Incomplete and Endogenous Take-Up of Unemployment Insurance Benefits*

Casey McQuillan
Princeton University
Washington ESD
(*Job Market Paper*)

Brendan Moore
Stanford University
Washington ESD

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Abstract

This paper investigates how the generosity of unemployment insurance (UI) affects take-up and the implications for optimal policy design. Standard models of UI begin their analysis with benefit receipt, yet take-up is highly incomplete: only around half of eligible workers claim benefits in the United States. We develop a model with incomplete take-up explained by the hassle of applying. More generous benefits induce workers on the margin to claim benefits, creating a fiscal externality without a corresponding utility gain. Our optimal policy condition extends the Baily-Chetty formula to include the take-up elasticity, which proves quantitatively important. Using administrative data from Washington State and a regression kink design (RKD), we find that a 10 percent increase in the weekly benefit increases take-up by 4.7 percent, which drives a 6.2 percent increase in the number of benefit payments. Previous work considers only claim duration by conditioning on benefit receipt, ignoring the take-up response and thus underestimating the fiscal cost. Combining our theory and empirical results, we show that endogenous take-up reduces the optimal benefit level by 29 percent and the cost-effectiveness of raising benefits by 27 percent. Together, these results highlight that incomplete and endogenous take-up is a first-order consideration in the optimal design of social insurance.

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1 Introduction

Unemployment insurance (UI) provides financial support to workers who lose their job through no fault of their own. These benefits replace a portion of lost wages while workers search for their next job, helping maintain some stability through periods of disruption and transition. In 2024, 7.5 million workers received a total of $36 billion in UI benefits in the U.S., representing roughly 1 in 20 workers. During recessions, even more workers rely on these benefits–in 2009, 21 million workers received a total of $128 billion, or roughly 1 in 7 workers. Despite the importance and scale of the UI program, take-up is highly incomplete: only about half of eligible workers claim benefits (Blank and Card, 1991; McCall, 1995; Anderson and Meyer, 1997).

Standard models of UI begin their analysis with benefit receipt, assuming that all eligible workers claim benefits. Yet when take-up is incomplete, the decision to claim becomes an additional margin through which workers respond to policy. In determining benefit levels, the conventional approach focuses on the insurance-incentive tradeoff: more generous benefits better insure workers against unexpected job loss but also reduce the incentive to find a new job. However, this framework overlooks that, in response to raising benefit levels, eligible workers may be more likely to claim benefits in the first place. In fact, one-third of workers who did not take up UI cited benefit levels or hassle costs as a reason.[1] Moreover, endogenous take-up generates a fiscal externality analogous to that arising from endogenous search effort and extended claim durations. Accounting for this behavioral response may fundamentally shift the optimal balance between the value that UI provides and the fiscal externalities it creates (Baily, 1978; Hopenhayn and Nicolini, 1997; Chetty, 2006).

This paper explores how the generosity of UI benefits affects take-up and the implications for policy. We focus on three main questions. First, how does the benefit level influence a worker's decision whether to claim UI? Second, how does incorporating this extensive-margin response reframe our understanding of the fiscal externality created by more generous benefits? Third, how does incomplete and endogenous take-up shape the optimal policy design? Answering these questions reveals the central role of take-up in determining the fiscal costs and welfare consequences of the UI program.

We begin by developing a theoretical model with incomplete and endogenous take-up arising from a worker-specific hassle cost. This model allows for incomplete take-up as well as for the take-up rate to respond to changes in the benefit level. We derive optimal

[1] This evidence comes from the 2018 Current Population Survey Unemployment Insurance Non-Filers Supplement, which asked eligible workers who did not claim benefits to report their reasons for non-filing. Additional results from the survey are presented in Table A.1.

policy conditions under three scenarios: a first-best solution with no behavioral response, one where workers choose search effort endogenously, and one where both search effort and take-up are endogenous. With no behavioral response, it is optimal to provide "full insurance" to workers. However, as we allow workers to choose their search effort and take-up, the behavioral responses drive a wedge between full insurance and the optimal benefit level. The key insight is that workers induced to claim in response to a marginal increase in the benefit level are indifferent between claiming and not claiming, and so there is no welfare gain from higher take-up that is due to more generous benefits. However, despite their indifference, these marginal claimants generate a fiscal externality. This model highlights that endogenous take-up, much like endogenous search effort, amplifies the fiscal cost of raising benefits. The elasticity of take-up becomes a key parameter in the optimal policy condition. Ultimately, optimal policy is determined by the total number of benefit payments, whether driven by higher take-up or longer claim durations.

Recognizing the theoretical importance, we outline an approach to measure take-up, total benefit payments, and workers' responsiveness to the weekly benefit level. We construct our sample of likely-eligible workers using employer-employee matched data from Washington State over the period from 2010 through 2019, using a similar approach as Anderson and Meyer (1997) and Lachowska et al. (2025). We then match this sample with administrative records of claims and benefit payments to determine whether each worker applied for or received benefits, how far they progressed into the application process, and the duration of their claim. To identify the causal effect on take-up, we exploit nonlinearities in the benefits schedule using a regression kink design (RKD).

Overall, we find that take-up is a significant margin of response for workers. Our results suggest that a 10 percent increase in benefit level leads to a 4.7 percent increase in take-up. This estimate is consistent with results from Anderson and Meyer (1997) that relies on variation in benefits across states and over time. After incorporating this take-up response, we estimate that a 10 percent increase in the weekly benefit leads to a 6.2 percent increase in the total number of benefit payments. Additionally, by tracking workers through the application process, we show that two-thirds of the effect on take-up can be attributed to an increase in the share of workers who file an initial claim, with the remainder due to workers being more likely to follow through on the subsequent steps in the application process. We validate these findings by demonstrating that the kinks in take-up and benefit payments track the kink in the benefit schedule as it moves, and that the effects are similar for workers who separated in mass layoff events.

We consider how endogenous take-up refines our understanding of previous work that conditioned on benefit receipt. In measuring the costs of more generous benefits, previous work only accounted for the intensive margin whereby benefit recipients extend their claim duration. The key methodological difference is that we focus on take-up and benefit payments for a sample of *likely-eligible workers*, whereas previous work analyzed claim duration for a sample of *UI recipients*.[2] Our analysis reveals two potential issues with conditioning on benefit receipt. First, the measure of the fiscal cost is incomplete without accounting for the extensive margin. Empirically, the take-up response more than triples the fiscal externality. Second, endogenous take-up may introduce a sample selection problem to even identifying the intensive margin response. Variation in benefit generosity may also affect who selects into the sample of UI recipients, which causes concerns if the determinants of take-up also influence claim duration.

Lastly, we combine our theoretical model and empirical results to assess the policy implications of endogenous take-up. First, we calibrate the model to determine the optimal benefit level under different counterfactuals. We find that endogenous take-up reduces the optimal benefit level by 29 percent, from \$633 to \$451. The wedge between full insurance and the optimal benefit nearly triples from \$98 to \$280 when we account for endogenous take-up in addition to endogenous search effort. Second, using the marginal value of public funds (MVPF) framework from Hendren and Sprung-Keyser (2020), we find that endogenous take-up reduces the marginal value of raising the weekly benefit by 27 percent. These results suggest that existing estimates of overstate the value of raising benefit levels. Consequently, increasing the weekly benefit may not be the most efficient use of funds; resources could instead be directed toward other public benefit programs or alternative ways to improve the UI program.

Contributions to the Literature

This paper contributes to several topics at the intersection of labor economics and public finance. First, we add to the understanding of incomplete take-up of public benefits by providing the first quasi-experimental evidence for the causal effect of benefit generosity on UI take-up. Within the context of the UI program, Blank and Card (1991) first examined trends in take-up rates, noting a large decline in the 1980s. Anderson and Meyer (1997) established a relationship between benefit levels and take-up rates, but their approach relied on cross-sectional variation over time and across states. We build on this work with administrative data and a research design that leverages within-labor-market variation in benefit levels to isolate the role of financial incentives from confounding factors such as administrative barriers, information frictions, and local labor market

[2] To identify this effect, Landais (2015) and Card et al. (2015a) employed an RKD, Meyer and Mok (2007), Chetty (2008), and Solon (1985) utilized a difference-in-differences approach, while Katz and Meyer (1990), and Kroft and Notowidigdo (2016) relied on policy variation across states and over time.

conditions. More recently, Lachowska et al. (2025) explores the role of employers in explaining differences in take-up across firms, arguing that employers can deter workers from taking up benefits by appealing their claims and creating more hassle. McQuillan and Moore (2025a) examines the role of incomplete information in explaining incomplete take-up, showing that targeted outreach can increase take-up. Beyond the UI program, this paper adds to a substantial body of research documenting that eligible individuals frequently fail to claim benefits across various U.S. social programs, including the Earned Income Tax Credit (Bhargava and Manoli, 2015; Linos et al., 2022), Medicaid (Moynihan et al., 2015), the Special Supplemental Nutrition Program for Women, Infants, and Children (Rossin-Slater, 2013), Temporary Assistance for Needy Families (Ziliak, 2015), Social Security Disability Insurance (Deshpande and Li, 2019), and the Supplemental Nutrition Assistance Program (Finkelstein and Notowidigdo, 2019).

Second, our paper advances the existing literature on how workers respond to more generous UI benefits by incorporating take-up into this framework. Our measure of the fiscal externality includes both the extensive margin of take-up and the intensive margin of claim duration, providing a more complete picture of the behavioral responses. Early work such as Solon (1985), Moffitt (1985), Katz and Meyer (1990), and Meyer (1990) first explored the relationship between UI benefit levels and average claim duration. More recent empirical work identifies causal effects using the regression kink design or a difference-in-differences approach (Landais, 2015; Card et al., 2015a; Meyer and Mok, 2007; Chetty, 2008). Other research considers a different dimension of benefit generosity, showing how increasing the maximum potential duration for benefits can similarly lead workers to remain on benefits for longer (Card and Levine, 2000; Lalive, 2007; Katz and Meyer, 1990; Johnston and Mas, 2018).

