The Benefits of Unemployment Insurance For Marginally Attached Workers *

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Abstract

Existing research consistently finds that unemployment insurance (UI) benefits delay job finding with limited effects on job quality, but focuses on changes in UI generosity while holding fixed access to re-employment services. Using employer-employee matched data from Washington State and a fuzzy regression discontinuity design around the eligibility threshold for UI, we find that benefit receipt minimally delays re-employment but substantially improves labor market outcomes. UI increases cumulative hours worked by approximately 15 full-time weeks and earnings by $14,000 in the two years following job loss, representing 37 percent and 50 percent increases, respectively. These gains are driven by improved job quality, as recipients experience longer tenure and higher wages with their next employer. Effects are larger for workers living near public employment offices, suggesting that access to re-employment services enhances search productivity. Expanding UI access by lowering the eligibility threshold is much more cost-effective than raising benefit levels or extending potential duration, as workers benefit from more stable, higher-paying re-employment that partially offsets its cost.

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1 Introduction

An extensive literature documents the negative effects of more generous unemployment insurance (UI) benefits on job finding (Katz and Meyer, 1990; Landais, 2015; Johnston and Mas, 2018; Cohen and Ganong, 2024). At the same time, evidence is sparse that these delays in re-employment allow workers to find better jobs (Schmieder et al., 2016). In standard wage-setting models, UI serves as a worker's outside option, so more generous benefits should strengthen workers' bargaining positions and lead to higher wages. Yet, this prior work has focused almost exclusively on intensive-margin variation in the benefit level and potential duration and accordingly has focused on particular groups local to the quasi-experiment.[1] The effects may be different when we compare workers who receive UI benefits versus workers who do not.

This paper evaluates the labor market effects of UI receipt for workers with low incomes who lose their jobs and nearly qualify for benefits. Specifically, we exploit the fact that in Washington State, a "sufficient work history" requires workers to accumulate at least 680 hours of employment during the period before the job loss in order to be eligible for benefits. This threshold creates a discontinuity in UI eligibility and subsequent benefit receipt that we leverage using a fuzzy regression discontinuity design (RDD). In all OECD countries, eligibility for UI benefits requires sufficient contributions through formal labor market experience.[2] The exact amount of earnings or hours that sets the boundary for extensive-margin UI access is policy-relevant and often local to workers who are marginally attached to the labor market.

Contrary to most previous work, our setting has two novel features. First, this design allows us to identify the effects of UI receipt rather than benefit generosity. This

[1] For example, such work has studied higher earners at the kink in the benefit schedule (Landais, 2015; Card et al., 2015; Bell et al., 2024), older workers at an age cutoff (Card et al., 2007; Lalive, 2007; Schmieder et al., 2012), or all workers in a state subject to state-level variation (Kroft and Notowidigdo, 2016)

[2] Most European countries require 6 or 12 months of work, with Italy being the least stringent requiring 3 months (Unédic, 2023). In all U.S. states except Washington, UI access depends on earning a minimum amount during a defined reference period as opposed to working for a minimum amount of hours.

distinction is meaningful, as variation in receipt creates differences in weekly search requirements and access to employment services that variation in generosity alone does not. Second, we focus on a population of workers with less stable employment and lower incomes, whereas most quasi-experimental variation in benefit generosity applies to higher-income workers or the broader population of claimants. The effects of UI may differ for these populations due to different liquidity constraints, preferences, or job search behavior.

We estimate that UI receipt on the extensive margin minimally delays re-employment but substantially increases cumulative hours worked and earnings once workers find a new job. Workers just above the eligibility threshold who receive UI work approximately 15 additional full-time weeks and earn $14,000 more in the two years following job loss, representing 37 and 50 percent increases, respectively. These gains come from more stable, higher-paying jobs. Unlike most prior research, our setting captures variation in UI receipt itself, which combines monetary benefits with the institutional features of mandatory work search requirements and access to public employment services.

Using employer-employee matched data, we restrict our analysis to instances of job loss around the monetary eligibility threshold of 680 hours. Workers with such histories are, by construction, marginally attached to the labor force: the typical worker in our sample records only 13 hours per week and earns roughly $11,000 during the previous year. These "marginally attached" workers are relatively concentrated in retail trade, food services and accommodation, and agriculture. Their labor force attachment is generally inconsistent, as only 59 percent record any work hours three years prior to their job loss.[3]

We first assess the validity of our identification strategy. It is conceivable that workers or employers could manipulate monetary eligibility. Employees may delay separation until they become eligible for UI. Alternatively, employers might lay off workers before they reach the eligibility threshold to avoid UI claims charged to their accounts that

[3]Specifically, we measure whether workers record positive hours in the ninth through 12th quarters prior to and after job loss.

would increase their payroll taxes (Lachowska et al., 2025). However, we show that the incidence of job loss is smooth across the eligibility threshold, alleviating concerns about precise manipulation. Additionally, we do not detect any discontinuities at the threshold in workers' characteristics or prior employment histories.

Next, we document the relevance of the threshold for benefit receipt. Satisfying the monetary eligibility condition leads to a 3.25 percentage point or 53 percent increase in UI receipt among workers experiencing job loss. This first-stage relationship is particularly strong, allowing us to study how UI receipt affects job search and re-employment outcomes. Workers appear somewhat aware of the threshold as UI applications increase modestly at the cutoff.[4]

We document negative but small and statistically insignificant effects of UI on hours worked in the same quarter of job loss, suggesting UI does little to prolong unemployment spells of marginal workers. Our point estimates suggest workers who receive UI return to work three full-time days later than those without access to benefits, and we can rule out delays larger than two full-time weeks. These small effects may be unsurprising given UI's benefit duration formula, whereby workers with limited work history also typically receive lower weekly benefits with shorter potential benefit durations. Indeed, the average claimant in our sample receives a weekly benefit of $200 with a potential duration of just over 17 weeks. Thus, unlike for the general population which has access to UI for up to 26 weeks (or longer in recessions), we expect smaller effects of UI receipt on nonemployment duration for our population of interest.

Despite documenting limited effects on the speed of re-employment, we find that meeting the eligibility threshold for UI substantially *increases* workers' employment hours, earnings, and job stability once re-employed. UI receipt increases hours worked by roughly

[4]Given the low take-up and relatively modest first-stage effect in our sample, it may be tempting to restrict analysis to UI applicants, similar to Leung and O'Leary (2020). However, the discontinuity in application rate at the threshold suggests there is selection into the applicant sample that would violate the identification assumptions of the RDD. This motivates us to instead use a sample of job losses. More details on this are provided in Appendix E.

600 hours – equivalent to 15 additional full-time weeks – in the two years after separation, representing a 37 percent increase. These gains are concentrated in the first six quarters and include the small negative re-employment effect in the same quarter as the job loss. We also find strong, statistically significant effects on earnings: workers who receive UI earn $14,868 more over the two years following job loss, a nearly 50 percent increase. These positive effects on earnings persist through three years, suggesting that UI facilitates matching to higher-paying jobs for this particularly vulnerable population.

Several additional findings suggest that UI receipt improves job quality upon re-employment, which leads to higher hours and earnings. First, the positive effect of UI receipt on hours is driven entirely by employment with the next employer after their job loss, as opposed to longer hours at *all* subsequent employers or an increase in the number of employers. Second, direct measures of job turnover show UI receipt leads to employment at significantly fewer firms in the two years following job loss, despite workers recording higher total hours worked. Third, we show UI receipt facilitates an increase of $3.32 in hourly wages in the quarters following job loss, although this estimate is imprecise and only marginally significant. Taken together, our findings on tenure, job stability, and hourly wages suggest that UI facilitates workers' transition into higher-quality, more stable jobs offering more hours and higher pay.

We then investigate the mechanisms by which UI increases earnings and hours for marginally attached workers without significant delays in re-employment. Using residential ZIP codes, we measure each worker's proximity to public employment offices. We find that the positive effects of UI receipt are substantially larger for workers who live near these offices, suggesting that access to re-employment services enhances the productivity of job search. This pattern holds across multiple labor market outcomes and is robust to alternative measures of distance and office accessibility. Most prior research focuses on variation in UI generosity holding access to services constant while standard theoretical models do not consider these aspects of UI benefits. In our setting, UI receipt bundles benefits payments with exposure to optional job search assistance and caseworker support, which means that our treatment effects incorporate the value of those services as well. These findings help reconcile how UI leads to meaningful improvements in job quality without significantly prolonging nonemployment spells by highlighting the role of institutional support in improving the efficiency of the job search process.

Lastly, we weigh the costs and benefits of expanding access to UI for marginally attached workers by lowering the eligibility threshold. We use the marginal value of public funds (MVPF) framework developed in Hendren (2016) and Hendren and Sprung-Keyser (2020). The MVPF measures the ratio of the willingness-to-pay for unemployment insurance benefits to net government costs, incorporating both direct program costs and fiscal externalities. Due to the consumption-smoothing benefits, Schmieder et al. (2016) estimates that each $1 in UI benefits is scaled by a factor of 1.17. In this case, the willingness-to-pay is even higher because UI receipt also increased medium-term earnings, which we account for by adding the portion attributable to higher hourly wages to workers' private value. On the cost side, providing $1 of additional UI benefits to these workers costs less than $1 because the government collects additional tax revenue on these workers' higher earnings. We estimate that tax revenue collected on higher earnings offsets 5.5 percent of the gross cost.

Overall, we conclude that lowering the eligibility threshold generates $2.57 in value for every $1 spent, with $2.44 in benefits for workers at a net cost to the government of $0.95. This estimate likely represents a lower bound, as it does not incorporate workers' additional value for job stability or preferences for working more hours when offered a higher hourly wage. Moreover, as shown in Leung and O'Leary (2020), workers denied access to UI may then increase costs for other programs like Temporary Assistance for Needy Families (TANF). Still, our MVPF estimate for lowering the eligibility threshold vastly exceeds those for increasing UI benefit level or duration (Hendren and Sprung-Keyser, 2020), making it the most cost-effective UI policy studied to date. Lastly, we identify several other U.S. states with a similar monetary eligibility condition that are also well-positioned fiscally to expand UI access for marginal workers and improve their labor market outcomes.

Contribution to the Literature – Our paper contributes to an extensive literature studying the labor supply effects of UI, which generally finds that increased UI generosity prolongs search duration (Katz and Meyer, 1990; Krueger and Meyer, 2002; Landais, 2015). This literature has focused almost exclusively on the *intensive* margin, leveraging quasi-experimental variation such as benefit schedule kinks (Huang and Yang, 2021; Bell et al., 2024), unexpected duration reforms driven by political processes (Card and Levine, 2000; Karahan et al., 2025), or discontinuous jumps in potential benefit duration due to age cutoffs (Lalive, 2008; Centeno and Novo, 2009; Nekoei and Weber, 2017). Importantly, these studies hold constant access to public employment services and the imposition of work search requirements across treatment groups.

Our paper is among the first to analyze the causal effect of UI receipt at the extensive margin. Leung and O'Leary (2020) and Jenkins (2024) focus on how UI receipt affects non-labor market outcomes such as welfare take-up and crime, respectively. Cohen and Schnorr (2023) studies the effects of separation eligibility on labor supply, while our paper focuses on monetary eligibility, a fundamentally different margin. Chao et al. (2025) measures the effect of monetary eligibility on post-separation earnings but does not observe UI receipt in their data, a key advantage in our analysis. Our work is also distinct from the latter two papers because Washington State, unlike most U.S. states, collects administrative hours records, which allow us to more accurately measure labor supply responses.[5]

Our research also contributes to a distinct corner of the UI literature focused on the

[5] When nonemployment must be inferred through earnings gaps in quarterly wage records, as with California records in Cohen and Schnorr (2023) or the LEHD in Chao et al. (2025), such measurement is notoriously difficult because severance and fringe benefit payouts at the end of employment spells make it difficult to reliably pin down a date of separation. The presence of hours data obviates this concern.

effects of benefits on wages and job quality. This literature generally finds no effect of UI generosity on job quality (Card et al., 2007; Van Ours and Vodopivec, 2008; Schmieder et al., 2016; Jäger et al., 2020). Two exceptions are Tatsiramos (2009) and Nekoei and Weber (2017), who estimate small positive earnings effects for European workers with longer potential benefit duration. However, the local nature of their estimate may not extrapolate to low-income U.S. workers who are on the margin of qualifying for UI at all, where the effects of benefit receipt on job quality may be stronger.

Second, our paper contributes to the literature focused on active labor market policies, especially job-search assistance and re-employment services for the unemployed. A meta-analysis by Card et al. (2018) finds that job search assistance programs yield relatively favorable impacts on participants' employment prospects, often shortening unemployment durations at low cost, consistent with more recent U.S. evidence (Michaelides and Mueser, 2020; McConnell et al., 2021). Black et al. (2003) finds that mandatory re-employment services reduced average claim duration among UI applicants, but this reflected a sharp increase in early UI exits rather than the success of the re-employment services themselves. Yet most studies evaluate job search assistance as a standalone intervention or hold UI receipt fixed. Our paper advances this literature by studying a setting where UI and re-employment services are bundled as workers who gain UI eligibility also become subject to search requirements and gain access to public employment offices. This allows us to examine how services embedded within the UI system may shape job search behavior and potentially enhance search productivity.

Lastly, our paper adds to a literature focused on lower-income workers with marginal attachment to the labor market. Public finance economists have studied program participation among this population (Moffitt, 2002; Leung and O'Leary, 2020; Ko and Moffitt, 2024). Macroeconomists emphasize their role in explaining aggregate unemployment rate fluctuations (Elsby et al., 2015), and labor economists have studied those in low-wage work in specific sectors such as agriculture (Clemens et al., 2018; Castillo et al., 2023) and leisure and hospitality (Allegretto and Nadler, 2015; Dube et al., 2016). Comparatively little work discusses the impacts of UI for this disadvantaged group of workers. One exception is Jackson et al. (2025), which documents expanding UI through Pandemic Unemployment Assistance led self-employed individuals, gig workers, and new labor market entrants to modestly reduce their earnings for every additional dollar of UI received.

The remainder of this paper is organized as follows. Section 2 describes the institutional details of the UI program, our data, and how we constructed the sample of job losses used in our analysis. Section 3 describes the fuzzy regression discontinuity design. Section 4 summarizes our main findings of the effects of UI receipt on job search and re-employment outcomes. Section 5 presents evidence of improved job quality and proposes possible mechanisms. Section 6 evaluates the policy implications of expanding UI eligibility to marginally attached workers. Section 7 concludes and offers avenues for future research.

2 Data and Institutional Setting

Unemployment benefits partially replace a worker's regular earnings for a limited time while they search for another job. In all U.S. states, UI eligibility is comprised of three broad conditions: first, a worker must have become unemployed "through no fault of their own" (i.e. disallowing instances of firings for cause and quits). Second, a UI recipient must demonstrate that they are actively seeking work. Lastly, a recipient must have worked a sufficient amount in their base year to be "monetarily eligible" for benefits, representing the idea that workers should have some degree of attachment to the labor market. This monetary eligibility criteria is the focus of our paper.

In all states but Washington, monetary eligibility is determined by accumulating a sufficient amount of earnings in a reference period, typically the year preceding job loss. However, Washington State is unique by being the only state that uses hours worked to determine monetary eligibility. Consequentially, while Washington is one of a small handful of U.S. states that record hours for all UI-covered employees, it is the only state that uses them to administer program eligibility. Thus, we can be particularly confident in the reliability of records the Washington State Employment Security Department (ESD) maintains as part of the state's UI payroll tax requirements (Lachowska et al., 2022).

As part of its UI system, Washington operates a network of public employment offices known as WorkSource. These offices provide re-employment services to UI recipients who are encouraged, but not required, to participate. Services include job search assistance, resume creation and development, career-related workshops, and personalized support from staff to connect workers with employers.[6] In section 5 we explore whether proximity to these offices affects the impact of UI on job outcomes.

Our main administrative data source is the employee-employer matched wage records which span all UI-covered employees on a quarterly basis. The records include worker- and employer-level identifiers, meaning earnings and hours are observed at each individual worker-firm pair. ESD also maintains UI claims records for all benefit applicants, which include information such as application date, determination (i.e. whether successful or unsuccessful), weekly benefit amount, and number of weeks receiving the benefit (for recipients). We leverage both the quarterly wage records and the UI claims records to assess the causal effect of receiving UI. The wage records consist of identifiers for the employee and employer which can be linked to the UI claims. The employer-employee matched data and claims data for this paper span 2008–2022.

In order to obtain information on workers' residential addresses and demographics, we merge the employer-employee matched data with records from the Washington State Department of Licensing (WADOL).[7] We are able to match roughly 54 percent of the 2011–2019 sample of job losses (whose construction is described below) to the WADOL data,

[6] For further information about WorkSource, visit https://www.worksourcewa.com/.

[7] This gives us the residential addresses and demographics associated with a worker's driver's licenses as of March 2024.

where most recent addresses would have been updated between 2018–2024 per Washington driver's license renewal requirements. We use this subsample when assessing whether the effect of benefit receipt varies based on a worker's proximity to a public employment office. Further details on the matching process are provided in Appendix C.

2.1 Monetary Eligibility

To be monetarily eligible for UI in Washington, an individual must have worked 680 hours in either their base year or alternate base year at the time they file for benefits. A worker's base year is the first four of the last five completed calendar quarters before the week in which they apply for benefits. A worker may be eligible for an alternate base year claim if and only if they have not accumulated 680 hours in their base year.[8] The *alternate* base year claim is the last four completed calendar quarters before the week in which a worker files their claim. The base and alternate base year definitions are illustrated visually in Figure 1.

The application of base and alternate base years functionally creates two thresholds for UI eligibility. For our purposes, it only matters that a worker is eligible for UI given *at least one* of their reference periods. For example, a worker who is just below the cutoff in their base period but above the cutoff in their alternate base period still qualifies for UI. A worker's "eligibility hours" following job loss are determined as the greater of their base year hours or their hours from the alternate base year. This measure best captures how close a worker is to satisfying the monetary eligibility condition.[9]

Washington's 680-hour threshold, equivalent to 17 full-time weeks of work, is stringent compared to other U.S. states' monetary eligibility standards, which are based on

[8] UI weekly benefit amounts are always calculated for recipients using the regular base year if that base year has at least 680 hours, even if using the alternate base year would result in a higher weekly benefit amount.

[9] In Appendix F, we separate the "eligibility hours" to allow for two distinct thresholds: (a) using a sample of workers not eligible in their base year, we exploit the threshold in alternate base year hours; (b) using a sample of workers not eligible in their alternate base year, we exploit the threshold in base year hours. Ultimately, we find estimates consistent with our main results.

earnings rather than hours. We quantify how Washington compares in terms of UI eligibility requirements for minimum wage workers in Appendix G.

2.2 Identifying Job Losses and UI Take-Up

2.2.1 Measuring Incidence of Job Loss

To identify job separations, we use the employer-employee matched data to assign every worker a primary employer for every quarter in which they are employed.[10] A job separation occurs when a worker records zero hours in the following quarter with their primary employer.[11] Not all job separations, however, satisfy the UI eligibility condition that workers lose their job "through no fault of their own." This definition of job separations would include individuals who dropped out of the labor force, switched jobs, were fired for cause, or quit voluntarily. Such workers are not eligible to receive UI benefits even if they are monetarily eligible and actively searching for a new job. To mitigate this concern, we focus our analysis on the subset of job separations that are most likely to satisfy all UI eligibility criteria.

We focus on job losses, which is one type of job separation. A job loss occurs when a worker experiences a job separation and a drop in total hours greater than 15 percent relative to the previous quarter but finds re-employment within five quarters. Focusing on job losses excludes two other types of job separations from our analysis – labor force exits and job-to-job transitions. A labor force exit occurs when a worker experiences a job separation and then does not record any employment for five consecutive quarters. A job-to-job transition happens when a worker switches employers within the same quarter as their separation, while total hours decrease by no more than 15 percent from the previ-

[10] If a worker has more than one employer in a quarter, then the primary employer is the employer for which they have accumulated the most hours working for in that quarter plus the two previous quarters.

[11] Additionally, a job separation is assigned to the quarter it is flagged when a worker's hours with their primary employer drop by at least 15 percent. If they do not experience such a drop in hours worked in that quarter, then the job separation is assigned to the following quarter when they record zero hours with their primary employer.

ous quarter. These three types of job separations are mutually exclusive and collectively exhaustive.[12] In Appendix B.2, we show our results are robust to a range of parameter choices for how we classify job losses.

We restrict our analysis to job losses because this group is most likely to satisfy the separation condition. Excluding labor force exits and job-to-job transitions mitigates the concern that workers in the sample experienced a job separation because they moved to another state, switched jobs, or stopped working altogether. Nevertheless, the sample of job losses may still include some who are not actually eligible for UI benefits due to firings with cause or voluntary quits into unemployment. As such, the overall take-up rate for this sample should be considered a conservative lower bound. However, as discussed later, this does not affect identification in the context of a fuzzy RDD. This approach is similar to the one used by Lachowska et al. (2025) to measure the role of employers in explaining incomplete take-up. In Appendix E, we outline the rationale for using a sample of job losses instead of constructing a sample based on UI applications, as done in Leung and O'Leary (2020).

2.2.2 Measuring UI Take-Up

With the sample of monetarily eligible job losses, we use the records of benefit applications and payments to determine whether an individual applied for and received benefits, and if applicable, the duration of their claim. The application and payment data features the weekly benefit amount, the effective date of claim, the amount paid, and the week the payment is associated with. Whereas the employer-employee matched data is at a quarterly frequency, claims data is recorded at a weekly frequency.

For each monetarily eligible job loss, we determine if the worker applied for benefits based on whether there is a record of a UI claim account for that worker with an effective

[12] Additionally, we consider whether the type of job separation a worker experiences is endogenous to their eligibility for UI benefits. Appendix Figure A.1 plots the share of all job separations that are classified as a job loss around the eligibility threshold, and we do not detect a discontinuity at the threshold.

date of claim between the month before the quarter of the job loss through five months after the end of the quarter of job loss. This window extends beyond the quarter of the job loss for two reasons: first, workers can submit a claim *before* job loss if they are given notice that they will be laid off; second, workers can submit a claim anytime during their unemployment spell.[13] Similarly, we determine if the worker received benefits based on whether there is a record of a UI payment made to the worker's claim account with an effective date of claim in the time window around the job loss. The claim duration equals the total number of payments made to that worker's claims account, corresponding to a spell of unemployment.

2.3 Sample Construction

Beyond the restrictions described in section 2.2.1 to isolate job losses, our baseline sample restricts to workers whose eligibility hours are within 150 hours of the 680 threshold – a sample of workers we term "marginally attached" due to their limited work history. To ensure the robustness of our estimates, we also employ smaller and larger bandwidths in our regression specifications throughout. Lastly, we drop workers whose eligibility hours are a multiple of 40 (e.g. 600, 640, 680, etc.). We make this restriction due to substantial heaping at these values (see Figure 2a), which can induce bias in estimating causal effects in RD designs (Barreca et al., 2016).[14] Workers with eligibility hours that are multiples of 40 are more likely to have been employed in non-hourly, full-time work and are systematically different than workers with eligibility hours that are slightly larger or smaller. We focus on job losses over nearly a full decade, from 2011Q3 to 2019Q1.

To limit the influence of outliers, we winsorize earnings and hours worked at the 5 percent level (2.5 percent in each tail). We apply the same winsorization procedure to

[13] Although rare, workers are even able to backdate claims to receive benefits for previous weeks if they provide the necessary documentation for it.

[14] Results are robust to dropping only workers with exactly 680 hours since this heaping right at the threshold can lead to unreliable estimates.

our hourly wage measure, which is constructed by dividing quarterly earnings by hours worked.

2.4 Descriptive Statistics

We use the employer-employee matched hours records to identify job losses with eligibility hours just around the threshold. This population, by its nature of limited work hours, is very distinct from the typical sample of workers who apply for UI upon separation. Table 1 summarizes key differences in earnings and wage history, UI utilization, and industrial composition between all job losses (column 1), job losses with eligibility hours within 150 (plus or minus) of the 680 threshold (column 2), and job losses after full-time work (at least 1,600 eligibility hours). The typical worker in our sample of interest earns $10,948 in the four quarters prior to job loss, compared to $61,268 for full-time workers who lose their jobs. Relative to the full-time population, our sample of interest earns lower hourly wages ($19/hour vs. $28/hour). While full-time workers' hours and earnings tend to be lower three years after job loss, our sample of interest experienced substantial hours and earnings *increases* three years after separation. This could be due in part to the well-known age profile of earnings, as marginally attached workers tend to be younger (Appendix Table C.1).

Our sample of marginally attached workers also interacts with the UI system in a fundamentally different way compared to most workers. By construction, roughly half of the local sample are monetarily eligible for UI benefits, compared to 61 percent of the total sample. Marginally attached workers apply for and receive UI at significantly lower rates than their full-time counterparts. While marginally attached workers have relatively high UI replacement rates (62 percent),[15] 60 percent are receiving the minimum weekly benefit amount and they can only claim UI for up to 17.2 weeks on average due to their

[15]This is the result of these workers receiving the minimum weekly benefit, which replaces more than half of their weekly wage.

short work history and the UI benefit formula. Thus, relative to the broader literature which typically studies potential benefit durations of 26 weeks (or longer), UI benefits for marginally attached workers are frontloaded with a higher replacement rate over a shorter potential duration.

Marginally attached workers are disproportionately represented in industries such as agriculture, fishing, and forestry (NAICS 11), retail trade (NAICS 44-45), administrative, support, and waste management services (NAICS 56), and arts, recreation, and hospitality services (NAICS 71-72). These industries typically exhibit lower UI take-up (Lachowska et al., 2025). Conversely, marginally attached workers are underrepresented in industries such as manufacturing, information, finance, real estate, and professional services.[16] In Appendix Table C.1, we document sample demographic characteristics for the subset we can link to WADOL records.[17] Marginally attached workers are substantially younger and more likely to be female compared to full-time workers.

3 Empirical Strategy

3.1 Fuzzy Regression Discontinuity Design

To estimate the causal impact of UI eligibility, we use a fuzzy regression discontinuity design (RDD) that exploits the monetary eligibility threshold, which qualifies workers who have accumulated at least 680 employment hours during their base period for UI benefits. This creates a cutoff that serves as a natural experiment for assessing the effects of UI receipt on key outcomes.

The RDD approach is "fuzzy" because UI receipt does not jump from 0 percent to 100

[16] Appendix Table A.1 documents the industry composition by traditional two-digit NAICS rather than collapsing sectors.

[17] Specifically, we link workers in the ESD wage records from 2011–2019 via their name and last four digits of their SSN to the same information provided by WADOL in 2024. We successfully matched 54 percent of the overall job loss sample to WADOL records. For matched records, this identifies a worker's gender, date of birth, veteran status, and disability status.

percent at the threshold. Above the threshold, some portion of the sample is likely ineligible due to the nature of their separation. Further, some that are eligible may not apply (Anderson and Meyer, 1997; Kuka and Stuart, 2021). Below the threshold, some workers receive UI because there may be initially unreported hours for cases such as military service or federal employment that are later reported upon filing an initial claim.[18]

Similar to a standard RDD, the fuzzy RDD approach relies on the assumption that workers just above and just below the eligibility threshold are similar in all respects except for their UI eligibility status. We support this assumption by showing there is no evidence of bunching or manipulation in eligibility hours and no discontinuous change in the composition of job losses at the threshold, (section 3.2). In section 3.3, we document a sufficiently strong discontinuity in UI receipt at the threshold. Since the only discontinuity at the threshold appears to be in UI eligibility, we can attribute any discontinuous jump in outcomes at this cutoff to be the effect of UI eligibility.

To formalize this, we estimate the following model using a bandwidth of 150 hours,[19] a second-order local polynomial regression, and uniform kernel weighting:

$$\begin{aligned} y_{it} = \beta_0 + \beta_1 \cdot 1(\text{EligHours}_i \geq 680) + \sum_{m=1}^{p} \beta_{1+m} \cdot (\text{EligHours}_i - 680)^m \\ + \sum_{n=1}^{p} \beta_{1+p+n} \cdot 1(\text{EligHours}_i \geq 680) \cdot (\text{EligHours}_i - 680)^n + \varepsilon_{it} \end{aligned} \tag{1}$$

where y_{it} represents the labor market outcome of interest for worker i in quarter t relative to job loss, $EligHours_i$ is the running variable capturing the number of hours worked with a threshold at 680, τ is the treatment effect of UI eligibility, and ε_i captures unobserved factors affecting the outcome. This regression recovers the intent-to-treat (ITT) effect β_1, namely the effect on y_{it} of becoming monetarily eligible.

[18]Our wage records are based on hours and earnings reported by employers to ESD on a quarterly basis and does not incorporate the audited amount of hours and earnings for those who actually apply for UI benefits.

[19]We show the robustness of our results to bandwidth choice in Appendix B.1.

We can also recover the local average treatment effect (LATE) of UI receipt on outcome y_{it} by first running the specification in Equation (1) to predict UI receipt, and then using predicted UI receipt to predict the outcome variable y_{it}. This is equivalent to an instrumental variables approach where the eligibility threshold serves as the instrument that creates quasi-experimental variation in UI receipt that we can exploit to identify the effect of UI receipt on job search and re-employment outcomes.

3.2 Validity of Identifying Assumptions

The primary concern with any RD design is that those above or below the threshold are systematically different from one another along some important characteristics that may influence the outcome variable (Imbens and Lemieux, 2008). In our setting, differences in the number or types of workers experiencing job loss on either side of the monetary eligibility threshold may arise if either workers or employers manipulate eligibility hours just around this threshold. Workers just below the threshold may try to accumulate more hours just to qualify for UI. Conversely, firms that are aware of workers' eligibility hours may differentially lay off those more likely to claim UI when they are ineligible for benefits. Such incentives exist with the experience rating system, whereby firms that discharge more UI claimants pay higher payroll taxes in the future. Indeed, using Washington's administrative UI records during a similar time frame, Lachowska et al. (2025) shows some employers seek to deter workers from claiming by aggressively appealing claims in an attempt to reduce their tax burden. Figure 2 mitigates this concern that workers or employers can precisely manipulate eligibility hours. Furthermore, Figure 3 demonstrates that the characteristics of our sample do not exhibit any discontinuities in the threshold that may affect identification.

Figure 2 provides evidence that the density of job losses is smooth at the eligibility threshold, suggesting that there is no manipulation around the cutoff. Figure 2a displays the distribution of job losses by eligibility hours, showing no noticeable discontinuity at the 680-hour threshold. To further validate this, Figure 2b focuses on our main sample, which excludes workers with eligibility hours that are multiples of 40, as these values exhibit substantial heaping. We perform a McCrary test to formally assess whether there is a discontinuity in the density of the running variable at the threshold (McCrary, 2008). The test confirms that there is no jump in the density of job losses at the 680-hour cutoff, reinforcing the validity of our identifying assumptions and supporting the robustness of our RDD design.

Figure 3 shows no systematic and discontinuous differences in key covariates at the threshold, a necessary condition for a valid regression discontinuity design. Figure 3a shows no systematic difference at the cutoff in a worker's estimated weekly benefit amount (WBA) if they were approved for UI. The same is true about the share of the sample receiving the minimum WBA (Figure 3b) and the maximum potential benefit duration if they were approved (Figure 3c). There is also no discontinuity in whether a worker accumulated more hours worked in their base year or alternate base year (Figure 3d). In Appendix Figures A.6, A.7, A.8, and A.9 we also show balance in the share of our sample belonging to each two-digit NAICS industry. We are reassured that there are no differences in our sample at the threshold aside from their eligibility for UI benefits.

3.3 First-stage Effect on UI Receipt

Figure 4a plots the probability of UI receipt against the claimants' (normalized) eligibility hours. A claimant qualifies for UI if they meet monetary eligibility requirements and are not disqualified for quitting or being fired.

The 680-hour eligibility threshold generates a strong first stage in UI receipt. Figure 4a illustrates the clear discontinuity in the probability of receiving UI benefits at the eligibility threshold, demonstrating a clear increase of 3.25 percentage points, representing a 53 percent increase. The F-statistic for this regression is nearly 2,300. Appendix Figure B.1 shows that the estimate is robust to bandwidth choice from 5 to 200 hours. Although the effect on UI receipt is strong and precise, its size is relatively modest: the first stage coefficient ranges from 3.25 to 3.42 percentage points depending on bandwidth choice, as shown in the first column of Table 2.

The observed discontinuity at the 680-hour threshold provides a valid instrument for UI receipt. Despite its strength, the modest size of the first stage necessitates careful interpretation of our second-stage results, since we scale the ITT effect by this first-stage to obtain the LATE. The LATE represents the estimated treatment effects for the specific subset of workers who comply with the eligibility criteria and whose receipt of UI is determined by the threshold. Focusing attention on such compliers ensures our results accurately reflect the causal impact of UI eligibility on labor market outcomes for marginally attached workers.

4 Effect on Labor Supply

This section examines the effect of UI receipt on time to re-employment, subsequent hours worked, and earnings. Analyzing all three outcomes is essential for capturing the full impact of UI on labor supply—not just whether workers return to work, but how much they work and how much they earn once re-employed.

4.1 Effect on Time to Re-Employment

First, we investigate whether UI receipt impacts how long a worker spends looking for a job. Our results suggest that UI receipt has a negative but imprecise and only marginally significant effect on immediate re-employment in the same quarter that job loss occurs. However, one quarter after the job loss, we estimate almost no difference in the probability of re-employment. Figure 5 shows the effects of UI receipt on re-employment in the same quarter as job loss and one quarter after job loss. As shown in Figure 5a, benefit receipt leads to a 16 percentage point decrease in the probability of immediate re-employment in that same quarter on a base of 36.5 percent. This effect is not significantly different from zero at the 5 percent level. As shown in Figure 5b, benefit receipt is associated with a 1.6 percentage point increase in the probability of having found re-employment one quarter after the layoff. The LATE estimates have large standard errors partly because cumulative re-employment is an indicator variable and thus measured rather coarsely.

In a standard job search model, more generous outside options such as UI benefits lead individuals to extend their job search. While the direction of our estimates is consistent with this prediction, these effects are ultimately minimal and short-lived. Table 2, column 2 also shows negative but imprecise point estimates. This negative but imprecise effect is robust to the choice of bandwidth and parameters defining job loss (Figures A.4a and B.17a, respectively).

The initial negative effect may be attributed to UI benefits reducing the immediate urgency to accept new employment. This effect dissipating by the following quarter suggests that UI benefits do not significantly prolong unemployment spells for marginally attached workers. Instead, it seems the benefits provide a short-term cushion that allows workers to look for a job for slightly longer without leading to substantial delays in re-employment.

4.2 Effect on Total Hours Worked

Our data also allows us to measure the effect of UI receipt on labor supply in terms of hours worked in the quarters after job loss, which may provide a more detailed and more nuanced understanding of how UI benefits affect re-employment. Figure 6 presents graphical evidence that in the two years following job loss, UI receipt led to an increase in hours worked of 603 hours, or equivalently 15 weeks of full-time work, which represents a 37 percent increase relative to the value just below the threshold. The corresponding estimates are listed in Table 4.

Figure 7a plots the LATE estimates on quarterly hours worked beginning three years before the job loss through three years after the job loss. No pre-trend or significant effect is detected in the quarters before job loss, further validating our identification strategy. In evaluating whether UI benefits delay re-employment, we find a negative and insignificant effect in only the same quarter as job loss equivalent to three days of full-time work, but we can rule out a modest decrease of more than two full-time weeks of work. This is consistent with the effect on cumulative re-employment presented earlier, with the added insight that this imprecise delay in re-employment in the quarter of job loss does not necessarily translate into a large decrease in labor supply as measured by hours. We still find UI receipt delays re-employment using this more precise measure, but the delay is minimal and short-lived.

In the quarters following job loss, we find a significant increase in hours worked. The peak of the effect occurs in the second and third quarters after job loss, where those eligible for UI work an extra 150 hours (3.75 full-time weeks) longer in these quarters than those ineligible for UI. Point estimates are highly consistent across different choices of bandwidths and parameters defining job loss (Appendix Figures A.4 and B.18). Figure 7b plots the cumulative effect of UI receipt on hours worked, rather than focusing on the effect quarter by quarter. The figure demonstrates that the cumulative effect on hours worked levels off in the sixth quarter after job loss. This substantial increase underscores the significant role that UI benefits play in supporting employment for marginally attached workers. Crucially, these gains to workers would be entirely missed if we only examined re-employment.

4.3 Effect on Total Earnings

In this section, we examine the impact of benefit receipt on total earnings following job loss. Intuitively, we would expect an increase in hours worked to translate into an increase in earnings, but the relative size of these effects may hint at the impacts on re-employment wages. Ultimately, we find increases in earnings that are even greater than the increases in hours worked.

Figure 8 presents the graphical evidence of the earnings effect by plotting the RDD for cumulative earnings from the time of job loss through two years. It reveals a substantial positive effect on cumulative earnings for those eligible for UI benefits compared to those who are not. We estimate UI receipt leads to an increase of $14,868 in cumulative earnings over this period, which represents a 50 percent increase relative to the value just below the threshold.

