings) and potential benefit duration (commonly 26 weeks). An average of 13.4 percent of new claims failed the monetary test during this period. Reopening claimants skip the monetary determination step because they have already established monetary eligibility.

Both new and reopened claims next undergo a *separation determination*, which assesses whether the claimant had a valid reason for leaving their employer. In most cases, claimants must have been laid off through no fault of their own; claimants who quit or who are fired for

[1]For overviews of the UI system, see O'Leary and Wandner (1997) and Woodbury (2014). For details about states' UI program parameters, see the Significant Provisions of State Unemployment Insurance Laws, available at https://oui.doleta.gov/unemploy/statelaws.asp.

[2]Reopened claims are officially known as "additional" claims. A third category is "transitional" claims, which are filed by workers who are switching from one "benefit-year" to another without having exhausted benefits. Transitional claims are excluded from the headline count of initial claims and have little bearing on continued claims, since claimants file weekly claims both before and after the transition.

[3]The base period varies across states but usually comprises the first four of the five most recent completed quarters. Monetary determinations often depend on both total and high-quarter base-period earnings, and some states require claimants to meet additional criteria, such as a minimum number of hours worked.

cause are generally ineligible for benefits.[4] The caseworker first considers the claimant's self-reported reason for separation, then contacts the former employer to verify the claimant's account.[5] Most eligible claims are quickly approved, but those flagged for a possibly invalid separation can take several weeks to resolve. Among initial claims that passed the monetary test, an average of 11.7 percent failed the separation test.

Throughout their unemployment spells, claimants must file weekly or biweekly *continued claims* certifying their ongoing eligibility, which depends primarily on how much (if anything) they earned in a given week, whether they actively looked for work, and whether they were available for work.[6] Eligibility is assessed on a weekly basis, and disqualifications may result in either temporary or permanent suspension of benefits. Benefits are likewise paid on a weekly basis. Payments were relatively prompt during this period: in over 90 percent of cases, payments began within four weeks of the first compensable week.

Workers may stop filing continued claims for several possible reasons. First, claimants become ineligible upon returning to work. Second, since eligibility requires active job search, claimants who exit the labor force also become ineligible. Third, claimants who reach their potential benefit duration exhaust their benefits. Finally, workers may stop filing because they are subject to benefit sanctions, believe themselves to be ineligible for other reasons, or decide that filing weekly claims is not worth the trouble.

2.2 State-level UI data

I track UI flows using state-level data from the DOL's Employment and Training Administration (ETA). States are required to submit regular reports on numerous aspects of UI administration. I use data submitted under ETA forms 207 (quarterly data on non-monetary

[4] Exceptions exist for claimants who quit for good cause, such as a significant reduction in wages, unsafe working conditions, harassment or discrimination, or quitting to accompany a spouse to a new location.

[5] Since employers' UI payroll taxes are experience-rated based on benefits paid to their laid-off workers, they have an incentive to dispute invalid separations (Lachowska, Sorkin, and Woodbury, 2023).

[6] Workers file continued claims beginning with their first week of unemployment or the week of their initial claim, whichever is later, and do so during waiting weeks, pending eligibility tests, and after establishing eligibility. Claimants with low but nonzero earnings in a given week may be eligible for partial benefits.

determinations), 218 (quarterly data on monetary determinations), 539 (weekly data on initial and continued claims), 5159 (monthly data on types of initial claims as well as the number of final payments), and 9051 (monthly data on payment delays).[7] While many of these data go back to the 1970s, weekly claim volumes are first reported in the mid-1980s, and state-level coverage is incomplete in the first few years of data.

The ETA data suffer from two notable sources of measurement error. First, states occasionally fail to submit a particular report, resulting in missing values for some observations. Second, the data sometimes exhibit pronounced outliers that likely represent data entry errors or administrative flukes. I address these issues in three ways. First, I impute missing values by interpolating valid state-level data. Second, I conduct my analysis at quarterly frequency to mitigate the noise in weekly and monthly data. Third, alongside seasonal adjustment, I use the Census Bureau's X13-ARIMA package's built-in outlier detection to replace aberrant values. Appendix Figure A.1 shows an example of outlier adjustment for the monetary denial rate in Massachusetts.

3 An accounting framework for UI claims

To understand how the insured unemployment rate changes over the business cycle, I decompose changes in the stock of continued claims into inflows and outflows. On the inflow margin, unemployed workers file initial claims. On the outflow margin, claimants exit via claim denial, job finding, benefit exhaustion, or other cessations in filing. In this section, I develop an accounting framework for UI claims and implement it using ETA data.

Since data on initial and continued claims are collected on a weekly basis, I begin by accounting for claims at weekly frequency. Abstracting from some institutional details, and suppressing state subscripts for brevity, I assume that C_t, the number of continued claims

[7] These data are available at https://oui.doleta.gov/unemploy/DataDownloads.asp.

seeking compensation for unemployment experienced in week t, can be expressed as

$$C_t = C_{t-1} + \underbrace{(I_t^N + I_t^R)}_{\text{initial claims}} - \underbrace{(D_{t-1}^M + D_{t-1}^S)}_{\text{denials}} - \underbrace{(X_{t-1} + W_t)}_{\text{other outflows}} \tag{1}$$

where I_t^N is new claims filed in week t, I_t^R is reopened claims, D_t^M and D_t^S are denials on monetary and separation grounds, respectively, X_t is the number of claims reaching exhaustion in week t, and W_t is an unobserved residual reflecting all other exits from UI between weeks $t-1$ and t, which I call *withdrawals*.

The time conventions in Equation (1) embed several simplifying assumptions. First, I assume that claimants start filing continued claims in the week of their initial claim, since they generally cannot seek retroactive benefits for weeks of unemployment preceding their initial claim. Second, I assume that eligibility is immediately assessed, such that denied applicants file only a single continued claim. Monetary determinations are usually swift, since state unemployment offices have ongoing access to the payroll data needed to calculate a claimant's base-period earnings. Most separation determinations are also prompt, though claims flagged for possible denial involve a longer period of fact-finding. Third, I assume that temporary lapses in filing reduce the *level* of continued claims but roughly cancel out in *changes*, since each temporary exit is accompanied by a subsequent resumption.

The ETA data are reported at a mixture of weekly, monthly, and quarterly frequencies. To convert all UI flows to a weekly basis, I first adjust continued claims for biweekly filing in a number of states.[8] Second, I set new and reopened claims equal to

$$I_t^N = \frac{I_{m(t)}^N}{I_{m(t)}^N + I_{m(t)}^R} I_t, \quad I_t^R = \frac{I_{m(t)}^R}{I_{m(t)}^N + I_{m(t)}^R} I_t \tag{2}$$

where I_t is total initial claims and $m(t)$ is the calendar month corresponding to week t. Third, I assume that denial rates are constant within quarters. Since only new claims

[8]Claimants in several states file continued claims on a biweekly basis, with each claim pertaining to two weeks of unemployment. While the ETA data convert claims from these states to weekly counts, unevenness in week-to-week inflows can result in an artificial sawtooth pattern in the published data. Following Cajner et al. (2020), I take a two-week moving average of claims in biweekly states to remove this artifact.

receive monetary determinations, I set $D_t^M = \delta_{q(t)}^M I_t^N$, where $\delta_{q(t)}^M$ is the share of new claims failing the monetary test in quarter $q(t)$, and $D_t^S = \delta_{q(t)}^S[(1-\delta_{q(t)}^M)I_t^N + I_t^R]$, where $\delta_{q(t)}^S$ is the share of initial claims failing the separation test. Fourth, as detailed in Appendix B, I compute weekly exhaustions by assuming that final payments are distributed uniformly throughout the month, then mapping final payments back to exhaustion dates using data on payment delays. With these pieces in place, I compute W_t by rearranging Equation (1).

The resulting weekly series are highly volatile, reflecting several sources of measurement error.[9] In addition, weekly claims are difficult to seasonally adjust, in part due to pronounced holiday effects whose timing varies from year to year (Cleveland and Scott, 2007). To mitigate these issues, and to align the UI series with other labor market data observed at lower frequencies, I aggregate all UI flows to the quarterly level, with weeks assigned to quarters based on the timing of the Saturday reference dates used in the ETA data.

I analyze UI flows at both state and national levels. To obtain national totals, I sum UI flows across the 53 UI programs, which include the 50 states, the District of Columbia, Puerto Rico, and the US Virgin Islands. For state-level analyses, I exclude the two territories, which are particularly prone to data issues. I seasonally adjust all quarterly series using the Census X-13 ARIMA package, separately for state- and national-level series. I use multiplicative seasonal adjustment to allow for scale changes in UI flows over the analysis period.

My analysis spans 1988–2019. The starting point reflects the availability of complete data on weekly claims. I exclude the COVID-19 recession, during which the UI system was transformed by emergency programs and plagued by measurement issues that preclude reliable implementation of my framework (Cajner et al., 2020; Price, 2021). While these institutional and measurement factors were largely resolved by 2022, I also exclude the post-pandemic period because, at the time of writing, no recession has been declared since then.

[9] First, while initial and continued claims are measured directly, construction of the remaining series requires strong assumptions about how claim composition, denial rates, and exhaustion rates are distributed within months and quarters. Second, claimants who are eventually denied may file continued claims for several weeks while eligibility is pending. Third, the monthly and quarterly data are based on which calendar days fall within each period, so that some claim-weeks straddle two periods. Finally, the raw state-level data sometimes exhibit weekly spikes that may reflect processing errors or abnormal events like hurricanes.

Finally, I restrict attention to regular state UI programs, as distinct from the Extended Benefits (EB) and Emergency Unemployment Compensation (EUC) programs that are frequently activated during recessions (Chodorow-Reich and Coglianese, 2019). While EUC, in particular, has played a prominent role in recent recessions, flows into and out of EB and EUC are largely determined by when the programs are triggered on or off. By focusing on regular state claims, I analyze a consistent set of institutions over the course of the business cycle. Because most claimants were eligible for up to 26 weeks of benefits during the recessions I study, my results are generally representative of UI flows among "short-term" unemployed workers who have been out of work for six months or less. Throughout the paper, *benefit exhaustion* refers to running out of regular benefits, even though claimants in some periods were able to transition immediately to EB or EUC.