Lastly, building on Anderson and Meyer (1997) and Kroft (2008), who explicitly model take-up as an endogenous choice, we develop a theoretical framework that uses our quasi-experimental estimates to re-assess the optimal benefit level.[3] We derive optimal policy conditions that generalize the Baily-Chetty formula to include the take-up elasticity, then use our empirical estimates to show that ignoring take-up leads to meaningfully different policy conclusions. As in Kroft (2008), our model builds on the foundational work of Baily (1978) and subsequent contributions by Gruber (1997) and Chetty (2006), which developed frameworks for weighing the costs and benefits of UI programs (Mit-

[3]Anderson and Meyer (1997) introduces a transaction cost to applying, while Kroft (2008) introduces take-up costs that are a function of the aggregate take-up rate. Kroft (2008) shows that this creates a "social multiplier" effect whereby these costs fall as more coworkers claim benefits. We do not incorporate this social learning mechanism into our model; instead, our focus is on the direct effect of the weekly benefit level on take-up.

man and Rabinovich, 2015; Kroft and Notowidigdo, 2016; Schmieder and Von Wachter, 2016; Landais et al., 2018; Ganong and Noel, 2019). Additionally, we revisit MVPF estimates from Hendren and Sprung-Keyser (2020), arguing that these estimates overstate the cost-effectiveness of raising UI benefit levels by failing to account for endogenous take-up.

The remainder of the paper is organized as follows. Section 2 develops a theoretical model of UI with incomplete and endogenous take-up and derives optimal policy conditions. Section 3 describes our institutional setting and data, as well as how we construct a sample of likely-eligible workers. Section 4 discusses identification, while Section 5 presents our empirical results. Section 6 evaluates how endogenous take-up affects our understanding of previous work examining benefit generosity and claim duration. Section 7 assesses the policy implications of endogenous take-up. Section 8 concludes.

2 Theoretical Model

In this section, we develop a theoretical model of UI with incomplete and endogenous take-up and derive optimal policy conditions. We begin with a first-best solution in which the social planner dictates search effort and take-up for workers. We then proceed in two steps: first, allowing workers to choose their search effort while take-up remains fixed, and then allowing both search effort and take-up to be endogenous to the benefit level. This model demonstrates that when workers respond to more generous benefits by claiming at a higher rate, this behavioral response amplifies the fiscal externality and lowers the optimal benefit level.

Our model builds on the intuition from Anderson and Meyer (1997) that more generous benefits should lead workers on the margin to claim benefits while also generalizing the results from Chetty (2006) to allow for incomplete and endogenous take-up. Kroft (2008) similarly modeled the take-up decision with hassle costs, although the analysis focused more on how these costs may be endogenous to the number of people who claim benefits as a way to highlight the role of social learning in program participation decisions.

2.1 Set Up

Workers can either be employed or unemployed. When employed, they earn income w_H and pay unemployment taxes τ; when unemployed, they have exogenous income w_L and receive the benefit b if they take up benefits ($T_i = 1$).[4] Consumption is hand-to-mouth so workers consume $w_H - \tau$ while employed and $w_L + T_i \cdot b$ while unemployed. There is a worker-specific hassle cost $q_i \in \mathbb{R}$ associated with claiming benefits, which is incurred directly to a worker's utility if they take up benefits. This hassle cost is distributed according to the cumulative distribution function $F(\cdot)$.

When unemployed and looking for a job, a worker chooses their search effort e_i, where we normalize e_i so that it represents the share of time spent employed. Consequently, $(1 - e_i)$ represents the share of time spent unemployed. Workers face an increasing and convex cost function for search effort $\psi(e_i)$. Lastly, the model uses state-dependent utility functions $v(\cdot)$ for employment and $u(\cdot)$ for unemployment to capture interactions between consumption and leisure, which may vary when an individual is employed versus unemployed.

Given the benefit b and tax τ, a worker's utility can be expressed as a function of their hassle cost q_i, search effort $e_i \in [0, 1]$, and take-up decision $T_i \in \{0, 1\}$ as

$$V(q_i, e_i, T_i) = e_i \cdot v\left(w_H - \tau\right) + (1 - e_i) \cdot u\left(w_L + T_i \cdot b\right) - T_i \cdot q_i - \psi(e_i) .$$

where the first two terms represent expected consumption utility, followed by hassle costs and search costs. This expression highlights the key tradeoffs facing workers. A worker prefers employment, but increasing search effort is costly. A worker could increase their income by claiming benefits, but then they incur the hassle q_i.

The balanced budget constraint equates the tax revenue collected on workers while employed with the benefits paid to claimants

$$e \cdot \tau = (1 - e_1) \cdot \theta \cdot b ,$$

where $e = E[e_i]$ is the average time spent employed for all workers, $e_1 = E[e_i | T_i = 1]$ is the average time spent employed for workers who claim benefits, and $\theta = E[T_i]$ is the overall take-up rate. We will similarly define $e_0 = E[e_i | T_i = 0]$ to be the average time spent employed for non-claimants. The left-hand side of this equation represents taxes collected while employed and the right-hand side represents benefits paid to claimants. The right-hand side is scaled by θ to reflect the fact that not all workers claim benefits and uses the duration of unemployment specific to claimants $(1 - e_1)$. The left-hand side is not scaled since the tax is collected from all workers while they are employed, regardless

[4] We assume that the income in the employed state is higher than income in the unemployed state so that $w_L < w_H$.

of whether they claim benefits.[5]

2.2 First-Best Solution

We first consider the case where the social planner decides the benefit level b, observes the hassle cost q_i for each worker, and can then determine their search effort e_i and take-up T_i subject only to the balanced budget constraint.

The social planner's problem can be simplified in two ways. First, the optimal search effort depends on take-up T_i but does not depend on the hassle cost q_i, since q_i enters the utility function separably. As a result, optimal search effort can be characterized by two parameters—search effort e_1 for claimants and search effort e_0 for non-claimants. Second, the optimal mapping from hassle cost to take-up is defined by a cutoff $\overline{q}$ such that $T(q_i) = 1$ if $q_i < \overline{q}$ and $T(q_i) = 0$ if $q_i \geq \overline{q}$.[6] As a result, optimal take-up can be characterized by the parameter $\overline{q}$ with overall take-up equal to $\theta = F(\overline{q})$.

In the first-best solution, the social planner chooses benefit level b, search effort e_1 for claimants and e_0 for non-claimants, and the cutoff point $\overline{q}$ in order to maximize social welfare W. The balanced budget constraint then determines the tax τ. The social planner's problem can be expressed

$$\begin{aligned} \max_{b,\, e_1,\, e_0,\, \overline{q}} \quad & W\left(b,\, e_1,\, e_0,\, \overline{q}\right) = \int_{-\infty}^{\overline{q}} V(q', e_1, 1)\ dF(q') + \int_{\overline{q}}^{\infty} V(q', e_0, 0)\ dF(q') \\ \text{s.t.} \quad & e \cdot \tau = (1 - e_1) \cdot \theta \cdot b\ . \end{aligned}$$

The optimal search effort partly depends on the subsequent change to the tax τ necessary to maintain a balanced budget. Differentiating the balanced budget constraint yields

$$\begin{aligned} \frac{\partial \tau}{\partial e_0} \cdot e &= -\tau \cdot (1 - \theta)\ , \\ \frac{\partial \tau}{\partial e_1} \cdot e &= -(\tau + b) \cdot \theta\ . \end{aligned}$$

For non-claimants, the fiscal externality arises from additional or forgone tax revenue

[5] Additionally, this model abstracts from the experience rating system used by most states, whereby the tax rate charged to employers varies based on the number of claims they are responsible for in recent years.

[6] Suppose this was not the case, so there is an optimal mapping where a worker m with hassle cost q_m takes up benefits, a worker n with hassle cost q_n does not take up benefits, and $q_m > q_n$. Since workers are identical except for their hassle cost, this means the social planner could create a welfare gain relative to the initial mapping of $q_m - q_n > 0$ by switching the values of e_i and T_i for the two workers so that worker m does not take up and worker n now does. This contradicts the assumption that our initial mapping was optimal. Therefore, no such mapping exists.

during employment. For claimants, changes in search effort generate a larger fiscal externality, as it affects both tax revenue and the amount of benefits paid.

We differentiate the welfare function $W\left(b,\, e_1,\, e_0,\, \overline{q}\right)$ with respect to e_1 and e_0, substitute in the fiscal cost, and rearrange the expression to determine the conditions for optimal search effort

$$
\begin{aligned}
e_1 \quad \text{such that} \quad & \underbrace{\psi'(e_1)}_{\text{Search Cost}} = \underbrace{v(w_H - \tau) - u(w_L + b)}_{\text{Private Benefit}} + \underbrace{v'(w_H - \tau) \cdot (\tau + b)}_{\text{Fiscal Externality}} \;, \\
e_0 \quad \text{such that} \quad & \underbrace{\psi'(e_0)}_{\text{Search Cost}} = \underbrace{v(w_H - \tau) - u(w_L)}_{\text{Private Benefit}} + \underbrace{v'(w_H - \tau) \cdot \tau}_{\text{Fiscal Externality}} \;.
\end{aligned}
$$

The social planner equalizes the marginal cost of greater effort for the worker on the left-hand side against the private benefit of employment plus the fiscal externality on the right-hand side. Interestingly, it is not clear whether the social planner will set search effort higher for the claimants or non-claimants in the first-best solution. Although increasing the search effort for claimants generates more cost-savings, the private benefit of employment is smaller for this group.

Next, consider optimal take-up as determined by the cutoff $\overline{q}$. A marginal increase in $\overline{q}$ leads workers with $q_i = \overline{q}$ to take up benefits, so the overall take-up rate increases by $\frac{\partial \theta}{\partial \overline{q}} = f(\overline{q})$ where $f(\cdot)$ is the probability density function for q_i. The fiscal cost of this change in take-up would be

$$
\frac{\partial \tau}{\partial \overline{q}} \cdot e = f(\overline{q}) \cdot [\quad \underbrace{(1 - e_1) \cdot b}_{\text{Additional Benefits Paid}} \quad + \quad \underbrace{(e_0 - e_1) \cdot \tau}_{\text{Change in Search Effort}} \quad].
$$

The tax τ must adjust to finance paying the benefit b to the share of new claimants $f(\overline{q})$ for the duration of their unemployment $(1 - e_1)$ as well as the change in tax revenue collected when these workers switch their search effort from e_0 to e_1.