Figure 9 considers how this effect on earnings over time. Figure 9a plots the effect on total earnings for each quarter, indicating a more persistent positive effect through roughly the eighth quarter after job loss. The second column of Table 4 provides the corresponding numerical evidence. Both Table 4 and Appendix Figure A.5 illustrate that these positive earnings effects are robust to the choice of bandwidth, while Figure B.19 show effects are robust to the choice of parameters governing the definition of job loss.

Figure 9b extends the analysis to cumulative earnings through 12 quarters after job loss. Unlike the effect on hours worked, the cumulative effect on earnings continues to grow beyond the first six quarters after job loss, demonstrating a more persistent effect of UI receipt on quarterly earnings. This cumulative effect underscores the long-term benefits of UI receipt for marginally attached workers, as it not only supports immediate financial needs but also contributes to sustained earnings growth over time.

The effect on cumulative earnings is larger than the effect on cumulative hours worked in percentage terms. Similarly, the comparison between the earnings effects in Figure 9a and the hours effects in Figure 7a reveals that while the impact on hours worked plateaus after the sixth post-job loss quarter, the effect on earnings continues to increase. This suggests that UI benefits may help marginally attached workers secure higher-paying jobs or higher-quality job matches, leading to more persistent earnings improvements compared to the temporary increase in hours worked. We explore evidence for this hypothesis in

Section 5.

5 Effects on Re-Employment Job Quality

Typical job search models predict that while UI may prolong initial jobless spells, it should also lead to better job matches (Acemoglu and Shimer, 2000; Shimer and Werning, 2008). The intuition is that UI benefits provide workers with the financial support needed to be more selective in their search, giving them more time to find jobs that are higher paying, more stable, or better match their skills. These improved job matches should result in longer job tenure and higher wages.

In practice, however, empirical evidence on the job match quality effects of UI generosity is relatively sparse, with most studies finding limited or no impact. Our analysis contributes to this literature by examining how UI receipt improves re-employment job quality for marginally attached workers. We consider three measures of job quality: (i) cumulative hours worked at the next employer, (ii) the number of unique employers, and (iii) re-employment hourly wages. Table 5 and Figures 10, 11, and 12 present the results.

5.1 Effect on Tenure, Job Turnover, and Wages

Tenure and Job Turnover

The increase in total hours worked is driven by an increase in total hours worked with the first employer after job loss (termed "next employer"). As shown in Figure 10, we estimate that workers who receive UI benefits record 694 more hours with their next employer over the two years following a job loss. Recall that all workers in the sample, by construction, have a next employer. This explains more than 100 percent of the effect on total hours worked, which means the gains in hours are driven entirely by work with the next employer. These significant positive results on hours worked at the next employer are robust to reasonable choices of bandwidth and job loss parameters (Appendix Figures

B.6 and B.20a).

Consistent with these results, we then show that UI receipt reduces the cumulative number of unique employers a worker records hours worked with after job loss. As shown in Figure 11a, we estimate that UI receipt reduces the number of employers by 1.6 in the two years following a job loss. This result is robust to reasonable bandwidth and job loss parameter choices, which nearly always exhibit significant negative effects (Appendix Figures B.6 and B.20b). Figure 11b illustrates the dynamic effect over time, whereby the effect of UI receipt on job turnover increases over time as workers move from job to job.

In Appendix Figure A.3, we decompose this result into the effect on part-time and full-time work separately, showing effects of UI receipt are entirely concentrated among full-time jobs. This further supports the notion that UI receipt leads to more stable jobs that offer longer hours.

Hourly Wages

Finally, we explore whether UI receipt boosts workers' hourly wages upon re-employment. As shown in Figure 12, there is a positive but only marginally statistically significant effect. We estimate that receiving UI benefits leads to a $3.32 increase in cumulative hourly wage, which represents an 18 percent increase above the value just below the threshold. This measure of hourly wage is based on earnings and hours worked over the two years following the job loss. As a result, the effect on cumulative hourly wage could be driven by workers who receive UI finding a job that offers a higher wage or these workers experiencing more wage growth given their longer tenures at the next employer. Figure B.6 shows how the point estimate of Figure 12 changes with the choice of bandwidth. The figure shows that for other reasonable choices (100 or 200), the effect on hourly wages is positive and statistically significant at the 5 percent level. Taken together, this is suggestive evidence that UI receipt increases hourly wages.[20]

[20] Appendix C explores heterogeneity in this positive wage effect by demographic group. Appendix

While standard search models predict wages should be affected by UI benefits, empirical evidence typically finds wages are not sensitive to the value of nonemployment (Jäger et al., 2020). We attribute the differences in our findings to the nature of the quasi-experiment, whereby workers at our threshold receive a much larger increase in the value of UI compared to the workers Jäger et al. (2020) studied in Austria. Moreover, workers induced to apply for UI in our setting have access to public employment services which may facilitate better job matching, as documented in subsection 5.2.

Taken together, UI benefits enable workers to match to better quality jobs, as evidenced by longer tenure at the next employer, reduced job turnover, and higher re-employment wages. This improved job quality contributes to the sustained positive effects on earnings observed in section 4.3, highlighting the long-term benefits of access to UI for marginally attached workers.

5.2 Proposed Mechanism of Public Employment Services

We present two findings that stand in tension with one another in the context of a standard job search model. On one hand, we find UI receipt does not meaningfully prolong nonemployment spells. On the other hand, we find robust positive effects of UI receipt on subsequent outcomes: hours worked, earnings, hourly wages, job stability, and tenure. In this section, we argue that the mechanism that reconciles these two facts is access to services offered by public employment offices.

A unique feature of our setting is that we observe variation in UI receipt on the extensive margin, which bundles benefit receipt with access to public re-employment services and job search requirements. This contrasts with most prior work which exploits variation in UI generosity on the intensive margin and holds access to services and search

Figure C.6 documents that the effect of UI on hourly wages is concentrated among workers in the 25–44 age group ($p = 0.12$). UI receipt does not appear to increase wages for younger (16–24) or older (45–59) workers. Similarly, Appendix Figure C.2 shows earnings effects are concentrated entirely among men ($p = 0.04$) with statistically zero effects for women ($p = 0.89$).

requirements fixed across treatment and control groups. In our context, eligible workers not only receive benefit checks while jobless, but are also subject to weekly job search requirements and are granted access to the suite of services provided by the state's public employment offices.

A growing literature shows that access to job search assistance and caseworker support can increase the effectiveness of job search, improving both speed and quality of re-employment. Active case management, eligibility monitoring, and re-employment services – including vacancy referrals and occupational recommendations – have been shown to enhance search intensity, reduce unemployment duration, and improve long-term employment outcomes (Dolton and O'Neill, 2002; Schiprowski, 2020; Altmann et al., 2022; Schiprowski et al., 2024). Motivated by this evidence, we explore whether proximity to public employment offices mediates the reduced-form effects we estimate. Specifically, we test whether the impact of UI receipt on subsequent earnings, hours, and wages is larger for workers who live closer to a WorkSource office – the state's public employment service provider. We posit that workers residing near these offices may be more likely to engage with the services offered, thereby improving the productivity of their job search. Further information on WorkSource offices in the state is contained in Appendix D.

Table 6 shows the estimates of UI eligibility on earnings, hours worked, and hourly wages separately for workers who live within four miles of a WorkSource office and those who live farther away. This analysis is restricted to the demographic subsample for which ZIP code of residence is available, allowing us to measure proximity to public employment offices.[21] Figure D.2 shows the existence of a first stage for each group, as both nearby and far away workers' UI receipt is strongly affected by the threshold.

Across all three outcomes, the estimated effects are substantially larger for workers who live closer to an office. For example, the LATE for earnings is over seven times larger for the near group than the far group ($45,189 versus $6,072), an estimate that is nearly

[21] This subsample represents 54 percent of our main sample, thus reducing our statistical power, especially when further dividing the sample based on proximity.

statistically significant for the group close to public employment offices ($p = 0.14$ compared to 0.65). Figure 13 visually illustrates this pattern, showing a clear difference in the intent-to-treat estimates for earnings by proximity to a WorkSource office. Similarly, we observe substantially larger effects on both hours worked and hourly wages for those closer to an office, although these estimates are imprecise (Appendix Figures D.3 and D.4) While we interpret these differences cautiously, they are consistent with patterns supporting the hypothesis that access to re-employment services may enhance the effectiveness of job search by improving search outcomes.

Our conclusion that the effects of UI are larger for workers closer to public employment offices is robust to alternative measures of proximity. First, we test a range of distance thresholds, comparing workers living within three miles or five miles of a WorkSource office to those farther away. Across all specifications, we continue to find larger estimated effects on earnings, hours, and wages for those living closer to offices, consistent with the hypothesis that proximity improves search productivity (Table D.2). Second, our baseline measure of proximity uses the distance to the nearest WorkSource office that offered walk-in services, but as a robustness check, we re-calculate distance including those without walk-in availability.[22] The results under this alternative measure remain qualitatively consistent (Table D.3), as the pattern of larger UI effects for workers living near employment offices persists across specifications. Taken together, these findings suggest physical proximity to a public employment office – and thus easier access to its services – amplifies the positive impact of UI on job search and labor market outcomes.

Evidence supporting the public employment office hypothesis does not necessarily rule out alternative theories. For example, it may be that the imposition of search requirements leads to especially effective search for this group of marginally attached workers. Moreover, UI receipt for low-income workers – who likely have limited liquidity to soften

[22]Our baseline measure only uses offices with walk-in availability because it is the most relevant form of access for workers living nearby. However, our alternative measure includes offices with scheduled appointments, as whether any office is nearby may still affect the likelihood that a worker calls to schedule an appointment. Washington's WorkSource offices and their walk-in capabilities are listed in Table D.1.

the blow of joblessness – may offer a stabilizing buffer that enables a more focused and productive job search. Even modest UI support may help low-income workers avoid immediate financial crises, such as missed rent or utility payments, and instead concentrate on securing stable re-employment. Increases in UI generosity may not have the same stabilizing force for higher-income workers near kinks in the benefit schedule, as studied in other research designs (Card et al., 2015; Landais, 2015; Bell et al., 2024), who are more likely to rely on personal savings during unemployment.

6 Policy Implications

In this section, we consider the policy implications of our main results. Specifically, the evidence that UI receipt improves labor market outcomes for marginally attached workers raises the question about whether policymakers should expand access to UI by lowering the eligibility threshold. Marginally attached workers would benefit from not only the consumption-smoothing benefits UI offers but also the medium-term gains in employment outcomes due to improved job quality. The government would need to finance these additional benefit payments, but since the delay in re-employment is limited and short-lived, there is no fiscal externality that drives up the cost. In fact, the cost of providing these benefits is partially offset by additional tax revenue collected on workers' higher earnings. To weigh the costs and benefits, we leverage the marginal value of public funds (MVPF) framework developed in Hendren and Sprung-Keyser (2020). Ultimately, we conclude that expanding access to UI benefits by lowering the 680-hour threshold is the most cost-effective policy change to the UI program that has been studied.

The MVPF framework measures the value generated by an additional dollar of government spending on a specific policy as the ratio of the beneficiary's willingness-to-pay for the policy to the net cost to the government. In terms of the benefits delivered, a worker at the threshold who takes up UI receives an average of $4,084 in benefit payments over the duration of their claim. We scale the value of these benefits by 1.16 since they provide insurance to workers during a jobless spell. Workers are generally risk-averse and place a premium on the consumption-smoothing benefits of UI (Gruber, 1997; Schmieder et al., 2016). In addition, our empirical findings indicate that UI receipt increases earnings over the two years after job loss by $14,868. Recall that this increase in earnings is due to both an increase in hours worked as well as an increase in hourly wage. Therefore, in determining how much a worker values this increase in earnings, we only consider the share of the increase that is due to an increase in the hourly wage while holding hours worked fixed at the counterfactual level. We estimate $5,438 of the excess $14,868 earnings over those two years is due to higher hourly wages and apply a time-discounting factor $\delta^2 = 0.96$ to these earnings.[23] This approach represents a lower bound if we assume that workers would prefer to work more hours when offered a higher hourly wage, that workers value job stability and reduced turnover beyond their indirect effects on earnings, and that the disutility from an hour of work has not changed significantly.

In terms of the net cost to the government, providing $1 in UI benefits to these workers costs less than $1 because the government collects tax revenue on these workers' higher earnings. Washington does not have an income tax, but there is an average 1.5 percent payroll tax collected from employers to fund the UI program. Our calculations suggest tax revenue collected on excess earnings would be $223 per beneficiary, which would offset 5.5 percent of the total cost to the government. While a 5.5 percent offset may seem modest, it stands in contrast to most UI policies, where fiscal externalities typically increase net costs to the government (Hendren and Sprung-Keyser, 2020).

Overall, our calculations suggest that spending $1 on a policy to lower the eligibility threshold will generate $2.57 in value, with $2.44 in benefits for workers at a net cost to the

[23] We estimate that UI receipt induces 600 more hours worked (from a base of 1,638) and an increase in hourly wage of $3.32/hour. To calculate how much earnings would increase without workers supplying more labor, we multiply the effect on hourly wage ($3.32) by the value of hours worked below the cutoff (1,638)

government of \$0.95.[24] This estimate likely understates the value delivered by expanding UI access since we take a conservative approach to how workers value the increase in their earnings. As a bounding exercise, we consider two different approaches. First, as a lower bound, we could assume that workers do not value the additional earnings resulting from UI receipt and only value the income support provided by the benefits. Excluding any impact on earnings in the numerator yields an MVPF of 1.23. Second, as an upper bound, we could assume workers value excess earnings at their dollar value, regardless of whether it's the result of higher wages or more hours worked. Equivalently, we could assume that any disutility from the increase in hours worked is offset by higher hourly wages and greater job stability. This approach yields an MVPF of 4.92.

As shown in Figure 14, our estimated MVPF is far greater than any of the MVPF estimates for UI policies considered in Hendren and Sprung-Keyser (2020), which range from 0.43 to 1.03. Even our lower bound of 1.23 would be greater than any of these other MVPF estimates. Furthermore, this paper is unique in presenting an MVPF for expanding access to UI benefits. Previous estimates are focused on more generous benefits for UI recipients, either through increases to the weekly benefit levels or extensions to potential duration.

We assess the external validity of these results to other U.S. states and identify which are most likely to benefit from expanding UI access, with further discussion in Appendix G. Although Washington's monetary eligibility rule is more stringent than that of any other state, our findings likely extrapolate to the handful of U.S. states with similarly high thresholds for low-wage workers. Nearly all of these states are in strong fiscal positions to support expanded UI access, with healthy UI trust fund balances and, unlike Washington, have the ability to recoup part of the associated cost through state income tax revenues as workers' earnings rise. Nevertheless, Washington's use of an hours-based eligibility

[24]
$$\text{MVPF} = \frac{\text{Beneficiary's WTP}}{\text{Net Cost to Government}} = \frac{4,084 \cdot 1.16 + 5,438 \cdot 0.96}{4,084 - 223} = \frac{2.44}{0.95} \approx 2.57$$

rule, while set at a high threshold, is arguably fairer than an earnings-based system, as it imposes the same standard across workers regardless of wage level. Finally, we caution that the large earnings effects we observe may partially reflect the role of re-employment services provided by the state of Washington; our findings are therefore most likely to generalize to states with similarly effective infrastructure for UI claimants.

Overall, our results suggest that expanding access to UI by lowering the eligibility threshold is a cost-effective way to support marginally attached workers through their unemployment spell and improve re-employment outcomes. Beyond immediate income support, our empirical results suggest that these benefits improve job stability and labor market outcomes for workers with limited delays to re-employment. Moreover, these employment gains partially offset the cost to the government of providing the benefits. Policymakers should explore expanding eligibility and access to UI – not just adjusting benefit levels or durations – as a tool to improve labor market outcomes for marginally attached workers.

7 Conclusion

In this paper, we use the discontinuity in benefit receipt created by the eligibility threshold to show that although UI benefits may slightly delay immediate re-employment, UI receipt improves medium-term outcomes by increasing total hours worked and earnings for marginally attached workers. We attribute these gains to improvements in re-employment job quality among these lower-income workers. Workers who receive UI benefits tend to have longer tenures with their next employer, experience less job turnover, and earn higher hourly wages. UI receipt enhances job stability and earnings for marginally attached workers, providing lasting benefits beyond the duration of their claim.

Moreover, our findings indicate that expanding UI eligibility to these marginally attached workers is a far more cost-effective policy change than raising benefit levels or extending the potential duration. According to the MVPF measure, every dollar spent on extending UI eligibility provides \$2.57 in value to the beneficiaries, making it the most cost-effective UI policy change studied to date. Workers are able to smooth consumption as UI benefits replace part of their wages, but also, there are subsequent improvements in labor market outcomes such as more stable and higher-paying re-employment. This increase in earnings partially offsets the cost of providing these benefits, so the fiscal externality actually reduces the total fiscal cost of expanding eligibility.

Our work also highlights areas for future research. Further evidence on mechanisms that reconcile findings that UI access does not prolong joblessness but increases job quality in this context is a natural next step. Another aspect of job search we could not sufficiently explore due to data limitations is the liquidity and consumption behavior of marginally attached workers. Future work should focus on understanding the role of liquidity constraints and access to wealth for this population, which is vital for evaluating the effectiveness of UI.

Overall, this paper provides robust evidence that extending UI eligibility to marginally attached workers creates long-term benefits. The positive impacts on job stability, earnings, and overall job quality underscore the importance of UI as a critical social insurance program that supports the financial security, economic mobility, and labor market participation for this population of marginally attached workers.

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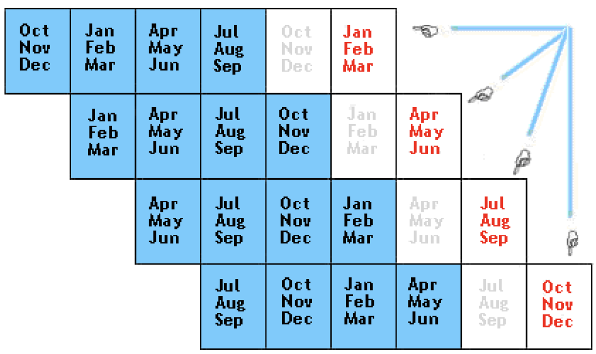
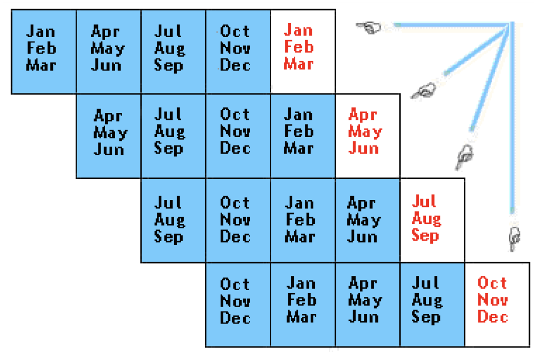
Tables and Figures

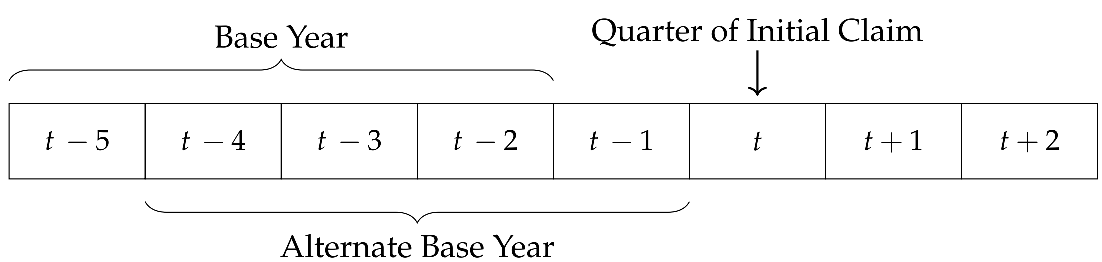
Figure 1: Base Period Definitions for Assessing Monetary Eligibility



(a) Base Year



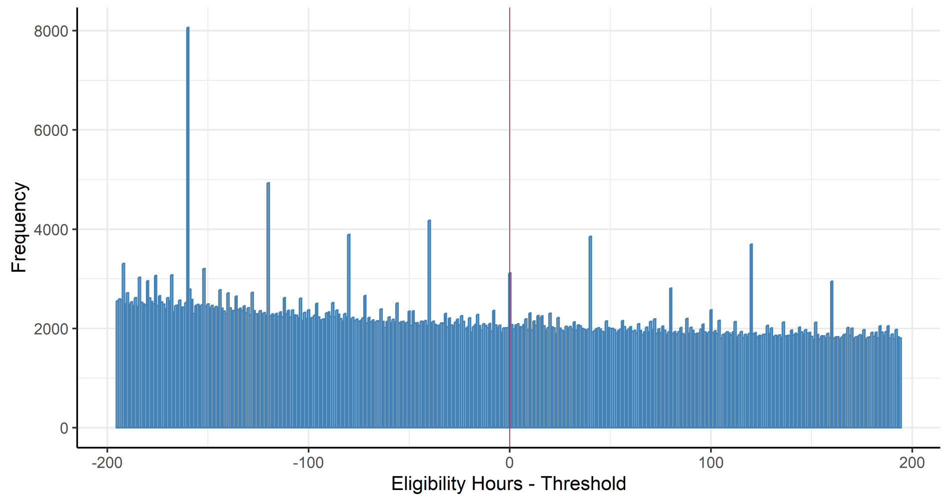
(b) Alternate Base Year



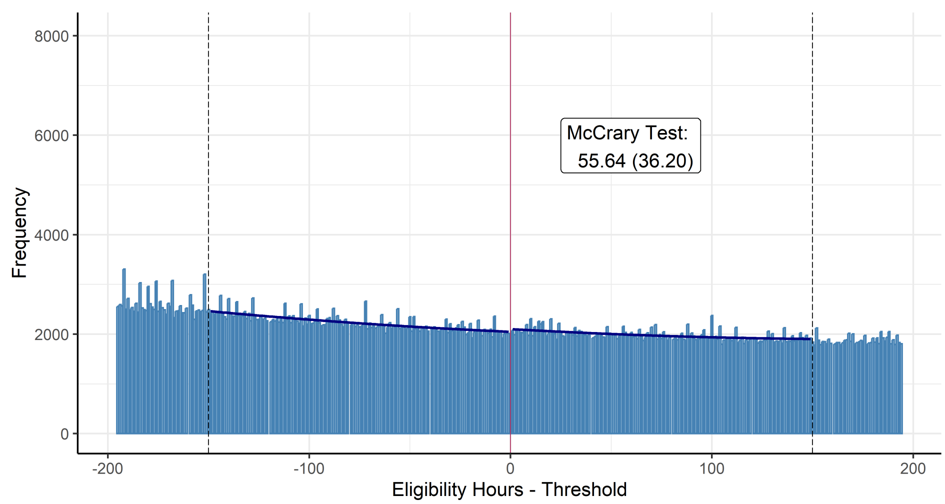
(c) Base Periods

Note: This figure illustrates how the base period is defined when assessing monetary eligibility. Panels (a) and (b) depict the base year and alternate base year, respectively, using diagrams featured on the website for the Washington State Employment Security Department. Panel (c) is the author's illustration.

Figure 2: Distribution of Eligibility Hours for Job Loss Sample



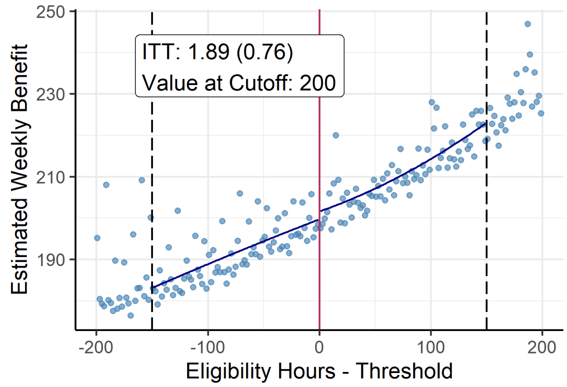
(a) Job Losses Local to Eligibility Threshold



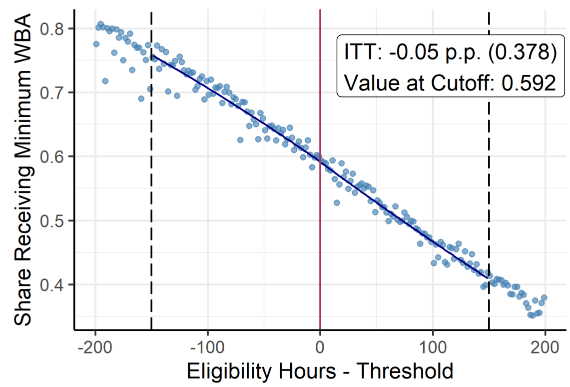
(b) McCrary Test for Job Losses

Note: These figures present the distribution of eligibility hours worked by those in the sample of job losses local to the threshold in Washington State occurring between 2011Q3 and 2019Q1. The red line denotes the 680 hour eligibility threshold. A worker's eligibility hours measure is the higher sum of hours worked in either the previous four quarters or the four quarters preceding last quarter. Panel (a) represents the distribution of eligibility hours local to the 680-hour threshold, while panel (b) removes multiples of 40 from panel (a) and conducts a McCrary test for a discontinuity in density at 680 hours. Bins are one hour in width to illustrate instances of heaping in panel (a), while such heaping is removed from panel (b). The "global distribution" of eligibility hours for all job losses is plotted in Appendix Figure A.2.

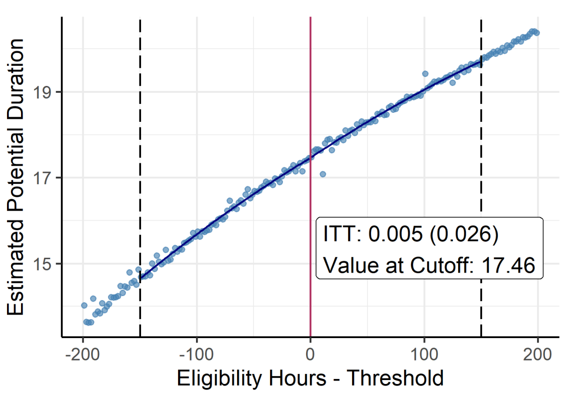
Figure 3: Worker Characteristic Balance around UI Eligibility Threshold



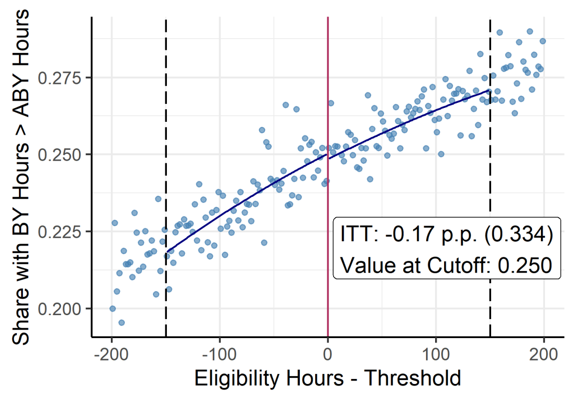
(a) Potential Weekly Benefit Amount



(b) Share Receiving Minimum Benefit



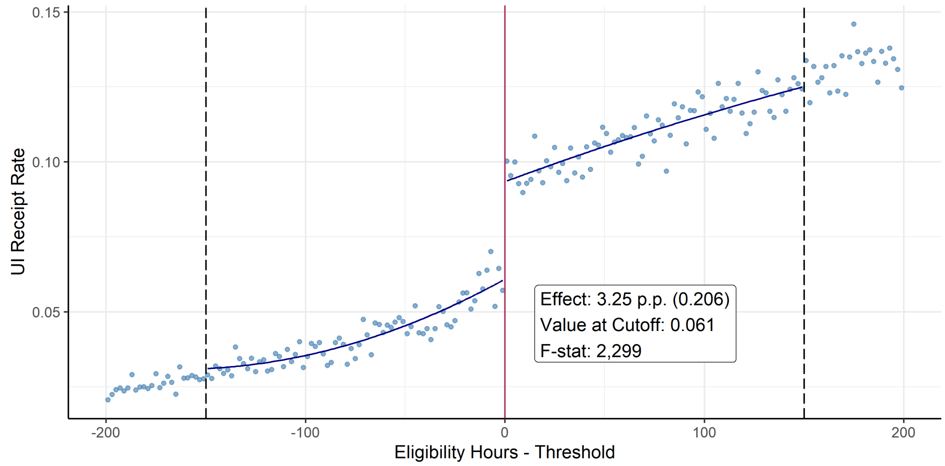
(c) Maximum Potential Benefit Duration



(d) Use of Base Year Hours

Note: Figure shows balance across threshold of eligibility hours for worker characteristics in job loss sample. Panel (a) calculates a worker's weekly benefit amount (WBA) based on their earnings. Panel (b) plots the share who receive the minimum WBA. Panel (c) calculates the maximum number of weeks a worker would be eligible for UI given their earnings. Panel (d) plots the share whose eligibility hours include their traditional (rather than alternate) base year, defined in Figure 1.

Figure 4: UI Receipt and Applications by Eligibility Hours

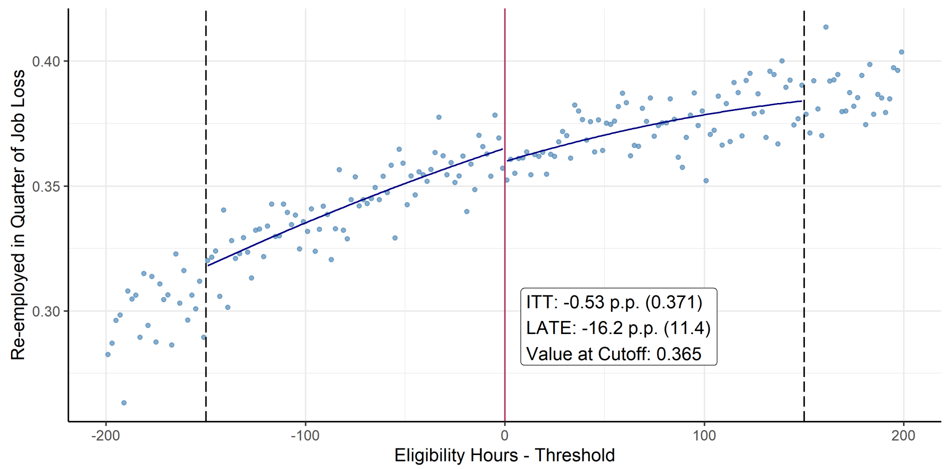


(a) UI Receipt Rate (First Stage)

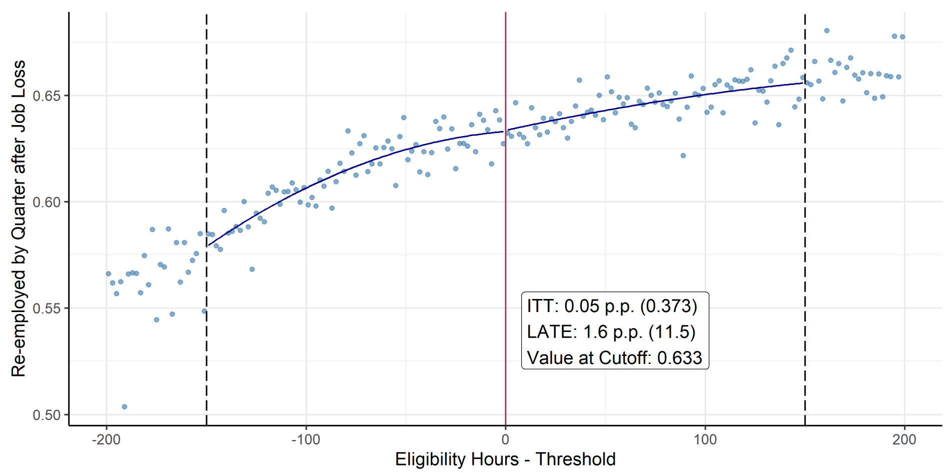
(b) UI Application Rate

Note: Panel (a) plots the share of job losses that result in UI receipt according to eligibility hours, while Panel (b) plots the share of job losses that result in a UI application according to eligibility hours

Figure 5: Cumulative Re-employment Probability by Eligibility Hours



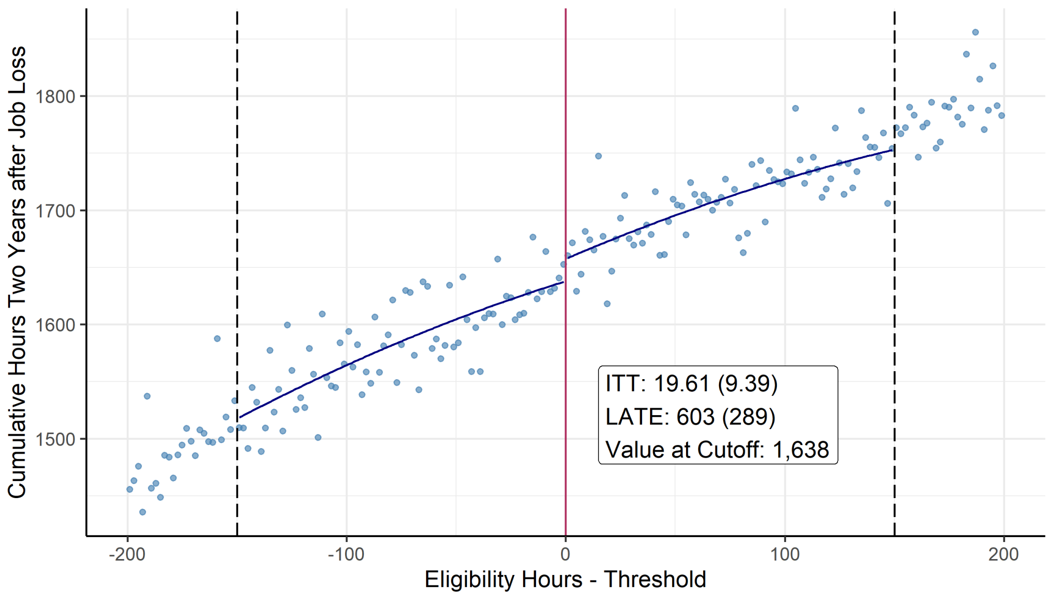
(a) Quarter of Job Loss



(b) Quarter After Job Loss

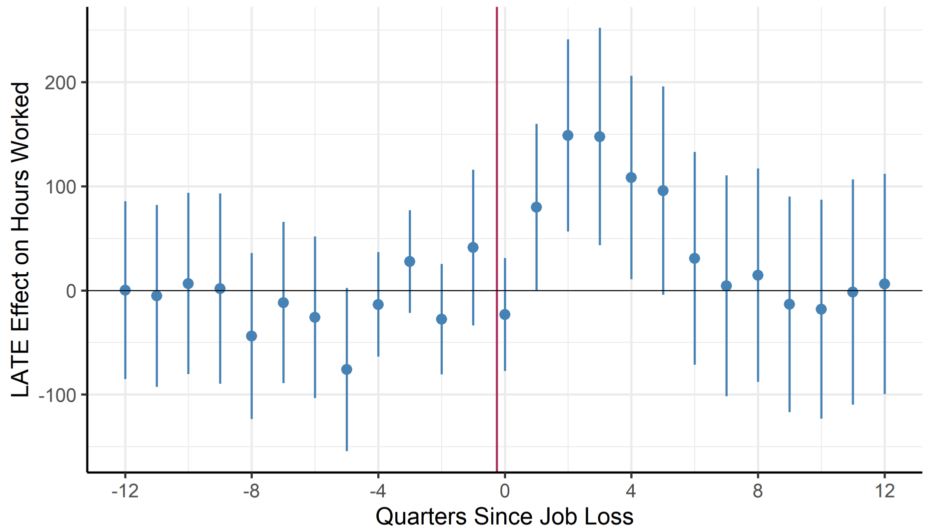
Note: Panel (a) plots the share of workers who experience a job loss that become re-employed in the quarter of separation. Panel (b) plots the share of workers who experience a job loss that become re-employed by the quarter after separation. Figure lists ITT estimate and LATE with standard errors in parentheses.

Figure 6: Effect of UI Receipt on Cumulative Hours Worked Over Two Years

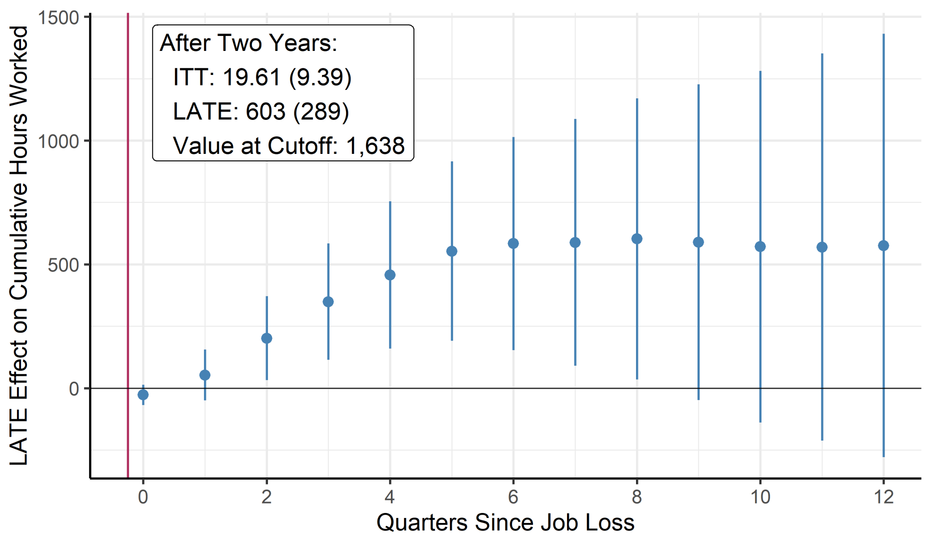


Note: This figure plots cumulative hours worked from the quarter of the job loss in t through $t+8$, excluding hours from their layoff employer in t. Second degree polynomials are fitted separately on each side of the threshold. Figure lists ITT estimate and LATE with standard errors in parentheses.