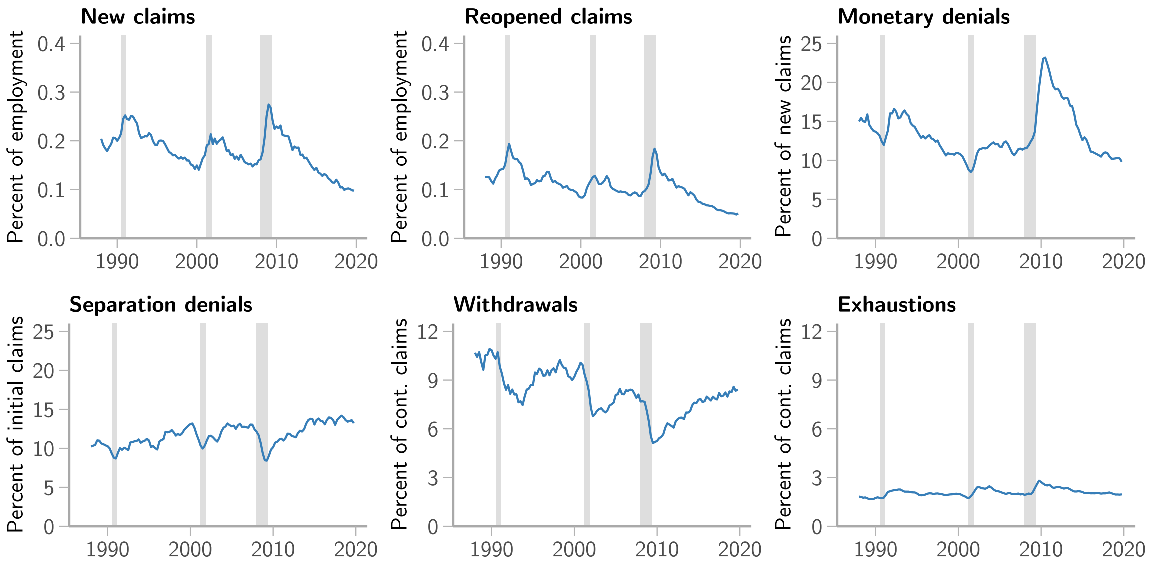
4 Basic facts about UI flows

I now have quarterly estimates of new and reopened claims, monetary and separation denials, exhaustions, and other withdrawals from UI. In this section, I first show how these flows evolved over the analysis period. Next, I show that the withdrawal rate closely tracks the job-finding rate among unemployed job losers, suggesting that it can be interpreted as a novel proxy for job finding. Finally, as a precursor to my more detailed state-level analysis, I show how each flow component contributes to national changes in in the IUR.

4.1 Three decades of UI flows

Figure 2 expresses these flow variables as rates by dividing initial claims by covered employment, monetary and separation denials by the number of initial claims experiencing each type of determination, and withdrawal and exhaustion rates by continued claims. New and reopened initial claims are strongly countercyclical, consistent with increased layoffs in a weaker labor market. Monetary denials rise in the aftermath of each recession: downturns

Figure 2: UI flow rates

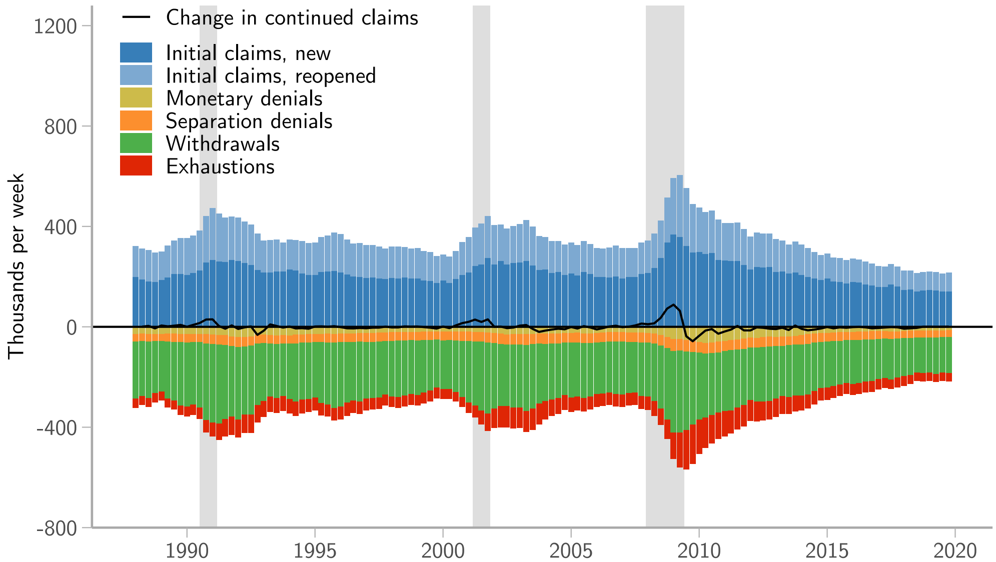


Notes: Quarterly averages of weekly UI flow rates, obtained by implementation of Equation (1).

erode workers' earnings and exhaust their entitlements, so that fewer claimants have enough base-period earnings to pass the monetary test. By contrast, separation denials fall during recessions, reflecting a compositional shift towards no-fault layoffs and away from quits and firings for cause. Consistent with lower job-finding rates, the withdrawal rate falls sharply during recessions, while the exhaustion rate rises. I revisit these national-level patterns in Section 5, where I analyze event studies around the onset of state-level recessions.

Figure 3 plots weekly changes in continued claims (black series) along with each of the inflow and outflow components that appear in Equation (1). Several facts emerge from this figure. First, net changes in continued claims are dwarfed by gross flows. Second, gross inflows and outflows are both countercyclical, with clear increases during each recession. The mirror-image relationship between inflows and outflows is unsurprising, since almost all claimants who enter UI exit the system within at most 26 weeks. Third, new claims account for the majority of inflows, but reopened claims make a significant contribution as well. Fourth, withdrawals net of denials and exhaustions account for the lion's share of outflows.

Figure 3: Decomposition of changes in continued claims



Notes: Quarterly averages of weekly UI flows, obtained by implementation of Equation (1).

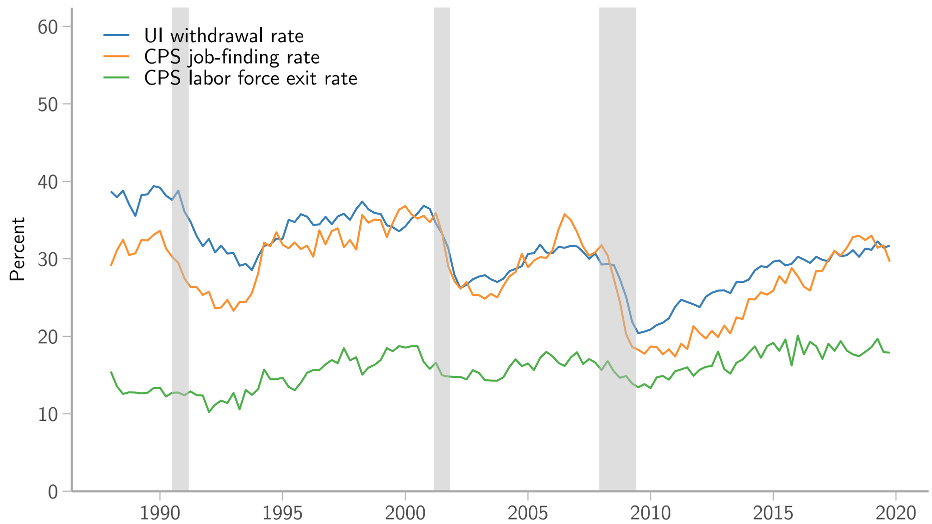
4.2 Withdrawals from UI as a proxy for job finding

Withdrawals from the UI system, net of denials and exhaustions, should primarily reflect reemployment and labor force exit. To gauge whether the withdrawal rate indeed captures these transitions, I compare it against transition rates among unemployed respondents to the Current Population Survey (CPS). Using CPS microdata provided by IPUMS (Flood et al., 2023a), I link individuals observed in back-to-back months, restrict the sample to individuals who report being unemployed due to job loss, track monthly transitions into employment or non-participation, and aggregate to the state or national level using longitudinal weights.[10] For an apples-to-apples comparison, I express both UI withdrawals and CPS transitions as monthly rates averaged to quarterly frequency.

Figure 4 plots the UI withdrawal rate (blue) against the job-finding rate (orange) and labor force exit rate (green) among CPS job losers. The withdrawal rate closely tracks the job-finding rate, suggesting that cyclical movements in UI withdrawals primarily reflect

[10]Following Madrian and Lefgren (2000), I validate cross-period individual linkages on the basis of sex, age, and race, and I exclude probable mismatches from this analysis. I also interpolate missing CPS flow rates for a couple of months in 1995, when respondents cannot be linked across surveys.

Figure 4: UI withdrawal rate vs. exit rates among unemployed job losers

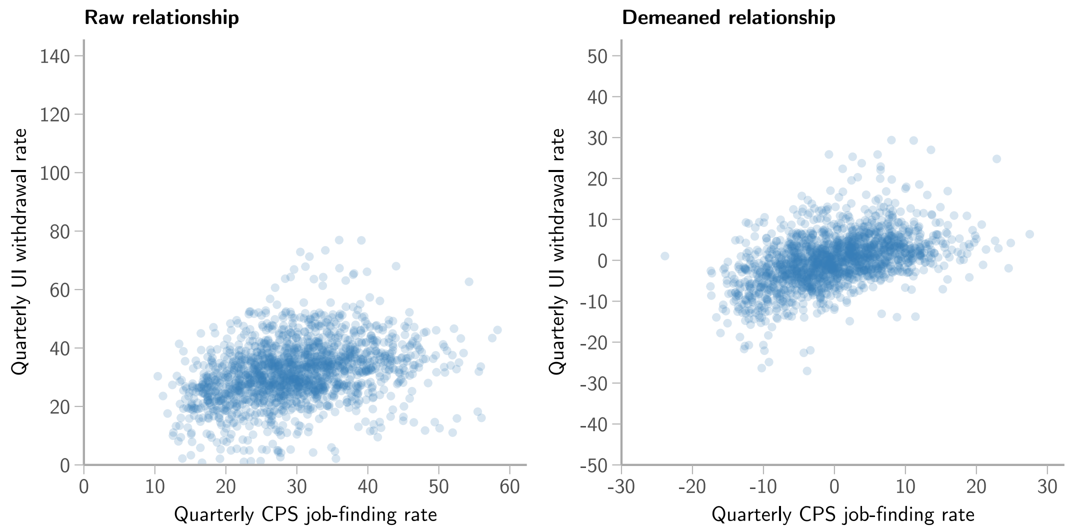


Notes: The UI withdrawal rate is calculated as in Equation (1). The job-finding rate and labor force exit rate are calculated using month-to-month transitions among longitudinally linkable CPS respondents. All series are seasonally adjusted quarterly averages of monthly flow rates.

changes in job finding. By contrast, labor force exit exhibits much more muted cyclical patterns. Since the withdrawal rate is computed as a residual, its close correspondence with an independent measure of job finding validates the usefulness of the accounting framework in Section 3. Furthermore, it justifies my interpretation of the withdrawal rate as a novel proxy for the job-finding rate that could be useful in future research.