We differentiate the welfare function $W\left(b,\, e_1,\, e_0,\, \overline{q}\right)$ with respect to $\overline{q}$, substitute in the fiscal externality, and then rearrange to derive the condition for the optimal cutoff

$$
\underbrace{V(\overline{q}, e_1, 1) - V(\overline{q}, e_0, 0)}_{\text{Private Benefit to Marginal Claimants}} = \underbrace{v'(w_H - \tau) \cdot [(1 - e_1) \cdot b + (e_0 - e_1) \cdot \tau]}_{\text{Fiscal Externality from Higher Take-Up}} \;.
$$

Intuitively, the optimal cutoff equalizes the private benefit to marginal claimants against the fiscal externality from higher take-up.

Given optimal search effort and take-up, we now consider the optimal benefit level b.

Since the social planner determines both search effort and take-up, the fiscal cost is equal to the mechanical cost of paying a marginally higher benefit to the share of workers who claim benefits θ for the duration of their unemployment spell $(1 - e_1)$. The fiscal cost from a change in benefit level b is

$$\frac{\partial \tau}{\partial b} \cdot e = (1 - e_1) \cdot \theta \ .$$

We differentiate the welfare function $W\left(b,\ e_1,\ e_0,\ \overline{q}\right)$ with respect to benefit b and set the first-order condition equal to zero, which yields the expression

$$\frac{\partial W}{\partial b} = (1 - e_1) \cdot \theta \cdot u'(w_L + b) - e \cdot v'(w_H - \tau) \cdot \frac{\partial \tau}{\partial b} \ = 0 \ .$$

We then substitute the fiscal cost of raising benefits $\frac{\partial \tau}{\partial b} \cdot e$ into the expression to give us the optimal policy condition

$$u'(w_L + b) = v'(w_H - \tau) \ .$$

This result indicates that in the first-best solution, the benefit b is set to achieve "full insurance" by equalizing the marginal utilities for claimants across the employed and unemployed states. Intuitively, if there is no behavioral response from workers that generates a fiscal externality, then full insurance is optimal.

2.3 Endogenous Search Effort

Next, we assume the social planner cannot observe a worker's search effort e_i, and instead, the worker chooses their search effort $e_i \in [0, 1]$ in response to the benefit level b, tax τ, and their take-up T_i. Additionally, take-up is now exogenously determined, outside of the control of the social planner and the worker, while we focus on how workers endogenously adjust their search effort. The worker's problem can be expressed as

$$\max_{e_i} V(q_i, e_i, T_i) = e_i \cdot v\left(w_H - \tau\right) + (1 - e_i) \cdot u\left(w_L + T_i \cdot b\right) - T_i \cdot q_i - \psi(e_i) \ .$$

By taking the first-order condition with respect to search effort e_i, it follows that the worker's optimal search effort $e^{\star}(b, \tau, T_i)$ equates the marginal cost of additional effort with the private benefit from a higher probability of employment. Optimal search effort is a function of take-up T_i, but since the hassle cost q_i enters separably in the utility function, the hassle cost q_i does not influence the worker's choice. The worker's optimal effort is

$$e^{\star}(b,\tau,T_i) = \begin{cases} e_1 \text{ such that } \psi'(e_1) = v(w_H-\tau) - u(w_L+b) & \text{if } T_i = 1\ , \\ e_0 \text{ such that } \psi'(e_0) = v(w_H-\tau) - u(w_L) & \text{if } T_i = 0\ . \end{cases}$$

Workers do not consider the fiscal externalities from changes in their search effort. This leads to lower search effort relative to the social planner's optimum for any given combination of benefit b, tax τ, and take-up T_i. Moreover, claimants now exert strictly less effort than non-claimants so that $e_1 < e_0$. The benefit b reduces the incentive to search for claimants, and this is no longer offset by the larger fiscal externality.

As before, the UI program is financed by the tax τ collected while workers are employed. However, since search effort changes in response to the benefit b, the cost of raising benefit levels includes this behavioral response. Differentiating the balanced budget constraint with respect to the benefit level b yields

$$\frac{\partial \tau}{\partial b} \cdot e = \underbrace{(1-e_1)\cdot\theta}_{\text{Mechanical Cost}} - \underbrace{\theta \cdot b \cdot \frac{\partial e_1}{\partial b}}_{\text{Search Effort (Benefits Paid)}} - \underbrace{\frac{\partial e}{\partial b}\cdot\tau}_{\text{Search Effort (Lost Revenue)}} .$$

There remains the mechanical cost of paying higher benefits to existing claimants, but now there are also costs arising from changes in search effort that affect both benefits paid and revenue collected.

The social planner chooses the benefit level b, taking into account both the balanced budget constraint and the worker's optimal response $e^{\star}(b,\tau,T_i)$. The planner's problem becomes

$$\begin{aligned} \max_b \quad & W(b) = \theta \cdot \int V(q', e_1, 1)\ dF(q'|T_i=1) + (1-\theta)\cdot \int V(q', e_0, 0)\ dF(q'|T_i=0) \\ \text{s.t.} \quad & e\cdot\tau = (1-e_1)\cdot\theta\cdot b \\ & e_i = e^{\star}(b,\tau,T_i)\ . \end{aligned}$$

Taking the derivative of the social welfare function with respect to benefit level b yields the first-order condition

$$\frac{\partial W}{\partial b} = (1-e_1)\cdot\theta\cdot u'(w_L+b) - e\cdot v'(w_H-\tau)\cdot\frac{\partial \tau}{\partial b} = 0,$$

where the change in search effort drops out by the envelope theorem.[7] We set the first-order condition equal to zero, substitute in the expression for $\frac{\partial \tau}{\partial b} \cdot e$, and normalize relative to the marginal utility of an additional dollar of income during the employed state. This yields the optimal policy condition

$$\frac{u'(w_L + b) - v'(w_H - \tau)}{v'(w_H - \tau)} = \underbrace{\varepsilon_{1-e_1,b}}_{\text{Claim Duration}} - \underbrace{\varepsilon_{e,b}}_{\text{Tax Revenue}} .$$

The right-hand side captures the two channels by which workers reducing their search effort in response to more generous benefits creates a fiscal externality. First, claimants may remain on benefits for longer, as represented by the elasticity of claim duration $\varepsilon_{1-e_1,b}$. Second, less tax revenue is collected because workers spend less time employed, as represented by the elasticity of tax revenue $\varepsilon_{e,b}$.

This optimal policy condition highlights that full insurance is not socially optimal when search effort e_i responds to the benefit b. This behavioral response creates a trade-off for the social planner between providing insurance for job loss and preserving the incentives to find re-employment. Additionally, the more responsive workers' search effort is to the benefit b — as indicated by larger values of $\varepsilon_{1-e_1,b}$ and $\varepsilon_{e,b}$ — then the larger the fiscal externality and consequently the larger wedge between full insurance and the optimal benefit level.

2.4 Endogenous Take-Up

We introduce endogenous take-up by assuming that the social planner cannot observe a worker's search effort e_i or their hassle cost q_i, and the worker chooses both their search effort $e_i \in [0, 1]$ as well as whether to take up benefits $T_i \in \{0, 1\}$ in response to the benefit b and tax τ. The worker's problem becomes

$$\max_{e_i, T_i} V(q_i, e_i, T_i) = e_i \cdot v\,(w_H - \tau) + (1 - e_i) \cdot u\,(w_L + T_i \cdot b) - T_i \cdot q_i - \psi(e_i) .$$

[7] The first-order condition including the change in search effort would be

$$\begin{aligned}\frac{\partial W}{\partial b} =& (1 - e_1) \cdot \theta \cdot u'(w_L + b) - e \cdot v'(w_H - \tau) \cdot \frac{\partial \tau}{\partial b} \\ &+ \frac{\partial e_1}{\partial b} \cdot \theta \cdot \left[v(w_H - \tau) - u(w_L + b) - \psi'(e_1)\right] \\ &+ \frac{\partial e_0}{\partial b} \cdot (1 - \theta) \cdot \left[v(w_H - \tau) - u(w_L) - \psi'(e_0)\right] = 0 \ .\end{aligned}$$

Since workers chose search effort e_1 and e_0 optimally, the terms $\left[v(w_H - \tau) - u(w_L + b) - \psi'(e_1)\right]$ and $\left[v(w_H - \tau) - u(w_L) - \psi'(e_0)\right]$ are equal to zero.

As before, optimal search effort depends on the gap in marginal utilities between employment and unemployment, which is captured by $e^\star(b,\tau,T_i)$. The only difference is that take-up T_i is now endogenously determined by the worker's hassle cost q_i.

Given search effort $e_0 = e^\star(b,\tau,0)$ and $e_1 = e^\star(b,\tau,1)$, optimal take-up can be characterized by the cutoff $\overline{q}$ such that workers with $q_i = \overline{q}$ are indifferent on whether to claim benefits with $V(\overline{q}, e_1, 1) = V(\overline{q}, e_0, 0)$.[8] It follows that optimal take-up can be expressed as a function of a worker's hassle cost q_i

$$T^\star(q_i) = \begin{cases} 1 & \text{if } q_i \leq \overline{q} \\ 0 & \text{if } q_i > \overline{q} \end{cases}.$$

where workers with $q_i < \overline{q}$ will take up $T_i = 1$ and workers with $q_i > \overline{q}$ prefer not to claim $T_i = 0$. Intuitively, workers choose take-up to maximize private utility without considering the fiscal externality. They claim benefits whenever the private gain is positive, even if the fiscal cost exceeds their private benefit, which reduces social welfare. For any values of e_1 and e_0, this leads to a lower cutoff and more take-up than the social planner would select in the first-best solution.