Figure 7: Effect of UI Receipt on Hours Worked Over Time



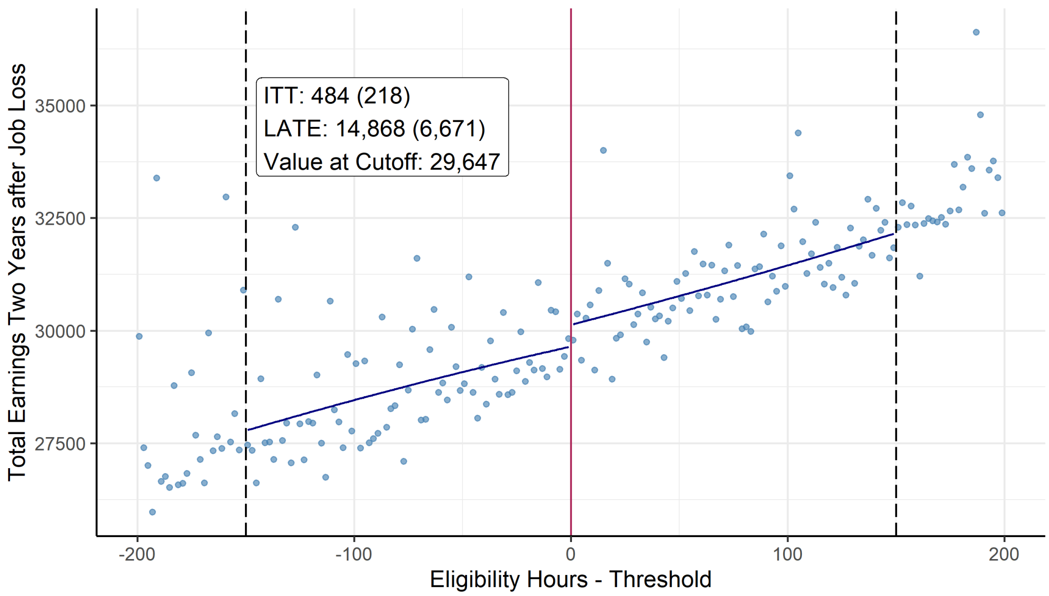
(a) Effect of UI Receipt on Total Hours Worked by Quarter



(b) Effect of UI Receipt on Cumulative Total Hours

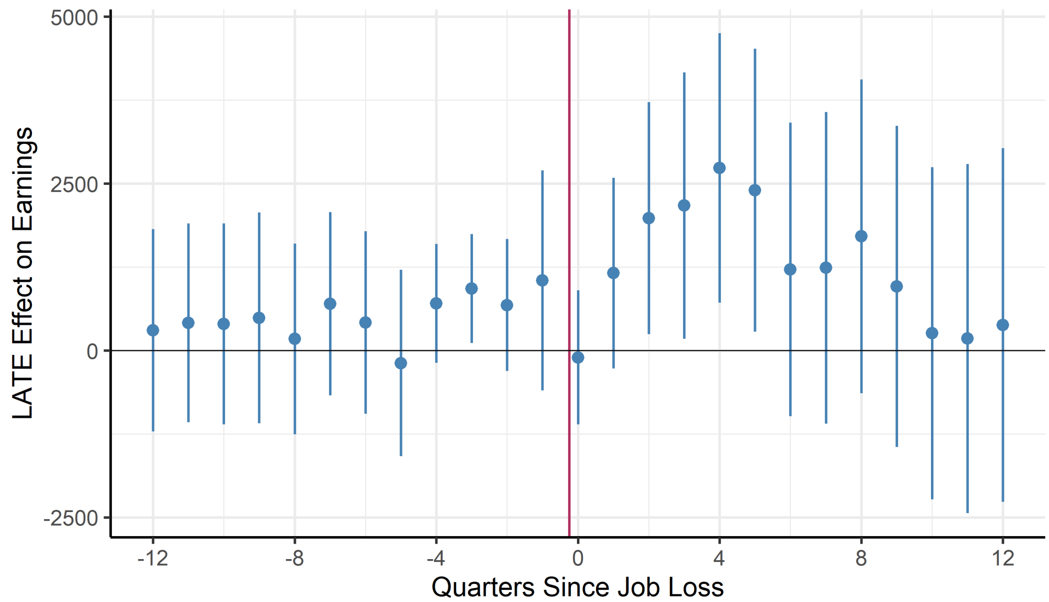
Note: These figures characterize the effect of UI access on workers' hours worked over time. Panels (a) and (b) illustrate the dynamic effect by plotting RDD point estimates for a running variable of eligibility hours and a dependent variable of total hours worked (point-in-time or cumulative, respectively). Error bars represent 95 percent confidence intervals.

Figure 8: Effect of UI Receipt on Cumulative Earnings Over Two Years

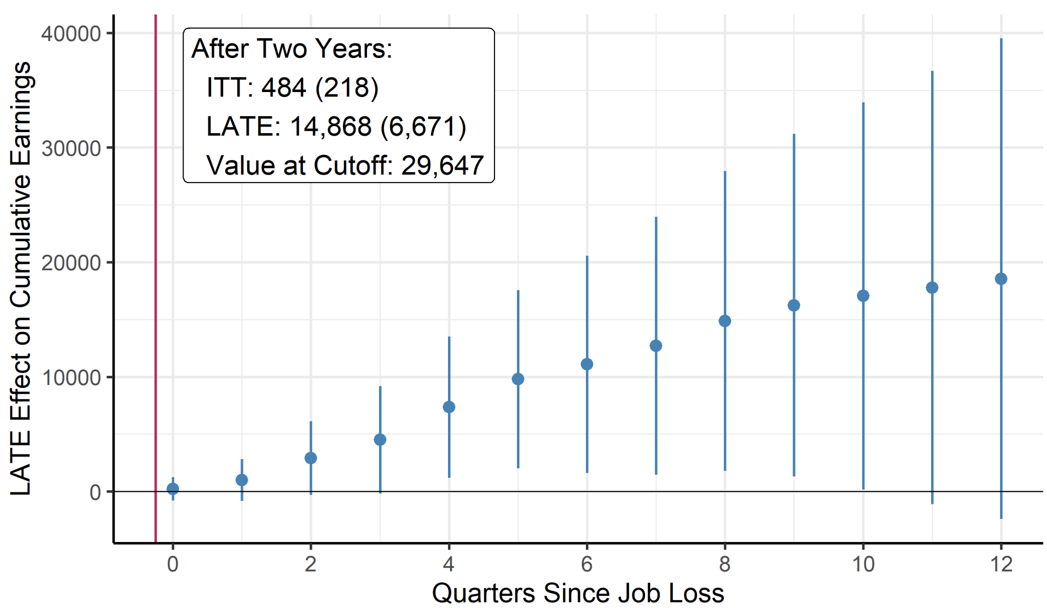


Note: This figure plots cumulative earnings from the quarter of the job loss in t through $t+8$, excluding earnings from their layoff employer in t. Second degree polynomials are fitted separately on each side of the threshold. Figure lists ITT estimate and LATE with standard errors in parentheses.

Figure 9: Effect of UI Receipt on Total Earnings Over Time



(a) Effect of UI Receipt on Total Earnings by Quarter



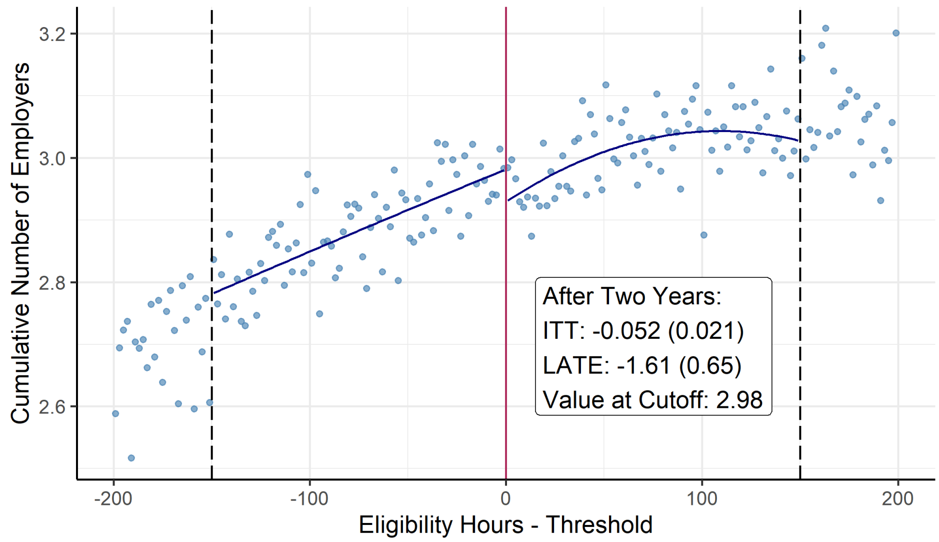
(b) Effect of UI Receipt on Cumulative Total Earnings

Note: These figures characterize the effect of UI access on workers' earnings over time. Panels (a) and (b) illustrate the dynamic effect by plotting RDD point estimates for a running variable of eligibility hours and a dependent variable of total earnings (point-in-time or cumulative, respectively). Error bars represent 95 percent confidence intervals

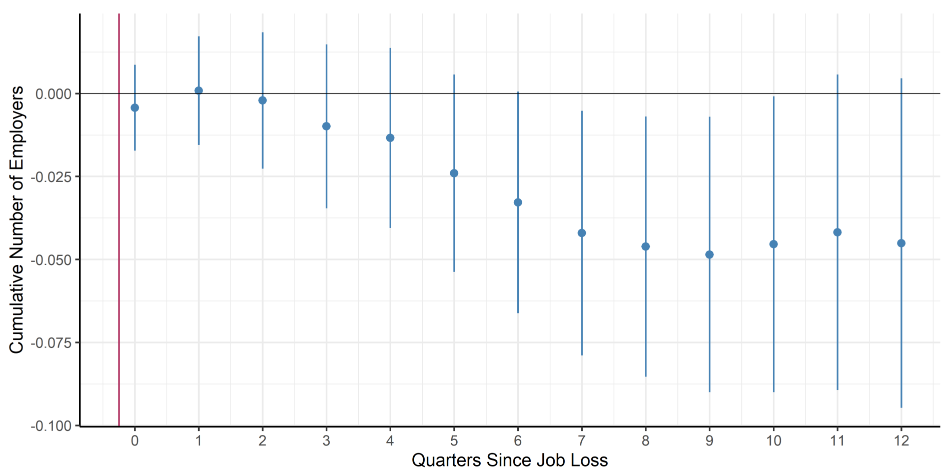
Figure 10: Effect of UI Receipt on Tenure with Next Employer

Note: Figure plots cumulative hours worked with one's first employer after separation ("next employer") from the quarter of the job loss in t through $t+8$ for individuals with eligibility hours near the threshold, excluding hours worked at their layoff employer in t. Each bin is a non-overlapping two-hour interval of (normalized) eligibility hours. Red vertical line denotes the minimum eligibility hours threshold. Second degree polynomials are fitted separately on each side of the threshold. Figure lists ITT estimate and LATE with standard errors in parentheses.

Figure 11: Effect of UI Receipt on Number of Employers



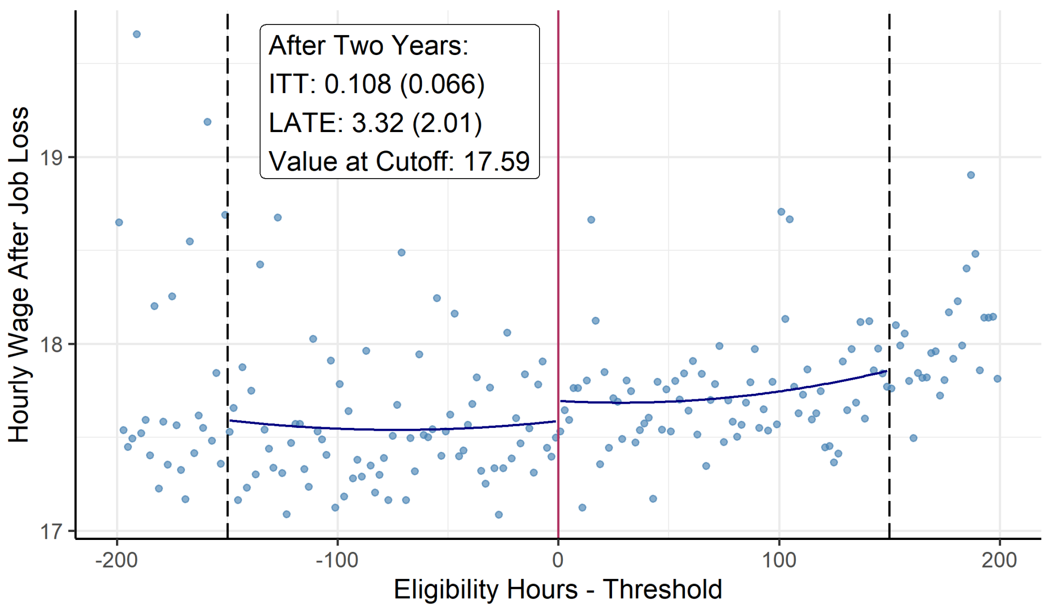
(a) Number of Employers after Two Years



(b) Cumulative Number of Employers Over Time

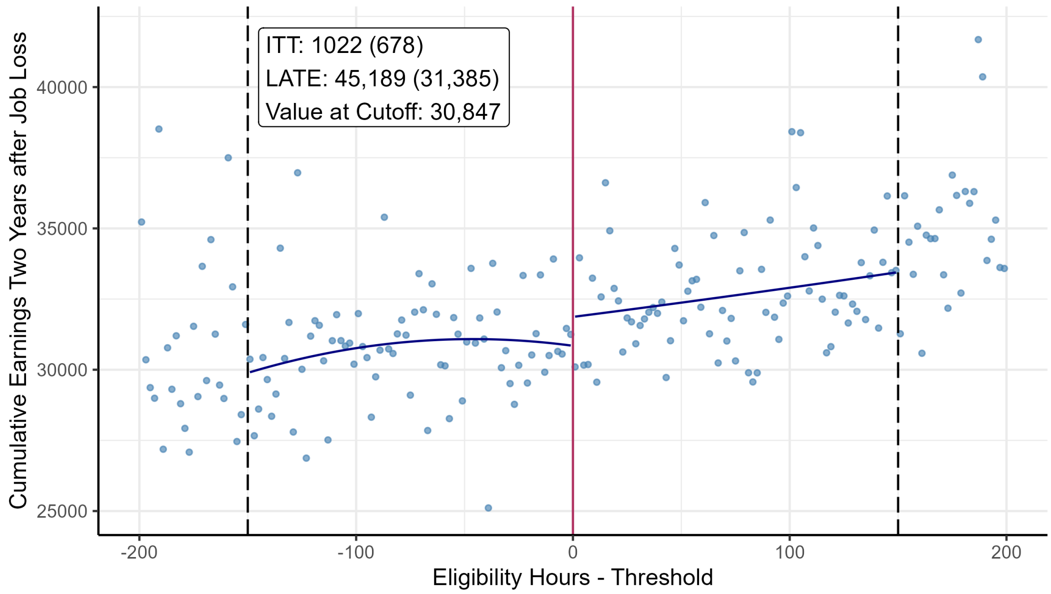
Note: Graphs illustrates effect of UI eligibility on a worker's number of unique employers in the subsequent two years. Panel (a) reports the traditional RDD graph with eligibility hours as the running variable and cumulative number of unique employers in the two years following job loss as the dependent variable. Panel (b) shows the dynamic effect of UI eligibility over time by plotting RDD point estimates for each quarter and their standard errors aggregated into time series graphs.

Figure 12: Effect of UI Receipt on Hourly Wage Over Two Years

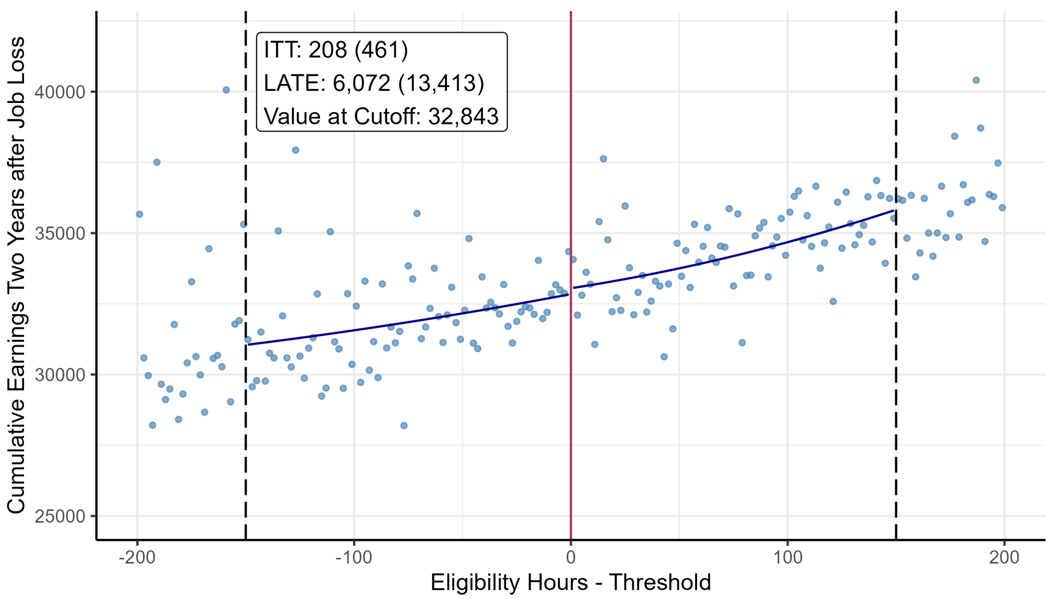


Note: Figure plots the effect of UI eligibility on hourly wages by reporting the traditional RDD graph with eligibility hours as the running variable and hourly wage in the eight post-job loss quarters as the dependent variable. Red vertical line denotes the minimum eligibility hours threshold. Second degree polynomials are fitted separately on each side of the threshold. Figure lists ITT estimate and LATE with standard errors in parentheses.

Figure 13: Effects on Earnings by Distance to WorkSource Office



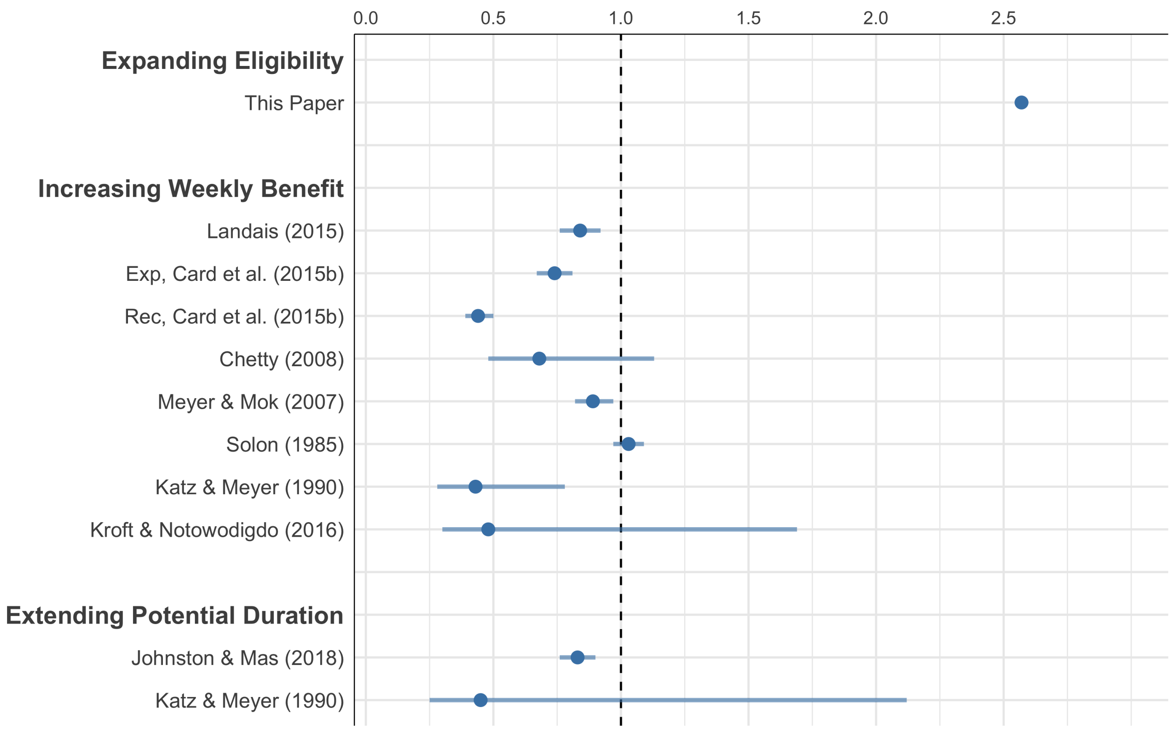
(a) Close to ($\leq$ 4 miles) WorkSource



(b) Far from ($>$ 4 miles) WorkSource

Note: These figures present the share of job losses that result in UI receipt according to UI eligibility hours, splitting the demographic subsample into which are close to or far from the closest WorkSource office that had walk-in services as of March 2025. Figure lists ITT estimate and LATE with standard errors in parentheses.

Figure 14: Comparison of MVPF Estimates for UI Policies



Note: This figure plots the MVPF estimate from this paper as well as the MVPF estimates from Hendren and Sprung-Keyser (2020). For estimates from Hendren and Sprung-Keyser (2020), each point includes the 95 percent confidence interval. Estimates are grouped by the relevant policy and listed based on the paper identifying the relevant effects.

Table 1: Summary Statistics of Overall and Local Job Loss Sample, 2014–2019

Variable	All	RDD	Full-Time
Earnings & Wage History			
Previous Year Earnings	26,151	10,948	61,268
Previous Year Hours	1,081.9	636.1	2,149.8
Previous Year Hourly Wage	31.95	18.99	29.02
Previous Year Hours with Separating Employer	845.9	467.1	1,781.7
Pre-Job Loss $[t-12, t-9]$:			
Annual Earnings	18,462	8,249	42,027
Annual Hours	769.6	447.4	1,524.8
Post-Job Loss $[t+9, t+12]$:			
Annual Earnings	28,842	19,475	53,222
Annual Hours	972.7	823.9	1,407.3
UI Utilization			
Monetarily Eligible	0.62	0.47	1
Application Rate	0.17	0.12	0.3
Receipt Rate	0.12	0.06	0.23
Benefit Level: Mean Replacement Rate	0.63	0.62	0.45
Benefit Level: As Share of Minimum WBA	1.84	1.28	2.96
Potential Maximum Duration (wks)	18.3	17.2	25.9
Share Receiving Min WBA	0.41	0.60	0.01
Share Receiving Max WBA	0.10	0.02	0.29
Industry (NAICS) of Separation			
11 Agriculture, Fishing, Forestry	0.10	0.12	0.06
21-23 Mining, Utilities, Construction	0.08	0.08	0.08
31-33 Manufacturing	0.06	0.05	0.10
42-49 Trade, Transportation	0.19	0.19	0.21
51-55 Information, Finance, Real Estate, Prof. Services	0.10	0.07	0.18
56 Administrative, Support, Waste Management Services	0.10	0.11	0.08
61-62 Educational and Health Care Services	0.15	0.13	0.15
71-72 Arts, Recreation, Hospitality Services	0.16	0.20	0.08
81 Other Services	0.03	0.03	0.03
92 Public Administration	0.02	0.02	0.02
N	3,871,225	448,402	964,554

Note: Table presents summary statistics for three types of job loss samples: all job losses (column 1), the RDD sample local to the threshold (+/- 150 hours) (column 2), and only workers with full-time work histories (> 1,600 hours in one's reference year) (column 3).

Table 2: Reduced-Form Effects on UI Receipt and Application

	UI Receipt	Application
Panel A. Main Estimates		
Estimate	3.25 p.p.	1.58 p.p.
	(0.206)	(0.273)
Value below threshold	0.061	0.139
Panel B. Alternate Bandwidths		
Bandwidth = 100		
Estimate	3.3 p.p.	1.7 p.p.
	(0.255)	(0.338)
Value below threshold	0.062	0.14
Bandwidth = 200		
Estimate	3.42 p.p.	1.63 p.p.
	(0.177)	(0.235)
Value below threshold	0.059	0.138

Note: Reduced-form effects are obtained by regressing the outcome indicated by the column heading on a constant, an indicator for being above the threshold, normalized reference year eligibility hours, and the interaction of being above the threshold and normalized eligibility hours, using observations within the bandwidth indicated.

Table 3: LATE Estimates on Re-employment Probability

	Re-employment in Same Quarter as Job Loss	Re-employment by One Quarter after Job Loss
Panel A. Main Estimates		
Estimate	-16.23 p.p.	1.61 p.p.
	(11.44)	(11.45)
Value below threshold	0.365	0.633
Panel B. Alternate Bandwidths		
Bandwidth = 100		
Estimate	-26.05 p.p.	1.59 p.p.
	(14.03)	(13.96)
Value below threshold	0.363	0.631
Bandwidth = 200		
Estimate	-9.37 p.p.	-2.51 p.p.
	(9.38)	(9.42)
Value below threshold	0.364	0.635

Note: LATE estimates are obtained by using eligibility hours to predict UI receipt and using this value to predict the listed outcome variable. Re-employment is defined as recording hours worked with an employer besides the one a worker separates from. Re-employment by the quarter after job loss is a cumulative measure.

Table 4: LATE Estimates on Cumulative Hours Worked and Earnings

	Cumulative Hours Worked	Cumulative Earnings
Panel A. Main Estimates		
Estimate	603	14,868
	(289)	(6,671)
Value below threshold	1,638	29,647
Panel B. Alternate Bandwidths		
Bandwidth = 100		
Estimate	388	20,500
	(352)	(8,137)
Value below threshold	1,646	29,558
Bandwidth = 200		
Estimate	756	15,790
	(239)	(5,536)
Value below threshold	1,637	29,794

Note: LATE estimates are obtained by using eligibility hours to predict UI receipt and using this value to predict the listed outcome variable. Cumulative hours and earnings are calculated over the two years following job loss.

Table 5: LATE Estimates on Re-employment Job Quality

	Cumulative Hours with Next Employer	Number of Unique Employers	Hourly Wage
Panel A. Main Estimates			
Estimate	694	-1.61	3.32
	(247)	(0.65)	(2.01)
Value below threshold	839	2.98	17.59
Panel B. Alternate Bandwidths			
Bandwidth = 100			
Estimate	648	-1.73	6.89
	(301)	(0.79)	(2.44)
Value below threshold	841	2.99	17.48
Bandwidth = 200			
Estimate	664	-0.98	3.13
	(203)	(0.53)	(1.66)
Value below threshold	841	2.97	17.62

Note: LATE estimates are obtained by using eligibility hours to predict UI receipt and using this value to predict the listed outcome variable. The cumulative hourly wage and the cumulative number of employers are calculated over the two years following job loss.

Table 6: Estimates of UI Receipt on Labor Market Outcomes by WorkSource Proximity

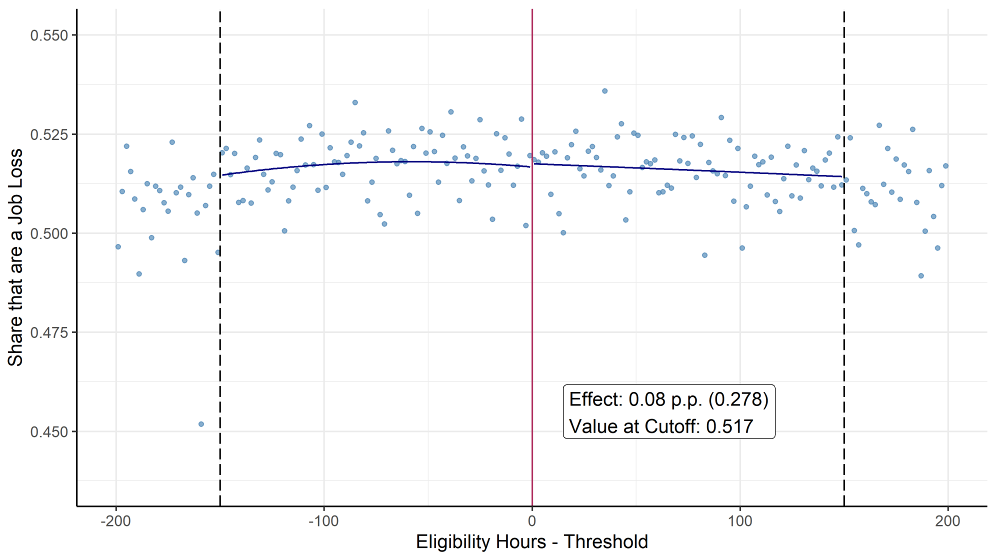
	Close to WorkSource ($\leq$ 4 miles)	Far from WorkSource ($>$ 4 miles)
First Stage on UI Receipt		
Reduced-form Effect	2.26 p.p.	3.42 p.p.
	(0.599)	(0.369)
Value below threshold	0.059	0.049
Effect on Total Earnings		
LATE Estimate	45,189	6,072
	(31,385)	(13,413)
Value below threshold	30,847	32,843
Effect on Hours Worked		
LATE Estimate	1,235	400
	(1,275)	(536)
Value below threshold	1,682	1,721
Effect on Hourly Wage		
LATE Estimate	13.60	4.09
	(9.73)	(4.20)
Value below threshold	17.98	18.59
N	68,848	165,478

Note: Table shows results for various dependent variables by proximity to a WorkSource office. Sample is split by whether a worker is close to or far from a WorkSource office with walk-in services according to the ZIP code of their home address (using matched WADOL records sample). LATE estimates are obtained by using eligibility hours to predict UI receipt and using this value to predict the stated outcome variable.

Appendix Contents

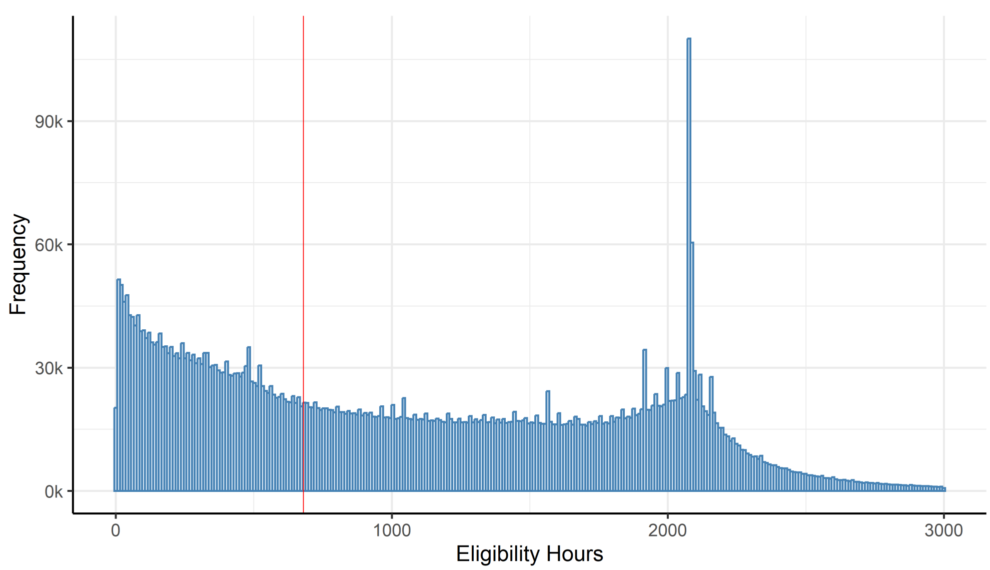
A Additional Figures and Tables

Figure A.1: Share of Job Separations Classified as a Job Loss



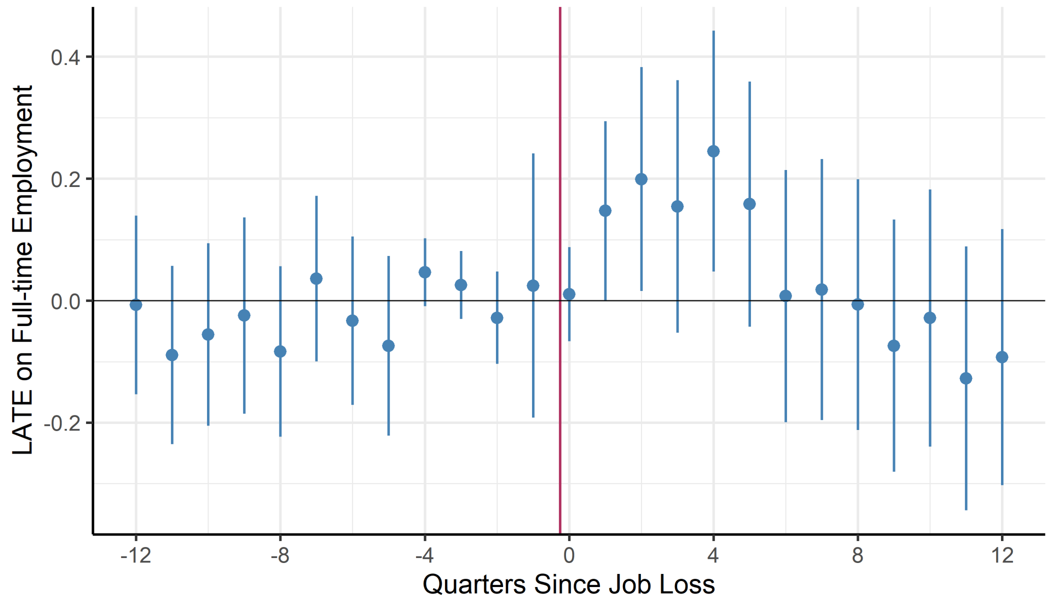
Note: This figure plots the share of all job separations classified according to eligibility hours. This analysis uses the sample of all job separations.

Figure A.2: Full Distribution of Eligibility Hours Worked for Job Loss Sample

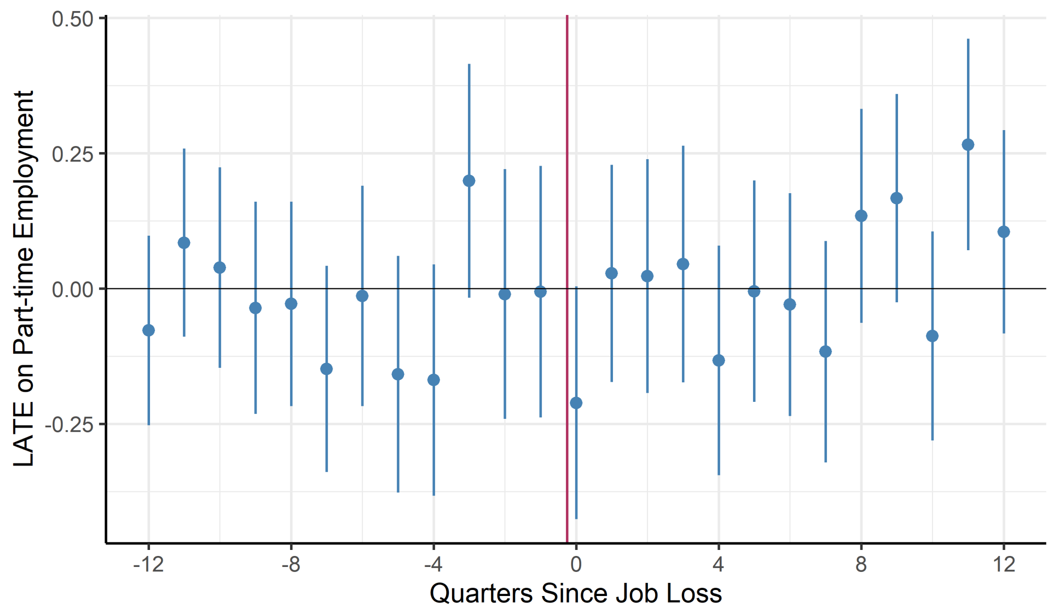


Note: This figures present the distribution of eligibility hours worked by *all workers* in the sample of job losses in Washington State occurring between 2011Q3 and 2019Q1. The 680-hour threshold is denoted by the red line. A worker's eligibility hours are the greater of the hours worked in their base year or alternate base year.