To further validate this interpretation, Figure 5 plots the relationship between UI withdrawals and CPS job finding at the state $\times$ year level. As shown in the left panel, the raw measures are positively correlated ($\widehat{\rho} = 0.34$). Since UI withdrawal rates may vary across states for a host of institutional and compositional reasons unrelated to labor market conditions, the right panel removes level differences between states by demeaning each measure within states and across years. The correlation strengthens ($\widehat{\rho} = 0.47$), consistent with the idea that changes in job-finding rates are a key driver of UI withdrawals.

Figure 5: Job finding and UI withdrawals at the state level



Notes: Each circle represents a state × year observation, where I take annual averages of monthly UI withdrawal rates and CPS job-finding rates among unemployed job losers. The right panel plots each observation minus the state-level mean value of each measure over the analysis period.

4.3 Flow contributions to the insured unemployment rate

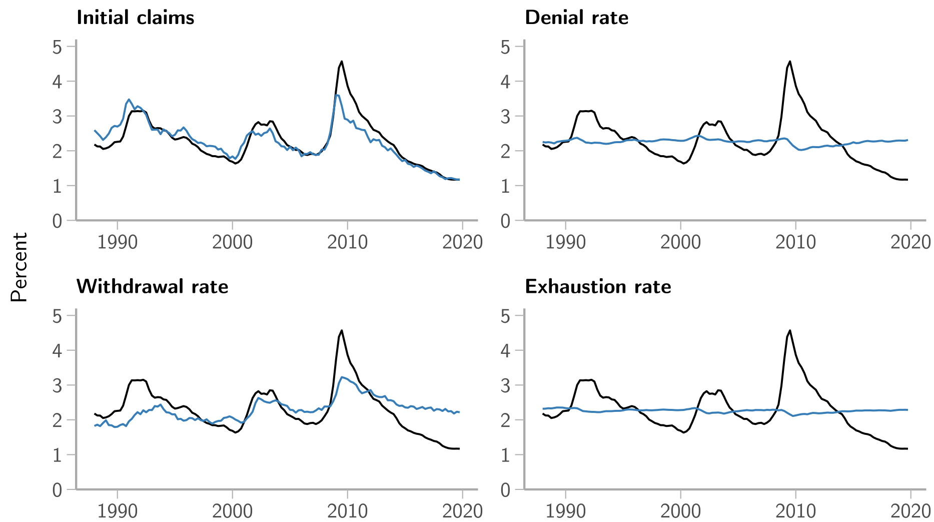
As a first step towards understanding the cyclical behavior of the insured unemployment rate (IUR)—the ratio of continued claims to UI-covered employment—I examine how each UI flow contributes to changes in the national IUR. As detailed in Appendix C, I begin by approximating the IUR with a "steady-state" IUR consistent with contemporaneous UI flows. Let ι_t, δ_t, ω_t, and χ_t denote the initial claims rate, (overall) denial rate, withdrawal rate, and exhaustion rate, respectively. Then the flow-consistent IUR is given by

$$IUR_t^* \equiv \frac{(1-\delta_t)\iota_t}{\omega_t + \chi_t} \tag{3}$$

Intuitively, the flow-consistent IUR depends on how initial claims, discounted by the denial rate, compare with outflows from the UI system. Because UI flows are relatively rapid—with claimants who enter the system exiting within one or two quarters—the flow-consistent IUR closely tracks the observed IUR (Appendix Figure A.2).

Next, to isolate each flow's contribution to the evolution of the IUR, I calculate a

Figure 6: Flow contributions to the evolution of the insured unemployment rate



Notes: In each panel, the black series shows the observed IUR, while the blue series shows a counterfactual IUR reflecting temporal variation only in the indicated flow rate (as in Equation (4)).

counterfactual version of IUR_t^* that holds all other flow rates constant at their average values over the analysis period. For example, to measure the contribution from initial claims, I compare the observed IUR against

$$IUR_t^{cf} \equiv \frac{(1-\overline{\delta})\iota_t}{\overline{\omega}+\overline{\chi}}, \tag{4}$$

where bars denote period means. Variation in IUR_t^{cf} is driven exclusively by variation in the initial claims rate. Combining this expression with similar series for denials, withdrawals, and exhaustions yields a first-order approximation of changes in the national IUR.

The top left panel of Figure 6 shows that changes in the initial claims rate explain most of the cyclical variation in the IUR. The bottom left panel shows that changes in the withdrawal rate also contribute to the cycle. Changes in the denial and exhaustion rates have much less bearing on changes in the IUR.[11] In the next section, I exploit the timing and severity of state-level recessions to verify and quantify these national-level patterns.

[11]Note that Figure 6 reflects only the direct effect of changes in *realized* denial rates among workers who apply for benefits. Changes in states' eligibility rules may indirectly affect the IUR by influencing the share of unemployed workers who file initial claims.

5 The cyclical behavior of UI flows

The insured unemployment rate is strongly countercyclical, which may reflect countercyclical inflows, procyclical outflows, or both. In this section, I analyze the evolution of state-level UI flows around the onset of recessions to understand the cyclical behavior of each flow component. I then decompose the recessionary increase in the IUR into contributions from each flow. I find that a rise in initial claims accounts for most of the increase in the IUR, though reduced withdrawals also play a significant role. Increased exhaustions have a small negative effect on the IUR, while changes in denial rates have negligible effects on net.

5.1 Event-study methodology

Three nationwide recessions occurred during the analysis period. To expand the number of events and increase statistical power, I analyze UI flows around the start of state-level recessions, defined based on turning points in the unemployment rate.[12] I construct quarterly state unemployment rates by averaging monthly data from the Local Area Unemployment Statistics (LAUS). I identify the start of recessions using an algorithm from Dupraz, Nakamura, and Steinsson (2025), who use a threshold rule to identify turning points while ignoring small wiggles in the unemployment rate. To illustrate this procedure, Appendix Figure A.3 plots the resulting recession dates in the state of Illinois. While most states experience three recessions roughly coincident with those at the national level, the exact timing varies across states, and some states experience a different number of recessions.

For each outcome y_{st} and each horizon $h \in \{-12, \ldots 20\}$, I estimate local projections at quarterly frequency using the specification

$$y_{s,t+h} - y_{s,t-1} = \alpha_h + \beta_h \cdot R_{st} + \varepsilon_{s,t+h}, \tag{5}$$

[12] At the national level, recession dates are determined by the National Bureau of Economic Research (NBER) based on multiple indicators of economic activity. NBER recession dates are unavailable at the state level; moreover, changes in unemployment may not coincide exactly with declines in economic activity.

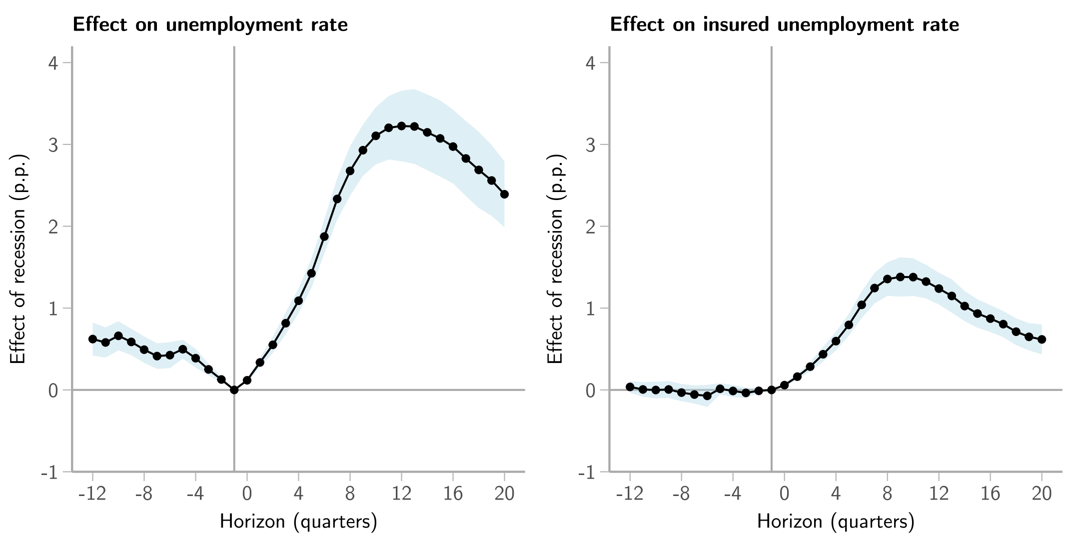
where R_{st} is an indicator for a recession starting in quarter t. The coefficients of interest $\widehat{\beta}_h$ trace out the cumulative evolution of an outcome before and after the onset of a recession. To obtain estimates representative of the UI system as a whole, I weight observations by the state's contemporaneous UI-covered employment. I cluster standard errors by state.

5.2 Recessionary changes in UI flows

To gauge the severity of the recessions used in my analysis, the left panel of Figure 7 plots the evolution of the unemployment rate (UR) around the start date of a recession. Because I define recessions based on turning points in the UR, it mechanically reaches a nadir in quarter $t = -1$. The UR then rises over the ensuing three years, peaks at 3.2 percentage points (p.p.) above its baseline value, and then declines as the economy recovers. This average increase masks heterogeneity between the shallower recessions in the early 1990s and early 2000s and the much larger Great Recession of the late 2000s.