When determining optimal benefit level b, the social planner must account for behavioral responses from workers in both search effort and take-up. The cost of raising benefits becomes

$$\frac{\partial \tau}{\partial b} \cdot e = \underbrace{(1-e_1)\cdot\theta}_{\text{Mechanical Cost}} + \underbrace{(1-e_1)\cdot b \cdot \frac{\partial \theta}{\partial b}}_{\text{Take-up}} - \underbrace{\theta \cdot b \cdot \frac{\partial e_1}{\partial b}}_{\text{Search Effort (Benefits)}} - \underbrace{\frac{\partial e}{\partial b}\cdot \tau}_{\text{Search Effort (Revenue)}}.$$

The social planner chooses the benefit b to maximize welfare, subject to the balanced budget constraint as well as the worker's optimal response functions $e^\star(b,\tau,T_i)$ and $T^\star(b,\tau,q_i)$.

[8]Suppose this was not the case, so workers choose take-up optimally and yet there exists a worker m and a worker n where $q_m > q_n$ but $T_m = 1$ and $T_n = 0$. Let e_0 and e_1 be given. Non-claimants do not incur their idiosyncratic hassle cost, so non-claimants experience the same utility and $V(q_m, e_0, 0) = V(q_n, e_0, 0)$. Conversely, since claimants do incur their idiosyncratic hassle cost, claimants with greater hassle costs experience less utility and $V(q_m, e_1, 1) < V(q_n, e_1, 1)$. Since worker m chooses take-up optimally, it must be that $V(q_m, e_1, 1) \geq V(q_m, e_0, 0)$. It follows that $V(q_n, e_1, 1) > V(q_m, e_1, 1) \geq V(q_m, e_0, 0) = V(q_n, e_0, 0)$, or $V(q_n, e_1, 1) > V(q_n, e_0, 0)$. Thus, it must be optimal for $T_n = 1$, which contradicts our initial assumption.

Therefore, the social planner's problem can be expressed

$$\begin{aligned}\max_{b} \quad W(b) = & \int V(q', e_i, T_i) \; dF(q') \\ \text{s.t.} \quad & e \cdot \tau = (1 - e_1) \cdot \theta \cdot b \\ & e_i = e^{\star}(b, \tau, T_i) \\ & T_i = T^{\star}(b, \tau, q_i) \; .\end{aligned}$$

The impact of an increase in benefit b on social welfare can be decomposed into its impact on three different types of workers. First, the share θ who claim benefits receive an increase in benefit b during unemployment and pay the cost of a higher tax τ in the employed state, which yields a welfare change equal to $(1 - e_1) \cdot u'(w_L + b) - e_1 \cdot v'(w_H - \tau) \cdot \frac{\partial \tau}{\partial b}$ for this group. Second, the share $(1 - \theta)$ who do not claim benefits receive the same income during unemployment and still pay the cost of a higher tax τ during employment, which yields a welfare change equal to $-e_0 \cdot v'(w_H - \tau) \cdot \frac{\partial \tau}{\partial b}$. Lastly, for the share $f(\overline{q})$ who are induced to change their take-up decision, there is no welfare effect because they were indifferent between claiming and not claiming. These marginal claimants are not made better off, and yet they do impose a fiscal cost.

Taking the derivative of the social welfare function with respect to benefit level b yields the first-order condition

$$\begin{aligned}\frac{\partial W}{\partial b} = (1 - e_1) \cdot \theta \cdot u'(w_L + b) - e \cdot v'(w_H - \tau) \cdot \frac{\partial \tau}{\partial b} \\ + f(\overline{q}) \cdot \underbrace{\left[V(\overline{q}, e_1, 1) - V(\overline{q}, e_0, 0)\right]}_{\text{Equal to Zero by FOC w.r.t. } T^{\star}(b,\tau,\overline{q})} = 0 \; .\end{aligned}$$

As before, the change in search effort drops out by the envelope theorem. Additionally, there is no welfare gain from the share $f(\overline{q})$ of workers induced to claim by the higher benefit because they are indifferent between claiming and not claiming.

We can substitute in the expression for $\frac{\partial \tau}{\partial b} \cdot e$ and normalize relative to the marginal utility of an additional dollar of income during the employed state. With incomplete and endogenous take-up, the optimal policy condition for benefit b becomes

$$\frac{u'(w_L + b) - v'(w_H - \tau)}{v'(w_H - \tau)} = \underbrace{\varepsilon_{\theta,b}}_{\text{Take-up}} + \underbrace{\varepsilon_{1-e_1,b}}_{\text{Claim Duration}} - \underbrace{\varepsilon_{e,b}}_{\text{Tax Revenue}} \; . \tag{1}$$

In this formulation, we can interpret the elasticity of take-up $\varepsilon_{\theta,b}$ as capturing the extensive margin of benefit receipt, or the change in the number of claimants. Meanwhile, the elasticity of average claim duration $\varepsilon_{1-e_1,b}$ reflects the intensive margin, or the change in claim duration among UI recipients. Alternatively, these two margins can be collapsed into the elasticity of benefit payments $\varepsilon_{\theta(1-e_1),b}$ as follows

$$\frac{u'(w_L+b)-v'(w_H-\tau)}{v'(w_H-\tau)} = \underbrace{\varepsilon_{\theta(1-e_1),b}}_{\text{Benefit Payments}} - \underbrace{\varepsilon_{e,b}}_{\text{Tax Revenue}}, \tag{2}$$

where the elasticity of benefit payments $\varepsilon_{\theta(1-e_1),b}$ captures fiscal cost of both more workers claiming benefits and claimants remaining on benefits for longer.

Additionally, this model with endogenous take-up represents a generalized version of Chetty (2006). If we assume perfect take-up so that $\theta = 1$ for any benefit b, then the elasticity of take-up with respect to benefit level is equal to zero $\varepsilon_{\theta,b} = 0$, the elasticity of benefit payments is equal to the elasticity of average claim duration $\varepsilon_{\theta(1-e_1),b} = \varepsilon_{(1-e_1),b}$, and the search effort for claimants is equal to aggregate search effort $e_1 = e$. The optimal policy condition then simplifies to the result from Chetty (2006). Alternatively, if we assume there are no hassle costs so that $q_i = 0$ for all workers, then this delivers the same result as well.

This model establishes the theoretical relevance of endogenous take-up to policy. As with search effort, endogenous take-up introduces a behavioral response to changes in the benefit b that the planner must account for. Empirically, the next question is whether workers actually do respond to more generous benefits by becoming more likely to claim. Ultimately, we find evidence to support this, and the magnitude of this response makes it quantitatively relevant.

3 Institutional Setting and Data

In this section, we begin with an overview of the UI program, eligibility criteria, and the application process for our setting of Washington State. Next, we discuss how we construct a sample of likely-eligible workers using administrative data. Lastly, we present descriptive statistics for the sample.

3.1 Institutional Setting

UI benefits provide temporary income to a worker when they lose their job through no fault of their own. This financial support helps workers cover expenses and smooth consumption through an unemployment spell, preventing further disruptions in their lives.

These benefits replace 50 percent of a worker's pre-job-loss wages, subject to specified minimum and maximum levels, for up to 26 weeks under normal circumstances. During recessions, UI programs have often been expanded by increasing benefit levels or extending their potential duration. In the United States, UI is a joint state-federal program with state governments administering benefits according to federal guidelines. However, within these guidelines, each state can determine its own eligibility rules and benefit schedule.

To be eligible for benefits in Washington State, a worker must satisfy three conditions. First, "separation eligibility" requires that the worker recently experienced a job separation through no fault of their own. This condition largely excludes workers who voluntarily quit or were fired with cause from receiving benefits. Second, "monetary eligibility" is satisfied if the worker has accumulated at least 680 hours during their base period. The base period is defined as the first four of the five most recently completed quarters. Alternatively, if the worker has not accumulated 680 hours over this period, they may qualify using the four most recently completed quarters as an alternative base period.[9] In all other states, monetary eligibility is determined by total earnings over a qualifying period. Third, "continuing eligibility" means that the worker is able, available, and actively seeking work. This condition prevents workers from claiming benefits for weeks when they are traveling on vacation and would disqualify workers who enroll as full-time students. To verify job search, workers must document at least three job search activities for each week that they claim benefits. Examples of these activities include contacting employers about job openings, attending job fairs, and updating their profile on websites like Indeed or LinkedIn.

Even when a worker meets these eligibility requirements, benefit receipt is not automatic and workers must then navigate the application process, as outlined in Figure 1. First, a worker files an initial claim online or over the phone, which typically takes 30 minutes to an hour. The worker verifies their previous employment and answers questions about the reasons for their job separation. Based on this information, the worker receives a preliminary determination letter explaining whether they qualify for benefits, and if so, the weekly benefit amount (WBA) they will receive. The worker's previous employer is then notified and given the chance to appeal the claim if they believe the worker misreported the reason for separating. Workers must then submit weekly claims for each week they intend to claim UI, though the first weekly claim will not result in payment and is

[9] Only a few states collect data on quarterly hours from employers, and Washington State is unique in that monetary eligibility is based on hours worked.Lachowska et al. (2022) examine the hours worked data in Washington State and conclude it is highly reliable.

considered the "waiting week." To verify they are actively searching, a worker must document that they completed three job search activities each week. These activities include updating a resume, writing a cover letter, contacting an employer, submitting a job application, or interviewing for a position. If a worker successfully completes all these steps, then they will receive a benefit payment.

Since this paper examines how weekly benefit levels affect take-up, a key question is whether workers understand their potential benefits and how they might learn about them. Prior to applying, workers can use the state's benefit estimation tool to calculate their expected weekly benefit amount, as shown in Figure 2. Once workers submit their initial claim, which is the first step in the application process, they receive a preliminary determination letter stating their weekly benefit amount as well as other program details. Additionally, survey evidence from McQuillan and Moore (2025a) suggests that workers are generally accurate in estimating their weekly benefit amount.[10] Overall, workers seem to understand their benefits, and for those who may be uncertain, there are multiple opportunities to learn about them both before and early on in the application process.