Figure A.3: Effect of UI Receipt on Full-Time and Part-Time Work



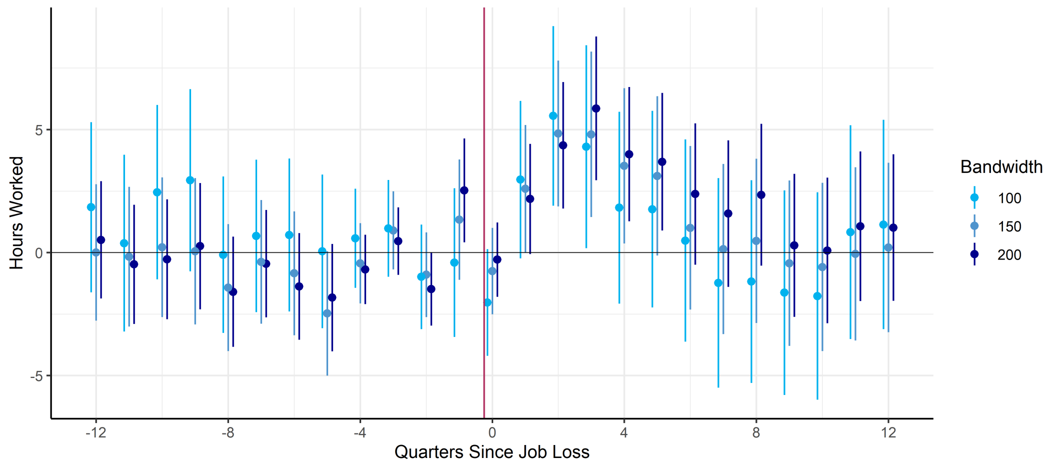
(a) RDD on Full-time Employment



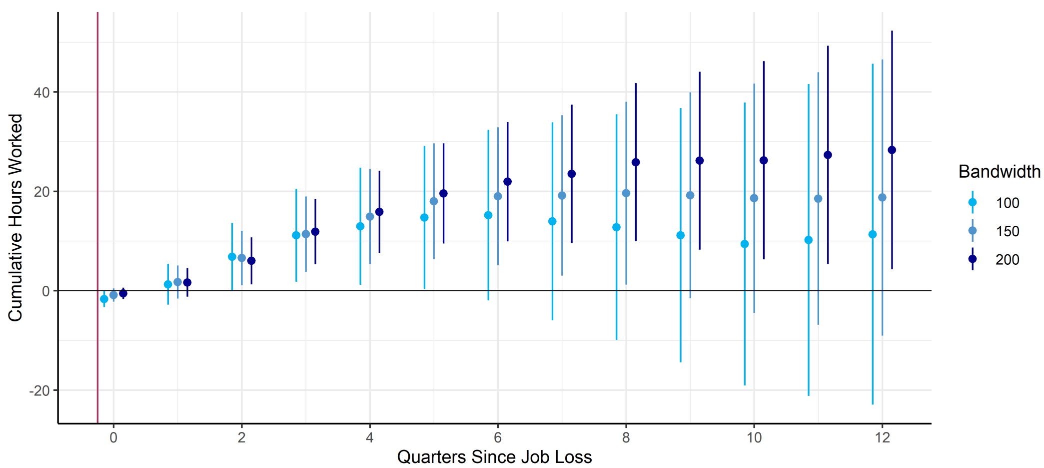
(b) RDD on Part-time Employment

Note: Graphs illustrates effect of UI eligibility on probability of full-time or part-time employment. Full-time employment in a quarter requires working at least 390 hours. Part-time employment is defined as working between 130 and 390 hours in a quarter.Panels illustrate the dynamic effect by plotting RDD point estimates for a running variable of eligibility hours and a dependent indicator variable for full-time or part-time work in a given quarter. Point estimates for each quarter and standard errors are aggregated to show the effect of UI eligibility over time.

Figure A.4: Effect of UI Eligibility on Total Hours Worked Over Time by RDD Bandwidth



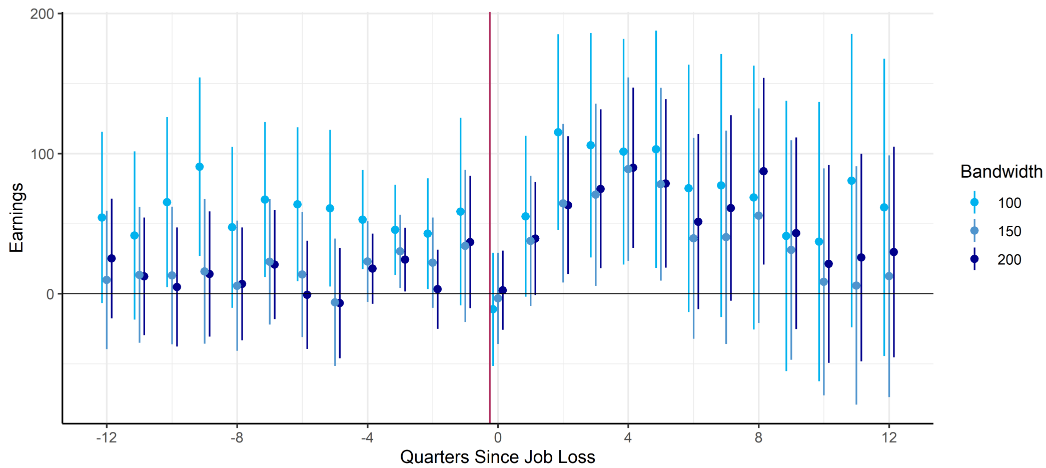
(a) Effect by Quarter



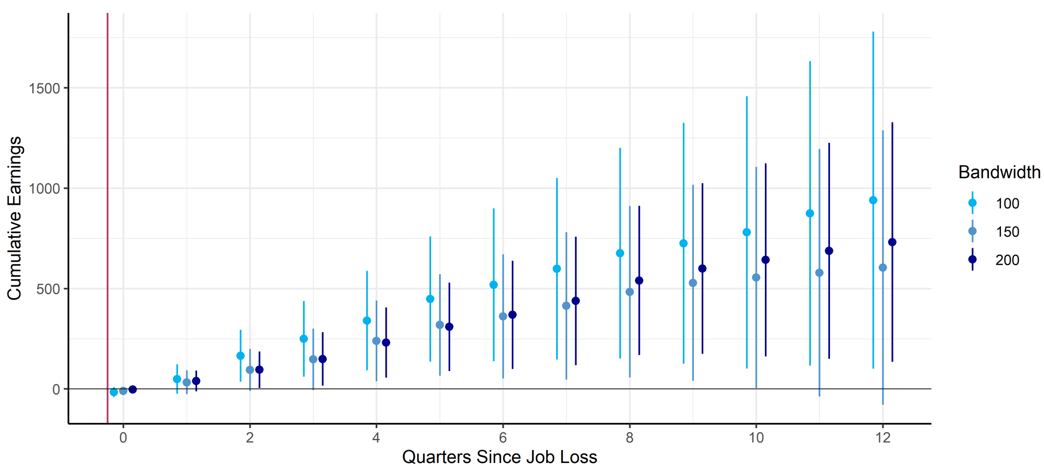
(b) Cumulative Effect

Note: Graph illustrates effect of UI eligibility on hours worked at various bandwidths (100, 150, and 200) by plotting RDD point estimates for a running variable of eligibility hours and a dependent variable of the lead or lag of total hours worked relative to job loss. Point estimates for each quarter and their standard errors are aggregated into graphs to show the effect of UI eligibility over time. Panel (a) reports effects for hours worked on a quarter-by-quarter basis, while panel (b) reports effects for cumulative hours worked.

Figure A.5: Effect of UI Eligibility on Total Earnings Over Time by RDD Bandwidth



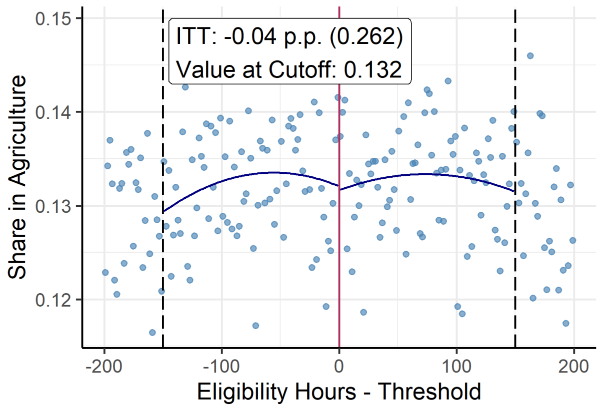
(a) Effect by Quarter



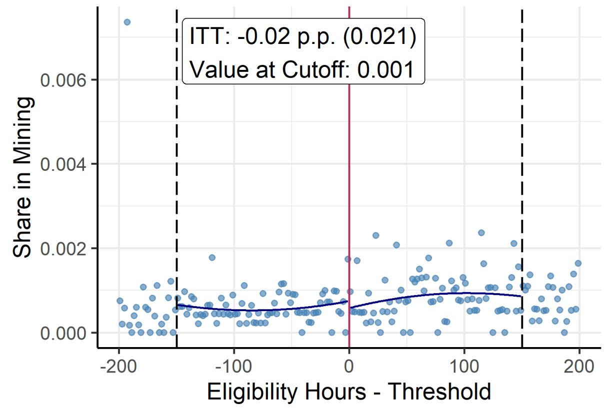
(b) Cumulative Effect

Note: Graph illustrates effect of UI eligibility on earnings at various bandwidths (100, 150, and 200) by plotting RDD point estimates for a running variable of eligibility hours and a dependent variable of the lead or lag of total earnings relative to job loss. Point estimates for each quarter and their standard errors are aggregated into graphs to show the effect of UI eligibility over time. Panel (a) reports effects for hours worked on a quarter-by-quarter basis, while panel (b) reports effects for cumulative hours worked.

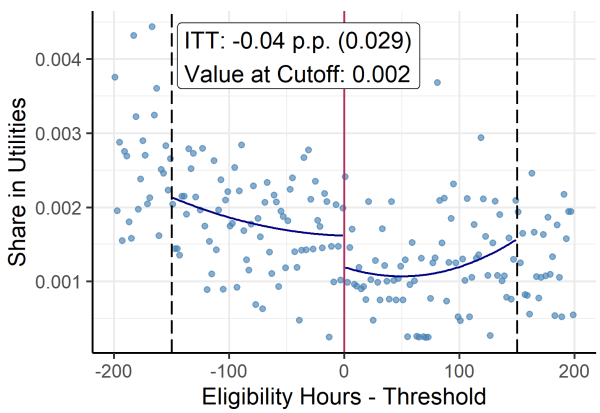
Figure A.6: Industry Share Balance around UI Eligibility Threshold, NAICS 11–23



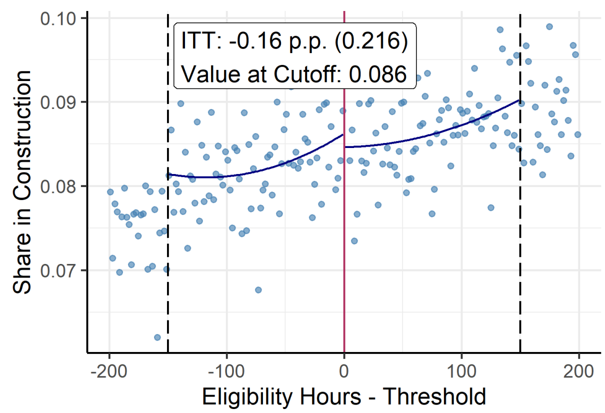
(a) Agriculture, Forestry, Fishing



(b) Mining and Oil and Gas Extraction



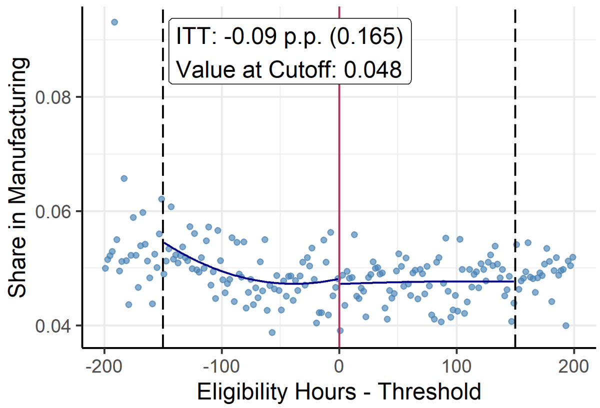
(c) Utilities



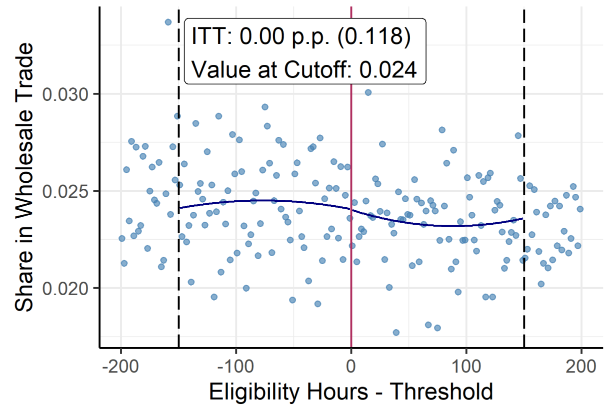
(d) Construction

Note: Figure shows balance across threshold of eligibility hours for share of job loss sample belonging to a specific 2-digit NAICS sector. Intent to Treat (ITT) effects of sectoral share of being above the 680-hour threshold is listed in percent points along with the standard error in parentheses.

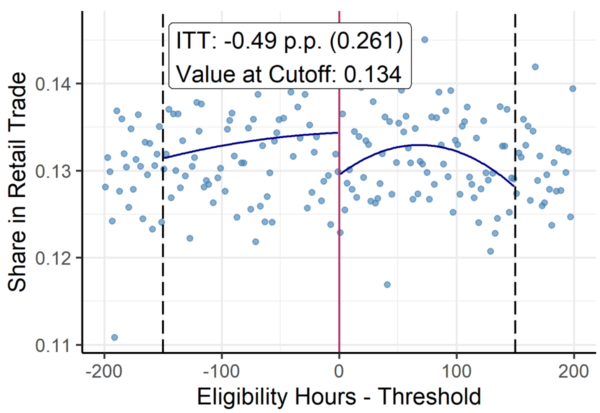
Figure A.7: Industry Share Balance around UI Eligibility Threshold, NAICS 31–48



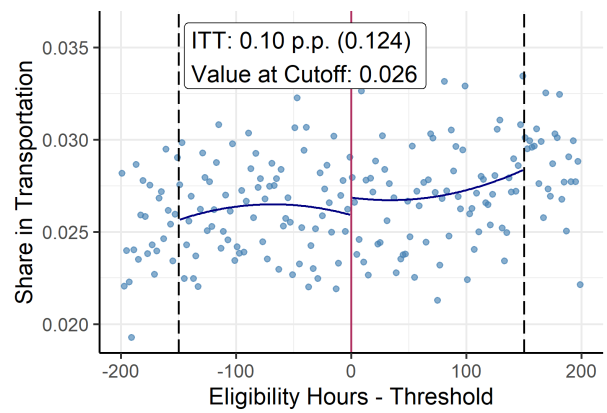
(a) Manufacturing



(b) Wholesale Trade



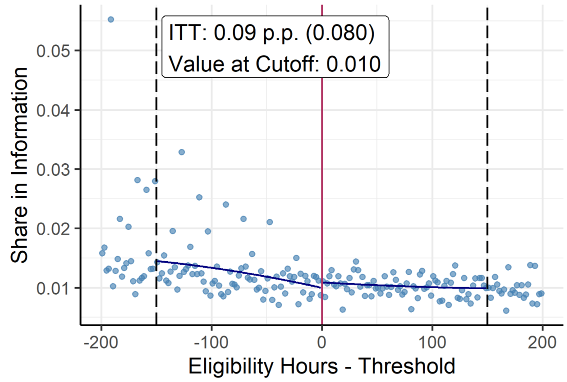
(c) Retail Trade



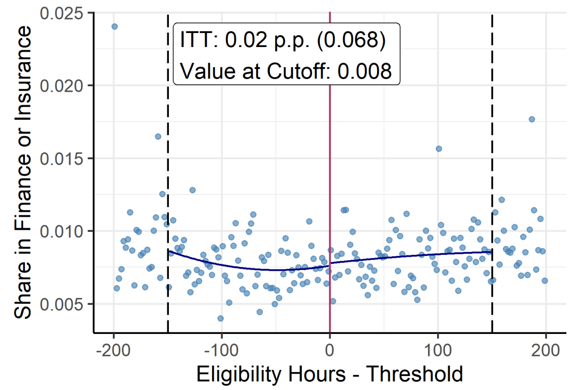
(d) Transportation and Warehousing

Note: Figure shows balance across threshold of eligibility hours for share of job loss sample belonging to a specific 2-digit NAICS sector. Intent to Treat (ITT) effects of sectoral share of being above the 680-hour threshold is listed in percent points along with the standard error in parentheses.

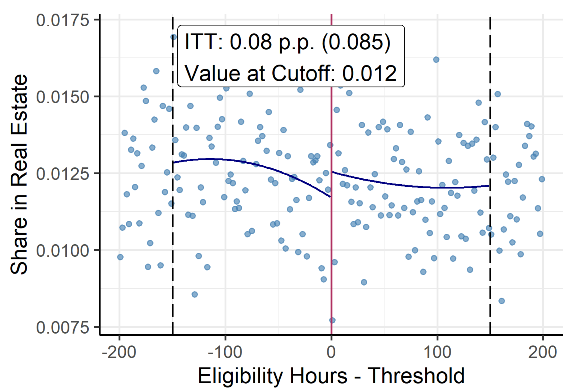
Figure A.8: Industry Share Balance around UI Eligibility Threshold, NAICS 51–56



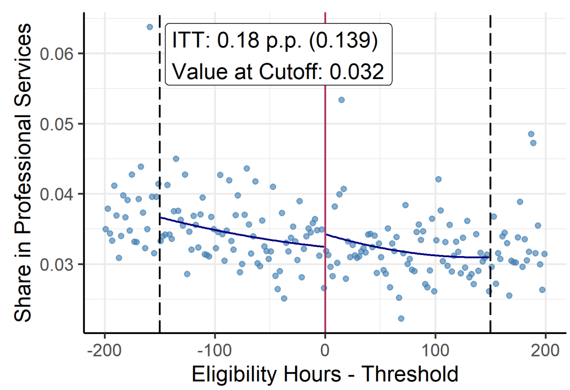
(a) Information



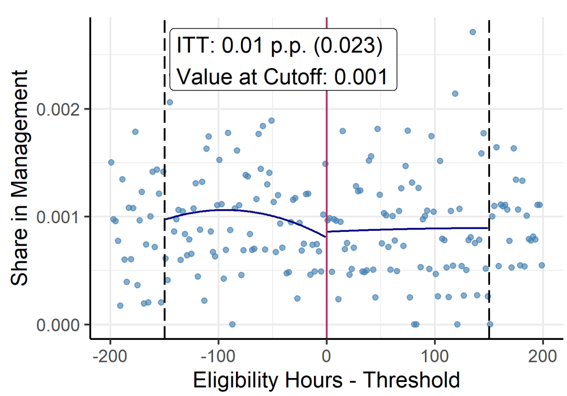
(b) Finance and Insurance



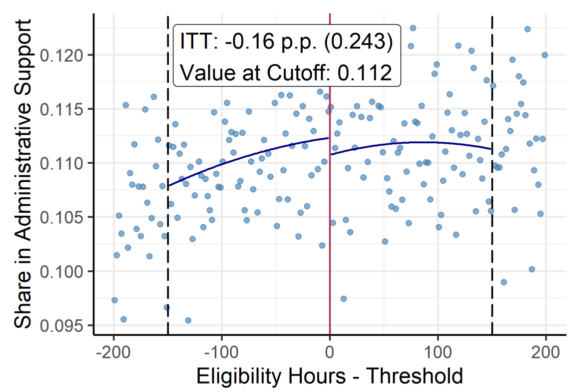
(c) Real Estate and Rental and Leasing



(d) Professional, Scientific, and Technical Services



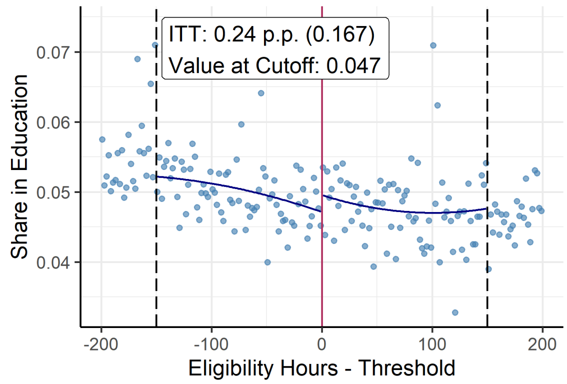
(e) Management of Companies



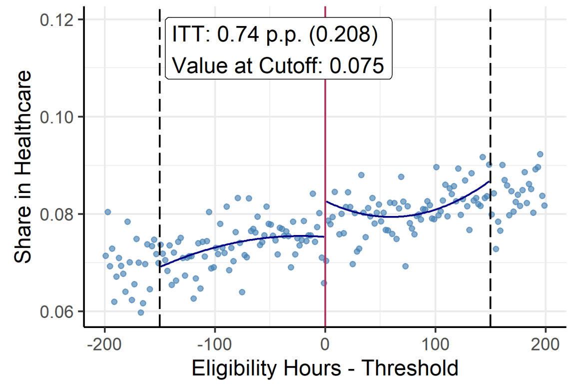
(f) Administrative and Support and Waste Management, Remediation Services

Note: Figure shows balance across threshold of eligibility hours for share of job loss sample belonging to a specific 2-digit NAICS sector. Intent to Treat (ITT) effects of sectoral share of being above the 680-hour threshold is listed in percent points along with the standard error in parentheses.

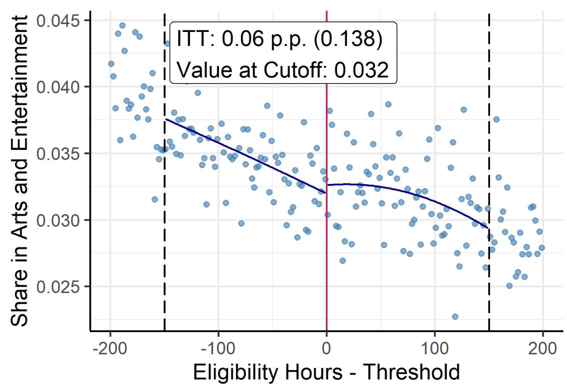
Figure A.9: Industry Share Balance around UI Eligibility Threshold, NAICS 61–92



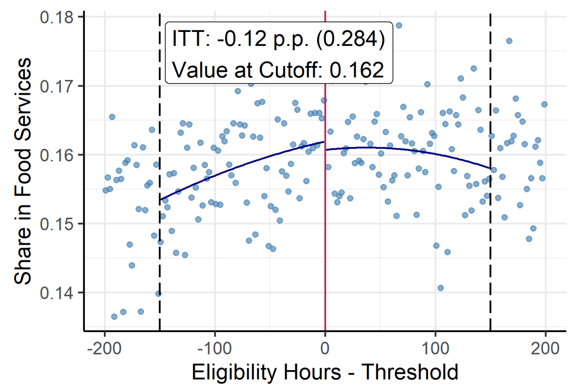
(a) Educational Services



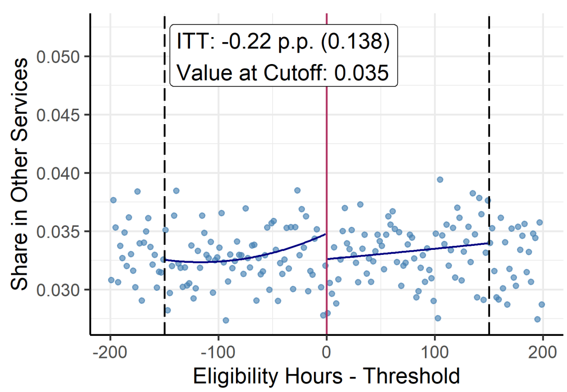
(b) Health Care and Social Assistance



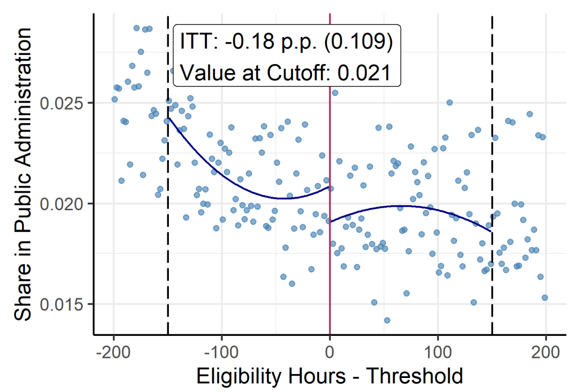
(c) Arts, Entertainment, and Recreation



(d) Accommodation and Food Services



(e) Other Services (except Public Admin.)



(f) Public Administration

Note: Figure shows balance across threshold of eligibility hours for share of job loss sample belonging to a specific 2-digit NAICS sector. Intent to Treat (ITT) effects of sectoral share of being above the 680-hour threshold is listed in percent points along with the standard error in parentheses.

Table A.1: Sample Industry Composition by 2-Digit NAICS

Variable	All	RDD	Full-Time
Industry (NAICS) of Separation			
11 Agriculture, Fishing, Forestry	0.103	0.131	0.060
21 Mining, Quarrying, and Oil and Gas Extraction	0.001	0.001	0.001
22 Utilities	0.001	0.002	0.002
23 Construction	0.079	0.084	0.075
31-33 Manufacturing	0.058	0.048	0.099
42 Wholesale Trade	0.032	0.024	0.057
44 Retail Trade	0.126	0.133	0.114
48-49 Transportation	0.030	0.027	0.040
51 Information	0.021	0.013	0.043
52 Finance and Insurance	0.016	0.008	0.036
53 Real Estate and Rental and Leasing	0.014	0.012	0.021
54 Professional, Scientific, and Technical Services	0.046	0.034	0.079
55 Management of Companies and Enterprises	0.001	0.001	0.002
56 Administrative, Support, Waste Management Services	0.101	0.112	0.082
61 Educational Services	0.061	0.049	0.028
62 Health Care and Social Assistance	0.093	0.077	0.128
71 Arts, Entertainment, and Recreation	0.035	0.033	0.015
72 Accommodation and Food Services	0.126	0.158	0.064
81 Other Services	0.033	0.033	0.029
92 Public Administration	0.023	0.020	0.024
N	5,526,547	645,309	1,339,553

B Robustness of Estimates

This section presents evidence of the robustness of our results to bandwidth choice and the definition of job loss.

B.1 Bandwidth Choice

In our main analysis, we use a bandwidth of 150 hours to define the sample local to the eligibility threshold. We show that our results are robust to bandwidth choice by plotting the estimates for our main outcomes when using bandwidths ranging from 5 hours to 200 hours. For example, in Figure B.1, we plot the reduced-form effect on UI receipt from a bandwidth of 5 hours through 200 hours as well as a 95 percent confidence interval. The baseline estimate of 150 hours is marked with a black dotted line. Figure B.2 plots the reduced-form effect on the probability of applying. Figure B.3 presents the LATE estimate on cumulative re-employment in the same quarter as job loss as well as by the quarter after job loss. Figures B.4 and B.5 plot the LATE estimate on cumulative hours and earnings, respectively. Figure B.6 plots the LATE estimate for each of our measures of re-employment job quality–cumulative hours with next employer, cumulative hourly wage, and number of unique employers. Overall, estimates are relatively stable across the range of bandwidths, which provides strong evidence that the bandwidth choice does not significantly impact our results or conclusions.

It is increasingly common for papers using a regression discontinuity design to rely on the optimal bandwidth selection outlined in Calonico et al. (2019) (CCT). There are two reasons why this paper does not use this approach in our main analysis. First, this approach would require a different bandwidth for each outcome. In total, we present estimates for more than 60 outcomes, including quarterly hours and earnings as well as covariates. Adjusting the bandwidth for each of these estimates effectively changes the sample we are using. We feel it is more intuitive to use the same bandwidth throughout our analysis.

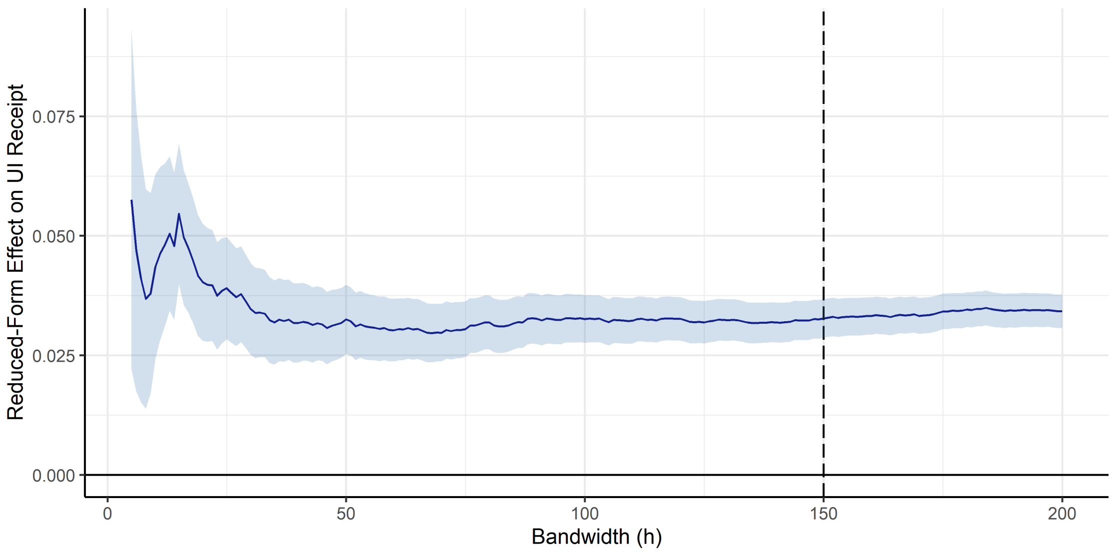
Second, this approach optimizes the bandwidth based on certain statistical properties, but ignores important institutional details. Specifically, we observe significant bunching in certain industries when the running variable is more than 200 hours below the eligibility threshold, a point which corresponds to one quarter of full-time work. Figure B.7 provides evidence of this bunching by plotting the share of observations belonging to Information Services (NAICS 2-digit code 51) or Retail Trade (NAICS 2-digit code 44 or 45) by eligibility hours. Information Services typically constitutes 2 to 3 percent of the sample, and the share then jumps to 20 percent around 200 hours below the threshold. Retail Trade comprises 12 to 13 percent of the sample, and the share increases to 27 percent with clear bunching around 200 hours below the threshold. Interestingly, these are the only two industries that exhibit such bunching. This is likely due to contracts or positions in these specific industries lasting almost exactly one quarter of full-time work. This bunching, although not near the relevant threshold and not a threat to our identification, creates a discontinuity in the sample that distorts estimates when using a bandwidth beyond 200 hours. However, the CCT optimal bandwidth selection does not account for this and may choose a bandwidth affected by this issue.

Still, we demonstrate the robustness of our estimates to using the CCT optimal bandwidth as well as for bandwidths beyond 200 hours. In order to do so, we extend our analysis of bandwidth robustness in three ways. First, we plot the estimates for a wider range of bandwidths from 5 hours to 350 hours. Second, we estimate these effects over our entire sample as well as after dropping the industries that exhibit bunching 200 hours below the threshold. Third, we calculate the CCT optimal bandwidth for both samples.

In Figure B.8, we plot the reduced-form effect on UI receipt over an extended bandwidth range from 5 hours through 350 hours for all observations as well as for a sample where we drop the industries that exhibit bunching. We mark the baseline estimate of 150 hours with a black dotted line, the CCT optimal bandwidth for the entire sample with a dotted blue line, and the CCT optimal bandwidth for the sample without bunching industries using a dotted red line. Figure B.9 replicates this plot for applications. Figure B.10 plot cumulative re-employment. Figures B.11 and B.12 plot cumulative hours and earnings, respectively. Figure B.13 plots our measures of re-employment job quality–cumulative hours with next employer, cumulative hourly wage, and number of unique employers.

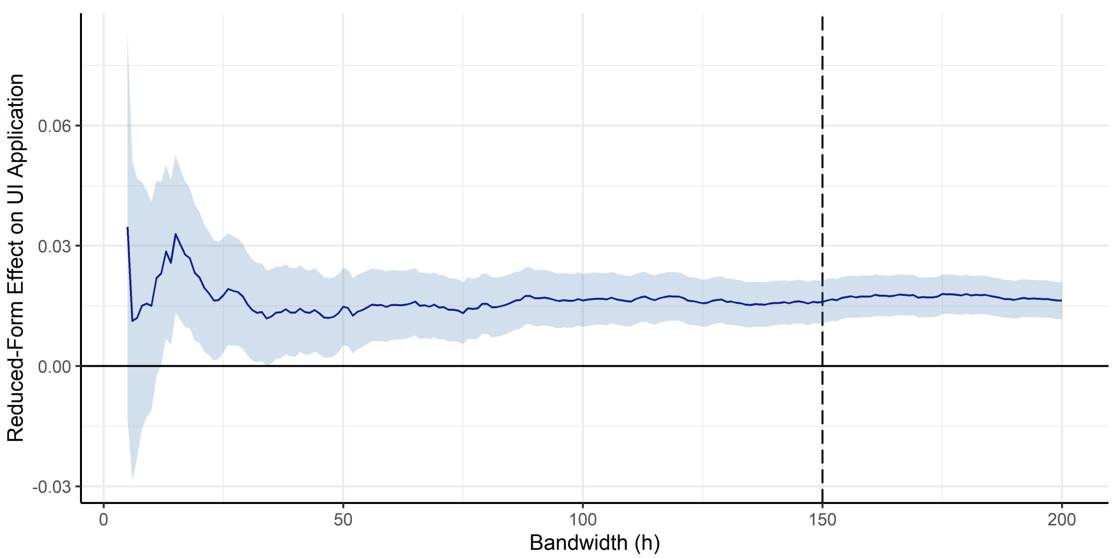
Three insights from this extended analysis further support the robustness of our results. First, whether we drop these industries that exhibit bunching does not seem to affect our estimates when using a bandwidth below 200 hours. Second, for bandwidths above 200 hours, LATE estimates over the entire sample diverge sharply from the estimates for the sample of the non-bunching industries before rebounding sharply beyond 250 hours. We conclude that estimates using the entire sample for bandwidths beyond 200 hours are unreliable. Third, estimates using the optimal bandwidth choice are consistent with our main results that use a bandwidth of 150 hours. The exception is when the optimal bandwidth for the entire sample is greater than 200 hours and thus affected by the bunching industries, in which case we argue that the estimate using the bandwidth of 150 hours is more reliable. Overall, we feel this strongly supports the robustness of our results as well as the choice to use a bandwidth of 150 hours in our baseline estimates.

Figure B.1: Reduced-Form Effect on UI Receipt across Bandwidths



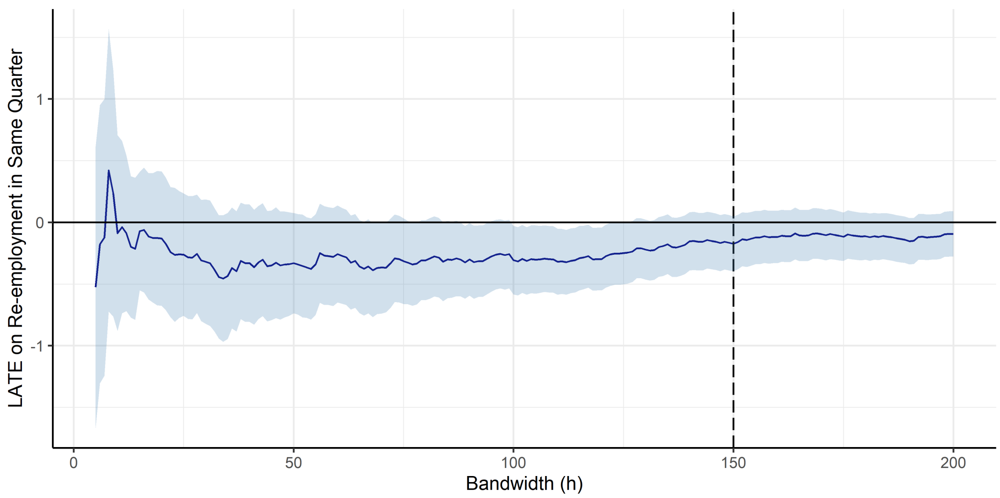
Note: This figure plots the estimated reduced-form effect of eligibility on UI receipt from a bandwidth of 5 hours through 200 hours. The shaded area represents the 95 percent confidence interval. The black dotted line represents the baseline estimate using a bandwidth of 150 hours.