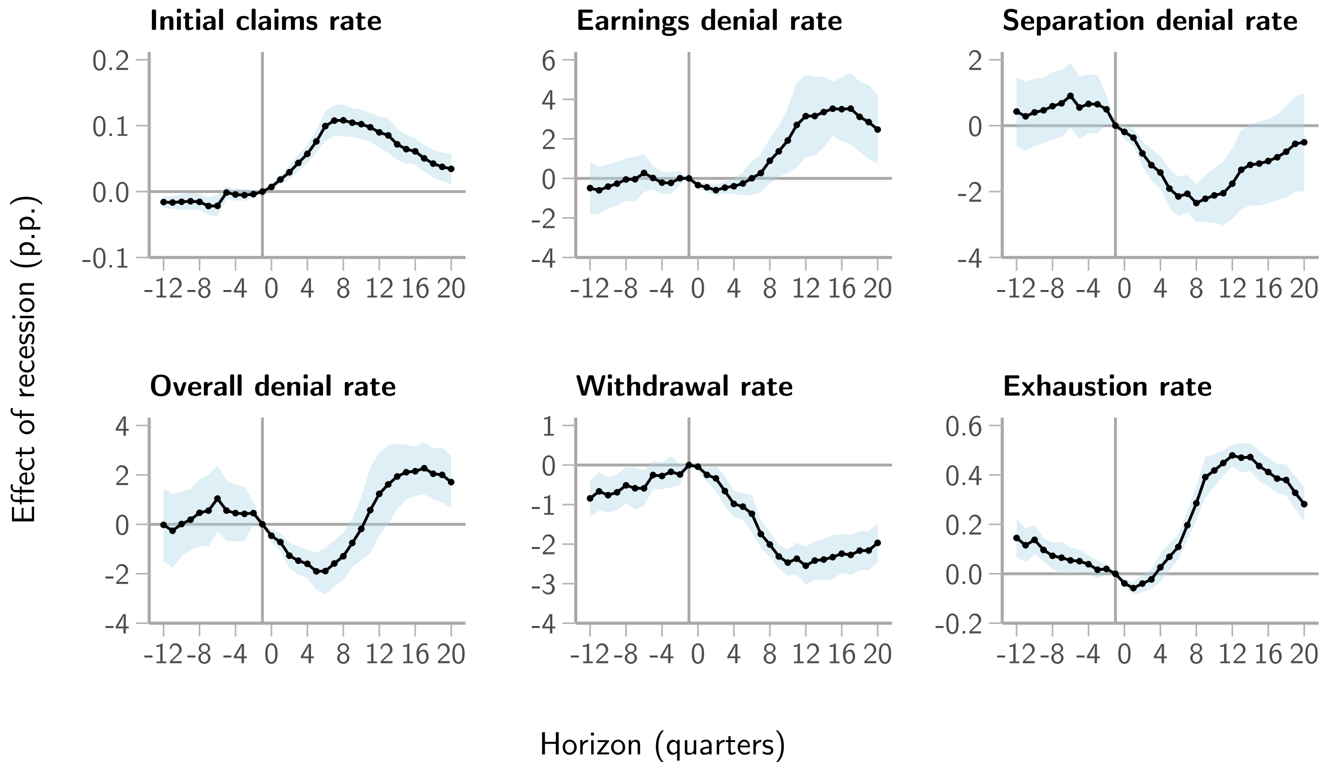
The right panel of Figure 7 shows the evolution of the IUR, which is broadly comparable

Figure 7: Recessionary increases in unemployment and insured unemployment



Notes: Event-study coefficients estimated from Equation (5). The insured unemployment rate is defined as the ratio of continued claims to UI-covered employment.

Figure 8: Recessionary changes in UI flow rates



Notes: Event-study coefficients estimated from Equation (5). The coefficients for initial claims, withdrawals, and exhaustions express the effect of a recession on weekly flow rates. The coefficients for denials express the effect of a recession on the share of initial claims experiencing each type of denial.

with the UR.[13] The IUR follows a path similar to that of the UR, peaking at 1.4 p.p. above its baseline 10 quarters into a recession. The relative increases in the two measures roughly line up with their average ratio over the analysis period: the IUR generally ranges between 30 and 40 percent of the UR, reflecting the fact that many unemployed workers are ineligible for benefits and many eligible workers do not seek benefits.

Turning to UI flow rates, Figure 8 examines how initial claims, denials, withdrawals, and exhaustions evolve over the course of a recession. Initial claims are steady heading into a recession, then rise over the next two years. Relative to UI-covered employment, the share of workers filing an initial claim in a given week peaks 0.1 p.p. above baseline two years after

[13]The IUR is defined as the ratio of continued claims to UI-covered employment, while the UR is the ratio of unemployment to the labor force. The two measures differ chiefly because many unemployed workers are not receiving UI benefits, but also because of more modest differences in the denominator.

the start of a recession. New and reopened claims rise in a similar fashion, with a slightly larger increase in new claims (Appendix Figure A.4).

Denials on monetary and separation grounds move in opposite directions. The monetary denial rate is flat for the first two years of a recession but rises thereafter; claims filed four years into a recession are 3.5 p.p. more likely to fail the monetary test. The lagged response of monetary denials is consistent with the fact that, as a recession wears on, fewer workers will have built up sufficient base-period earnings to qualify for UI, and workers who previously qualified have already exhausted their entitlements. Separation denials fall during recessions by up to 2.3 p.p., consistent with a compositional shift towards claimants with no-fault layoffs; indeed, denial rates on the grounds of both quits and firings for cause decline during recessions (Appendix Figure A.5). On net, overall denials fall below baseline initially but rise above baseline in the latter stages of a recessionary cycle.

Weekly withdrawals from the UI system, net of denials and exhaustions, decline significantly over the first three years of a recession, reaching a low point 2.5 p.p. below baseline, and remain low even five years later. The decline in withdrawals is likely driven primarily by depressed job finding among unemployed job losers (Figure 4), though it may also reflect a lower rate of labor force exit during recessions (Rothstein, 2011). The share of continued claimants exhausting benefits in a given week rises by up to 0.5 p.p. during recessions, since a lower job-finding rate implies that more claimants use up all of their benefits.

5.3 Decomposing the rise in the IUR

How does cyclicality in these UI flows translate into changes in the insured unemployment rate? To answer this question, I compare the observed IUR to a series of counterfactual IURs that shut down the contribution from recessionary changes in each flow.

Decomposition methodology. I first rewrite Equation (1) to derive a law of motion for the weekly IUR. Let t index quarters and $w \in \{1, 2, \ldots, 13\}$ index weeks within a quarter, and again suppress state subscripts. Dividing by UI-covered employment $E_{t,w}$ yields

$$IUR_{t,w} = (1 - \delta_t)\iota_t + \left(\frac{1}{1 + g_t, w} - \omega_t - \chi_t\right) IUR_{t,w-1}, \tag{6}$$

where $g_{t,w}$ is the average weekly rate of employment growth and $IUR_{t,0} \equiv IUR_{t-1,13}$.[14] In this equation, ι_t is weekly initial claims as a share of employment, δ_t is the overall denial rate, and ω_t and χ_t are the withdrawal and exhaustion rates as shares of continued claims. I assume that these rates are constant within quarters.

To isolate the contribution of initial claims to the recessionary increase in the IUR, I compare the observed IUR at each event horizon to a counterfactual series that holds the initial claims rate fixed at its baseline value. To do so, I first iterate Equation (6) forward to obtain IUR_{t+h} for each quarterly horizon h.[15] Next, I construct a counterfactual IUR^{cf}_{t+h} by iterating Equation (6) with ι_{t-1} in place of $\iota_{t+k}, k \in \{0, \ldots, h\}$ in each successive period after baseline. I then estimate another set of state-level local projections with the difference in these series on the left-hand side:

$$IUR_{s,t+h} - IUR^{cf}_{s,t+h} = \alpha_h + \beta_h \cdot R_{st} + \varepsilon_{s,t+h} \tag{7}$$

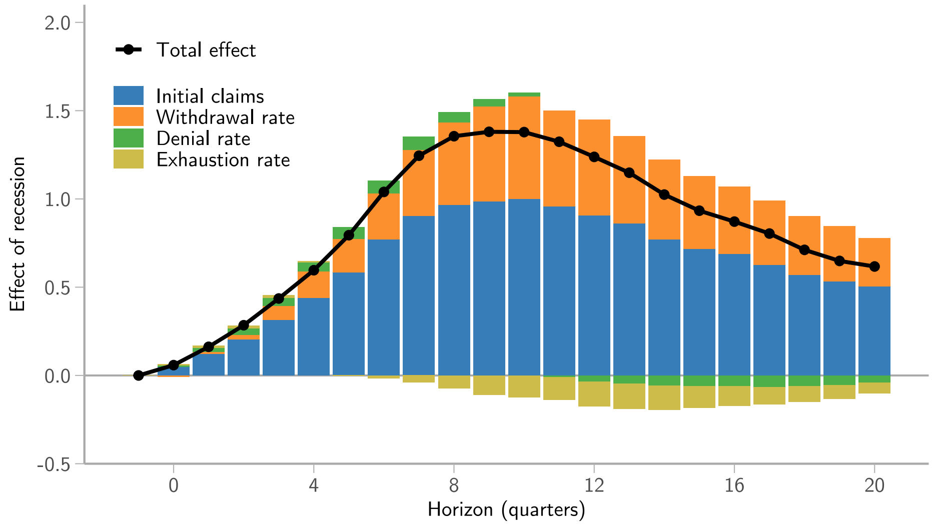
This procedure transforms changes in the initial claims rate into "IUR space" to estimate how recessionary increases in initial claims contribute to changes in the IUR.

In a similar fashion, I isolate the effects of denials, withdrawals, and exhaustions by repeating this procedure with each respective rate held fixed at baseline. Doing so yields a first-order decomposition of changes in the IUR, with an approximation error reflecting higher-order interactions between the flow components over the course of a recession.

[14] The ETA measure of covered employment, E_t, is constant within each quarter. I assume that employment grows by $g_{t,w} \equiv \frac{1}{13}\frac{E_t - E_{t-1}}{E_{t-1}}$ each week within the quarter.

[15] I construct the "observed" IUR by iterating the law of motion—rather than using the observed value directly—because of small approximation errors in Equation (6). By using the same procedure to construct $IUR_{s,t+h}$ and $IUR^{cf}_{s,t+h}$, these errors are differenced out.

Figure 9: Decomposition of the recessionary increase in the IUR



Notes: Contributions of recessionary changes in UI flows to changes in the insured unemployment rate, computed as defined in the text and equal to the $\widehat{\beta}_h$ coefficients in Equation (7).