3.2 Data and Descriptive Statistics

Our analysis uses administrative data from Washington State's Employment Security Department (ESD) covering the period from 2010 through 2020. This data includes employer-employee matched records from all UI-covered jobs detailing quarterly earnings and hours worked as well as records of UI applications and benefit payments. Using the quarterly employment data, we identify job separations where the worker is likely to be eligible for UI benefits. Next, using the data on UI applications and benefit payments, we determine whether they applied for benefits, how far in the application process they made it, whether they ultimately received benefits, and, if so, the number of benefit payments they received.

First, we identify job separations using the employer-employee matched data. We assign each worker a primary employer for every quarter in which they are employed. If a worker has more than one employer in a quarter, then the primary employer is the one which they have accumulated the most hours working for in that quarter plus the two previous quarters. We define a job separation as occurring whenever a worker records

[10] McQuillan and Moore (2025a) conducts a nationwide survey of workers who experienced a job loss and did not apply for UI. One of the questions includes asking workers what they believe they would receive as a weekly benefit and comparing this to an imputed benefit using their reported wages. They find 29 percent of worker are accurate within \$50 and the majority (52 percent) are accurate within \$100. This is plotted in Figure A.1.

zero hours in the next quarter with the employer that was their primary employer in the current quarter.[11] Next, we restrict the sample to workers who satisfy the monetary eligibility condition. Once we identify the quarter in which the job loss occurs, we can assess the worker's monetary eligibility using the quarterly hours worked in the employer-employee matched data. The unemployment office uses these same records to make their eligibility determination, although workers can appeal if they believe their hours have been misreported.

The ideal sample to study take-up would be all workers that recently experienced an eligible job separation. Although we can observe when a worker separates from an employer and whether they are monetarily eligible, it is more difficult to determine whether the worker lost their job "through no fault of their own." Separation eligibility is not observable and only assessed when a worker files a UI claim. Job separations will include workers who dropped out of the labor force, switched jobs, were fired with cause, or quit voluntarily. In these cases, workers would not be eligible to receive UI benefits, even if they are monetarily eligible and actively searching for a new job.

To mitigate this issue, we focus our analysis on workers most likely to be eligible for benefits and exclude job separations where it is less likely that the worker satisfies the separation condition. This approach follows that used by Anderson and Meyer (1997) and Lachowska et al. (2025) to estimate overall take-up rates. First, we exclude "job-to-job transitions" where it seems the worker left voluntarily for another job. A job-to-job transition occurs when a worker experiences a job separation and then, in the same quarter, records hours worked with a different employer such that their total hours worked does not drop by more than 15 percent relative to the previous quarter. The decrease in total hours of 15 percent corresponds to approximately two weeks of lost work in that quarter, which is the minimal amount of time necessary for a worker to go through the process of claiming benefits. Second, we exclude "labor force exits" where it seems the worker left the labor force altogether. A labor force exit occurs when a worker experiences a job separation and then does not record any employment for five consecutive quarters.

As a result, the main sample is composed of instances of "job loss" where a worker experiences a job separation, a disruption in total employment greater than 15 percent relative to the previous quarter, and then finds re-employment within five quarters.[12]

[11] To determine the exact timing of a job separation, we apply the following rule: If hours decreased by 15 percent or more relative to the previous quarter, we assume the separation occurred during the quarter when hours were last recorded with that employer. If hours worked with the primary employer decreased by less than 15 percent (or increased) relative to the previous quarter, we assume the separation occurred at the end of that quarter and assign it to the subsequent quarter when the worker reports zero hours with that employer.

[12] The definition of job loss includes instances where the worker finds re-employment with the same

These three types of job separations are mutually exclusive and collectively exhaustive, ensuring that every job separation in our data falls into exactly one category. We focus on the job losses since these are most likely to involve eligible workers. Still, these restrictions are not perfect. For example, the sample of job losses may include some workers who are not eligible for UI benefits due to a firing with cause or voluntary quit. As such, the estimated take-up rate for this sample could be considered a lower bound for the true take-up rate among eligible workers. To further address eligibility concerns, we will present our main results using a sample of workers who experienced job loss during mass layoffs, who are thus more likely to have lost their jobs through no fault of their own and be eligible for UI.[13]

There is the third condition — "continuing eligibility" — that requires a worker be able, available, and actively seeking work. However, we do not further restrict the sample based on this eligibility condition for two reasons. First, if a worker is not able and available for work, it is unlikely they will record any employment after their job separation. These workers are more likely to be classified as labor force exits and to have been dropped from our sample already. Second, we view the job search requirements as part of the hassle costs that deter some eligible workers from taking up benefits. If a worker satisfies the separation condition and monetary eligibility, they can choose to complete the necessary job search activities in order to receive benefits.

With this sample of likely-eligible workers, we use the records of benefit applications and payments to determine whether a worker applied for benefits, how far into the application process they made it, whether they received benefits, and if so, the number of payments they received. Whereas the employer-employee matched data is at a quarterly frequency, this data is recorded at a weekly frequency. We define a worker as having applied for benefits if they submitted an initial claim at any point from the month before the quarter of the job loss through six months after the quarter of job loss has ended. This window extends beyond the quarter of the job loss for two reasons. First, it extends before the quarter of job loss because workers can submit a claim before the job loss if they are given notice they will be laid off. Second, it extends well after the quarter of job loss because workers can submit an initial claim anytime during their unemployment spell. Although rare, workers can even backdate claims to receive benefits for previous weeks

employer they had previously separated from. As a result, our sample would include workers who claimed benefits while waiting to be recalled. In these cases, detecting the separation requires the worker to record no employment with this employer for at least one quarter.

[13] We define a 'mass layoff' as occurring when the employer experiences a significant contraction in their total hours and at least five other workers also separate from that employer in the same quarter or adjacent quarters. We consider contraction thresholds of 5, 15, and 30 percent.

if they provide the necessary documentation.[14]

We determine if the worker received benefits based on whether there is a record of any payments made to the worker's claim account. We measure how far into the application process a worker progressed by the number of weekly claims submitted. We assume the first weekly claim refers to the 'waiting week' and all subsequent weekly claims are payable. Although we will examine each step of the application process in our analysis, we will use benefit receipt as our measure of take-up for two reasons. First, we are interested in how hassle costs may deter workers from taking up benefits and there are these additional steps after submitting an initial claim, each of which presents an opportunity for workers to drop out. In fact, in our sample, only 74 percent of workers that file an initial claim ultimately received a benefit payment. Second, we are focused on how changes in take-up impact the total fiscal cost of the UI program, and the fiscal cost from benefit payments is much greater than from processing additional applications.[15]

In addition to take-up, our other main outcome is the number of payments made to a worker following a job loss. This variable is defined for the entire sample of job losses with non-recipients receiving zero payments. In contrast, "claim duration" refers to the number of weekly payments made to UI recipients, and so conditions on benefit receipt. We will use claim duration in our analysis when revisiting previous work that relies on a sample of UI recipients. To calculate benefits, we compute each worker's weekly wage as the sum of their two highest-earning quarters during the base period divided by 26 weeks, with the weekly benefit set at 50 percent of this wage subject to minimum and maximum benefit levels. This calculation is performed for all workers to represent what they would receive if they had claimed benefits. We validate the calculation against the actual WBAs for UI recipients in our sample, and it is accurate to the dollar in over 97 percent of cases.[16]

Table 1 presents descriptive statistics for the entire sample in the first column. In total, there are just under 3.4 million instances of job loss over the period from 2011-Q3 through 2019-Q1. In the year before separating from their job, these workers earned an average of $37,785 while working 1,566 hours at an hourly wage of $23.10. Only 28

[14] We find that most claims are filed within the the first six weeks of the quarter of job loss.

[15] Our primary focus is whether workers initially take up benefits, but take-up decisions continue throughout the unemployment spell. Workers may stop claiming benefits before exhausting their eligibility due to the hassle of meeting job search requirements and filing weekly claims, representing an alternative form of "incomplete take-up." However, distinguishing this choice from re-employment is difficult in practice.

[16] Our WBA calculation may differ from the actual WBA for two main reasons: first, if the worker misreported earnings; second, if the initial claim is filed in a different quarter than we identify the job loss, shifting the base period.

percent of workers submit an initial claim with 20.7 percent ultimately receiving benefits. On average, these workers would receive a weekly benefit of $348, with 14.8 percent of all job losses receiving the minimum weekly benefit amount and an almost equal 15.2 percent receiving the maximum. The largest industries in this sample are trade, transportation, and utilities (19.8 percent), education and health services (15.8 percent), and professional and business services (15 percent), while smaller industries include natural resources and mining (8.8 percent), information (2.5 percent), and government (2 percent).

4 Identification Strategy

4.1 Regression Kink Design

We identify a causal effect of the weekly benefit level on take-up and the number of benefit payments by exploiting non-linearities in the benefits schedule with a regression kink design (RKD). This empirical approach leverages the fact that the weekly benefit b is a known function of a worker's weekly wage, which becomes the assignment variable V. Specifically, benefits increase linearly with weekly wage up to the maximum WBA and then remain constant beyond that point, creating a "kink" in the benefits schedule. The key insight of the RKD is that if there is a causal effect of benefit b on an outcome Y, then the kink in the benefit schedule should produce a corresponding kink in the relationship between the assignment variable V and outcome Y at the same point. By comparing the relative size of the kink in outcomes to the kink in benefits, we can quantify the causal effect of the weekly benefit b on the outcome Y.