Figure B.2: Reduced-Form Effect on UI Application across Bandwidths

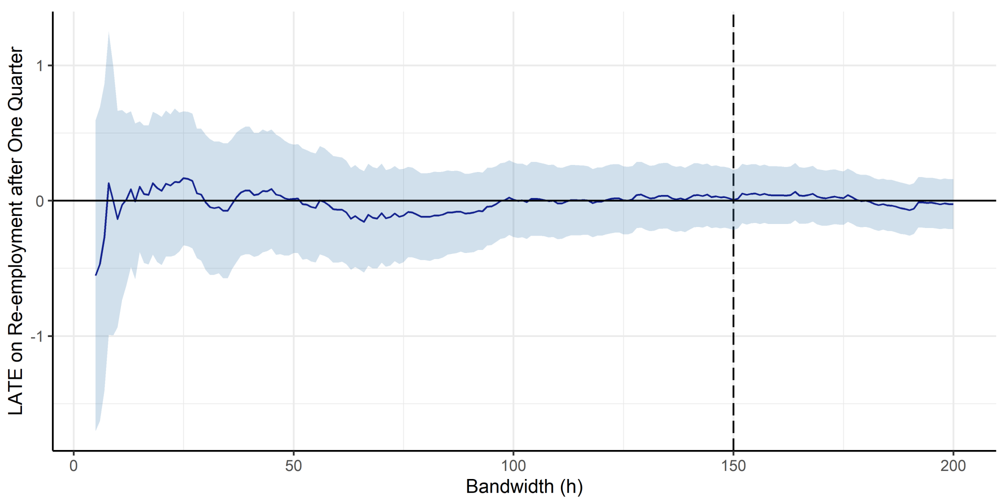


Note: This figure plots the estimated reduced-form effect of eligibility on UI applications from a bandwidth of 5 hours through 200 hours. The shaded area represents the 95 percent confidence interval. The black dotted line represents the baseline estimate using a bandwidth of 150 hours.

Figure B.3: LATE Effect on Re-employment across Bandwidths



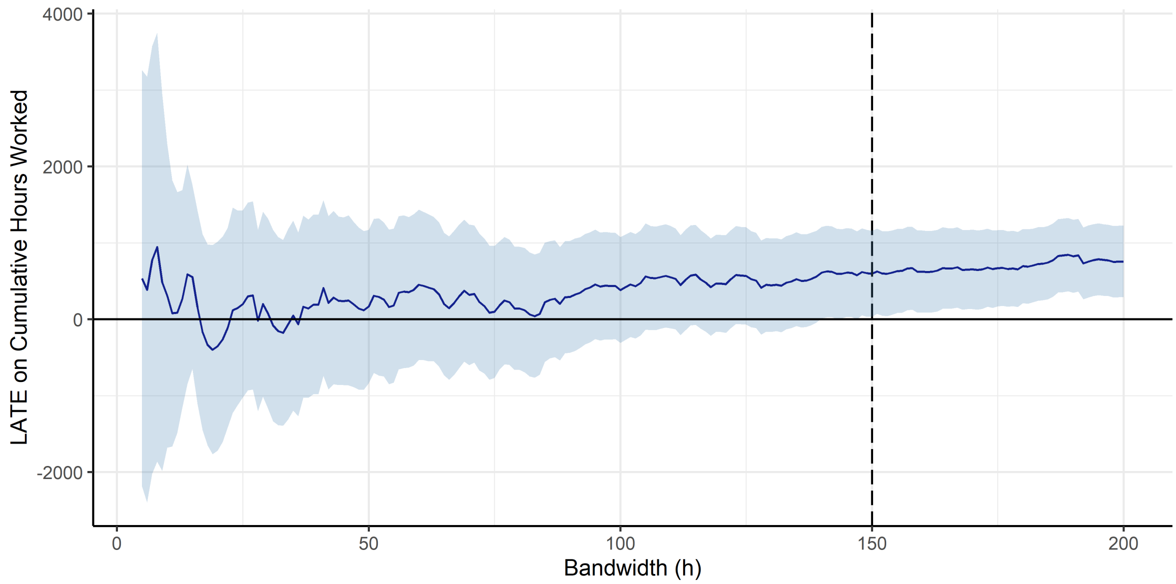
(a) Re-employment in quarter of job loss



(b) Re-employment by quarter after job loss

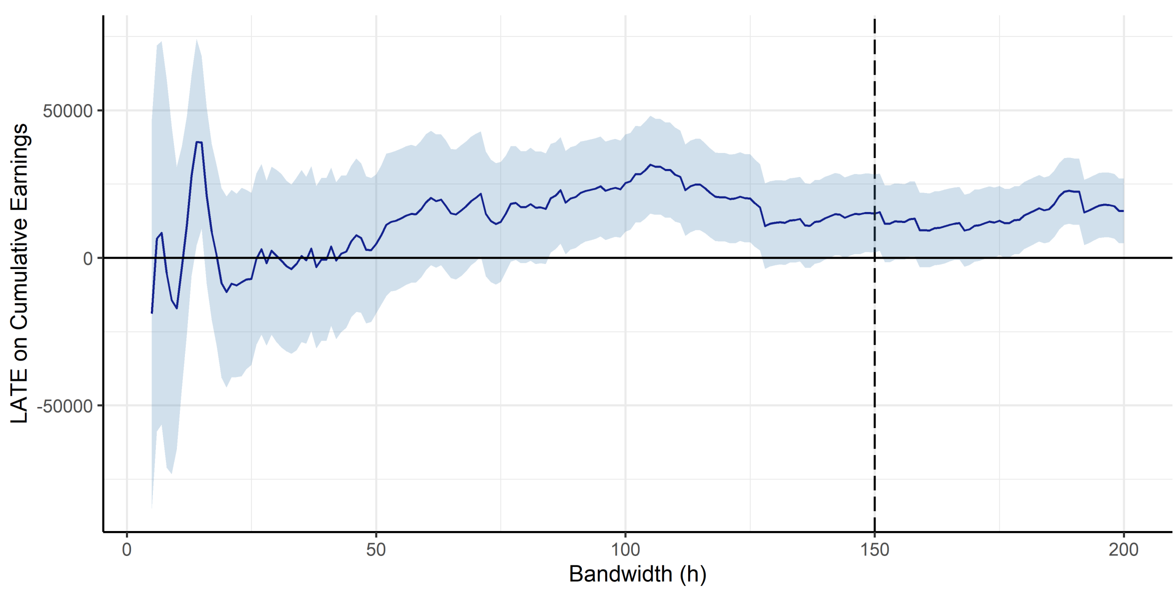
Note: This figure plots the estimated LATE of UI receipt on the probability of re-employment from a bandwidth of 5 hours through 200 hours. The shaded area represents the 95 percent confidence interval. The black dotted line represents the baseline estimate using a bandwidth of 150 hours.

Figure B.4: LATE Effect on Cumulative Hours Worked across Bandwidths



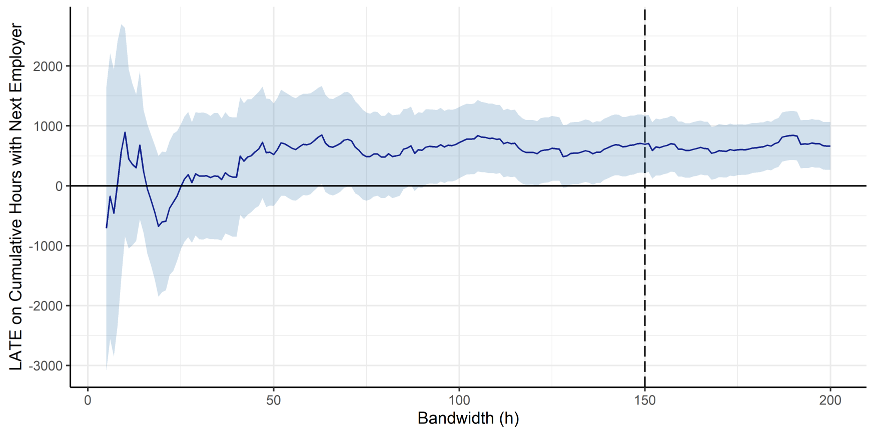
Note: This figure plots the estimated LATE of UI receipt on cumulative hours worked in the two years following job loss from a bandwidth of 5 hours through 200 hours. The shaded area represents the 95 percent confidence interval. The black dotted line represents the baseline estimate using a bandwidth of 150 hours.

Figure B.5: LATE Effect on Cumulative Earnings across Bandwidths

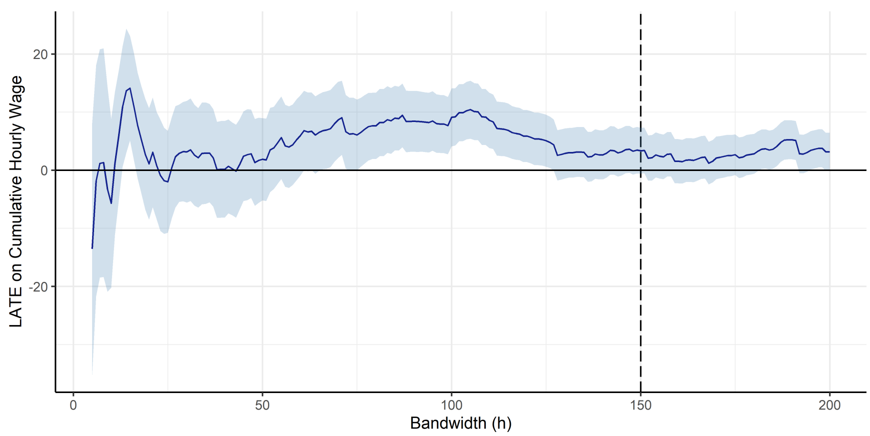


Note: This figure plots the estimated LATE of UI receipt on cumulative earnings in the two years following job loss from a bandwidth of 5 hours through 200 hours. The shaded area represents the 95 percent confidence interval. The black dotted line represents the baseline estimate using a bandwidth of 150 hours.

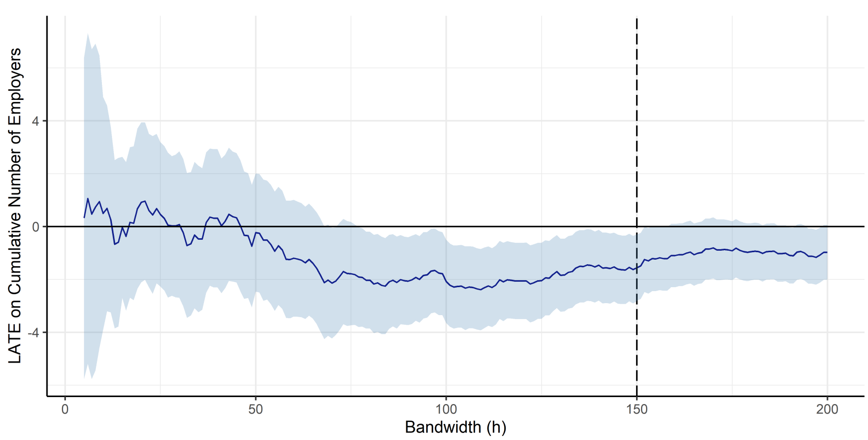
Figure B.6: LATE Effect on Re-employment Job Quality across Bandwidths



(a) Cumulative Hours Worked with Next Employer



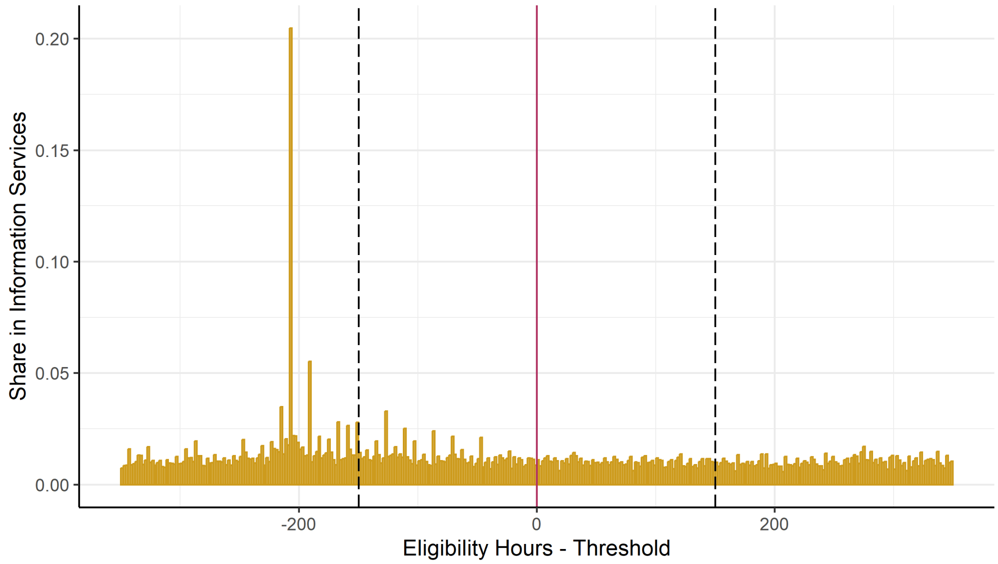
(b) Cumulative Hourly Wage



(c) Cumulative Number of Employers

Note: This figure plots the estimated LATE of UI receipt on our measures of re-employment job quality from a bandwidth of 5 hours through 200 hours. The shaded area represents the 95 percent confidence interval. The black dotted line represents the baseline estimate using a bandwidth of 150 hours.

Figure B.7: Industries with Bunching Issues

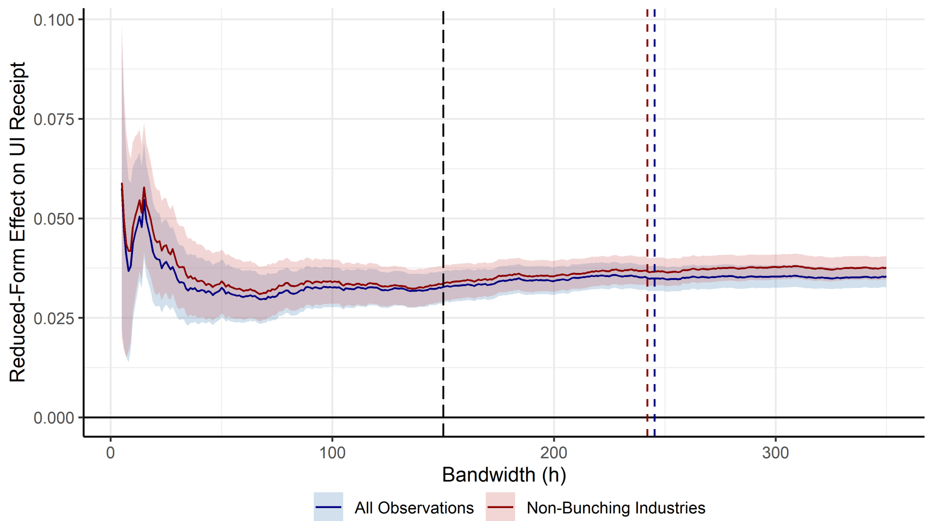


(a) Information Services

(b) Retail Trade

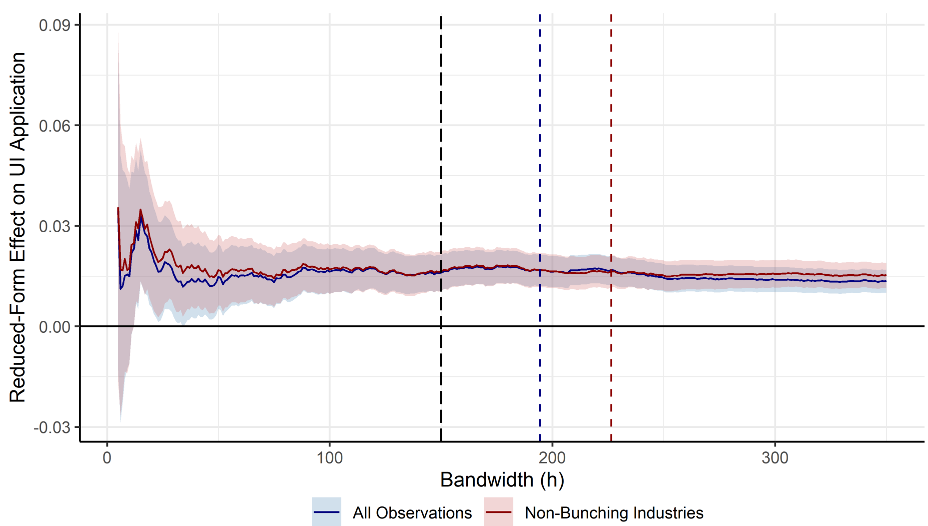
Note: This figure plots the share of observations belonging to that industry using 2-hour bins. The black dotted lines represent the bandwidth fo 150 hours used in our baseline estimates. The red line represents whether the eligibility threshold is.

Figure B.8: Reduced-Form Effect on UI Receipt across Extended Bandwidths



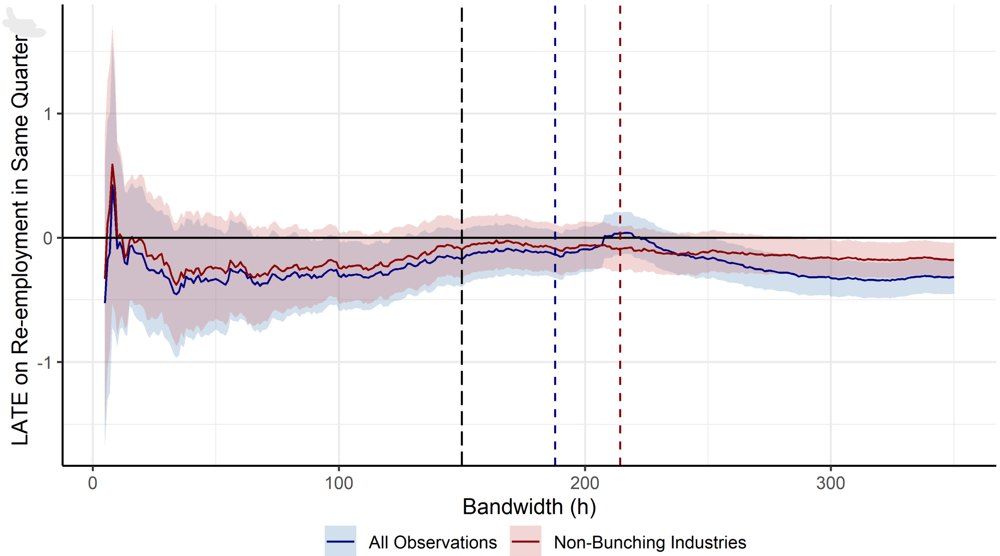
Note: This figure plots the reduced-form effect of eligibility on UI receipt from a bandwidth of 5 hours through 350 hours for the entire sample in blue and a subsample in red that drops industries that exhibit bunching. The shaded areas represents the respective 95 percent confidence intervals. The black dotted line represents the baseline estimate using a bandwidth of 150 hours while the blue and red lines mark the optimal bandwidth according to the CCT procedure for the respective samples.

Figure B.9: Reduced-Form Effect on UI Application across Extended Bandwidths

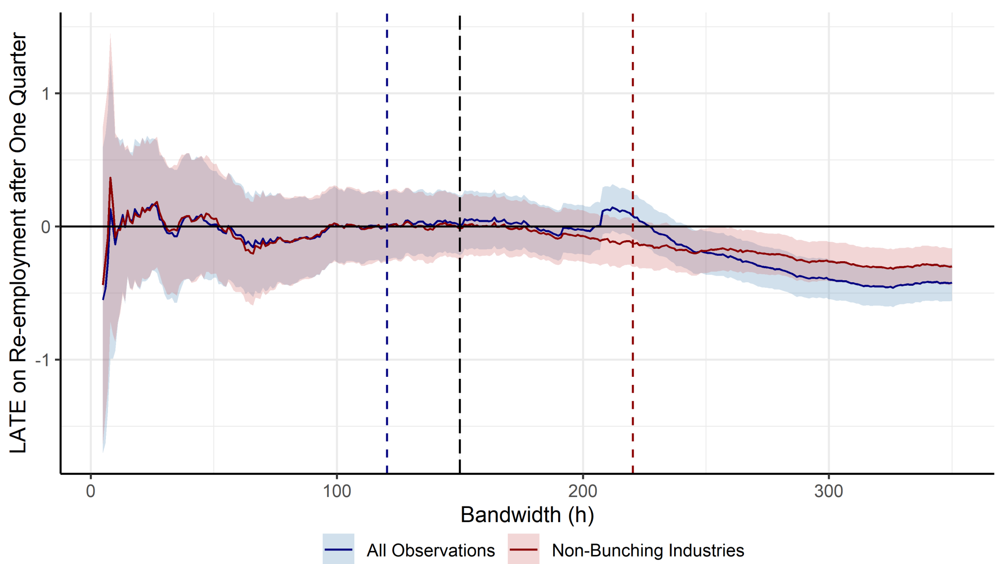


Note: This figure plots the reduced-form effect of eligibility on UI application from a bandwidth of 5 hours through 350 hours for the entire sample in blue and a subsample in red that drops industries that exhibit bunching. The shaded areas represents the respective 95 percent confidence intervals. The black dotted line represents the baseline estimate using a bandwidth of 150 hours while the blue and red lines mark the optimal bandwidth according to the CCT procedure for the respective samples.

Figure B.10: LATE Effect on Re-employment across Extended Bandwidths



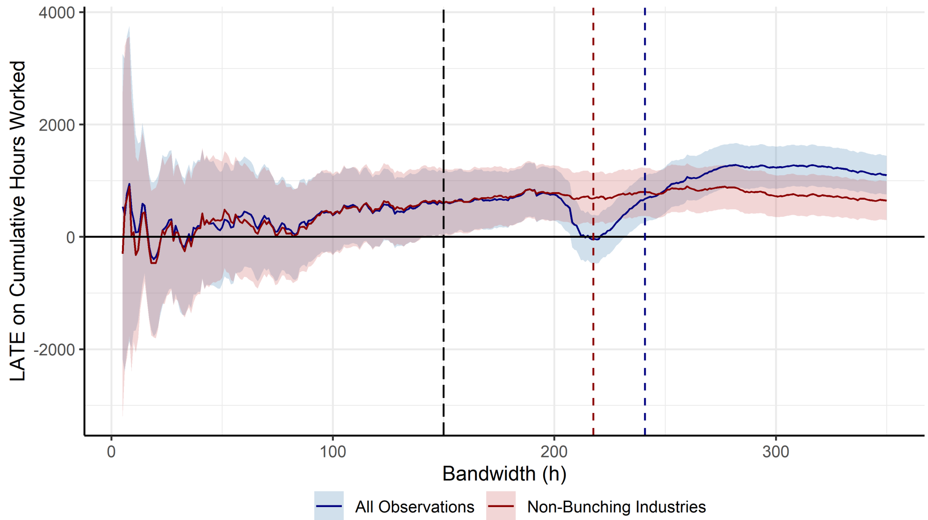
(a) Re-employment in quarter of job loss



(b) Re-employment by quarter after job loss

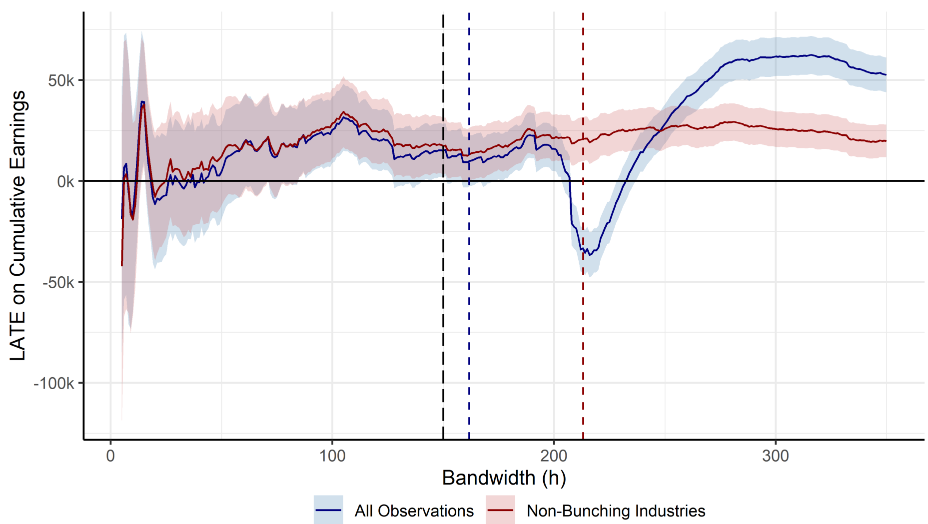
Note: This figure plots the estimated LATE of UI receipt on the probability of re-employment from a bandwidth of 5 hours through 350 hours for the entire sample in blue and a subsample in red that drops industries that exhibit bunching. The shaded areas represents the respective 95 percent confidence intervals. The black dotted line represents the baseline estimate using a bandwidth of 150 hours while the blue and red lines mark the optimal bandwidth according to the CCT procedure for the respective samples.

Figure B.11: LATE Effect on Cumulative Hours Worked across Extended Bandwidths



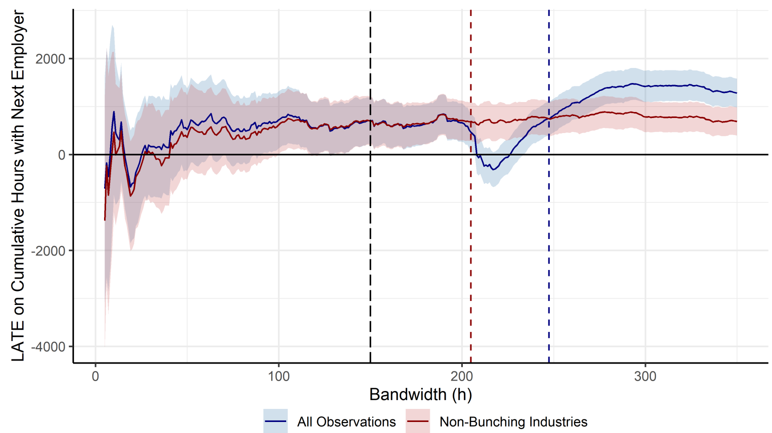
Note: This figure plots the estimated LATE of UI receipt on cumulative hours worked in the two years after job loss from a bandwidth of 5 hours through 350 hours for the entire sample in blue and a subsample in red that drops industries that exhibit bunching. The shaded areas represents the respective 95 percent confidence intervals. The black dotted line represents the baseline estimate using a bandwidth of 150 hours while the blue and red lines mark the optimal bandwidth according to the CCT procedure for the respective samples.

Figure B.12: LATE Effect on Cumulative Earnings across Extended Bandwidths

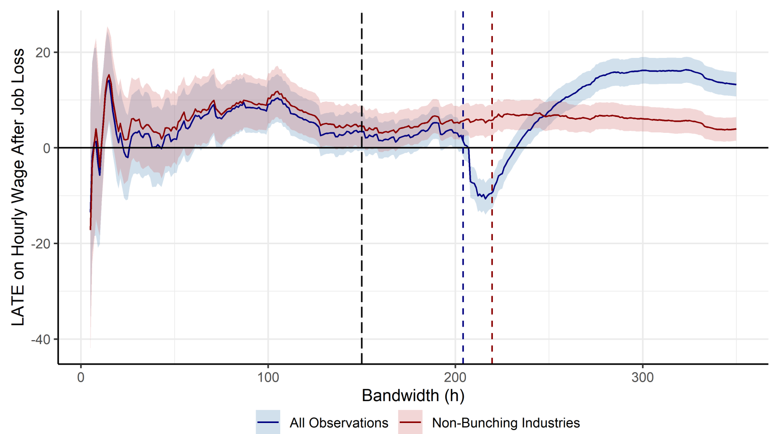


Note: This figure plots the estimated LATE of UI receipt on cumulative earnings in the two years after job loss from a bandwidth of 5 hours through 350 hours for the entire sample in blue and a subsample in red that drops industries that exhibit bunching. The shaded areas represents the respective 95 percent confidence intervals. The black dotted line represents the baseline estimate using a bandwidth of 150 hours while the blue and red lines mark the optimal bandwidth according to the CCT procedure for the respective samples.

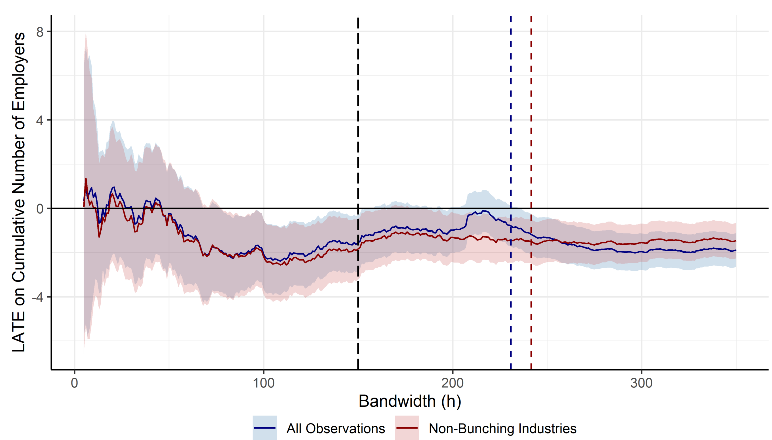
Figure B.13: LATE Effect on Re-employment Job Quality across Extended Bandwidths



(a) Cumulative Hours Worked with Next Employer



(b) Cumulative Hourly Wage



(c) Cumulative Number of Employers

Note: This figure plots the estimated LATE of UI receipt on our measures of re-employment job quality from a bandwidth of 5 hours through 350 hours for the entire sample in blue and a subsample in red that drops industries that exhibit bunching. The shaded areas represents the respective 95 percent confidence intervals. The black dotted line represents the baseline estimate using a bandwidth of 150 hours while the blue and red lines mark the optimal bandwidth according to the CCT procedure for the respective samples.

B.2 Definition of Job Loss

Our sample consists of instances where a worker experiences a job loss, which is defined as a job separation where the worker experiences a drop in total hours greater than 15 percent and returns to employment within the next 5 quarters. In this section, we consider the robustness of our results to this definition of job loss.

In constructing our sample, we first identify job separations using the quarterly employment data. Specifically, we flag a job separation when a worker does not record any hours worked in the next quarter $t + 1$ with their primary employer from the current quarter t.[25] We then assign the job separation to quarter t if the worker's hours at the primary employer dropped by more than 15 percent between quarters $t - 1$ and t. Otherwise, the job separation is assigned to the following quarter $t + 1$. This allows us to differentiate between instances where a worker separated from their job during a quarter versus at the end of the quarter.

Next, we classify each job separation as a job loss, a job-to-job transition, or a labor force exit. A job loss occurs when a worker experiences a drop in total hours greater than 15 percent and then returns to employment within the next five quarters. A job-to-job transition occurs when a worker has a new employer in the same quarter as the job separation and their total hours worked does not drop by more than 15 percent from the previous quarter. A labor force exit occurs when a worker does not record re-employment for five consecutive quarters following a job separation. These categories are mutually exclusive and collectively exhaustive over the set of job separations. We then restrict our analysis to workers who experience job loss, as these are the cases where the worker is most likely to be eligible for UI benefits.

The definition of job loss is determined by two parameters. First, the sufficient drop in hours that constitutes a disruption in employment, which is 15 percent in our baseline estimates. This is used to determine the timing of a job separation and then to distinguish between a job loss and a job-to-job transition, with larger values leading to more job separations being classified as a job-to-job transition instead of a job loss. Second, the sufficient number of quarters without re-employment that categorizes a job separation as a labor force exit, which is 5 quarters in our baseline estimates. This parameter distinguishes job loss from labor force exit, with larger values leading to more job separations being classified as a job loss instead of a labor force exit.

To assess the robustness of our results to the definition of job loss, we present the estimated effects when varying these two parameters. We consider a sufficient drop in hours equal to 10, 15, 20, or 25 percent and a sufficient number of quarters equal to 4, 5, 6, 7, or 8 quarters. Additionally, to account for a possible interaction between these two parameters, we consider the most lenient definition of job loss (10 percent and 8 quarters) and the most strict definition (25 percent and 4 quarters).

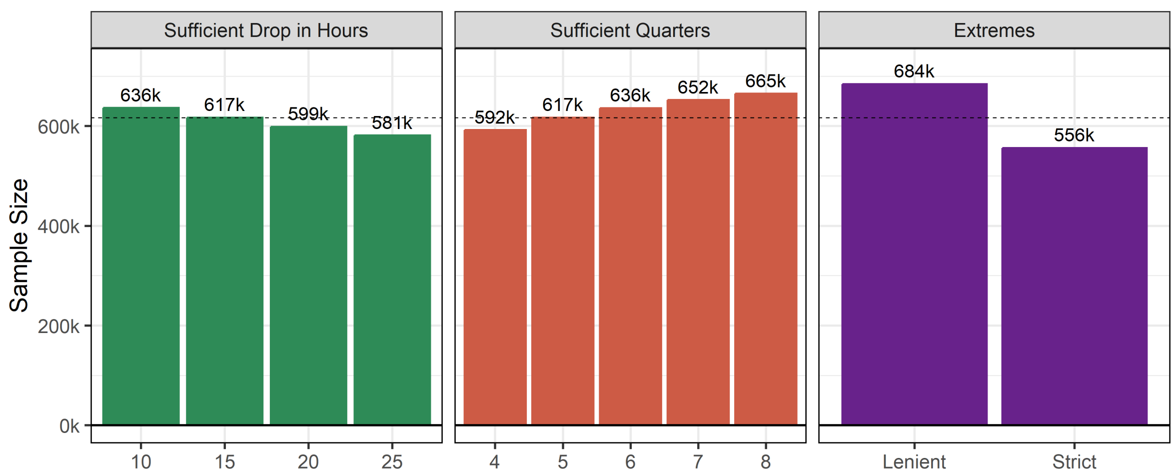
First, in Figure B.14, we plot the size of the sample across the different definitions of job loss. As we increase the sufficient drop in hours from 10 percent to 25 percent, the sample shrinks from 636k to 581k. A we increase sufficient quarters from 4 to 8, the sample grows

[25] A worker's primary employer in quarter t is defined as the employer with which they accumulated the most hours worked with over the period from $t - 2$ through t among the set of employers they recorded hours worked with in quarter t.

from 592k to 665k. Lastly, the most strict definition of job loss results in 556k observations while the most lenient definition yields a sample size that is more than 20 percent larger at 684k. This demonstrates how much the definition can change the overall size of the sample we use.

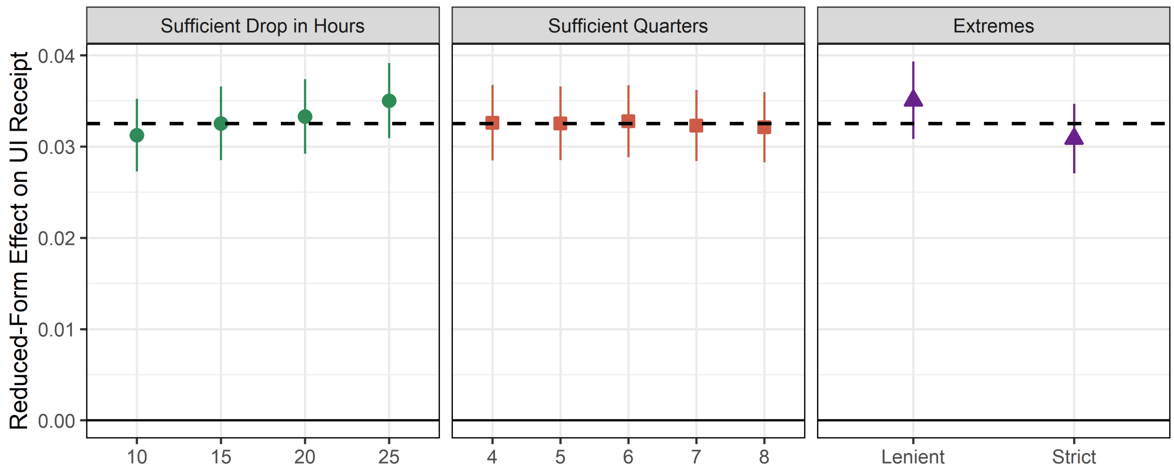
Despite these differences in sample size, our estimates are consistent across definitions of job loss. In Figure B.15, we plot the reduced-form effect on UI receipt by varying the sufficient drop in hours, varying the sufficient quarters, and using the most extreme definitions. The dotted line marks our baseline estimate. We do not find any significant differences across the definitions. Figure B.16 replicates this analysis for applications. Figure B.17 plots the effect on cumulative re-employment. Figures B.18 and B.19 plot the effects on cumulative hours and earnings, respectively. Figure B.20 plots the effect on our measures of re-employment job quality–cumulative hours with next employer, cumulative hourly wage, and number of unique employers. Overall, this suggests that our results are robust to the definition of job loss.

Figure B.14: Sample Size across Job Loss Definitions



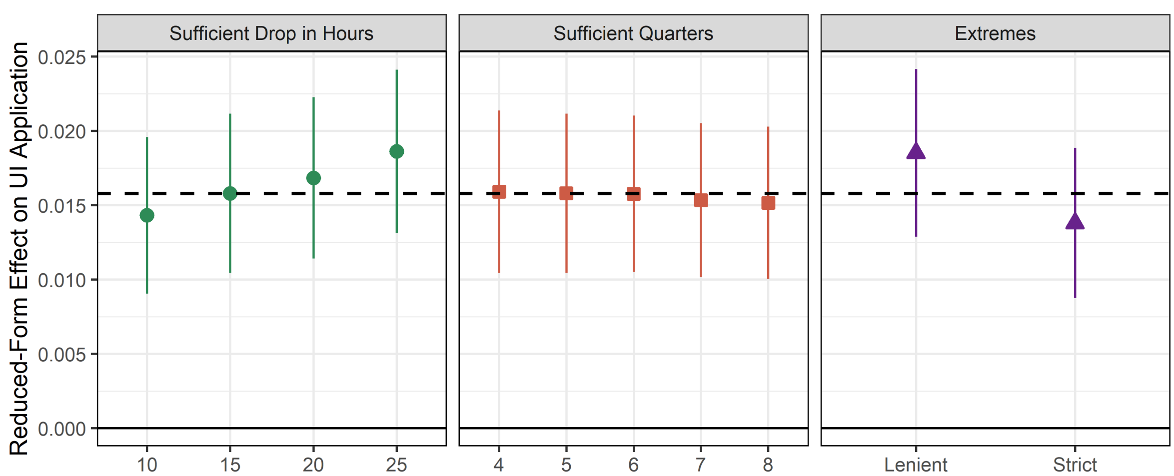
Note: This figure plots the sample size local to the eligibility threshold while varying the parameters that define job loss. The black dotted line represents the estimate in our baseline estimates.