Decomposition results. Figure 9 shows the resulting decomposition. Rising initial claims (blue bars) drive most of the 1.4 p.p. increase in the IUR observed 10 quarters after baseline, contributing 1.0 p.p. in that quarter. Decreased withdrawals (orange) make a significant contribution as well, contributing 0.6 p.p. in that same quarter. Denials (green bars) have a negligible effect on the IUR, boosting or depressing it by no more than 7 basis points (b.p.), in part reflecting the offsetting effects of changes in monetary and separation denials. Rising exhaustions (yellow) slightly reduce the IUR, by a maximum of 15 b.p. Adjusting for the approximation error, the takeaway is that initial claims account for about two thirds of the recessionary increase in the IUR, while decreased withdrawals account for about one third.

The drop in withdrawals likely reflects a combination of less job finding, fewer labor force exits, and fewer benefit sanctions. A larger share of job losers remain in the labor force during recessions (Figure 4) and hence are potentially eligible for UI. In addition, fewer claimants are sanctioned for failing to meet ongoing eligibility requirements, such as engaging in job search and meeting reporting requirements (Appendix Figure A.6).[16] Both of these

[16]Consistent with the decline in these non-monetary, non-separation sanctions, the share of continued claims that eventually receive compensation increases during recessions (Appendix Figure A.7).

factors show up as fewer withdrawals within my framework. As such, the orange bars in Figure 9 are likely an upper bound on the contribution from reduced job finding alone.

Robustness. To assess the robustness of these results, I repeat the decomposition procedure using two alternative specifications. First, I examine how *national* UI flows evolve around the start of *national* recessions by estimating

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h \cdot R_t + \varepsilon_{t+h}, \tag{8}$$

Second, I repeat the state-level analysis using a dose-response specification in which the recession indicator is multiplied by D_{st}, defined as the trough-to-peak increase in the unemployment rate in a recession that starts at time t:

$$y_{s,t+h} - y_{s,t-1} = \alpha_h + \beta_h \cdot D_{st} \cdot R_{st} + \varepsilon_{s,t+h} \tag{9}$$

This latter specification exploits variation in both the timing and the severity of state-level recessions. Consistent with my main specification, both of these approaches show that about two thirds of the recessionary increase in the IUR reflects a rise in initial claims, with fewer withdrawals playing a secondary role (Appendix Figure A.8, Appendix Figure A.9).

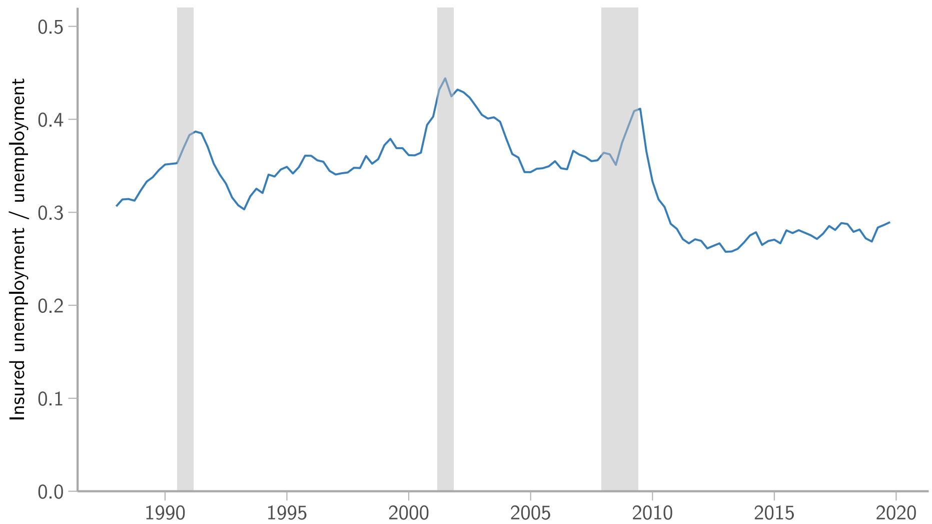
6 The excess countercyclicality of UI claims

Insured unemployment—the number of continuing claimants—is more cyclical than total unemployment. To illustrate this point, Figure 10 shows that the share of unemployed workers who are filing continued claims rises during recessions and falls during expansions.[17] Since recessionary increases in the IUR are driven primarily by a sharp rise in initial claims, a natural question is: why are initial claims so countercyclical?

To answer this question, I decompose the contribution of initial claims to the recession-

[17] Continued claims as a share of unemployment fell significantly and persistently after the Great Recession. The secular drop in this share is likely due partly to state-level policy changes, such as reductions in potential benefit duration and increased sanctions, that reduced UI eligibility and take-up (Vroman, 2018).

Figure 10: Share of unemployed workers filing continued claims



Notes: Ratio of insured unemployment to the number of unemployed workers.

ary increase in the IUR into three channels: (i) increased flows into unemployment; (ii) a compositional shift among newly unemployed workers towards job losers and away from quitters and entrants; and (iii) an increase in the number of claims filed per job loser.

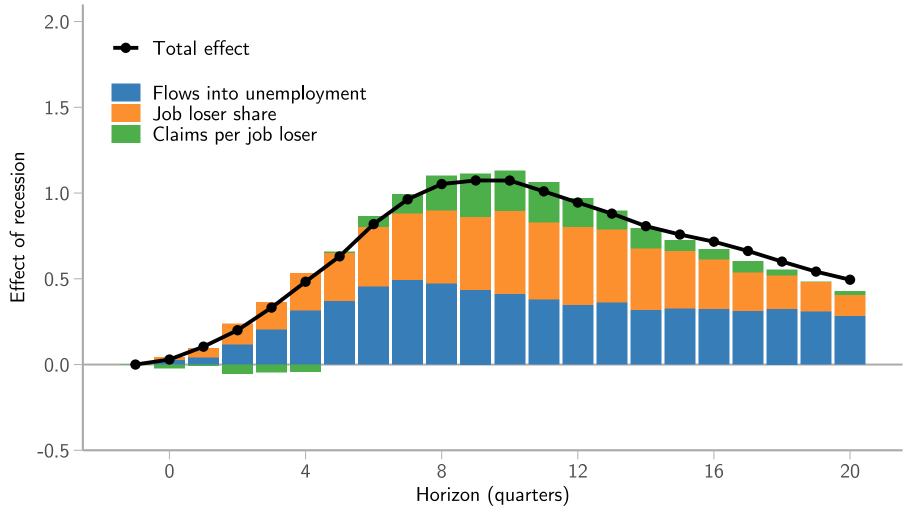
I start by decomposing the initial claims rate as

$$\frac{I_t}{E_t} \equiv \frac{U_t^{\text{new}}}{E_t} \cdot \frac{J_t^{\text{new}}}{U_t^{\text{new}}} \cdot \frac{I_t}{J_t^{\text{new}}} \tag{10}$$

where U_t^{new} is the number of individuals entering unemployment in a given month (either from employment or from non-participation) and J_t^{new} is the number of new job losers. Appendix D details how I compute these terms using monthly CPS data on employment, unemployment, reasons for unemployment, and unemployment durations. My approach is adapted from Shimer (2005) and adjusts for time-aggregation bias in the observed month-to-month flow rate into unemployment. Because unemployment duration is only reported in the CPS microdata from 1994 forward, I restrict this analysis to the years 1994–2019.

Adapting the methodology laid out in Section 5.3, for each period t and horizon h, I compute a counterfactual series IUR_{t+h}^{cf} isolating the contribution from flows into unemployment by holding $\frac{U_t^{\text{new}}}{E_t}$ fixed at its baseline value, while allowing all other terms to evolve

Figure 11: Subdecomposing the contribution from initial claims to changes in the IUR



Notes: Decomposition of the overall contribution of increased initial claims to the recessionary increase in the IUR, computed by combining Equation (10) with the event-study methodology developed in Section 5.3.

freely over time. I use the same procedure to isolate the contributions from the job-loser share and from initial claims per job loser. With these series in hand, I again estimate state-level local projections as in Equation (5) to measure the contribution of each component to the recessionary increase in the IUR. As in my earlier analysis, summing these components yields a first-order approximation to the overall contribution from initial claims.

As shown in Figure 11, all three channels contribute to the recessionary increase in the IUR. First, the IUR rises because a larger number of individuals are entering unemployment. Second, it rises further because a larger share of these individuals are job losers—as opposed to quitters and labor force entrants, who are generally ineligible for UI. Finally, a larger share of job losers file initial claims, imparting a modest additional boost to the IUR. Increased filing likely reflects a combination of greater eligibility rates—consistent with the fact that workers laid off during recessions have higher pre-separation wages (Mueller, 2017)—and an increased take-up rate among those eligible for UI (Trenkle, 2024), which could arise because workers expect and experience longer unemployment durations during recessions. Since the second and third channels affect insured unemployment but not total unemployment, the IUR is more countercyclical than the overall unemployment rate.

7 Conclusion

The insured unemployment rate is a key barometer of labor market conditions, but its cyclical properties are not well understood. I develop a novel framework for decomposing changes in the IUR into contributions from initial claims, claim denials, job finding, and benefit exhaustion. Using state-level variation in the timing of recessions, I show that initial claims explain about two thirds of the recessionary increase in the IUR, with decreased withdrawals accounting for the remainder. Because the increase in initial claims reflects increases not only in flows into unemployment, but also in the job loser share of these flows and the number of claims filed per job loser, the IUR is more countercyclical than the unemployment rate.

My framework can be extended to analyze additional questions about UI and the labor market. First, it provides a useful point of departure for understanding secular changes in UI stocks and flows, such as the persistent decline in the share of unemployed workers filing continued claims in the aftermath of the Great Recession. Second, my novel proxies for state- and national-level job-finding rates complement existing measures derived from the Current Population Survey. A statistical model combining the two series—such as a Kalman filter—could yield improved measures of job finding as an input into analyses of factors affecting labor market dynamics. Third, while I end my analysis in 2019 to circumvent the complications posed by the COVID-19 pandemic, my framework can be readily extended to the post-pandemic period. Although implementing my methodology at monthly or weekly frequency would present additional measurement challenges, doing so could yield a timely new indicator of current labor market conditions.

References

Ahn, Hie Joo and James D. Hamilton. 2019. "Heterogeneity and Unemployment Dynamics." *Journal of Business and Economic Statistics*, 38(3): 554–569.

Barnichon, Regis and Christopher J. Nekarda. 2012. "The Ins and Outs of Forecasting Unemployment: Using Labor Force Flows to Forecast the Labor Market." *Brookings Papers on Economic Activity*, Fall 2012: 83–131.