Card et al. (2015b) formalized the framework and necessary assumptions under a general non-separable model, showing the RKD identifies the marginal effects of b on Y as the estimand

$$\alpha = \frac{\Delta Y'}{\Delta b'} = \frac{\lim_{v \to k^+} \frac{dE[Y|V=v]}{dv} \;-\; \lim_{v \to k^-} \frac{dE[Y|V=v]}{dv}}{\lim_{v \to k^+} b'(v) \;-\; \lim_{v \to k^-} b'(v)} \tag{3}$$

where this expression compares the kink in the slope of the outcome variable Y as a function of the assignment variable V in the numerator to the kink in the slope of the the treatment variable b as a function of the assignment variable V. This marginal effect is local to workers around the kink, representing a weighted average with the weight assigned to a worker reflecting their relative likelihood of being at the kink $V = k$. Given this marginal effect, we can then calculate the elasticity of the outcome Y with respect to benefit b as

$$\varepsilon_{Y,b} = \frac{\partial Y}{\partial b} \cdot \frac{b(V=k)}{E[Y|V=k]} = \alpha \cdot \frac{b(V=k)}{E[Y|V=k]} \tag{4}$$

where $b(V=k)$ and $E[Y|V=k]$ represent the weekly benefit and expected outcome at the kink.

The numerator in Equation 3 can be identified by estimating the change in the slope of the conditional expectation function $E[Y|V=v]$ at the kink. We estimate this value using the following local linear regression specification:

$$Y_i = \beta_0 + \beta_1 \cdot V_i + \beta_2 \cdot \mathbb{1}[V_i \geq k] \cdot (V_i - k) + \eta_i \tag{5}$$

where Y is the outcome variable, V is the assignment variable, and $\mathbb{1}[V \geq k]$ is an indicator for whether observations are above the kink point. The coefficient β_2 estimates the numerator of our estimand $\Delta Y'$, or the change in the slope of the conditional expectation at the kink point. To ensure observations are local to the kink, we restrict the sample to a bandwidth h such that $|V-k| \leq h$ for all observations. In our main analysis, we will use a bandwidth equal to \$400, although we show the robustness of results to alternative bandwidth choices.[17] Additionally, since this regression estimates the expectation function $E[Y|V=v]$, we will use this specification to estimate the expected outcome at the kink $E[Y|V=k]$ when computing elasticities.

The denominator of our estimand is known exactly since the weekly benefit level b is a deterministic function of weekly wage V. Figure 3a displays the benefits schedule for fiscal years 2011 through 2018. For eligible workers, UI benefits replace 50 percent of their weekly wage up to the maximum WBA. Below the maximum WBA threshold, a one-dollar increase in weekly wages raises benefits by 50 cents, so $\lim_{v\to k^-} b'(v) = 0.5$. Above the maximum WBA, benefits remain constant regardless of additional earnings, so $\lim_{v\to k^+} b'(v) = 0$. The denominator of our estimand is therefore $\Delta b' = -0.5$. In Washington State, the maximum WBA is updated annually at the start of each fiscal year, and so the location of the kink varies over time.[18] In order to pool observations across years, we normalize the assignment variable by centering weekly wages around each year's kink point, as shown in Figure 3b. This transformation places the kink at zero

[17] Increasingly, it is common for empirical work to rely on a procedure for selecting the optimal bandwidth, such as the one proposed by Calonico et al. (2019). However, Card et al. (2016) show that these methods can perform worse than "suboptimal" bandwidths in some contexts and recommend demonstrating robustness across a range of bandwidth choices.

[18] The maximum WBA is indexed to wages such that it is equal to 63 percent of the average weekly wage during the previous year.

for all observations while preserving the derivative $b'(V)$ and leaving the denominator unchanged at -0.5.

4.2 Identifying Assumptions and Interpretation

Identification with the RKD relies on three assumptions. First, there is a first-stage whereby the treatment $b(V)$ is a known function, everywhere continuous, and continuously differentiable except for the point k where $\lim_{v \to k^+} b'(v) \neq \lim_{v \to k^-} b'(v)$. Second, the direct effect of the assignment variable V on the outcome Y must be smooth through the kink point. We define "smooth" to mean that there is no discontinuous change in slope at that point, or equivalently, that the first derivative of the function is continuous. Otherwise, if the direct effect of V on Y changes at the kink point, then the observed kink in the relationship between V and Y could be driven by the assignment variable itself rather than by the treatment variable b. Third, assuming there exists a non-negligible population in the neighborhood of the kink, the density of the assignment variable V is continuous and smooth through the kink point.

All three assumptions are satisfied or at least seem plausible in our context. The first assumption is satisfied by policy design: as we previously described, weekly wage mechanically determines weekly benefit level through the UI formula with a kink created by the maximum WBA. Regarding the second assumption, there is no clear reason why weekly wage would have a direct effect on take-up or the number of benefit payments that exhibits a kink at the maximum WBA threshold. Weekly wage is determined by the timing and distribution of earnings across quarters during the base period, so even otherwise comparable workers may have variation in their weekly wages simply due to when they earned their income and the timing of their job loss. For the third assumption, we can empirically test whether the density of the assignment variable V is smooth at the kink. A potential threat to identification would be precise manipulation of the assignment variable V—either by workers seeking to maximize their benefits or by employers seeking to reduce their tax liability.[19] However, such precise manipulation seems highly unlikely because it would require the worker or employer to know well in advance the exact timing of the job separation as well as the benefits schedule, which may not even be finalized at that time.

We test for manipulation in the running variable using the density test from McCrary (2008). Figure 4 plots the density of observations against the normalized weekly wage

[19] In Washington State, taxes on employers for the UI program are experience-rated so that employers with more workers who claim UI benefits are charged a higher rate. Therefore, employers have an incentive to discourage workers from claiming or to lower their benefit levels.

in Panel 4a and the change in density in Panel 4b. The density in Panel 4a appears relatively smooth through the kink point. Notably, we would not expect the kink in the benefits schedule to create bunching in the density, since the weekly benefit level itself is continuous at the kink. Instead, if workers or employers were responding to the kink, we might expect to see a change in the slope of the density function. As shown in Panel 4b, we do not observe a discontinuous change in the slope of the density at the threshold. Overall, this evidence supports the assumption that neither workers nor their employers strategically manipulate weekly wages in anticipation of job loss.

The identification assumptions also imply that the composition of workers should evolve smoothly around the kink point. Essentially, worker characteristics should not exhibit a corresponding "kink" at the point where the benefit formula changes. Such a discontinuous change may cause concern that the kink in the outcome variable is not driven by the kink in the treatment, but instead by kink in the observable characteristics. In Figure 5, we examine this assumption by plotting earnings and hours worked in the year before job loss against the normalized weekly wage. We find no evidence of discontinuous changes in any of these characteristics at the kink point.[20]

Recall that our sample is composed of instances of job loss where workers are likely eligible for UI benefits. We now consider how focusing on job loss and including ineligible workers affects identification and the interpretation of our results. One concern may be that benefit generosity influences the type of job separation a worker experiences. For instance, a higher weekly benefit level might encourage a worker who would otherwise exit the labor force to instead search for employment. Alternatively, a lower weekly benefit level might incentivize a worker to ensure they have new employment lined up before separating. If this were the case, we would expect to see a kink in the share of separations classified as a job loss at the kink in the benefit schedule. However, as shown in Figure A.2, we do not observe such a kink; instead, the classification of job separations is smooth, and even linear, through the kink point. This suggests that the type of job separation is not endogenous to the weekly benefit level.

Another concern is that, although we focus on workers most likely to be eligible for UI benefits, some workers in the sample may actually be ineligible due to reasons such as voluntary quits or terminations with cause. Importantly, this does not threaten identification of a causal effect, as long as the share of eligible workers is smooth through the kink point, which seems highly plausible. However, it does impact the interpretation of our

[20] Annual earnings and weekly wage are closely related, although subtly different. Annual earnings is calculated as the sum of earnings in the four quarters before job loss whereas the weekly wage is based a worker's two highest quarters of earnings during their base period.

estimate to be an intention-to-treat (ITT) effect as workers who are not eligible to claim benefits are, in effect, not treated. If we assume that a portion λ of our sample is eligible at the kink, then we can scale the estimated effect $\hat{\alpha}$ by this term to obtain the average treatment effect on eligible workers so that $\alpha = \hat{\alpha}/\lambda$. It follows that our estimates of the marginal effect are a lower bound for the effect on eligible workers, similar to how estimates of take-up in our sample represent a lower bound for the true take-up rate among eligible workers.

This same logic does not apply to our estimates of the elasticity. Under the assumption that both the marginal effect and average outcome scale proportionally with eligibility, the estimated elasticity approximates the true elasticity:

$$\hat{\varepsilon}_{Y,b} = \hat{\alpha} \cdot \frac{\hat{b}}{\hat{Y}} = \frac{\alpha}{\lambda} \cdot \frac{b(V=k)}{E[Y|V=k]/\lambda} = \alpha \cdot \frac{b(V=k)}{E[Y|V=k]} = \varepsilon_{Y,b}. \tag{6}$$

where $\hat{b}$ and $\hat{Y}$ are estimates for the weekly benefit and outcome in our sample while $b(V=k)$ and $E[Y|V=k]$ are the values for eligible workers at the kink. Since benefit is a function of weekly wage, we know that $\hat{b} = b(V=k)$ at the kink point. Essentially, since both the marginal effect and the average outcome variable should be scaled by the share of eligible workers λ, these terms cancel out when calculating the elasticity.

Finally, given that our estimates represent local treatment effects for workers near the kink in the benefits schedule, we consider how this local sample differs from the overall sample of likely eligible workers. Column 2 of Table 1 presents descriptive statistics for workers whose weekly wages are within \$400 of the kink point, while Column 1 presents these same statistics for the entire sample. We find that workers in the local sample have substantially higher prior-year earnings (\$54,443 versus \$37,785), work more hours (1,879 versus 1,566), and earn higher hourly wages (\$30.84 versus \$23.10). Reflecting their higher earnings, workers in the local sample would receive more generous benefits if they take up, with higher average weekly benefit amounts (\$578 versus \$348), a higher share receiving the maximum WBA (33.7% versus 15.2%), and none receiving the minimum WBA (0% versus 14.8%). These workers also differ in terms of UI utilization: workers in the local sample are more likely to submit initial claims (37.3% versus 28.0%) and more likely to receive benefits (31.6% versus 20.7%). The local sample also has a different industry composition, with greater representation in construction (17.3% versus 8.6%) and less representation in leisure and hospitality (4.6% versus 13.5%). Overall, workers around the kink in the benefits schedule tend to be more stably employed with higher earnings than the overall sample.