Figure B.15: Reduced-Form Effect on UI Receipt across Job Loss Definitions



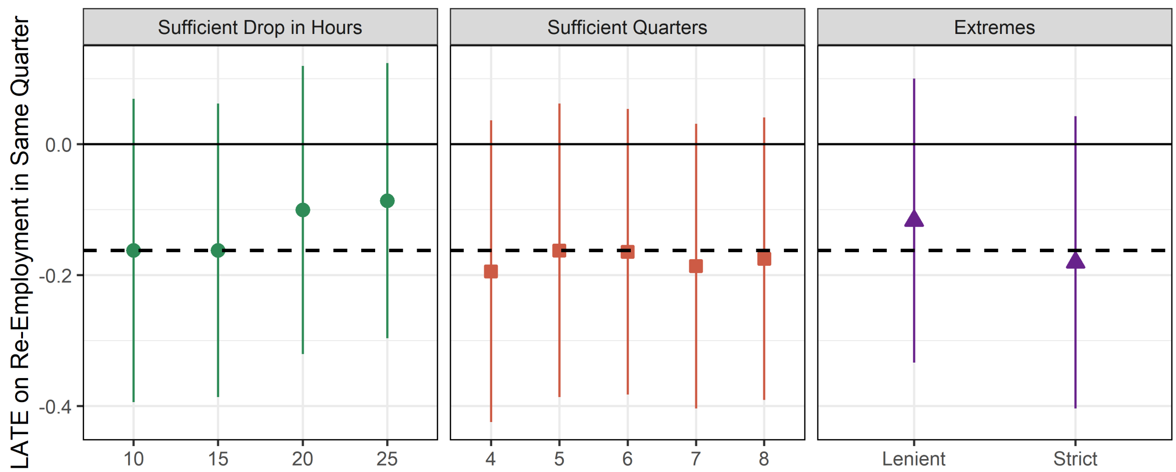
Note: This figure plots the reduced-form effect of eligibility on UI receipt while varying the parameters that define job loss. The black dotted line represents the estimate in our baseline estimates.

Figure B.16: Reduced-Form Effect on UI Application across Job Loss Definitions

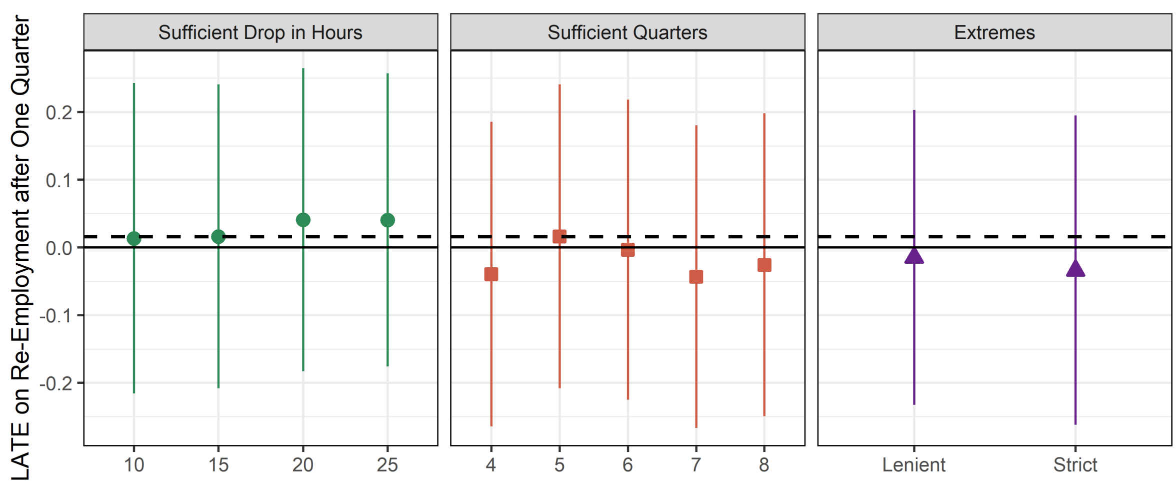


Note: This figure plots the reduced-form effect of eligibility on UI application while varying the parameters that define job loss. The black dotted line represents the estimate in our baseline estimates.

Figure B.17: LATE Effect on Re-employment across Job Loss Definitions



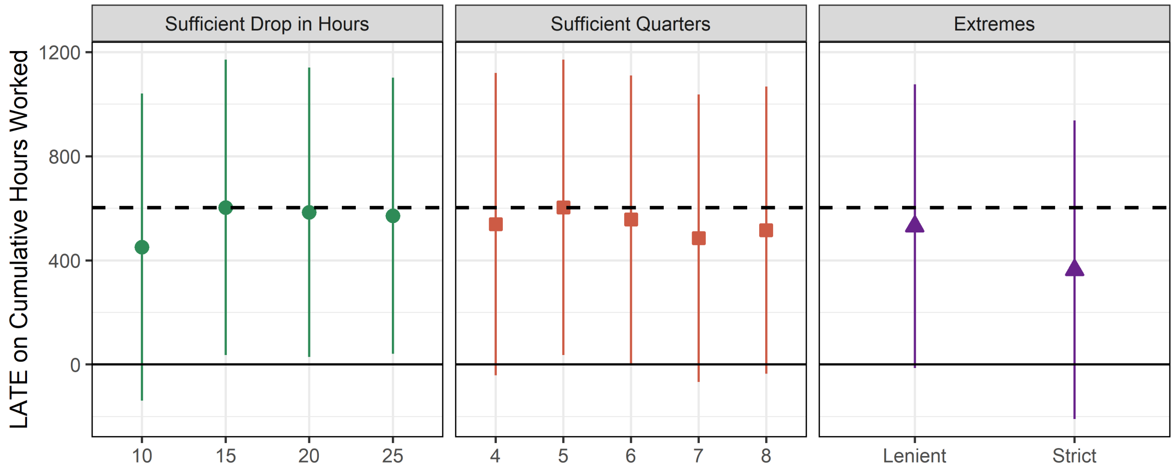
(a) Re-employment in quarter of job loss



(b) Re-employment by quarter after job loss

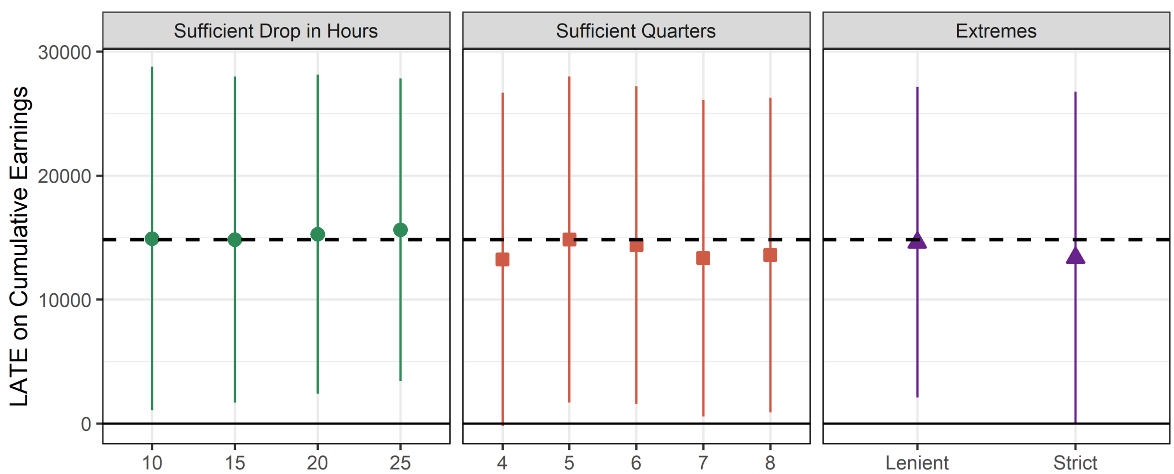
Note: This figure plots the estimated LATE of UI receipt on the probability of re-employment while varying the parameters that define job loss. The black dotted line represents the estimate in our baseline estimates.

Figure B.18: LATE Effect on Cumulative Hours Worked across Job Loss Definitions



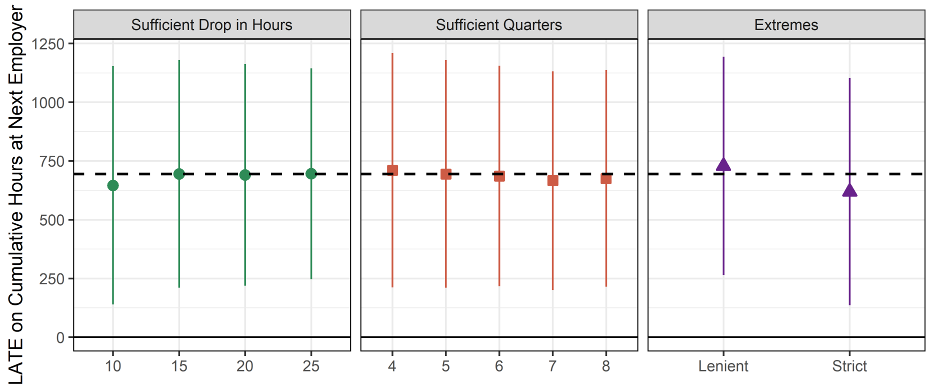
Note: This figure plots the estimated LATE of UI receipt on cumulative hours worked in the two years after a job loss while varying the parameters that define job loss. The black dotted line represents the estimate in our baseline estimates.

Figure B.19: LATE Effect on Cumulative Earnings across Job Loss Definitions

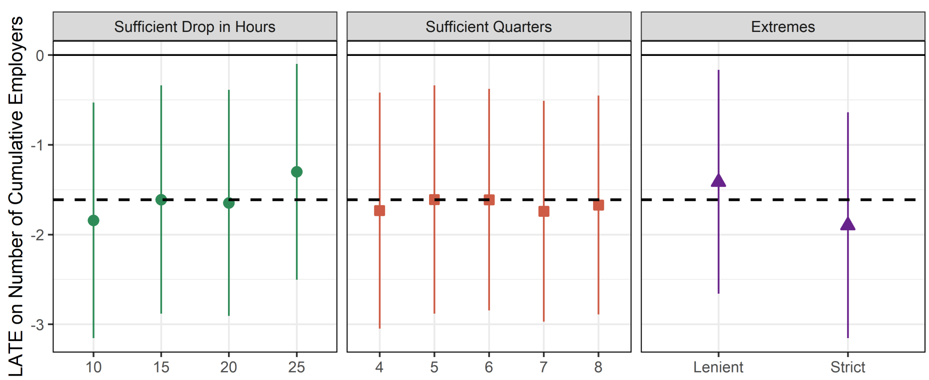


Note: This figure plots the estimated LATE of UI receipt on cumulative earnings in the two years after a job loss while varying the parameters that define job loss. The black dotted line represents the estimate in our baseline estimates.

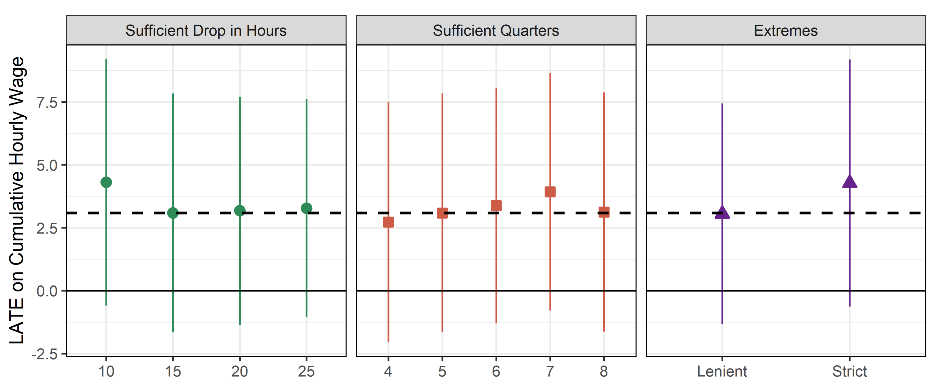
Figure B.20: LATE Effect on Re-employment Job Quality across Job Loss Definitions



(a) Cumulative Hours Worked with Next Employer



(b) Cumulative Number of Employers



(c) Cumulative Hourly Wage

Note: This figure plots the estimated LATE of UI receipt on our measures of re-employment job quality while varying the parameters that define job loss. The black dotted line represents the estimate in our baseline estimates.

C Subsample with Demographic Information

While the employer-employee matched wage records used to identify job losses do not contain demographic information or residential address, the ESD sought to overcome this limitation by entering a data sharing agreement with the Washington State Department of Licensing (WADOL), the state agency that issues driver's licenses. The WADOL records include the most recent mailing address of every Washington resident with a valid driver's license[26], along with the license-holder's full name, last four digits of their Social Security Number (SSN), sex, date of birth, disability status, and veteran status. These WADOL records were pulled and shared with ESD in January 2024 as authorized by the agency's Data Governance Committee and federal Driver Privacy Privacy Protection Act (18 U.S.C. §2721).

To merge the wage and WADOL records, researchers match on individual names within groups according to the last four digits of SSN, which drastically reduces the dimensionality of the string matching. The string matching itself uses the stringdist function in R, matching every name in the wage records with the best corresponding name in the WADOL data based on their Jaro-Winkler score. A match was considered sufficiently accurate if the distance score was less than 0.1. Researchers manually verified matches below this threshold to confirm their reliability, ensuring that only accurate matches were used for merging wage records with driver's license addresses.

The authors express gratitude to Madeline Veria-Bogacz for facilitating the data sharing agreement between ESD and WADOL.

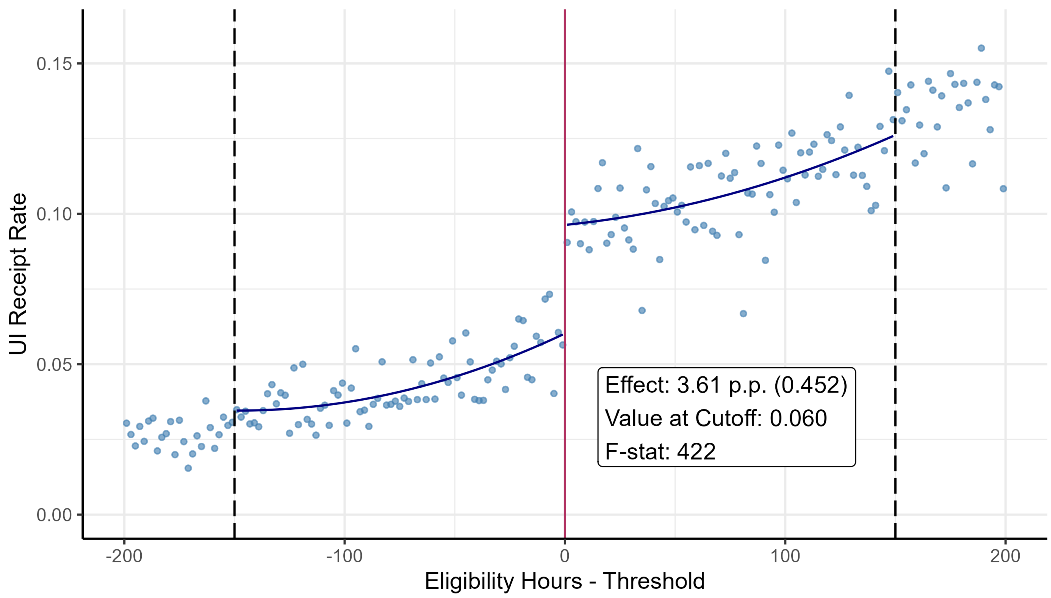
[26]Roughly 90 percent of the 16+ civilian population holds a driver's license. Mailing addresses must be updated every six years.

Table C.1: Summary Statistics of Job Loss Sample with Demographics, 2014–2019

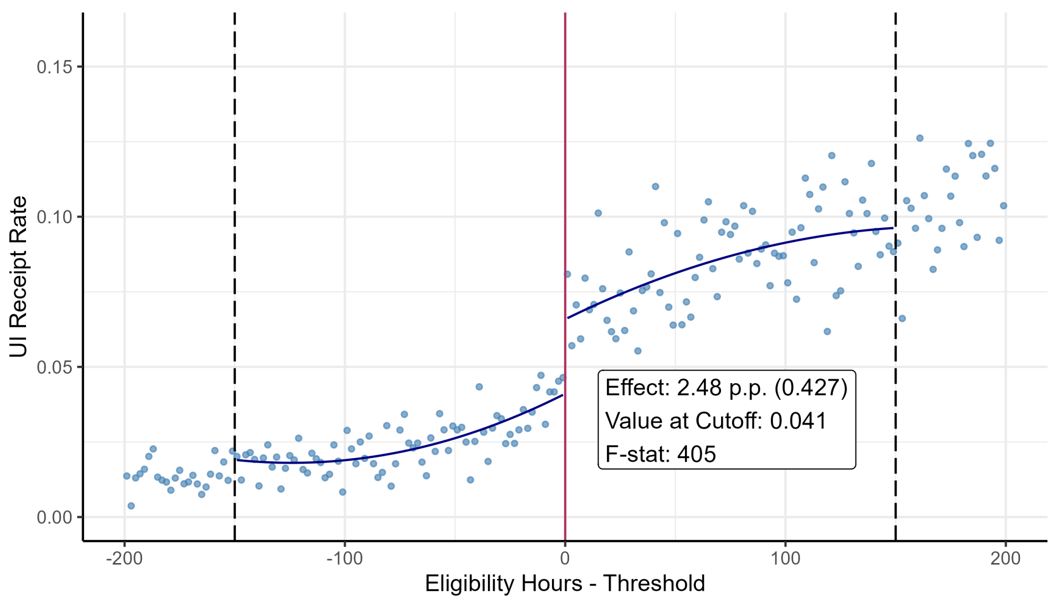
Variable	All	RDD	Full-Time
Demographics			
Median Age at Job Loss	29	26	37
Share Female	0.43	0.45	0.38
Share Veteran	0.02	0.02	0.02
Share with Disability	0.04	0.04	0.05
Earnings & Wage History			
Previous Year Earnings	27,610	10,787	64,828
Previous Year Hours	1,098.2	635.4	2,141.8
Previous Year Hourly Wage	32.19	18.9	30.69
Previous Year Hours with Separating Employer	873.9	470.6	1,811.1
Pre-Job Loss $[t-12, t-9]$:			
Annual Earnings	19,968	8,562	45,607
Annual Hours	796.4	460.9	1,554.9
Post-Job Loss $[t+9, t+12]$:			
Annual Earnings	32,788	22,048	60,152
Annual Hours	1,065.7	919.8	1,494.4
UI Utilization			
Monetarily Eligible	0.62	0.47	1
Application Rate	0.19	0.13	0.33
Receipt Rate	0.13	0.06	0.25
Benefit Level: Mean Replacement Rate	0.63	0.63	0.44
Benefit Level: As Share of Minimum WBA	1.86	1.27	3.02
Potential Maximum Duration (wks)	18.3	17.1	25.9
Share Receiving Min WBA	0.11	0.02	0.31
Share Receiving Max WBA	0.11	0.02	0.31
Industry (NAICS) of Separation			
11 Agriculture, Fishing, Forestry	0.04	0.05	0.02
21-23 Mining, Utilities, Construction	0.08	0.08	0.08
31-33 Manufacturing	0.06	0.05	0.11
42-49 Trade, Transportation	0.21	0.21	0.22
51-55 Information, Finance, Real Estate, Prof. Services	0.11	0.08	0.20
56 Administrative, Support, Waste Management Services	0.11	0.13	0.08
61-62 Educational and Health Care Services	0.14	0.12	0.15
71-72 Arts, Recreation, Hospitality Services	0.18	0.22	0.08
81 Other Services	0.04	0.04	0.03
92 Public Administration	0.02	0.02	0.02
N	2,152,042	242,168	564,948

Note: Table presents summary statistics for three types of job loss samples that are matched to demographic characteristics from WADOL: all job losses (column 1), the RDD sample local to the threshold (+/- 150 hours) (column 2), and only workers with full-time work histories (> 1,600 hours in one's reference year) (column 3).

Figure C.1: UI Receipt Rate (First Stage) by Gender



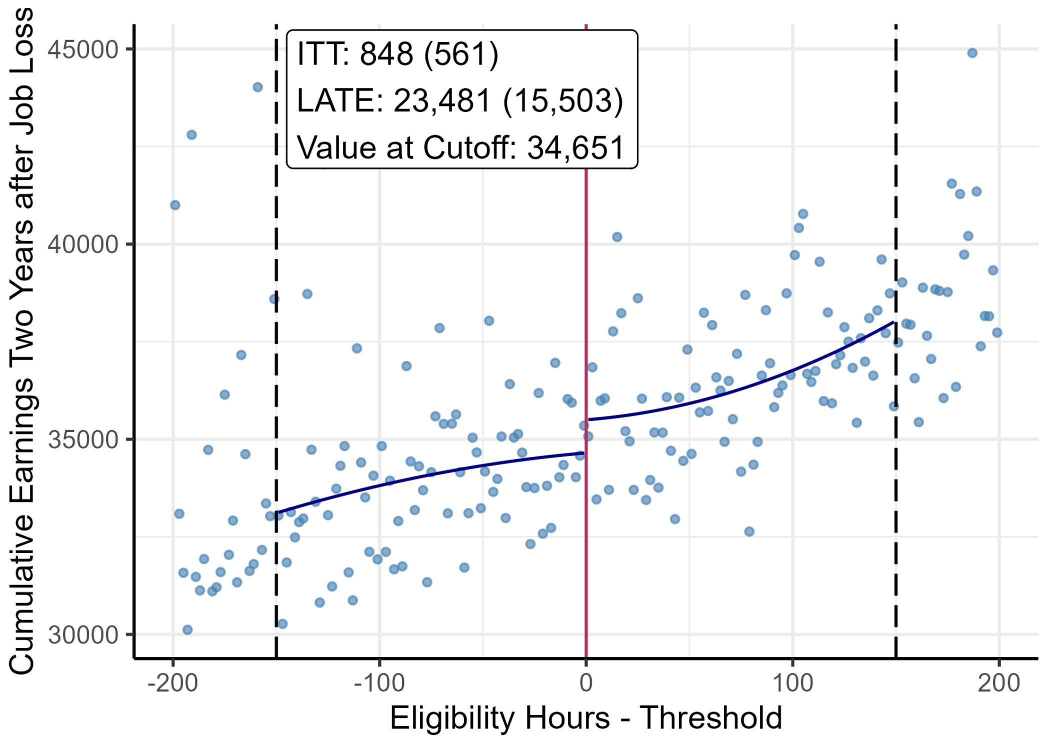
(a) Men



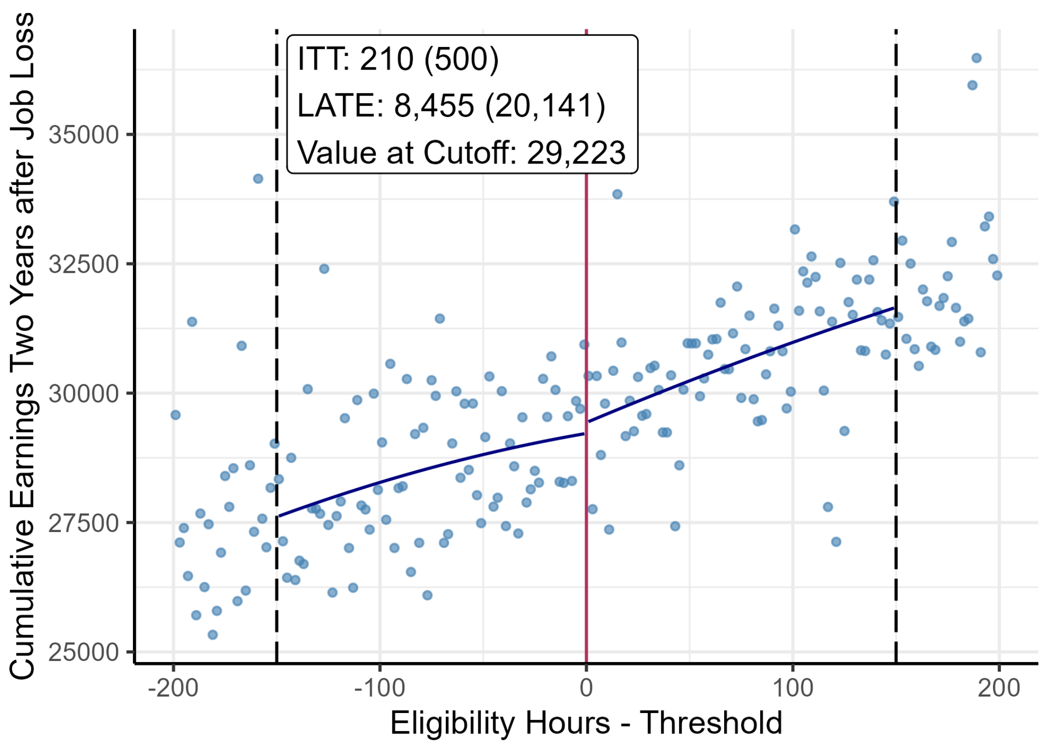
(b) Women

Note: These figures present the share of job losses that result in UI receipt according to UI eligibility hours, splitting the demographic subsample by gender.

Figure C.2: Effect of UI Eligibility on Earnings by Gender



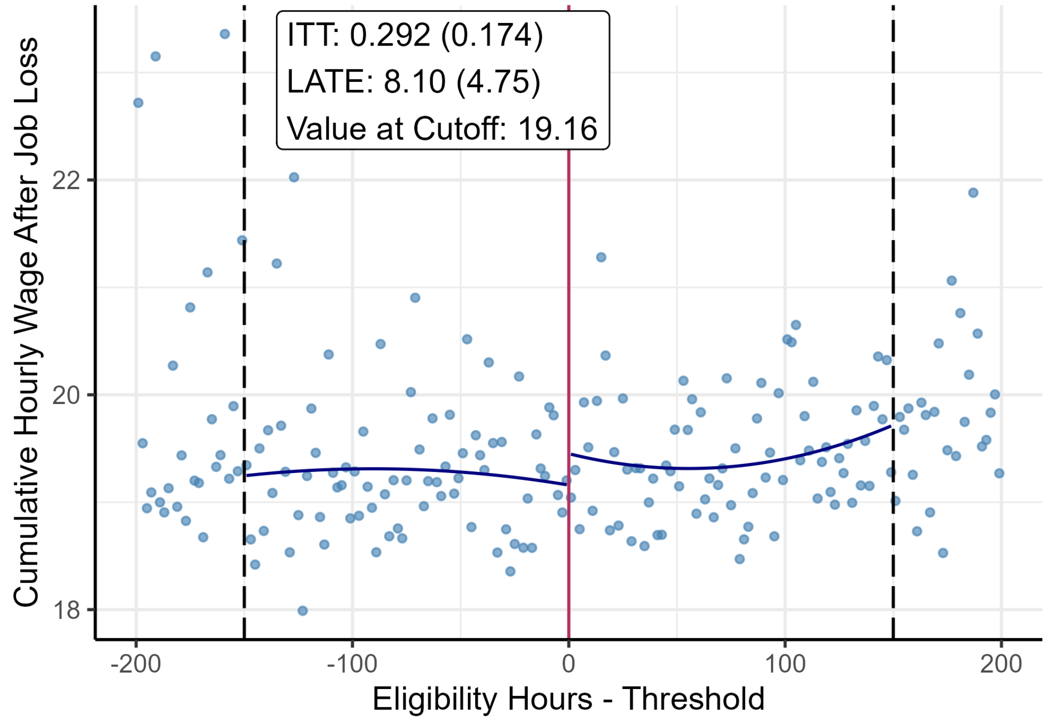
(a) Men



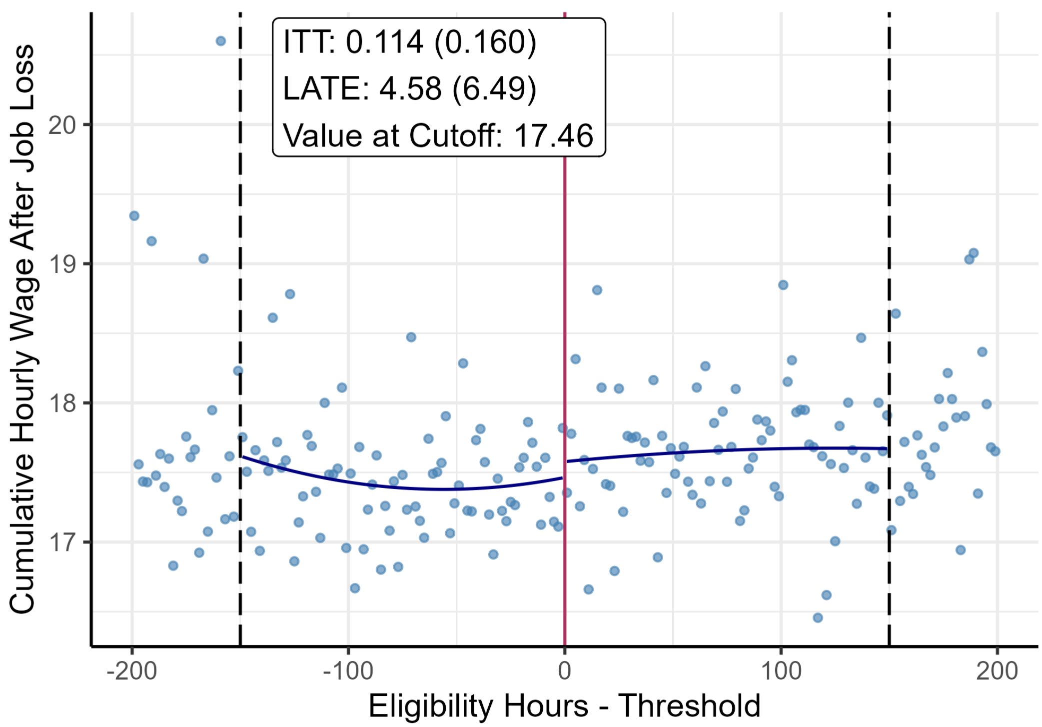
(b) Women

Note: Graphs illustrates effect of UI eligibility on earnings, reporting traditional RDD graphs with eligibility hours as the running variable and earnings in the eight post-job loss quarters as the dependent variable.

Figure C.3: Effect of UI Eligibility on Hourly Wage by Gender



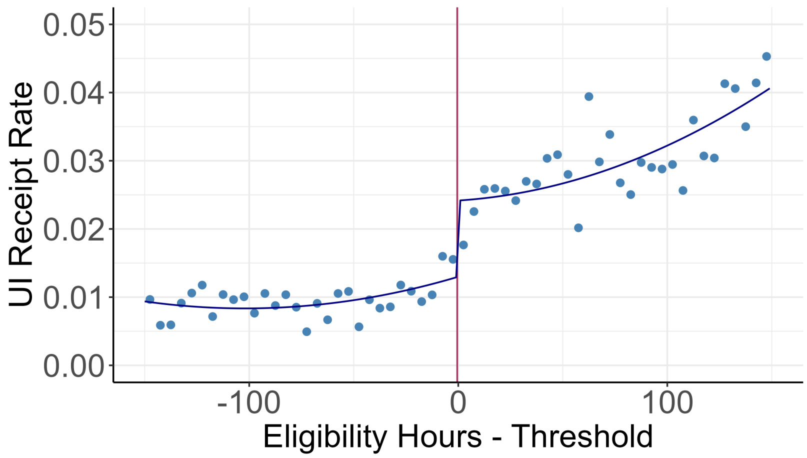
(a) Men



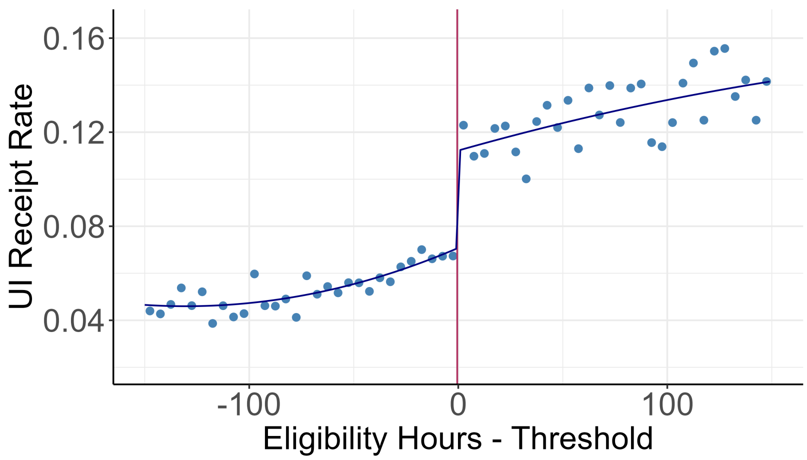
(b) Women

Note: Graphs illustrates the effect of UI eligibility on hourly wages, reporting traditional RDD graphs with eligibility hours as the running variable and hourly wage in the eight post-job loss quarters as the dependent variable.

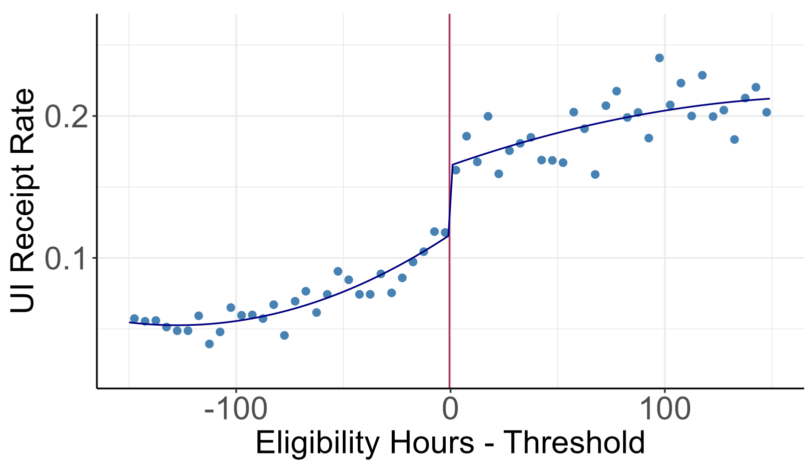
Figure C.4: UI Receipt Rate (First Stage) by Age



(a) Age 18–24



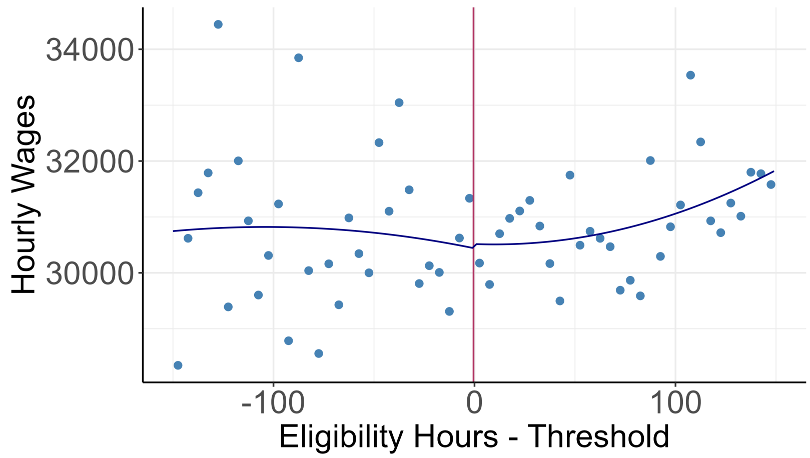
(b) Age 25–44



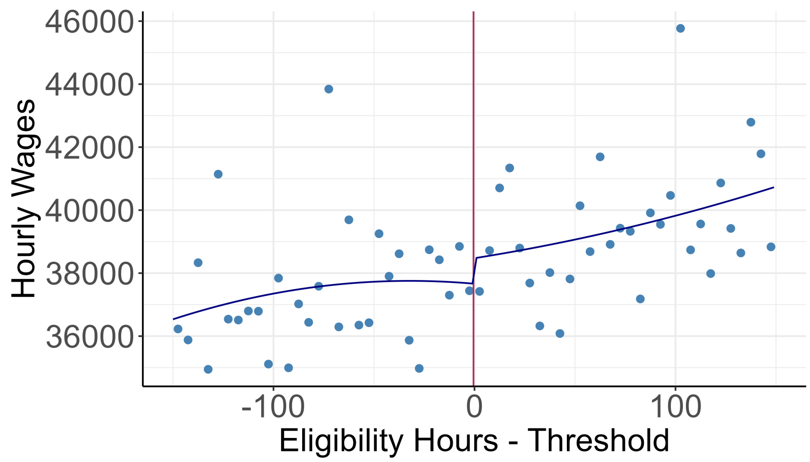
(c) Age 45+

Note: These figures present the share of job losses that result in UI receipt according to UI eligibility hours, splitting the demographic subsample by age.