Cajner, Tomaz, Andrew Figura, Brendan M. Price, David Ratner, and Alison Weingarden. 2020. "Reconciling Unemployment Claims with Job Losses in the First Months of the COVID-19 Crisis." Federal Reserve Board, Finance and Economics Discussion Series No. 2020-055.

Chodorow-Reich, Gabriel and John Coglianese. 2019. "Unemployment Insurance and Macroeconomic Stabilization." Hamilton Project policy proposal.

Cleveland, William P. and Stuart Scott. 2007. "Seasonal Adjustment of Weekly Time Series with Application to Unemployment Insurance Claims and Steel Production." *Journal of Official Statistics*, 23(2): 209–221.

Darby, Michael R., John C. Haltiwanger, and Mark W. Plant. 1986. "The Ins and Outs of Unemployment: the Ins Win." NBER working paper no. 1997.

Dupraz, Stéphane, Emi Nakamura, and Jón Steinsson. 2025. "A Plucking Model of Business Cycles." *Journal of Monetary Economics*, 103766: 1–14.

East, Chloe N. and David Simon. 2024. "The Safety Net and Job Loss: How Much Insurance Do Public Programs Provide?" *Journal of Public Economics*, 238(105171).

Elsby, Michael W. L., Ryan Michaels, and David Ratner. 2015. "The Beveridge Curve: A Survey." *Journal of Economic Literature*, 53(3): 571–630.

Elsby, Michael W., Ryan Michaels, and Gary Solon. 2009. "The Ins and Outs of Cyclical Unemployment." *American Economic Journal: Macroeconomics*, 1(1): 84–110.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, Daniel Backman, Annie Chen, Grace Cooper, Stephanie Richards, Megan Schouweiler, and Michael Westberry. 2023a. "IPUMS CPS: Version 11.0 [dataset]." Minneapolis, MN: IPUMS. https://doi.org/10.18128/D030.V11.0.

Fujita, Shigeru and Garey Ramey. 2009. "The Cyclicality of Separation and Job Finding Rates." *International Economic Review*, 50(2): 415–430.

Hall, Robert E. 2005. "Job Loss, Job Finding, and Unemployment in the US Economy over the Past Fifty Years." *NBER Macroeconomics Annual*, 20: 101–137.

Lachowska, Marta, Isaac Sorkin, and Stephen A. Woodbury. 2023. "Firms and Unemployment Insurance Take-Up." NBER working paper no. 30266.

Madrian, Brigitte C. and Lars John Lefgren. 2000. "An Approach to Longitudinally Matching Current Population Survey (CPS) Respondents." *Journal of Economic and Social Measurement*, 26(1): 31–62.

Mueller, Andreas I. 2017. "Separations, Sorting, and Cyclical Unemployment." *American Economic Review*, 107(7): 2081–2107.

O'Leary, Christopher J. and Stephen A. Wandner, ed. 1997. *Unemployment Insurance in the United States: Analysis of Policy Issues.* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Price, Brendan M. 2021. "Why Have Initial Unemployment Claims Stayed So High for So Long?" Federal Reserve Board, FEDS Notes.

Rothstein, Jesse. 2011. "Unemployment Insurance and Job Search in the Great Recession." *Brookings Papers on Economic Activity*, Fall 2011.

Shimer, Robert. 2005. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies." *American Economic Review*, 95(1): 25–49.

Shimer, Robert. 2012. "Reassessing the Ins and Outs of Unemployment." *Review of Economic Dynamics*, 15(2): 127–148.

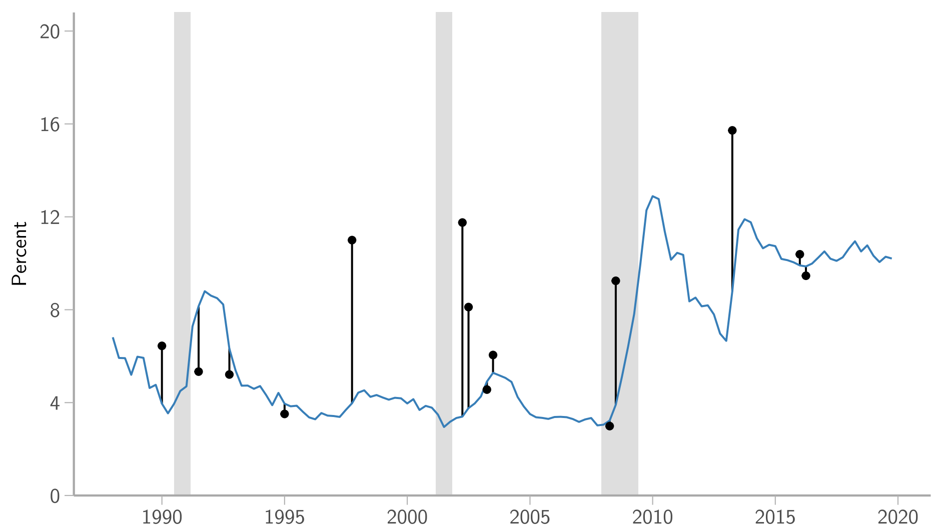
Trenkle, Simon. 2024. "Unemployment Insurance Receipt, Take-Up and Labor Market Conditions." Working paper.

Vroman, Wayne. 2018. "Unemployment Insurance Benefits: Performance Since the Great Recession." Urban Institute research report.

Woodbury, Stephen. 2014. "Unemployment Insurance." In *Oxford Handbook of US Social Policy.* 471–490.

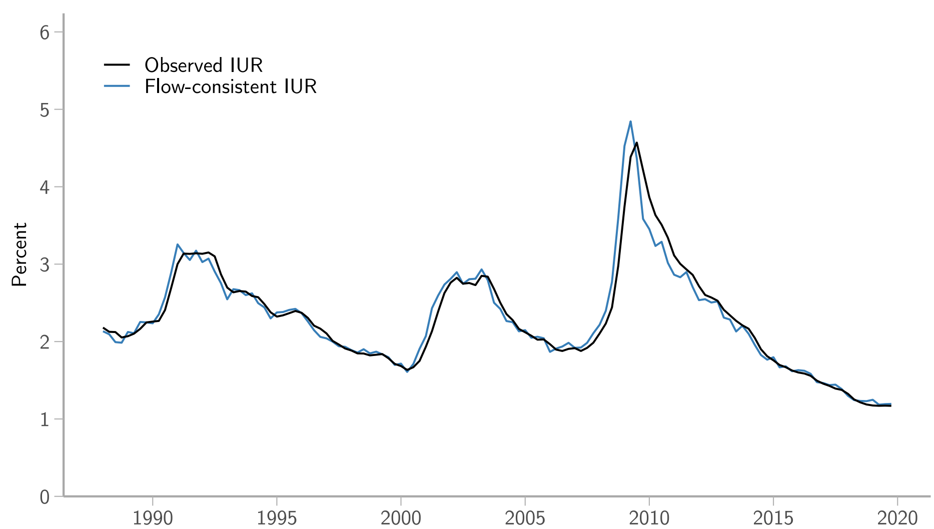
A Additional Figures and Tables

Appendix Figure A.1: Adjusting for outliers in the Massachusetts monetary denial rate



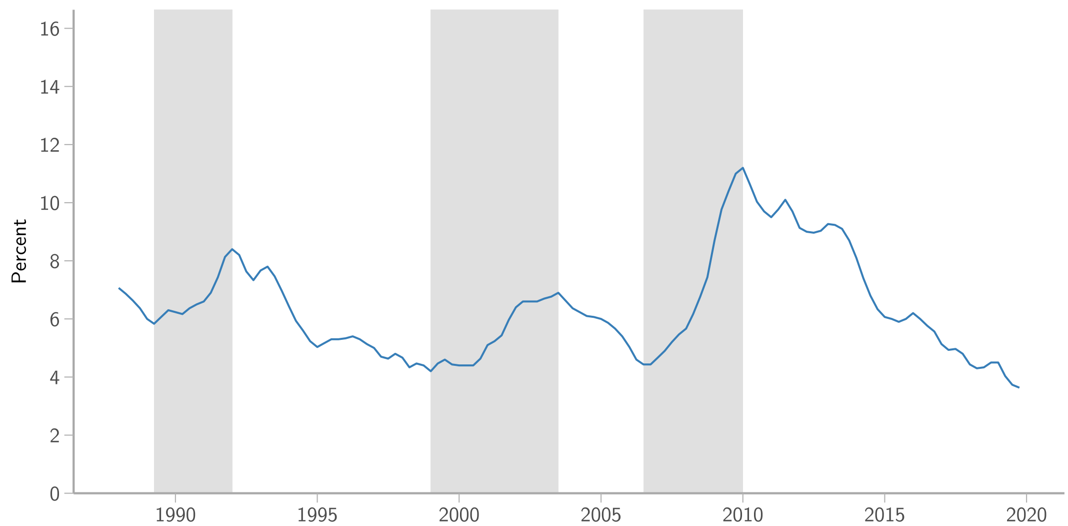
Notes: Example of automatic outlier adjustment supplied by the Census X-13 ARIMA package, using Massachusetts's monetary denial rate. The black dots are replaced by model predictions.