5 Empirical Results

In this section, we employ the RKD framework to estimate the effect of the weekly benefit level on take-up, the application process, and the total number of benefit payments. We find that higher weekly benefit levels lead workers to apply for and receive benefits at a higher rate, which then contributes to an increase in the number of benefit payments.

5.1 The Effect on Take-up

We estimate a significant effect of the benefit level on benefit receipt, which we will use as a proxy for take-up in our analysis. In Figure 6, we plot benefit receipt against the normalized weekly wage and observe strong evidence of a kink at the same point where there is a kink in the benefits schedule. The figure shows that benefit receipt increases with weekly wage up to the kink point, and then exhibits a discontinuous change such that benefit receipt remains relatively flat or even declines steadily as the weekly wage increases beyond that point. We estimate the marginal effect from Equation 3, where the numerator is identified via the regression in Equation 5 with benefit receipt as our outcome variable and the denominator is exactly identified by the benefits schedule. The regression estimates are presented in Column 1 of Table 2. The marginal effect α_θ represents the percentage point increase in benefit receipt among our sample of likely-eligible workers that would result from a \$1 increase in weekly benefit level. The results suggest a \$100 increase in the weekly benefit level would lead to a 2.32 percentage point increase in take-up. The 95 percent confidence interval on this effect ranges from 1.90 to 2.74 percentage points.[21]

To convert this marginal effect into an elasticity, we use the average weekly benefit and the average take-up rate around the kink point. The average weekly benefit in our sample is \$653, which accounts for workers local to the kink having slightly different benefits levels as well as workers in different fiscal years facing different benefits schedules. The take-up rate is 32.4 percent at the kink. This calculation yields an estimated elasticity of take-up ε_θ of 0.467. This elasticity suggests that a 10 percent increase in the weekly benefit level would lead to a 4.7 percent increase in the take-up rate. The 95 percent confidence interval for the estimated elasticity ranges from 0.382 to 0.553. This estimate is consistent with Anderson and Meyer (1997), who report an elasticity of 0.33-0.60 using cross-state

[21] Recall that the window for take-up spans from the month before the quarter of the job loss through six months after the quarter of job loss has ended. However, most claims are filed within the first six weeks of the quarter when job loss occurs. Additionally, we found our estimates are robust to varying the window for take-up.

variation in benefit levels. Similarly, earlier studies using regression analysis, such as McCall (1995) and Blank and Card (1991), report a similar range of 0.23-0.58, respectively.

5.2 The Effect on the Application Process

Since we found that higher benefit levels increase take-up, we would expect more generous benefits to encourage more workers to apply for benefits and to follow through with their claims. Using administrative data, we can track workers' progress through the application process as outlined in Figure 1. The first step is to submit an initial claim, followed by a weekly claim for the "wait week" that will not result in payment. Finally, in the following week, a worker can file a weekly claim that, if successful, will result in a benefit payment.

The majority of workers who begin the application process complete it, but not all. In the sample of likely-eligible workers local to the kink in the benefits schedule, 36 percent submit an initial claim, and then 96 percent of those file a claim for their waiting week, and then 97 percent of those ultimately file a payable weekly claim. Workers may drop out of the application process for several reasons. First, workers may not be eligible due to the separation condition. Specifically, after the initial claim, employers can contest whether the worker's separation was "through no fault of their own." Second, workers may find re-employment during their waiting week and thus no longer qualify for benefits. Third, workers may be deterred by the hassle of this multi-step process.

To examine how benefit generosity affects workers navigating the application process, we estimate the marginal effect of an increase in the weekly benefit level on the likelihood that a worker completes each one of these steps. We plot the probability of submitting an initial claim, waiting week claim, and payable claim against the normalized weekly wage in Panels 7a, 7b, and 7c respectively. Table 3 presents the corresponding regression estimates, marginal effects, elasticities, and confidence intervals. As we move from Panel 7a to Panels 7b and 7c, the share of workers who complete a given part of the application process is lower for the later steps of the application process. Additionally, the kink in the outcome variable becomes more apparent at each step.

Interestingly, the effect on initial claims is smaller than the effects on benefit receipt. A $100 increase in the weekly benefit level would cause a 1.50 percentage point increase in the share of workers submitting an initial claim, compared to a 2.32 percentage point increase in benefit receipt. Similarly, the elasticity of initial claims is smaller than the elasticity of benefit receipt, although this follows directly from the relative size of the marginal effects and the fact that the share of workers receiving benefits is mechanically lower than the share submitting an initial claim. The size of the marginal effect increases for the later parts of the application process with a \$100 increase in the weekly benefit level associated with a 1.79 percentage point increase in the likelihood of a worker filing a waiting week claim and a 1.93 percentage point increase in the probability of submitting a payable weekly claim.

It appears that roughly two-thirds of the take-up effect arises from more workers filing an initial claim, while the remaining third reflects greater follow-through in later stages of the application process. This pattern makes sense given the timing of benefit information during the application process. Recall that workers are informed of their exact weekly benefit amount shortly after submitting an initial claim. If some workers have imperfect information about their potential benefits, the impact of benefit level on their decision may be realized at this point. Additionally, after learning about their benefits, workers still need to submit a weekly claim and then wait a full week before filing their first payable claim. The hassle of these additional steps may cause some workers to abandon their claim, particularly if their benefits are lower than expected.

5.3 The Effect on the Number of Benefit Payments

Given the effect on benefit receipt and application, we next estimate the effect of benefit level on the number of benefit payments. Recall that for our sample of likely-eligible workers, the number of benefit payments is equal to zero for those who do not take up and receive no benefit payments. Therefore, the effect on the total number of benefit payments we estimate incorporates both the extensive margin effect whereby more workers take up benefits as well as the intensive margin effect whereby workers who receive benefits remain on these benefits for longer.

In Figure 8, we plot the average number of benefit payments to likely-eligible workers against the normalized assignment variable and see strong evidence of a kink at the same point where there is a kink in the benefits schedule. Once again, there is a strong and positive relationship between benefit payments and weekly wage up to the kink, and then a discontinuous change such that, as weekly wages increase, the average number of benefit payments declines beyond the kink point. Column 2 of Table 2 presents the regression estimates, marginal effect, and elasticity along with standard errors and confidence intervals. The marginal effect $\alpha_{\theta(1-e_1)}$ suggests a \$100 increase in the weekly benefit level would lead to a 0.51 increase in the number of benefit payments per job loss. The 95 percent confidence interval on this effect ranges from 0.43 to 0.60. To convert this estimate into an elasticity, we use the average number of benefit payments at the kink k of 5.4.

This calculation yields an estimated elasticity of benefit payments $\varepsilon_{\theta(1-e_1)}$ equal to 0.619, suggesting a 10 percent increase in the weekly benefit level would cause a 6.2 percent increase in the total number of benefit payments. The 95 percent confidence interval for this elasticity ranges from 0.520 to 0.718.

5.4 Validation and Robustness

We conduct additional analysis to validate our main findings and assess their robustness to alternative specifications. First, we show that the kinks in benefit receipt and the number of benefit payments track the kink in benefits as it shifts over time. Next, we show that our main results hold when using a sample of workers who lost their job during a mass layoff. Lastly, we show robustness to bandwidth choice and the definition of job loss.

Tracking the Kink Over Time

In our baseline estimates, we normalize weekly wages to pool observations across different fiscal years in which workers faced different benefit schedules. Alternatively, we could estimate the effects separately for each year without normalizing. This approach exploits changes to the benefits schedule to assess whether workers are truly responding to the weekly benefit level, or if the estimated effects are driven by idiosyncrasies of a specific point in the wage distribution. Ultimately, we find evidence that the kinks in take-up and the number of benefit payments shift as the kink in the benefits schedule moves over time, suggesting that workers are indeed responding to benefit levels.

In Figure A.4, we plot benefit receipt against the weekly wage before normalization for each year from 2011 through 2018, with regression estimates presented in Table A.2. The effect of a \$100 increase in weekly benefit level ranges from 0.68 to 3.42 percentage point increase in take-up, while the elasticity ranges from 0.166 to 0.753. These estimates are less precise than those in our main analysis due to splitting the sample by fiscal year. Still, almost all estimates are statistically significant at the 5 percent level, with FY 2017 being the only exception. Furthermore, the kink in benefit receipt appears to track the kink in the benefits schedule as it moves each year. Although the change is relatively small from year to year, the difference becomes more apparent when comparing the early years of the sample, where the kink occurs around weekly wages of \$1,200, with the later years, where the kink is just above \$1,500. The kink in benefit receipt persists even as the overall take-up rate in the sample varies considerably from year to year, likely due to macroeconomic conditions. The persistence of these results across years provides compelling evidence that workers are responding to the benefits schedule.

In Figure A.5, we plot the average number of benefit payments against the weekly wage before normalization for each year, with corresponding regression estimates in Table A.3. The kink in benefit payments similarly tracks the kink in benefit level across years. The estimated effects are fairly consistent over time: a $100 increase in weekly benefit level increases the average number of benefit payments by 0.23 to 0.70, with elasticities of 0.348 to 0.823. Moreover, this relationship holds even as macroeconomic conditions vary, affecting typical job search duration as well as the average number of benefit payments made to workers. Once again, these estimates are less precise due to splitting the sample based on fiscal year, and yet all effects are statistically significant at the 5 percent level. These results further reinforce our conclusion that workers are responding to benefit levels.

Mass Layoff Sample

To further address any concerns about UI eligibility, we examine whether our results hold when restricting to workers who lost their jobs during mass layoffs. Workers who separated during a mass layoff are more likely to have been separated through no fault of their own, and thus satisfy separation eligibility and qualify for UI benefits. We define a mass layoff event as occurring when at least five other workers also separate from that employer in the same quarter or adjacent quarters and the employer experiences a "sufficient contraction" in hours worked. We consider three different thresholds for what constitutes a sufficient contraction: 5, 15, and 30 percent reductions in hours of employment.