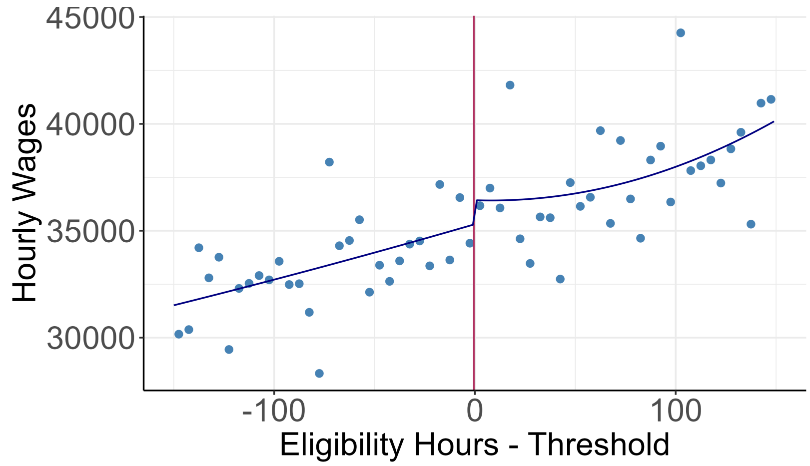
Figure C.5: Effect of UI Receipt on Earnings by Age Group



(a) Age 18–24



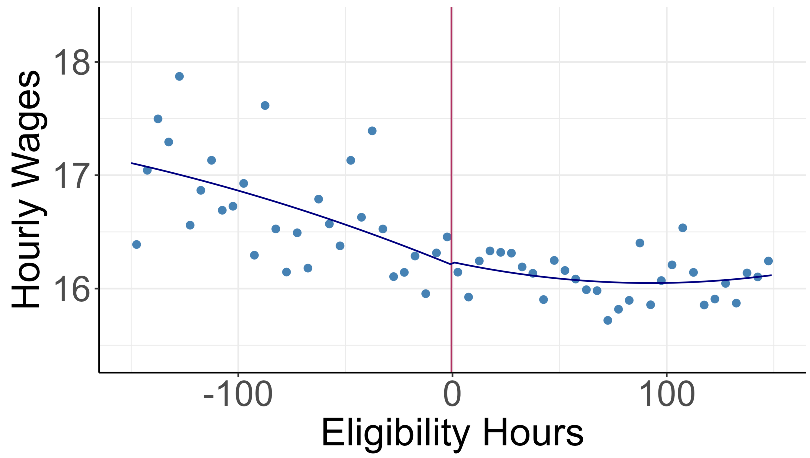
(b) Age 25–44



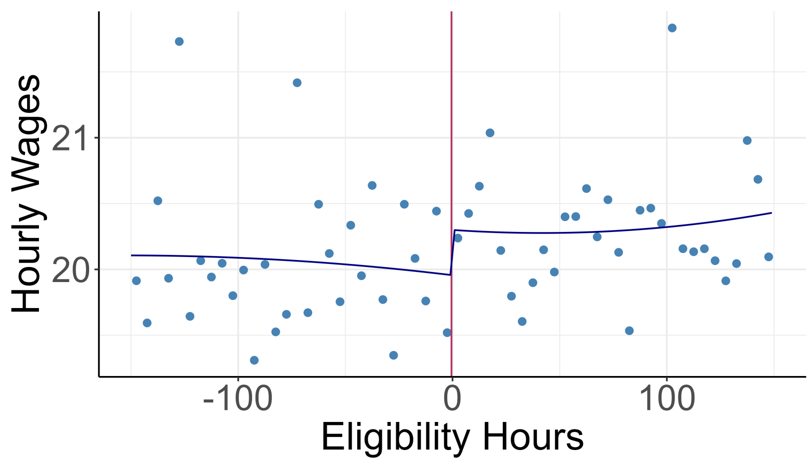
(c) Age 45–59

Note: Graphs illustrates effect of UI eligibility on total earnings, reporting traditional RDD graphs with eligibility hours as the running variable and earnings in the eight post-job loss quarters as the dependent variable.

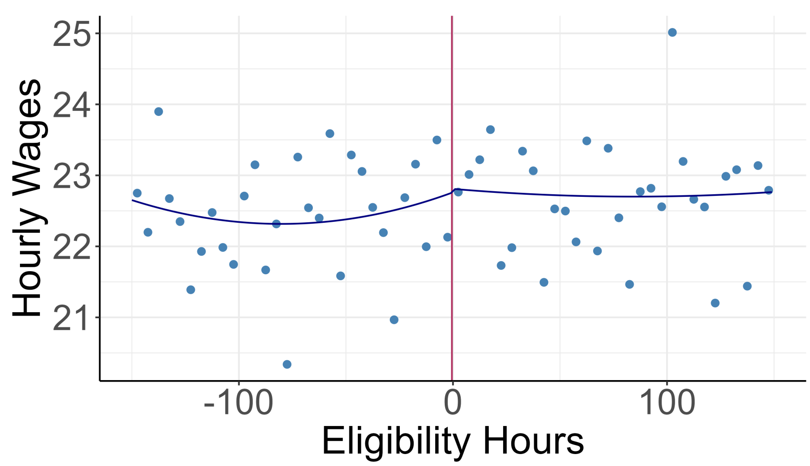
Figure C.6: Effect of UI Receipt on Hourly Wage by Age Group



(a) Age 18–24



(b) Age 25–44

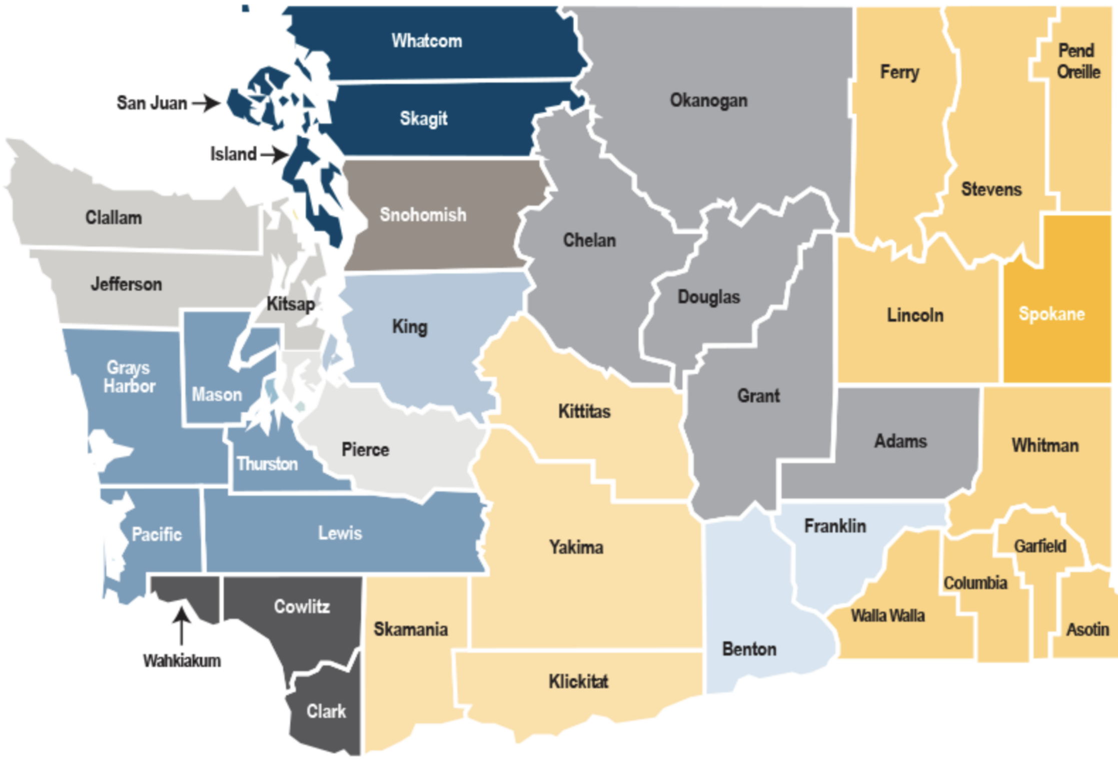


(c) Age 45–59

Note: Graphs illustrates effect of UI eligibility on hourly wages, reporting traditional RDD graphs with eligibility hours as the running variable and hourly wage in the eight post-job loss quarters as the dependent variable.

D Public Employment Offices

Figure D.1: Map of Washington Counties and Twelve WorkSource Service Regions



Note: This map displays the twelve WorkSource service regions defined by the Washington State ESD, which coordinate the provision of re-employment services across counties. Each color represents a distinct service region served by a network of WorkSource offices.

Table D.1: WorkSource Offices Information

WorkSource Name	County	ZIP	Open	Walk In
Clarkston Connection	Asotin	99403	✓	✓
Columbia Basin	Benton	99336	✓	✓
Vancouver	Clark	98660	✓	✓
Cowlitz/Wahkiakum	Cowlitz	98626	✓	✓
Clallam County	Clallam	98382	✓	✓
Wenatchee Valley	Douglas	98802	✓	✓
Republic	Ferry	99166	✓	
Central Basin	Grant	98837	✓	✓
Grays Harbor County	Grays Harbor	98520		
Island	Island	98277	✓	✓
Auburn	King	98002	✓	✓
Downtown Seattle	King	98121	✓	✓
North Seattle	King	98103	✓	
Rainier	King	98144	✓	✓
South Seattle	King	98106	✓	✓
Kitsap County	Kitsap	98383	✓	✓
Ellensburg	Kittitas	98926	✓	✓
Goldendale	Klickitat	98620	✓	✓
White Salmon	Klickitat	98672	✓	✓
Lewis County	Lewis	98531	✓	✓
Mason County	Mason	98584	✓	✓
Okanogan	Okanogan	98841	✓	✓
Newport	Pend Oreille	99156	✓	
Long Beach	Pacific	98631	✓	✓
Pierce	Pierce	98405	✓	✓
Pierce at South Hill Mall	Pierce	98373	✓	✓
Skagit	Skagit	98273	✓	✓
Stevenson	Skamania	98648		
Spokane	Spokane	99202	✓	✓
Next Generation Zone	Spokane	99202	✓	✓
Everett	Snohomish	98201	✓	✓
Colville	Stevens	99114	✓	
Thurston County	Thurston	98512	✓	✓
Pullman	Whitman	99163	✓	
Whatcom	Whatcom	98225	✓	✓
Union Gap	Yakima	98903	✓	✓
Valley Mall	Yakima	98903	✓	✓
Sunnyside	Yakima	98944	✓	✓
Walla Walla	Walla Walla	99362	✓	✓

Note: This table lists all WorkSource offices in Washington State, indicating their county, ZIP code, whether they are open, and whether walk-in services were available as of March 2025.

Table D.2: UI Eligibility Estimates on Labor Market Outcomes by WorkSource Proximity

	Constant	LATE	Percent Increase	p-value
Panel A. Distance Threshold: 3 Miles				
Earnings				
Close to WorkSource ($\leq$ 3 miles)	31,558	34,836	110%	0.26
Far from WorkSource ($>$ 3 miles)	34,090	19,296	57%	0.25
Hours				
Close to WorkSource ($\leq$ 3 miles)	1,679	550	33%	0.61
Far from WorkSource ($>$ 3 miles)	1,719	578	34%	0.30
Hourly Wage				
Close to WorkSource ($\leq$ 3 miles)	18.13	6.69	37%	0.47
Far from WorkSource ($>$ 3 miles)	18.83	7.80	41%	0.12
Panel B. Distance Threshold: 5 Miles				
Earnings				
Close to WorkSource ($\leq$ 5 miles)	32,315	51,033	158%	0.11
Far from WorkSource ($>$ 5 miles)	34,160	12,830	38%	0.44
Hours				
Close to WorkSource ($\leq$ 5 miles)	1,688	1,102	65%	0.31
Far from WorkSource ($>$ 5 miles)	1,721	389	23%	0.48
Hourly Wage				
Close to WorkSource ($\leq$ 5 miles)	18.44	9.99	54%	0.30
Far from WorkSource ($>$ 5 miles)	18.86	6.93	37%	0.16

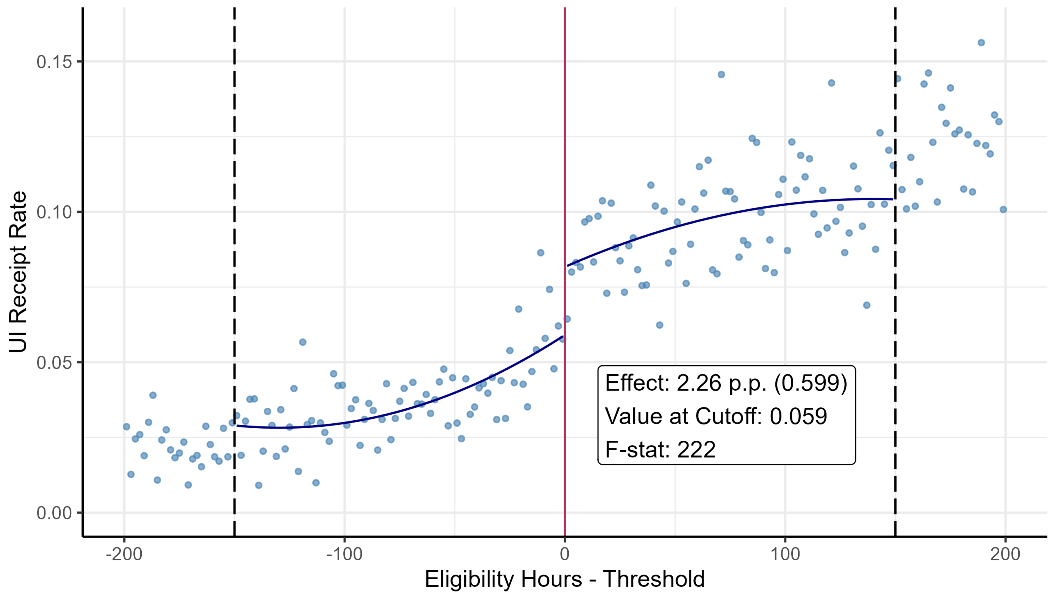
Note: Table columns show regression discontinuity constant to the left of the threshold, the LATE (intent-to-treat coefficient of interest scaled by first-stage estimate), percentage effect (i.e. $100\times$(column 3)/(column 2)), and the p-value of the intent-to-treat coefficient of interest. Sample is split by whether a worker is close to or far from a WorkSource office with walk-in services according to the ZIP code of their home address (using matched demographic subsample).

Table D.3: UI Eligibility Estimates on Labor Market Outcomes by WorkSource Proximity (Any Open)

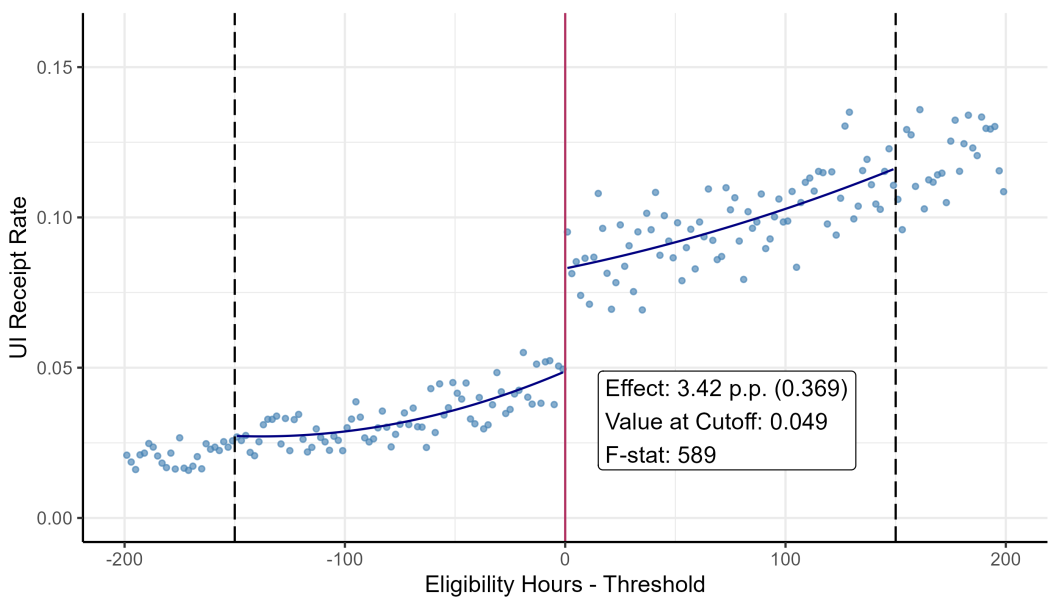
	Constant	LATE	Percent Increase	p-value
Panel A. Earnings				
Close to WorkSource ($\leq$ 4 miles)	32,741	63,342	193%	0.06
Far from WorkSource ($>$ 4 miles)	33,908	10,453	31%	0.52
Panel B. Hours				
Close to WorkSource ($\leq$ 4 miles)	1,688	1,006	60%	0.39
Far from WorkSource ($>$ 4 miles)	1,720	441	26%	0.42
Panel C. Hourly Wage				
Close to WorkSource ($\leq$ 4 miles)	18.64	13.64	73%	0.19
Far from WorkSource ($>$ 4 miles)	18.70	6.01	32%	0.20

Note: Table columns show regression discontinuity constant to the left of the threshold, the LATE (intent-to-treat coefficient of interest scaled by first-stage estimate), percentage effect (i.e. 100$\times$(column 3)/(column 2)), and the p-value of the intent-to-treat coefficient of interest. Sample is split by whether a worker is close to or far from an open WorkSource office according to the ZIP code of their home address (using matched demographic subsample).

Figure D.2: UI Receipt Rate (First Stage) by Distance to WorkSource Office



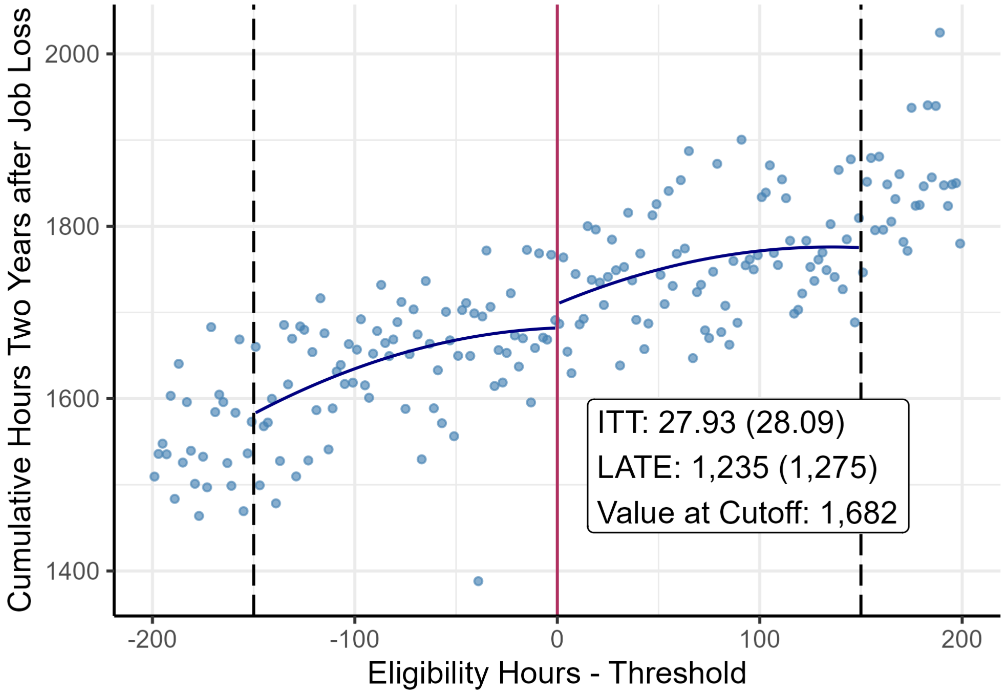
(a) Close to ($\leq$ 4 miles) WorkSource



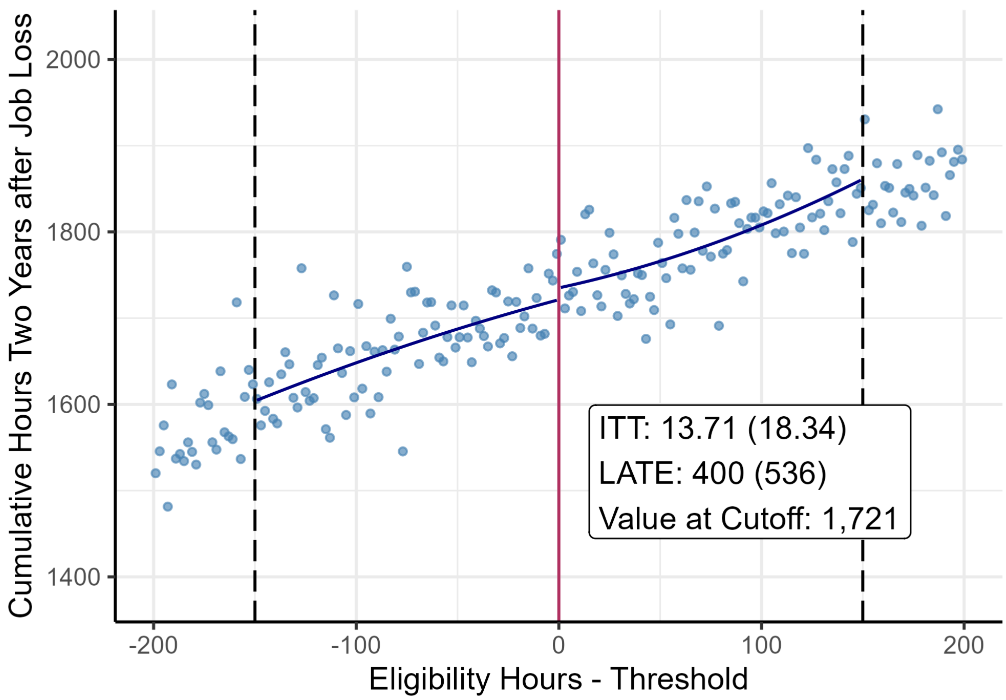
(b) Far from ($>$ 4 miles) WorkSource

Note: These figures present the share of job losses that result in UI receipt according to UI eligibility hours, splitting the demographic subsample into which are close to or far from the closest WorkSource office that had walk-in services as of March 2025.

Figure D.3: RDD for Cumulative Hours Worked, t to $t+8$ by Distance to WorkSource



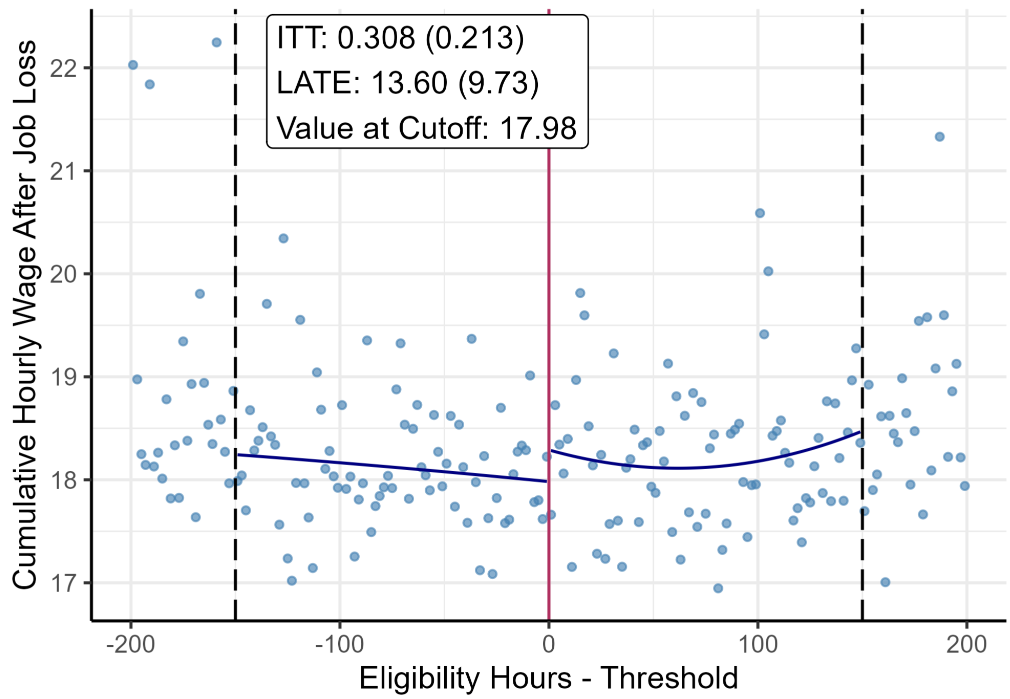
(a) Close to ($\leq$ 4 miles) WorkSource



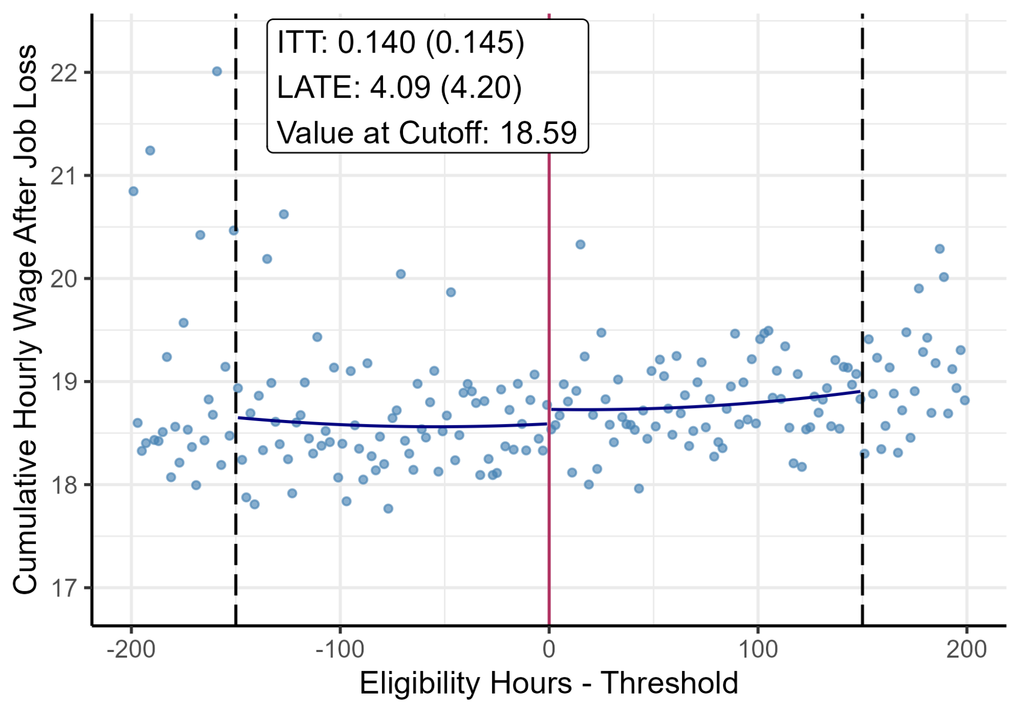
(b) Far from ($>$ 4 miles) WorkSource

Note: Figures plot the cumulative hours worked from the quarter of job loss in t through $t+8$ (excluding hours from their layoff employer in t), splitting the demographic subsample by those who are close to or far from the closest WorkSource office that had walk-in services as of March 2025. Second degree polynomials are fitted separately on each side of the threshold.

Figure D.4: RDD for Hourly Wage, t to $t+8$ by Distance to WorkSource



(a) Close to ($\leq$ 4 miles) WorkSource



(b) Far from ($>$ 4 miles) WorkSource

Note: Figures plot the hourly wage following job loss through $t+8$ (for quarters in which hours are non-zero), splitting the demographic subsample by those who are close to or far from the closest WorkSource office that had walk-in services as of March 2025. Second degree polynomials are fitted separately on each side of the threshold.

E Issues with an Application-based Approach

This section identifies the issues with an alternative approach where, instead of using a sample of workers who recently experienced job loss, we use a sample of workers who applied for UI benefits. This application-based approach could potentially improve the relevance of the eligibility threshold, leading to a much larger first-stage effect on benefit receipt as well as more precise causal estimates. However, we ultimately find evidence of selection into the sample UI applicants that could bias estimates. We conclude that using a sample of job losses is necessary to estimate valid causal effects in our context.

As outlined in Section 2, this paper constructs a sample of workers who recently experienced job loss. Ultimately, we find a strong effect of the eligibility threshold on benefit receipt in our job loss sample with an F-statistic of 2,299. However, the size of the first-stage effect is small in absolute terms, as becoming eligible leads to an increase in benefit receipt of 3.25 percentage points. This is unsurprising given benefit receipt is relatively low in our job loss sample, as workers just above the eligibility threshold receive benefits less than 10 percent of the time. Still, a small first-stage effect limits the precision of our LATE estimates. Therefore, we explored alternative ways to construct a sample where the eligibility threshold is relevant and strongly affects benefit receipt.

We considered an application-based approach, as utilized by Leung and O'Leary (2020). In constructing the applications sample, we assume a job loss occurs in the quarter when a worker submits their application for UI benefits. Using quarterly employment data and records of UI payments, we can then calculate their eligibility hours, determine whether they received benefits, and measure labor market outcomes. As shown in Figure E.1, the application-based approach would increase the size and strength of the first-stage effect, as we find a 37.4 percentage point increase in UI receipt at the threshold with an F-statistic of 7,335. These results are promising, but further investigation reveals several issues.

A valid regression discontinuity design requires that, aside from their eligibility for benefits, no other factors cause a discontinuous change in the sample at the threshold. Unfortunately, we find evidence that threatens identification. First, there is bunching in applications just above the threshold. As shown in Figure E.2, the sample using applications fails the McCrary test, with a 25 percent increase in density at the threshold.[27] Second, there are discontinuities in observable characteristics at the threshold. For example, as shown in Figure E.3, workers above the eligibility threshold worked significantly fewer hours in the quarter prior to submitting their application. Both the bunching and the discontinuous change in observable characteristics create concern that applicants around the threshold are not comparable.

We explore these issues further using our sample of job losses. First, the bunching seems to be driven by workers above the threshold being more likely to apply for UI benefits.[28] As shown previously in Figure 4b, becoming monetarily eligible leads to an increase of 1.6 percentage points or 12 percent in the application rate. Given there is no

[27] Interestingly, Leung and O'Leary (2020) does not find evidence of bunching above the eligibility threshold in their context.

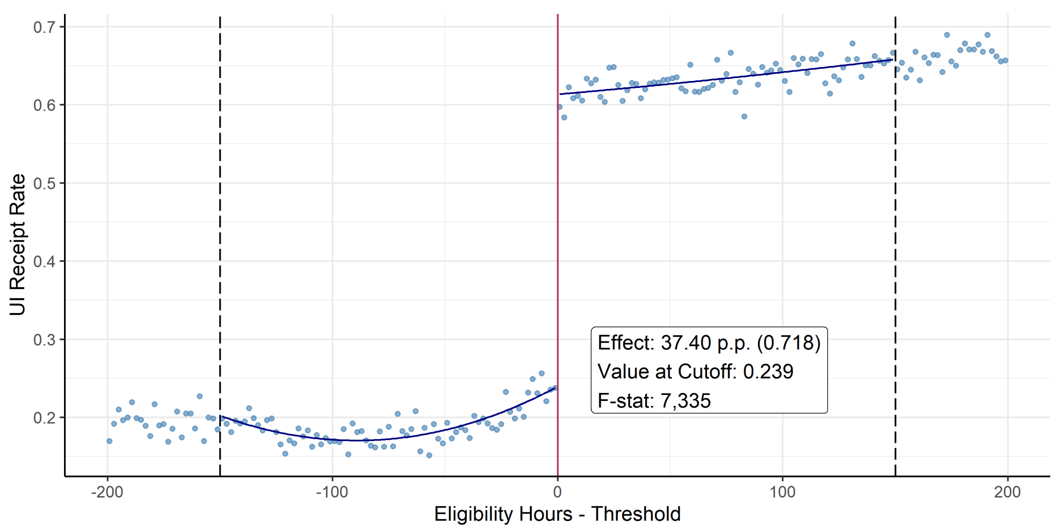
[28] Conversely, at least some workers are discouraged from applying because they do not meet the monetary eligibility requirement.

bunching in the sample of job losses (Figure 2), the increase in applications directly translates to bunching in the density of applicants. If workers who apply only when eligible differ systematically from those who apply regardless, then there will be a discontinuous change in the sample of applicants at the threshold that could bias our estimates.

Second, the differences in employment history may be driven by the timing of a worker's application. As shown in Figure E.4, workers just below the eligibility threshold are more likely to submit their application and receive benefits in the next quarter after job loss. Essentially, workers who are just short of eligibility in the quarter of job loss may delay their application until the eligibility period shifts in the following quarter, assuming they still have not found re-employment. This strategic timing could contribute to the bunching in the density of applicants above the threshold. Additionally, if applicants just above the threshold actually lost their jobs much earlier and delayed their claim, this could explain the differences in employment history discussed earlier and shown in Figure E.3. If re-employment outcomes differ for workers who delayed their application, then this may introduce bias into our estimates when using the sample of applicants.

Clearly, bunching above the eligibility threshold and the strategic timing of applications create serious concerns about identification using an application-based approach.[29] Fortunately, neither of these are issues when using the sample of job losses as we do in our main analysis.

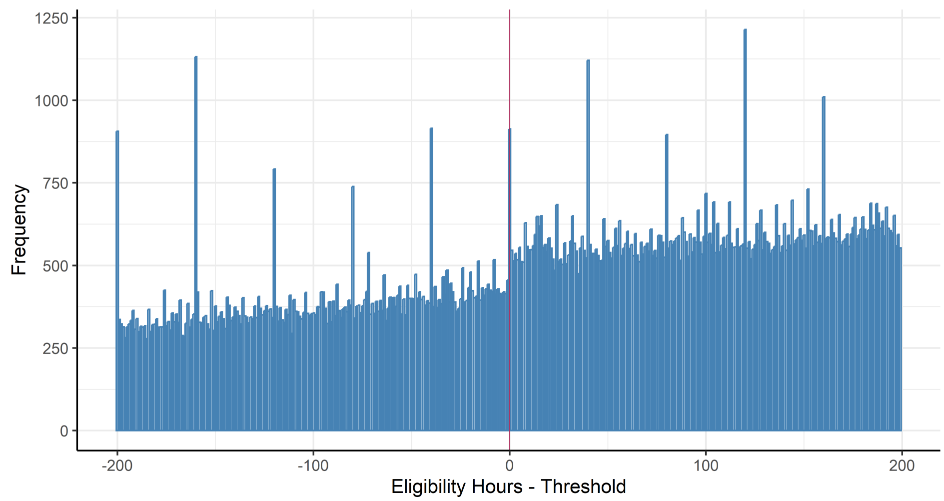
Figure E.1: UI Receipt Rate by Eligibility Hours in Applications Sample



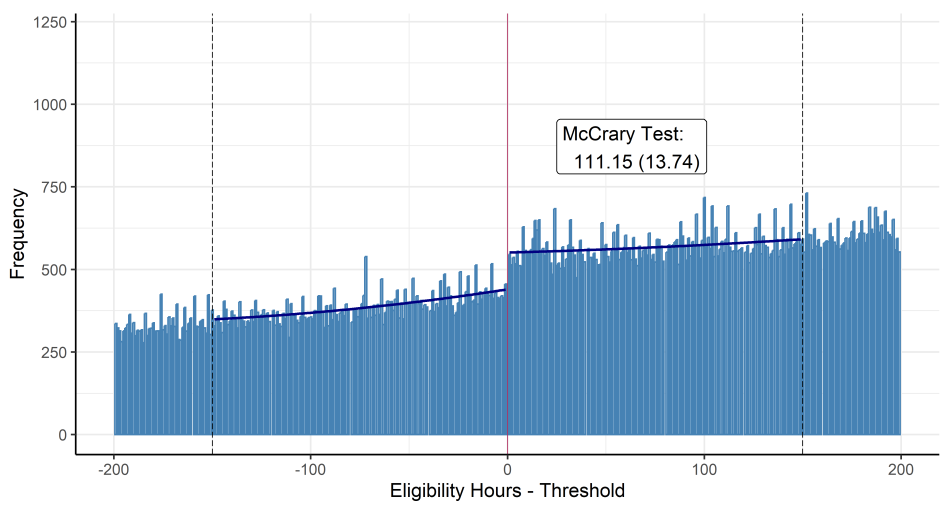
Note: This figure plots UI receipt rate according to eligibility hours for the sample of UI applicants.

[29]Interestingly, the results from the application-based approach are also qualitatively different than those in our main analysis. Ignoring the significant difference in hours worked in the quarter before applying, the LATE estimates would suggest that UI receipt decreases labor supply in the quarter of job loss and the following quarter before leading to a marginally significant increase in hours worked for five quarters.