Appendix Figure A.2: Insured unemployment rate consistent with current UI flows



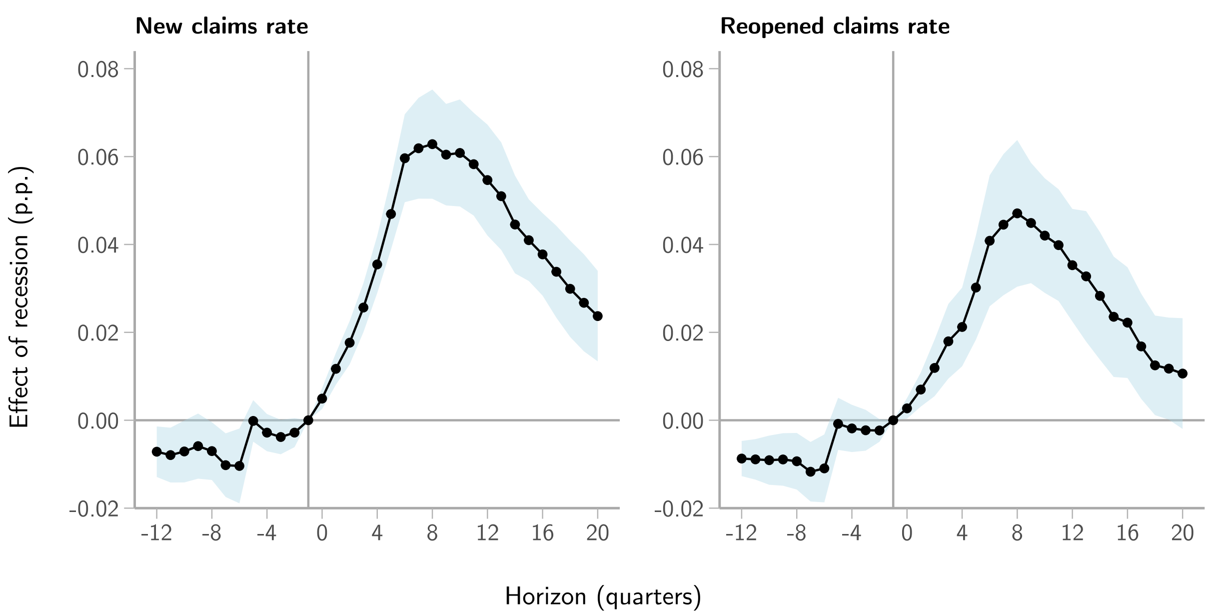
Notes: The flow-consistent insured unemployment rate is the IUR derived in Equation (3), as implied by the current initial claims, denial, withdrawal, and exhaustion rates. The series is multiplied by a scale factor to align it with the average level of the observed IUR over the analysis period.

Appendix Figure A.3: Turning points in Illinois's unemployment rate



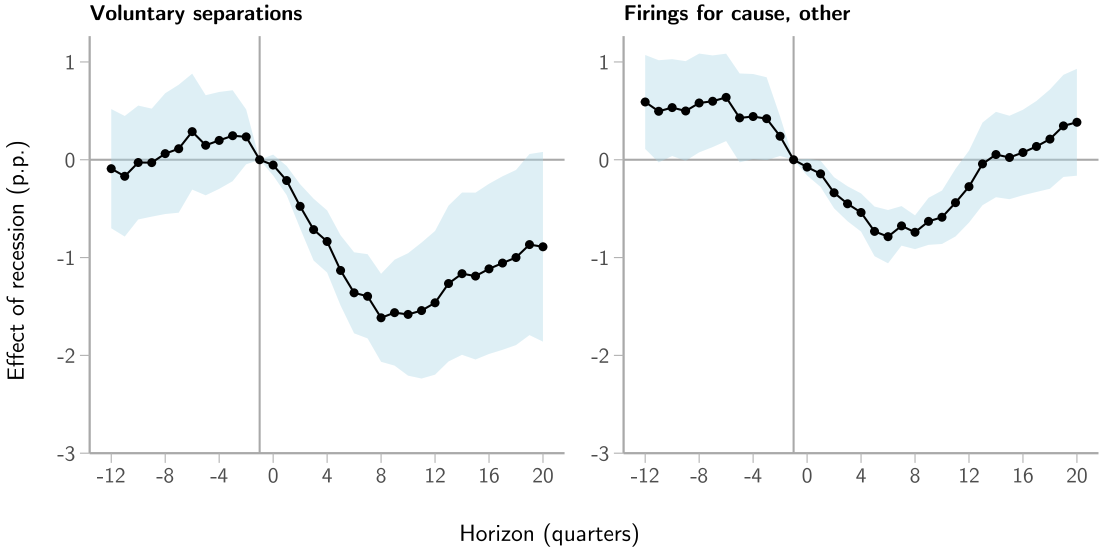
Notes: Recession dates are defined using an algorithm from Dupraz, Nakamura, and Steinsson (2025), who identify turning points in the unemployment rate using a threshold rule that disregards small wiggles.

Appendix Figure A.4: Recessionary changes in new and reopened initial claims



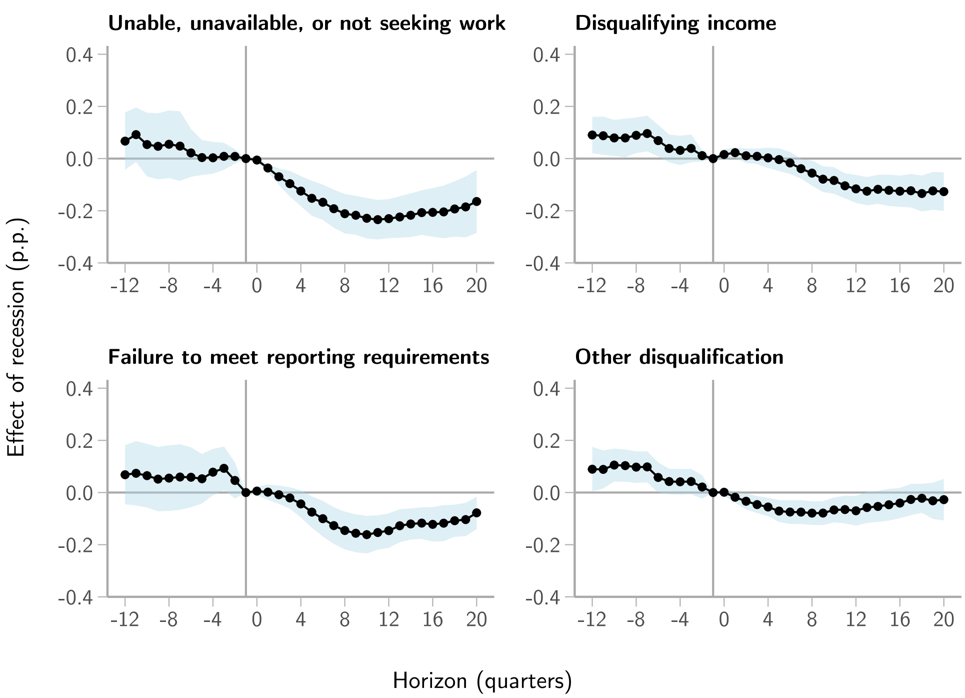
Notes: Event-study coefficients estimated from Equation (5). Each series is expressed as the number of claims filed in a given week divided by UI-covered employment.

Appendix Figure A.5: Recessionary changes in separation denial rates, by reason



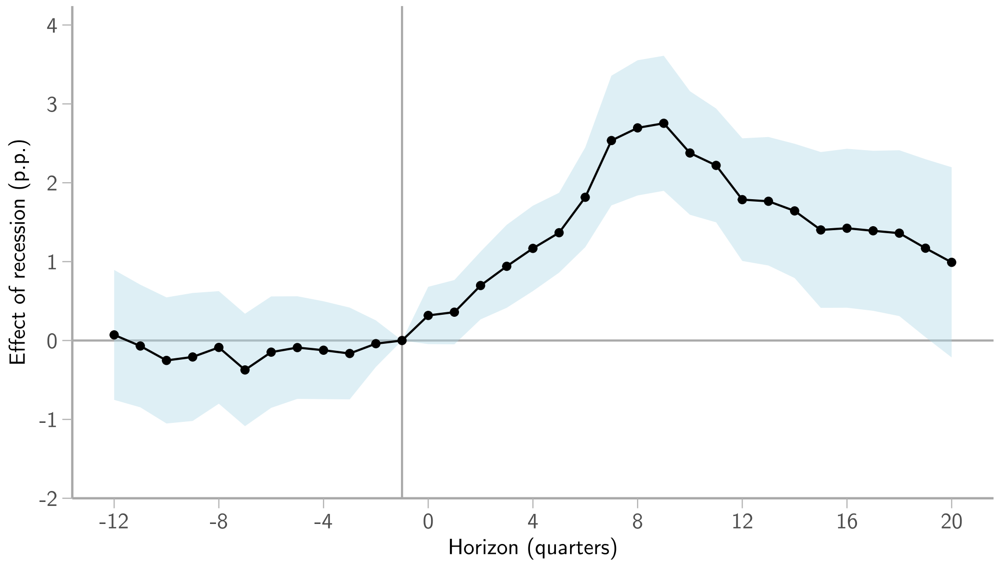
Notes: Event-study coefficients estimated from Equation (5). Each series is expressed as the number of denials for the indicated reason as a share of initial claims.

Appendix Figure A.6: Recessionary changes in non-monetary, non-separation denials



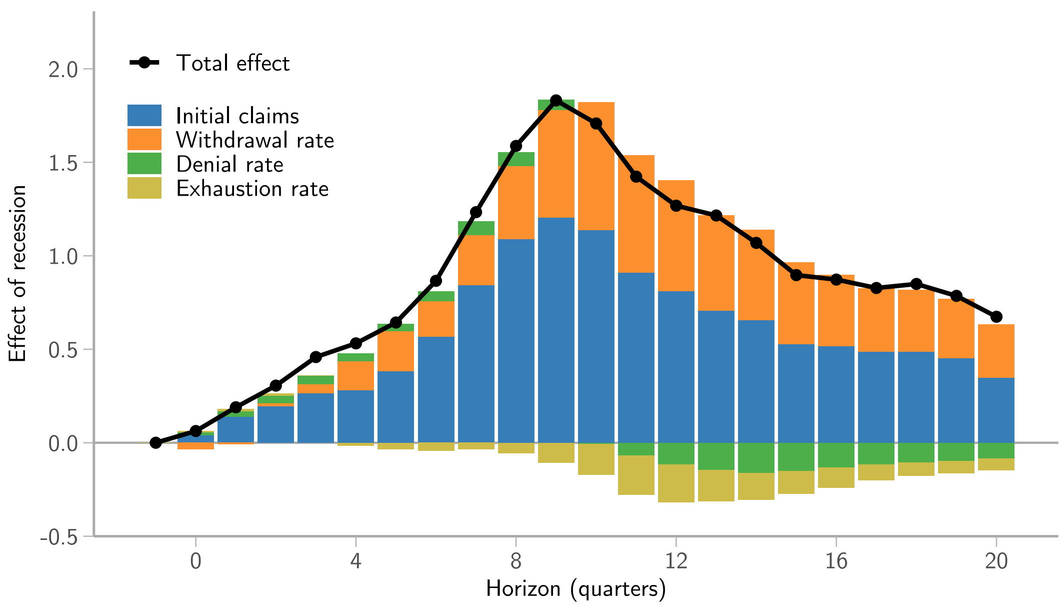
Notes: Event-study coefficients estimated from Equation (5). Each series is expressed as the number of denials in a given week divided by the number of continued claims.

Appendix Figure A.7: Recessionary changes in the share of continued claims that subsequently receive compensation



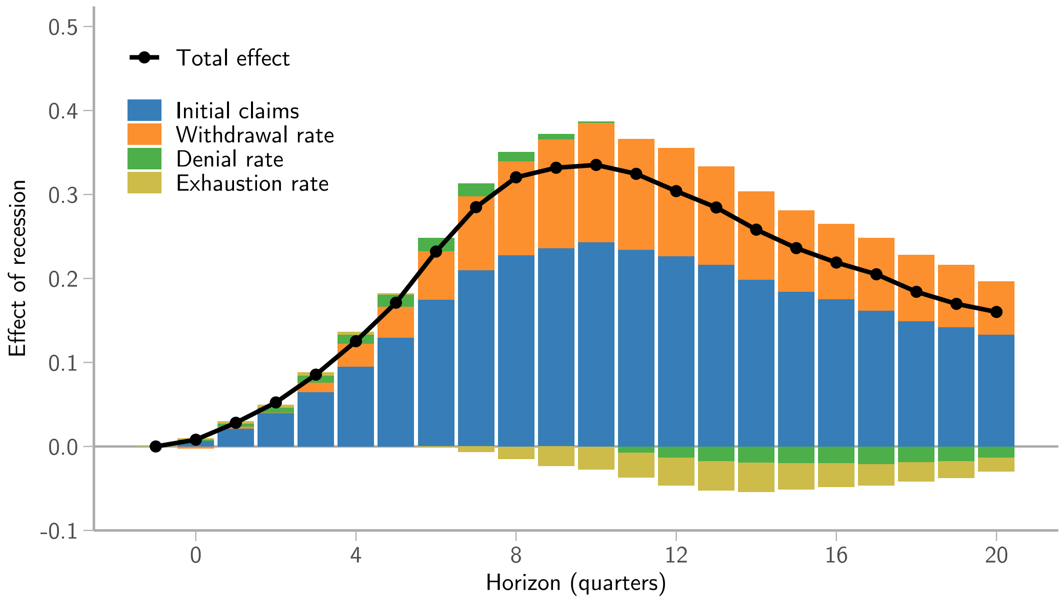
Notes: Event-study coefficients estimated from Equation (5).

Appendix Figure A.8: Decomposition of the IUR using national-level recessions



Notes: Event-study coefficients estimated from Equation (8).

Appendix Figure A.9: Decomposition of the IUR using dose-response recessions



Notes: Event-study coefficients estimated from Equation (9).

B Imputing weekly benefit exhaustions

I impute weekly benefit exhaustions by using data on payment delays to map final payments back to probable exhaustion dates.

In ETA form 9051, states report the number of *all* payments in a given month broken down by the number of weeks elapsed since the corresponding continued claim (i.e., the corresponding week of unemployment). Lacking data on delays for final payments specifically, I assume that these delays are distributed identically to average delays among all payments. To avoid attributing very long lapses between exhaustions and final payments, I restrict attention to payments issued within eight weeks. I then compute the share of payments by number of weeks delayed. Since the ETA 9051 data are only available starting in 1997, I impute payment delays for 1988–1996 using the distribution of payment delays over the first available decade, 1997–2006, which averages through different parts of the business cycle. To allow for possible seasonal differences in the timeliness of payments, I do this imputation separately for each calendar month.

In ETA form 5159, states report the number of final payments—paid to claimants who have reached exhaustion—issued each month during my analysis period. I assume that final payments are uniformly distributed across all calendar days within the month, then aggregate daily payments to the reference weeks used in ETA data on initial and continued claims (prorating payments for weeks that span multiple months). Next, I merge the weekly final payment counts from ETA 5159 with the monthly distribution of payment delays from ETA 9051. Finally, I use the delay shares to map these final payments back to their corresponding claim-weeks. Since I focus on delays lasting up to eight weeks, I am able to use pre-pandemic data from January and February 2020 to impute exhaustions in late 2019.

C A flow-consistent insured unemployment rate

In Section 4.3, I construct counterfactual IURs that isolate the contribution of each UI flow to changes in the observed national IUR. To do so, I rewrite Equation (1) to derive a "steady-state" or "flow-consistent" IUR consistent with contemporaneous IUR flows.

Suppressing state subscripts, set $C_t = C_{t-1}$, as we have in steady state, and suppose that all flow rates are constant for two consecutive quarters, so that I can use t in place of $t-1$ wherever the latter appears. Combine initial claims and denials by setting $I_t \equiv I_t^N + I_t^R$ and $D_t \equiv D_t^M + D_t^S$. Let ι_t, δ_t, ω_t, and χ_t denote the initial claims rate, denial rate, withdrawal rate, and exhaustion rate, respectively. Starting with Equation (1),

$$\begin{aligned} C_t &= C_{t-1} + I_t^N + I_t^R - D_{t-1}^M - D_{t-1}^S - X_{t-1} - W_t \\ 0 &= I_t - D_t - W_t - X_t \end{aligned}$$

Dividing by UI-covered employment E_t and rearranging yields

$$\begin{aligned} 0 &= \frac{I_t}{E_t} - \frac{D_t}{I_t}\frac{I_t}{E_t} - \frac{W_t}{C_t}\frac{C_t}{E_t} - \frac{X_t}{C_t}\frac{C_t}{E_t} \\ 0 &= \iota_t - \delta_t \iota_t - \omega_t IUR_t^* - \chi_t IUR_t^*, \end{aligned}$$

where IUR^*_t denotes the IUR consistent with contemporaneous UI flows. Reinterpreting t as indexing quarters and isolating the flow-consistent IUR yields Equation (3):

$$IUR^*_t = \frac{(1-\delta_t)\iota_t}{\omega_t + \chi_t},$$

The flow-consistent IUR deviates from the observed IUR for two reasons. First, because Equation (1) characterizes *changes* in continued claims, it does not speak directly to the *level* of continued claims. In addition to transitional dynamics, observed claims may deviate consistently from flow-consistent claims due to measurement errors or temporary lapses in claiming. In practice, IUR_t and IUR^*_t differ by a scale factor that is roughly constant over the analysis period. To highlight cyclical changes in the IUR, I level-adjust IUR^*_t by multiplying it by the average of $\frac{IUR_t}{IUR^*_t}$ over the analysis period.

Second, the two series differ because, at a given point in time, the IUR is unlikely to be in the momentary steady state implied by current flows. In particular, changes in the flow-consistent IUR tend to lead changes in the observed IUR since it takes time for the actual stock of continued claimants to catch up with changes in UI flows. Since quarterly UI flows are large relative to the stock, however, this convergence happens relatively quickly, and the two series are quite close in practice (Appendix Figure A.2).

D Decomposing initial claims

Using monthly Current Population Survey (CPS) microdata provided by IPUMS (Flood et al., 2023a), I calculate the number of newly unemployed and newly laid-off individuals, separately by state, over 1994–2019. Doing so allows me to analyze how flows into unemployment, compositional shifts among the newly unemployed, and changes in filing rates among job losers contribute to the recessionary increase in the IUR.

Computing state-level unemployment rates and job-loser rates. I begin by constructing a sample of civilian CPS respondents aged 15 or older. Let i, s, and m index individuals, states, and year-months, respectively. Let u_{ism} be an indicator for whether i is unemployed, let j_{ism} indicate whether i cites job loss as their reason for unemployment, and let u^{new}_{ism} and j^{new}_{ism} indicate the subset of individuals who have been unemployed for no more than four weeks. Using final cross-sectional weights provided by IPUMS, I average these indicators across individuals and across months to obtain shares u_{st}, j_{st}, u^{new}_{st}, and j^{new}_{st} for each state s and each year-quarter t. I seasonally adjust each series, separately by state, using the Census X13-ARIMA package. Since the state-level series have occasional zeroes, I do so using additive seasonal factors.

Adjusting for time-aggregation bias. The cross-sectional share of individuals who are newly unemployed is an approximate measure of flows into unemployment, but it suffers from what Shimer (2005) termed time-aggregation bias. Because the CPS defines labor market status based on a respondent's activities during a single reference week out of the month, individuals who both enter and exit unemployment within the same month have unobserved unemployment spells.

Shimer (2005) proposes an adjusted flow rate into unemployment that corrects for time-aggregation bias. While Shimer abstracts from labor market entry, I retain non-participants in my sample, so that Shimer's separation rate can be interpreted as the flow rate into unemployment. Start with a law of motion for the unemployment rate:

$$u_m = u_{m-1}(1 - f_m) + u_m^{\text{new}},$$

where f_m is the share of unemployed workers who obtain employment between months $m-1$ and m. Rearranging this equation gives

$$f_m = 1 - \frac{u_m - u_m^{\text{new}}}{u_{m-1}}, \tag{11}$$

which can be calculated from the CPS microdata.[1]

Shimer notes that CPS respondents who enter unemployment in a given month have an average of two weeks to obtain employment before the next month's reference week. His observation implies the approximate relationship

$$u_m^{\text{new}} = s_m(1 - u_{m-1}) \left(1 - \frac{1}{2} f_m\right),$$

where s_m is the share of not-unemployed individuals (whether employed or out of the labor force) who enter unemployment. Isolating s_m gives

$$s_m = \frac{u_m^{\text{new}}}{(1 - u_{m-1}) \left(1 - \frac{1}{2} f_m\right)}, \tag{12}$$

The takeaway is that the newly unemployed and new job-loser rates understate true flows into unemployment by a scale factor equal to the denominator in Equation (12).

To adjust for time-aggregation bias, I calculate this scale factor at quarterly frequency—call it α_t—using national-level data to reduce the noise associated with measurement of the job-finding rate. I then define adjusted state-level measures of new unemployment by setting

$$\begin{aligned} \widetilde{u}_{st}^{\text{new}} &\equiv \frac{u_{st}^{\text{new}}}{\alpha_t} \\ \widetilde{j}_{st}^{\text{new}} &\equiv \frac{j_{st}^{\text{new}}}{\alpha_t}, \end{aligned}$$

which represent the number of newly unemployed individuals as a share of the population. To convert these shares into levels comparable with UI-covered employment, I multiply them by each state's sum of the CPS population weights, then multiply them by the ratio of LAUS unemployment to CPS unemployment to counteract the greater noisiness of the CPS measures. Doing so yields the estimates of U_t^{new} and J_t^{new} that appear in Equation (10).

[1]Since workers who start out unemployed, then exit and reenter unemployment within the same month are captured by u_m^{new}, the job-finding rate is not subject to time-aggregation bias.