Figure E.2: Distribution of Eligibility Hours for UI Applicants



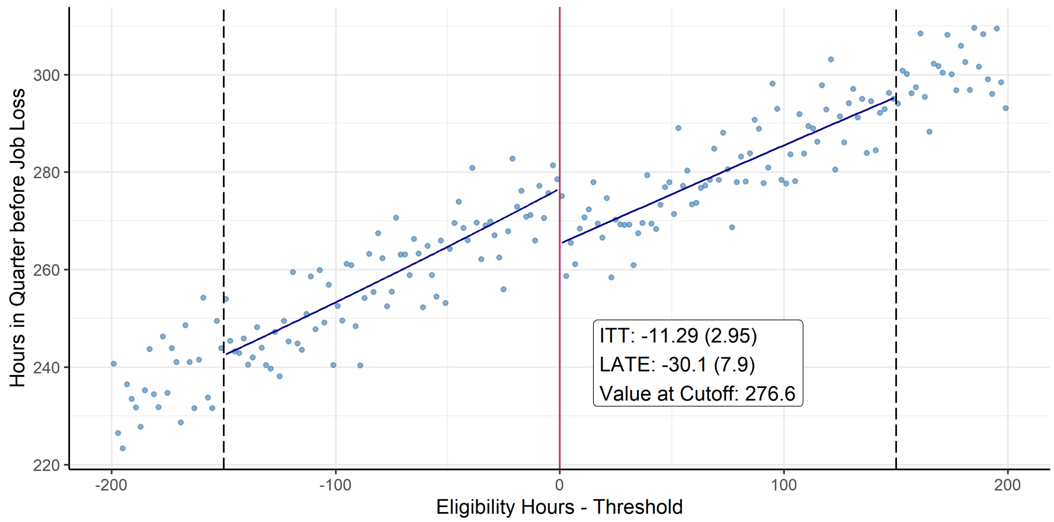
(a) UI Applicants Local to Eligibility Threshold



(b) McCrary Test for UI Applicants

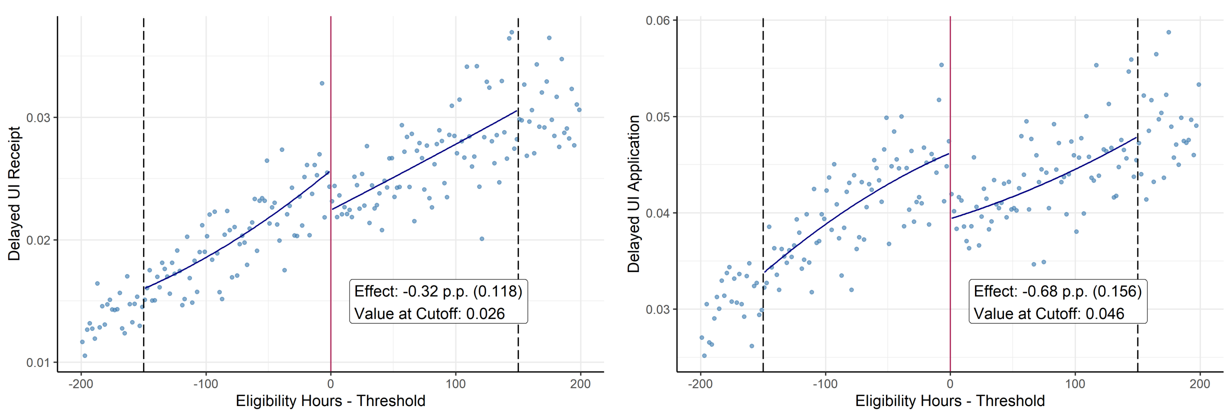
Note: These figures present the distribution of eligibility hours worked by those in the sample of UI applicants local to the threshold in Washington State occurring between 2011Q3 and 2019Q1. The red line denotes the 680 hour eligibility threshold. A worker's eligibility hours measure is the higher sum of hours worked in either the previous four quarters or the four quarters preceding last quarter. Panel (a) represents the distribution of eligibility hours local to the 680-hour threshold, while panel (b) removes multiples of 40 from panel (a) and conducts a McCrary test for a discontinuity in density at 680 hours. Bins are one hour in width to illustrate instances of heaping in panel (a), while such heaping is removed from panel (b).

Figure E.3: Hours Worked in Quarter before UI Application



Note: This figure plots the hours worked in the quarter before job loss according to eligibility hours. Job loss is assumed to be in the same quarter as the worker applies for UI benefits. This analysis uses the sample of UI applicants.

Figure E.4: Reduced-form Effect on Delayed Benefit Receipt and Application



(a) Delayed Benefit Receipt

(b) Delayed Application

Note: Panel (a) plots the share of job losses where the worker receives delayed UI benefits, while panel (b) plots the share of job losses where the worker delays their application for UI benefits. Delayed benefit receipt is defined as receiving benefit payments to a account opened in the quarter after the job loss. Delayed application is defined as submitting an initial claim in the quarter after the job loss. This analysis uses the sample of job losses.

F Two-Dimensional Regression Discontinuity

In this section, we consider an alternative approach—the two-dimensional regression discontinuity—to exploit the requirement that workers accumulate 680 hours worked in their base period by separately considering the base year and alternate base year. We find this approach yields similar results, although standard errors are larger as this approach estimates effects using two smaller samples. Ultimately, this affirms the robustness of our results to an alternative identification strategy as well as the decision to collapse these two discontinuities into one discontinuity in our main analysis.

In our main analysis, we measure "eligibility hours" for each worker as the greater of their hours worked during the base year or their hours worked during the alternate base year.[30] Workers with eligibility hours greater than 680 are monetarily eligible, while workers below this threshold are not eligible for benefits. Figure F.1 captures the basic intuition for the regression discontinuity.

Alternatively, we could separately exploit the 680-hour threshold using a worker's base year and a worker's alternate base year. This approach separates "eligibility hours" into base year hours and alternate base year hours, and then analyzes the two distinct eligibility thresholds. Figure F.2 outlines the logic for this two-dimensional regression discontinuity. Essentially, the base year discontinuity compares workers whose hours worked in their base year put them just above or below the 680-hour threshold, conditional on not being eligible in their alternate base year.[31] The potential advantage is that this approach may yield a better comparison and thus more accurate estimates. Additionally, we may be able to determine whether the effects of UI receipt are different for these two distinct eligibility thresholds.

Ultimately, we find results consistent with our main analysis, although standard errors are larger as this two-dimensional approach creates two smaller samples. Figure F.3 shows a similar increase in benefit receipt at both eligibility thresholds–3.11 percentage points for the base year discontinuity and 3.32 percentage points for the alternate base year discontinuity. Figure F.4 plots the LATE estimate on quarterly hours and earnings from our main analysis, the base year discontinuity, and the alternate base year discontinuity. The effects are not significantly different. The increase in hours worked and earnings seems more persistent in the base year discontinuity, although these estimates use a smaller sample and have larger standard errors. Table F.1 presents the reduced-form effect on benefit receipt as well as the LATE estimates on cumulative hours worked and cumulative earnings. Consistent with Figure F.4, we find larger, although noisier, effects on these cumulative measures from the base year discontinuity.

Overall, this two-dimensional approach does not seem to improve the accuracy of our estimates or allow us to detect any heterogeneity in the effects on different workers. Still, the consistency of results provides more evidence of the robustness of our estimates.

[30] Recall that Figure 1 illustrates how base year and alternate base year are defined.

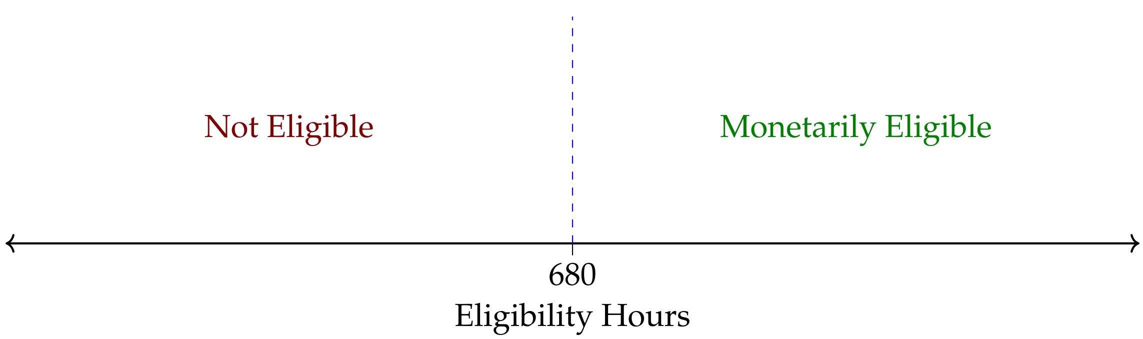
[31] Conversely, the alternate base year discontinuity compares workers whose hours worked in their alternate base year put them just above or below the 680-hour threshold, conditional on not being eligible in their base year.

Table F.1: Comparing Estimates from Two-Dimensional RD

	Baseline	Two-Dimensional RD	
		Base Year	Alternate BY
First-stage on UI Receipt			
Reduced-form Effect	3.25 p.p.	3.11 p.p.	3.32 p.p.
	(0.206)	(0.357)	(0.251)
Value below threshold	0.061	0.043	0.067
Cumulative Hours Worked			
LATE Estimate	603	1,152	472
	(289)	(561)	(338)
Value below threshold	1,638	1,408	1,718
Cumulative Earnings			
LATE Estimate	14,868	32,661	7,334
	(6,671)	(12,955)	(7,850)
Value below threshold	29,647	26,052	30,996
Number of Observations	616,989	171,097	451,759

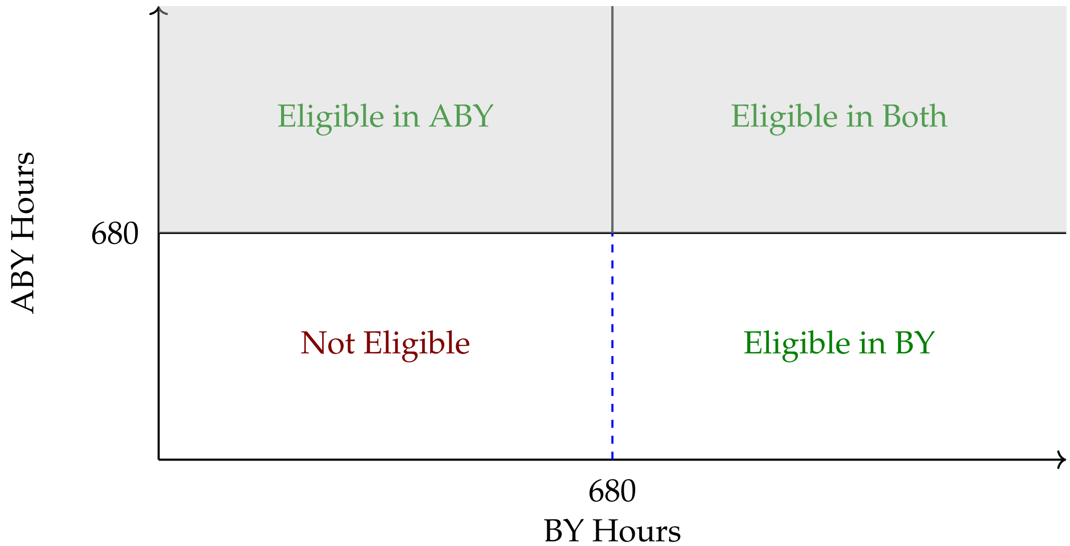
Note: This table reports the reduced-form effect of becoming eligible on UI receipt as well as the LATE estimate of UI receipt on cumulative hours worked and earnings. Estimates are reported using the discontinuity in our main analysis, the base year discontinuity, and the alternate base year discontinuity. Standard errors are reported in parentheses.

Figure F.1: Eligibility Discontinuity in One-Dimensional RD

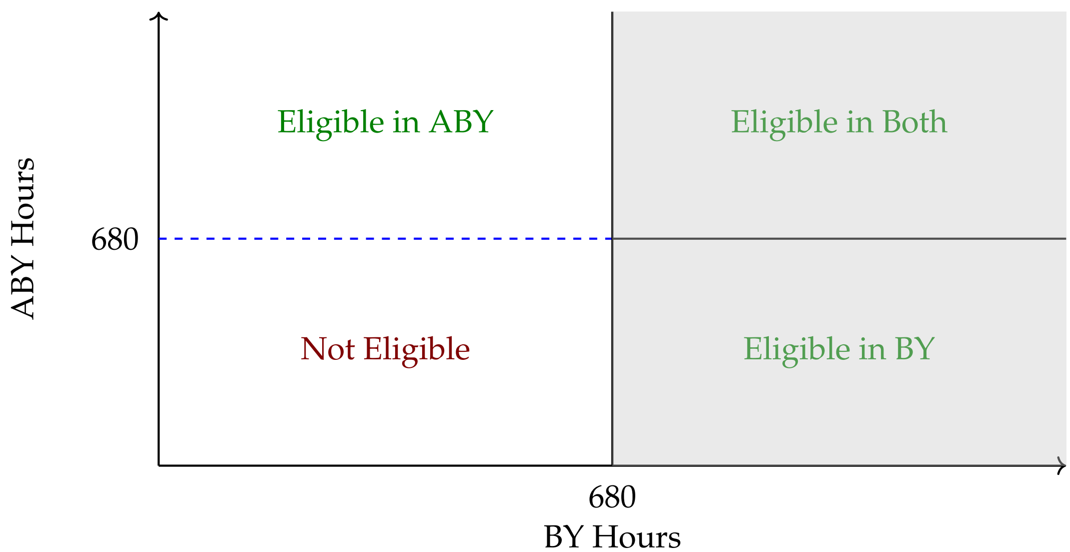


Note: Figure represents conceptual discontinuity in eligibility hours measure, which is the the greater of their hours worked during the base year or their hours worked during the alternate base year.

Figure F.2: Eligibility Discontinuities in Two-Dimensional RD



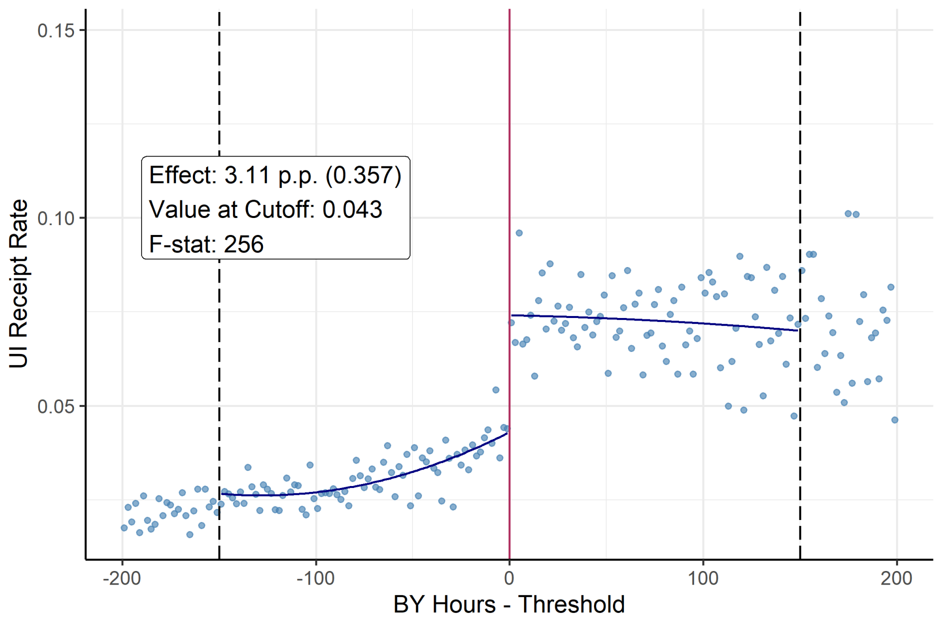
(a) Base Year Discontinuity



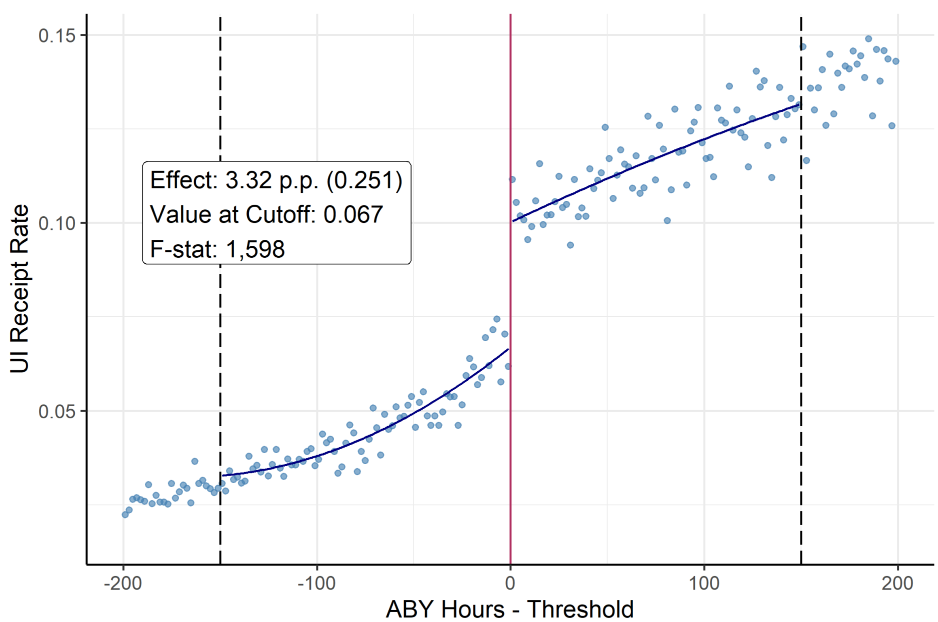
(b) Alternate Base Year Discontinuity

Note: Each panel isolates one of two eligibility thresholds – base year (top) and alternate base year (bottom) – plotted in blue dashes, by comparing workers just above and below 680 hours in one year, conditional on ineligibility in the other. Gray-shaded regions are excluded because they include workers eligible under both or the other definition.

Figure F.3: Reduced-Form Effect on Benefit Receipt in Two-Dimensional RD



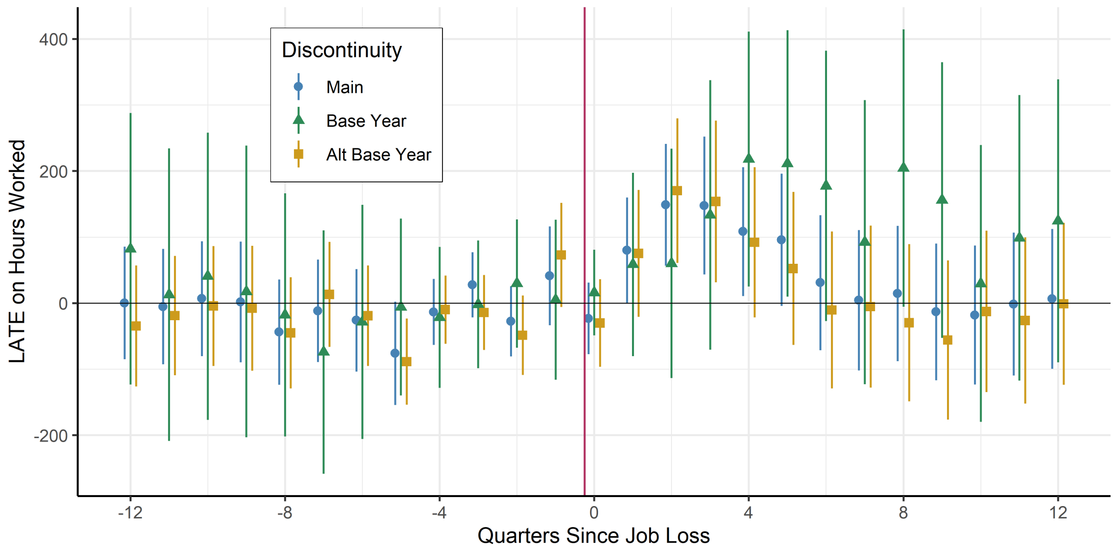
(a) Base Year Discontinuity



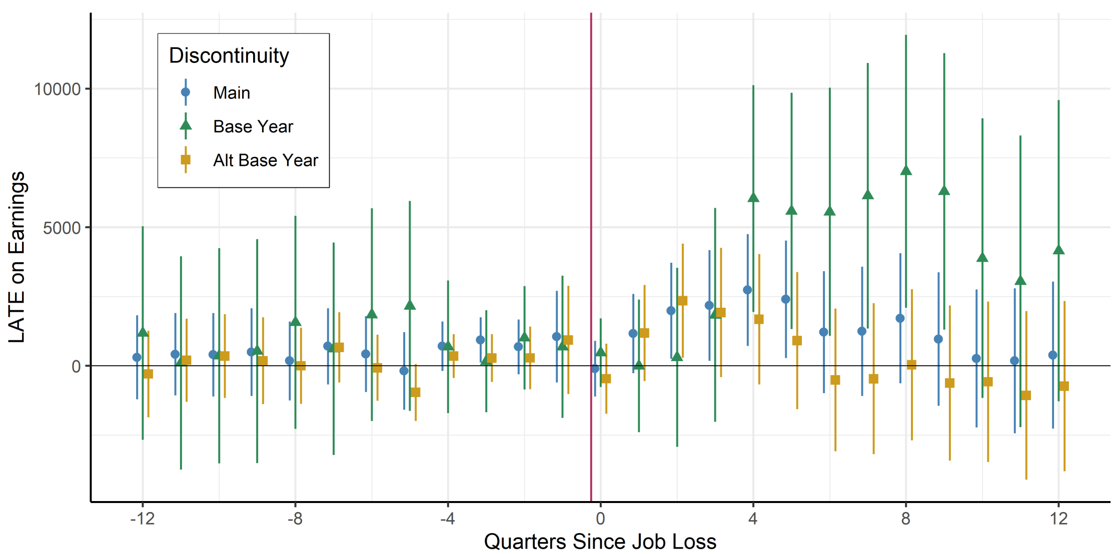
(b) Alternate BY Discontinuity

Note: This figure plots the share of job losses where the worker receives UI benefits by their hours worked. Panel (a) uses the base year discontinuity while panel (b) uses the alternate base year discontinuity.

Figure F.4: LATE on Quarterly Hours and Earnings in Two-Dimensional RD



(a) LATE on Hours Worked by Quarter



(b) LATE on Earnings by Quarter

Note: This figure plots the LATE estimate of UI receipt on quarterly hours worked and earnings using the discontinuity in our main analysis, the base year discontinuity, and the alternate base year discontinuity. Error bars represent 95 percent confidence intervals. Panel (a) plots effects on hours worked while panel (b) plots the effect on earnings.

G External Validity and Policy Implications

This appendix section explores the external validity of this paper's findings to other states' monetary eligibility thresholds. In all states besides Washington, eligibility for UI benefits requires a sufficient amount of earnings in the base period rather than a number of hours worked. While this makes our findings from Washington somewhat more difficult to extrapolate to other states, our goal is to understand where Washington's 680-hour cutoff lies in the distribution of monetary eligibility standards and to identify which states have similar effective thresholds. This helps guide where policy recommendations based on our findings may be most applicable.

Methodology

To enable meaningful comparisons, we calculate the number of hours a minimum wage worker in each state would need to work in order to meet that state's earnings-based eligibility threshold in 2023, the most recent year for which we have data.[32] Because lowering the monetary eligibility threshold would most likely expand eligibility for low-wage workers, our external validity exercise focuses on minimum wage workers.

This approach provides an upper bound on the number of hours required to qualify, since workers earning more than the minimum wage would meet monetary eligibility thresholds with fewer hours. We also use statutory state minimum wages and do not account for local jurisdictions that enforce higher minimums.

External validity: Washington is more stringent than other states

As listed in Table G.1, Washington's 680-hour requirement is the most stringent threshold in the country when other states' monetary eligibility thresholds are translated into hours worked at the state minimum wage, although it is not an extreme outlier in the national distribution. The average threshold across states is 307 hours, with a median of 319 hours, less than half of Washington's requirement. If all states had the same minimum wage as Washington while keeping their monetary eligibility thresholds fixed in dollar terms, Washington would appear even more stringent compared to other states.

However, under current eligibility rules and wage laws, eleven states come reasonably close to Washington's threshold, as their hours to qualify at the minimum wage are within six full-time weeks of Washington's standard of 680 hours (i.e. 17 full-time weeks). They include Utah, South Carolina, Arizona, Michigan, Kansas, Indiana, Wyoming, Ohio, Nebraska, Maine, and Kentucky. These states have UI systems with eligibility requirements similarly stringent to Washington's because of high statutory base period wages needed to qualify in all cases, and in some cases, low minimum wages (UT, SC, KS, IN, WY, KY).

External validity: Washington's minimum WBA is more generous than other states

Another of our analysis' external validity relates to the generosity of the weekly benefit amounts (WBAs) available to qualifying workers. Washington stands out in this regard, offering the second-highest minimum WBA in the country (Table G.1). This pattern is

[32] We collect monetary eligibility information from the US Department of Labor ETA at this link: `https://oui.doleta.gov/unemploy/pdf/uilawcompar/2023/monetary.pdf`. Minimum wage data was downloaded from FRED.

consistent with a broader national trend: states with more stringent monetary eligibility criteria often provide more generous minimum benefits. Figure G.1 illustrates this relationship, with each panel plotting a state's minimum WBA against the stringency of its eligibility standard. Panel (a) uses the statutory earnings threshold, while Panel (b) translates thresholds into hours worked at the minimum wage. Washington's relatively generous UI benefit floor may help explain the sizable impacts we observe on job quality: higher UI benefits can provide the liquidity necessary for workers to search for a higher-paying job with more stable hours.

Among the aforementioned states with more stringent imputed hours thresholds to qualify for UI, the most similar states to Washington in terms of sizable minimum weekly benefit amounts are Utah ($446 per week), Arizona ($229), Kansas ($153), Ohio ($149), and Maine ($108). Utah, in particular, closely mirrors Washington along both dimensions, and may even yield larger effects on job quality given its high minimum WBA. While benefit levels vary, the presence of a meaningful floor in each of these states suggests that UI receipt may similarly enable more selective job search among low-wage workers, increasing the potential for stable, higher-paying re-employment.

Fiscal Considerations: Trust Funds and Taxes Among the 11 states for whom our results for the effect of UI receipt on earnings and job quality are most likely to extrapolate – the first eleven listed in Table G.1 after Washington – it is also important for policymakers to consider each state's fiscal readiness to support expanded eligibility, as well as their capacity to recoup public spending through income tax revenues from higher post-unemployment earnings.[33]

As shown in Table G.2, all eleven states we identify as most comparable to Washington in terms of UI stringency are currently in strong fiscal positions to expand UI eligibility to marginally attached workers. Each of these states is running a positive UI trust fund balance per capita – a condition that does not hold in several larger states such as California and New York. Particularly notable are Wyoming, Maine, and Kansas, whose per capita UI reserves exceed that of Washington. These states are in especially sound fiscal condition, providing policymakers with the opportunity to expand UI access without immediate pressure to raise employer payroll taxes or cut other benefits.

In addition to strong UI fund balances, all states in Table G.2, with the exception of Wyoming, impose positive marginal income tax rates on low-income workers, making them better positioned than Washington to recoup part of the fiscal cost of expanded UI access through increased income tax revenue. The table reports the marginal tax rate on a single filer earning $30,000, a typical income level for marginal workers affected by UI eligibility expansions. States such as Maine, South Carolina, Kansas, Nebraska, Utah, Michigan, and Kentucky all levy marginal rates of at least 4% at this income level. As a result, these states in particular stand to financially benefit from improved labor market outcomes among marginal UI recipients, as higher post-unemployment earnings translate directly into increased state revenue.

[33] We collect information on the balance of state UI trust funds from the US Department of Labor ETA at this link: https://oui.doleta.gov/unemploy/docs/trustFundSolvReport2024.pdf

Summary of Extrapolation and Policy Implications

Based on both eligibility stringency and minimum UI generosity, our findings are most likely to extrapolate to five states: **Utah, Arizona, Kansas, Ohio, and Maine**. These states combine relatively high minimum work requirements for low-wage workers with sizable minimum weekly benefit amounts, suggesting institutional environments similar to Washington's along the key dimensions that shape the labor market effects of UI receipt.

In terms of fiscal capacity, a broader set of states appear well-positioned to expand UI eligibility and benefits for marginally attached workers. Based on both a healthy UI trust fund balance and the presence of a state income tax that allows for partial fiscal recovery through increased earnings, the states best situated for reform include: **Utah, South Carolina, Michigan, Arizona, Kansas, Indiana, Nebraska, and Maine**. These states may be particularly well-suited to consider policy changes that broaden UI access for low-wage workers while maintaining long-term fiscal sustainability.

Table G.1: Hours-Translated UI Eligibility Thresholds by State, 2023

State	Base Period Wages Needed to Qualify	Minimum UI Weekly Benefit Amount (WBA)	Minimum Wage	Hours to Qualify at Min Wage
Washington	-	$342	$15.74	680.0
Utah	$4,800	$446	$7.25	662.1
South Carolina	$4,455	$42	$7.25	614.5
Arizona	$8,103	$229	$13.85	585.1
Michigan	$5,879	$81	$10.10	582.1
Kansas	$4,200	$153	$7.25	579.3
Indiana	$4,200	$50	$7.25	579.3
Wyoming	$4,200	$45	$7.25	579.3
Ohio	$5,220	$149	$10.10	516.8
Nebraska	$4,891	$70	$10.50	465.8
Maine	$6,216	$108	$13.80	450.4
Kentucky	$3,230	$39	$7.25	445.5
Iowa	$2,840	$90	$7.25	391.7
New Hampshire	$2,800	$32	$7.25	386.2
North Dakota	$2,795	$43	$7.25	385.5
Massachusetts	$5,700	$98	$15.00	380.0
Pennsylvania	$2,718	$68	$7.25	374.9
New Jersey	$5,200	$99	$14.13	368.0
Texas	$2,664	$74	$7.25	367.4
Rhode Island	$4,600	$71	$13.00	353.8
Montana	$3,337	$163	$9.95	335.4
Minnesota	$3,500	$38	$10.59	330.5
New York	$4,650	$136	$14.20	327.5
Idaho	$2,340	$72	$7.25	322.8
Alabama	$2,314	$45	$7.25	319.2
Vermont	$4,199	$72	$13.18	318.6
Florida	$3,400	$32	$11.00	309.1
Georgia	$2,200	$55	$7.25	303.4
Wisconsin	$1,890	$54	$7.25	260.7
Arkansas	$2,835	$81	$11.00	257.7
West Virginia	$2,200	$24	$8.75	251.4
Virginia	$3,000	$60	$12.00	250.0
Alaska	$2,500	$56	$10.85	230.4
Tennessee	$1,560	$30	$7.25	215.2
Oklahoma	$1,500	$16	$7.25	206.9
New Mexico	$2,454	$86	$12.00	204.5
Missouri	$2,250	$40	$12.00	187.5
Colorado	$2,500	$25	$13.65	183.2
Louisiana	$1,200	$35	$7.25	165.5
Mississippi	$1,200	$30	$7.25	165.5
Maryland	$1,800	$50	$13.25	135.8
Illinois	$1,600	$51	$13.00	123.1
South Dakota	$1,288	$28	$10.80	119.3
North Carolina	$780	$15	$7.25	107.6
Oregon	$1,000	$196	$13.50	74.1
California	$1,125	$40	$15.50	72.6
Nevada	$600	$16	$9.50	63.2
Delaware	$720	$20	$11.75	61.3
Connecticut	$600	$42	$14.00	42.9
Hawaii	$130	$5	$12.00	10.8

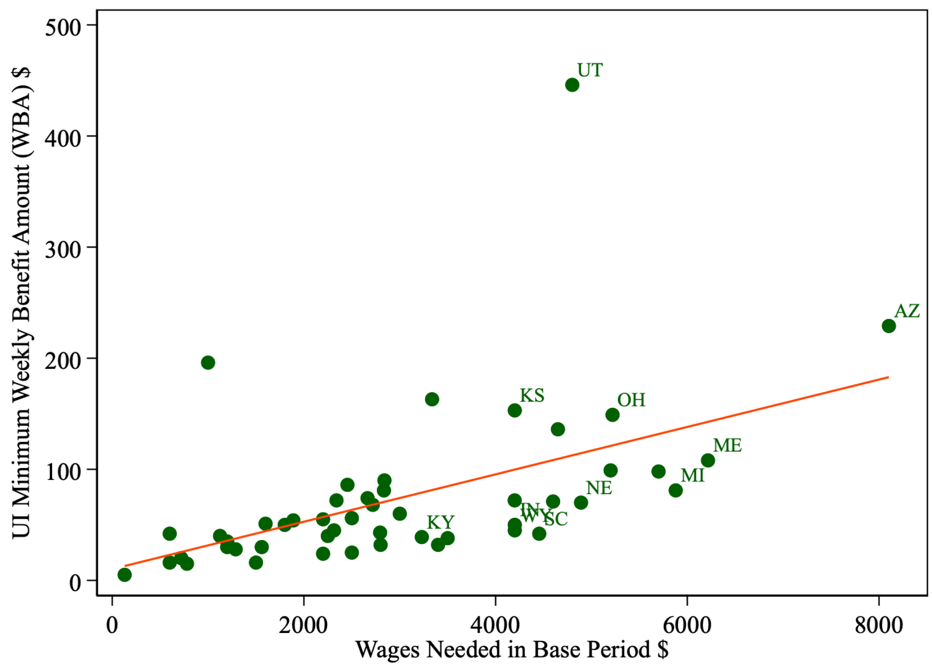
Notes: Column (2) represents the minimum amount of earnings needed in the base period to be monetarily eligible. Column (5) equals column (2) divided by column (4), excepting Washington. All values are from 2023 except column (3), minimum WBA, which is from 2024.

Table G.2: Fiscal Context for States with High UI Stringency and Generosity

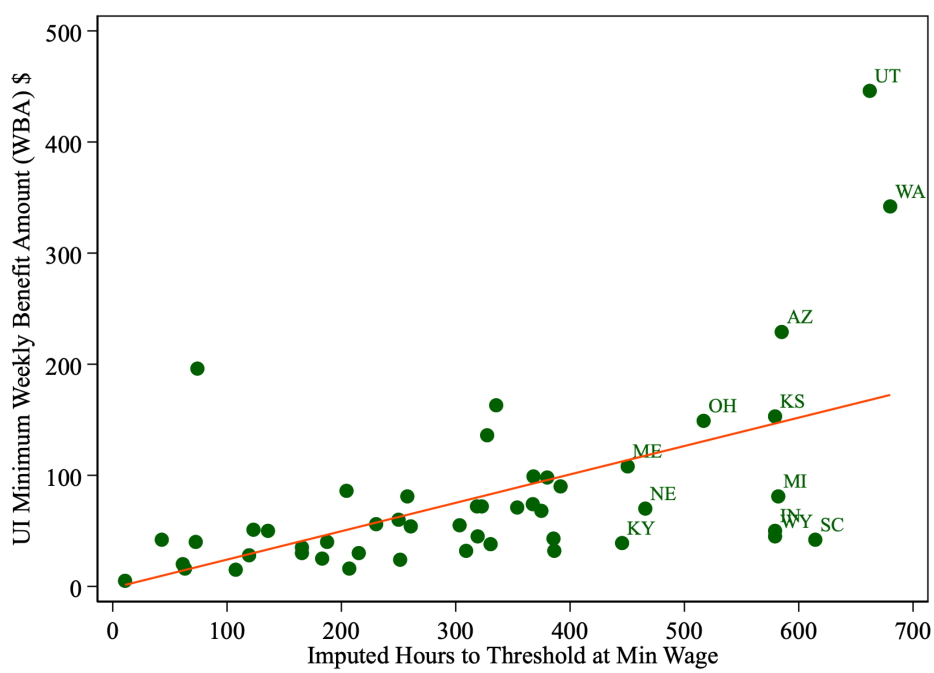
State	Hours to Qualify at Min Wage	UI Trust Fund Balance (per capita)	State Income Tax Rate at $30,000 Income
Washington	680.0	$445.36	0.00%
Utah	662.1	$341.03	4.55%
South Carolina	614.5	$291.64	6.20%
Arizona	585.1	$212.34	2.50%
Michigan	582.1	$225.32	4.25%
Kansas	579.3	$496.64	5.58%
Indiana	579.3	$225.15	3.00%
Wyoming	579.3	$803.87	0.00%
Ohio	516.8	$142.91	2.75%
Nebraska	465.8	$268.38	5.01%
Maine	450.4	$501.05	6.75%
Kentucky	445.5	$180.30	4.00%

Note: "Hours to Qualify at Min Wage" as calculated in Table G.1. UI trust fund balances are measured per capita and reflect each state's net reserves and population estimate as of 2024. State income tax rates reflect marginal rates on wage income for a single filer earning $30,000 in 2025. Table only displays states whose monetary eligibility conditions for minimum wage workers are similar to Washington's.

Figure G.1: Minimum Weekly Benefit and Monetary Eligibility Stringency by State



(a) Minimum WBA vs. Base Period Earnings Required for UI Eligibility



(b) Minimum WBA vs. Imputed Hours to UI Eligibility at Minimum Wage

Note: Figure shows scatterplots of each state's minimum weekly benefit amount (WBA) from 2024 on the y-axis and a measure of monetary eligibility stringency on the x-axis. Panel (a) presents the statutory amount of earnings needed to qualify for UI and omits Washington. Panel (b) converts this amount to the number of hours needed to work at the minimum wage in that state and includes Washington's 680 hour rule.