Figures A.6 and A.7 present the elasticities of take-up and benefit payments, respectively, when restricting to job losses that occurred during mass layoff events, with corresponding regression estimates in Tables A.4 and A.5. The mass layoff samples are considerably smaller than our main sample, with the sample based on the 5 percent contraction including about half of the observations and the sample based on the 30 percent contraction using about a quarter of the observations. Still, the estimates for workers who experience job loss during a mass layoff are very similar to our baseline results. The elasticity of take-up ranges from 0.47 to 0.59 in the mass layoff samples, compared to the baseline estimate of 0.47. Similarly, the elasticity of benefit payments ranges from 0.63 to 0.76 compared to the baseline estimate of 0.62.[22] The consistency of these estimates mitigates concerns that our main analysis cannot perfectly isolate workers who are truly

[22]Interestingly, the take-up rate does not actually increase in the mass layoff samples, with 32.4 percent of workers at the kink receiving benefits in our main sample versus 27 to 32 percent across the mass layoff samples. However, we do find that the take-up rate increases when using a mass layoff sample for job-to-job transitions. It seems that using a mass layoff sample better approximates UI eligibility for a sample of job separations, but that there are not these same improvements when focusing on a sample of job losses.

eligible for UI benefits.

Robustness to Bandwidth Choice

We use a bandwidth of $400 to define the sample local to the kink in the benefits schedule in our main analysis. We show that our results are robust to this choice by plotting the estimated elasticities when using bandwidths ranging from $5 to $600. Figures A.8 and A.9 plot the estimated elasticities of take-up and benefit payments, respectively, as a function of bandwidth. Both estimates are extremely imprecise for bandwidths below $50, become relatively stable and statistically significant around a bandwidth of $150, and then remain stable through a bandwidth of $500—with take-up ranging from 0.33 to 0.55 and benefit payments ranging from 0.43 to 0.75. Beyond a bandwidth of $500, both estimates begin to trend upwards.

Robustness to Definition of Job Loss

We focus our analysis on workers who experience a job loss, which we define as a job separation with a drop in total hours exceeding 15 percent followed by re-employment within five quarters. Job loss represents one of three types of job separation, distinct from a job-to-job transition where the worker switches employers immediately without experiencing the 15 percent drop in hours, and from labor force exits where a worker does not record re-employment within five quarters. We assess the robustness of our results to this definition by varying the key parameters that determine what qualifies as job loss.

The classification of job separations depends on two thresholds. First, the sufficient drop in hours, which is set at 15 percent in our baseline estimates. If we increased this threshold, then more job separations would be 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. If we increased this threshold, then more job separations would be classified as a job loss instead of a labor force exit.

We test alternative definitions of job loss by varying the sufficient drop in hours to be 10, 15, 20, and 25 percent and varying the sufficient quarters to be 4, 5, 6, and 7 quarters. Additionally, to assess potential interactions between these parameters, we test the most lenient definition (10 percent drop, 8 quarters) and the most strict definition (25 percent drop, 4 quarters). As shown in Figure A.10, the share classified as a job loss ranges from 42 percent to 51 percent as we vary the sufficient drop in hours and from 45 percent to 49 percent as we vary the sufficient quarters. For the extreme pairs, the most lenient definition classifies 53 percent of separations as job losses while the most stringent definition considers 40 percent of separations to be job losses. Relative to our main sample, these definitions lead to a 13 percent increase and a 15 percent decrease, respectively, in the size of the sample.

Our main findings remain remarkably consistent as we vary the definition of job loss. Figures A.11 and A.12 present the estimated elasticities of benefit receipt and benefit payments, respectively, across alternative definitions with the dashed line marking our baseline estimate. The point estimates and confidence intervals are nearly identical across all specifications, showing no systematic pattern as we vary either the hours threshold or the re-employment window. Even the extreme pairs yield estimates in line with our baseline estimates. The robustness of these effects demonstrates that our results are not driven by a particular definition of job loss, and instead, apply broadly for workers experiencing a disruption in their employment.

5.5 Heterogeneity

In this section, we assess whether there is heterogeneity in the effect of benefit level on take-up and the number of benefit payments based on whether a worker has previously applied for benefits or the industry in which the worker was previously employed.

5.5.1 Effects by Previous UI Experience

Our empirical results suggest that a worker's decision to take up benefits is affected by their weekly benefit, which relies on the assumption that workers understand the benefits schedule and what their weekly benefit would be. If workers who have previously claimed benefits have a better understanding of the system, then these workers may be more responsive to the kink in the benefits schedule relative to workers who have never applied for benefits before. To test this, we use a sample of likely-eligible workers from 2016-Q1 through 2019-Q1, separating the sample based on whether the worker submitted an initial claim during a pre-period from 2011-Q1 through 2013-Q4.[23] Approximately 23 percent of likely-eligible workers previously applied for benefits in the pre-period.

Figures A.13 and A.14 plot benefit receipt and the average number of benefit payments, respectively, based on whether a worker has previously submitted an initial claim. The corresponding regression estimates are presented in Table A.6. We find that the marginal effect of a $100 increase in weekly benefit level is similar for workers who have never applied for benefits and workers who previously applied, with increases of 1.42 and 1.76 percentage points in benefit receipt, respectively, and increases of 0.29 and 0.45 in the

[23] We drop data from 2015 from this analysis since a worker cannot open another claim for one year after opening a claim.

average number of benefit payments, respectively. However, the average benefit receipt and number of benefit payments are much lower for workers who have never applied for benefits before, leading to much higher elasticities for these workers. For workers who have never received benefits, the elasticity of take-up is 0.441 while the elasticity of benefit payments is 0.577. For workers who previously applied for benefits, these elasticities are 0.247 and 0.417, respectively. These results are nearly identical when we distinguish instead between workers who received benefits in the pre-period.

Overall, these results do not suggest that workers who previously interacted with the UI program are more responsive to the kink in the benefits schedule. Instead, the key difference between these two groups is their baseline take-up rates, with workers who previously submitted an initial claim being much more likely to claim benefits following a job loss. However, our ability to detect such heterogeneity may be limited by the relatively short pre- and sample period.

5.5.2 Effects by Previous Industry

We consider how the effect of benefit level on take-up or the number of benefit payments varies by which industry the worker was previously employed. Figure A.15 plots the estimated elasticity of take-up for each industry. Most of these estimates are not significantly different than the estimate for the entire sample. However, there seems to be no effect of benefit level on take-up for government workers or those previously employed in trade, transportation, and utilities. We estimate a negative elasticity for workers previously employed in education and health services, although this seems to be partly driven by a low baseline take-up rate as show in Figure A.16.[24] The estimated effects for each industry are reported in Table A.7.

Figure A.15 plots the estimated elasticity of benefit payments for each industry. The estimates seem to follow a similar trend as the elasticity of take-up. This is not surprising given that the elasticity of benefit payments can be decomposed into the elasticity of take-up plus the elasticity of claim duration. Once again, the estimates for most industries are not significantly different from the estimate for the entire sample, with smaller elasticities for workers previously employed in government, trade, transportation, and utilities, or education and health services. Table A.8 reports the estimated effects for each industry.

[24] Due to seasonal fluctuations in this industry, it is incredibly difficult to identify likely-eligible workers.

6 Conditioning on Benefit Receipt

Previous work examining how benefit levels affect claim duration relied on samples of *UI recipients*. As a result, empirical analysis focused on the intensive margin response—whether more generous benefits lead claimants to remain on UI longer. Within our framework of incomplete and endogenous take-up, these estimates best approximate the elasticity of claim duration $\varepsilon_{1-e_1,b}$. In contrast, by using a sample of *likely-eligible workers* and incorporating the extensive margin response, this paper provides a more complete picture of the fiscal cost of raising benefit levels. This distinction has important implications: we would predict a 10 percent increase in benefits would increase the fiscal externality by 1.6 percent if only considering claim duration, versus 6.2 percent when also accounting for higher take-up.

In this section, we replicate the approach of conditioning on benefit receipt to assess the relative importance of the take-up elasticity and the elasticity of claim duration. We then discuss the potential issues with conditioning on UI receipt as these estimates understate the fiscal externality and may suffer from selection bias.

6.1 The Effect on Claim Duration

Following prior research, we estimate the effect of benefit levels on claim duration using samples restricted to *UI recipients*. Specifically, we construct two samples: first, UI recipients within our sample of likely-eligible workers; second the universe of all UI recipients from administrative records spanning the same period. The first sample maintains consistency with our earlier analysis of take-up and benefit payments, while the second sample more closely mirrors the approach in previous studies.

Figure 9 plots average claim duration against normalized weekly wage. Panel 9a uses recipients in our main sample, while Panel 9b uses all recipients from the compensation records. In both, claim duration rises slightly with weekly wage up to the kink, then the slope shifts such that duration declines beyond the kink.[25] Table 4 reports regression estimates, marginal effects, elasticities, and confidence intervals. With our main sample, Column 1 reports that a $100 increase in weekly benefits increases average claim duration by 0.42 weeks, with a 95 percent confidence interval of [0.28, 0.56] and an elasticity of 0.161 [0.107, 0.215]. With the sample based on compensation records, Column 2 reports similar results: a 100*increaseraisesclaimdurationby*0.29*weeks*, *withanelasticityof*0.139.*Thesimilarityacrosssample*

[25] Because we condition on benefit receipt, average claim duration in both samples is mechanically higher than the average number of payments among likely-eligible workers.

[26] UI recipients in our main sample have a longer average claim duration at the kink (16.7 weeks) com-

These results align with prior research estimating the elasticity of claim duration to range from 0.1 to 0.9, though our estimates lie toward the lower end. Figure A.19 plots comparable elasticities and confidence intervals from previous studies, grouped by identification strategy. This paper is most similar to Card et al. (2015a) and Landais (2015), which also use a regression kink design to estimate effects on claim duration. Using data from Missouri, Card et al. (2015a) reports an elasticity of 0.36 during the expansion from 2003–2007 and a higher elasticity of 0.65–0.90 during the 2008–2013 recession and recovery. Landais (2015) finds an average elasticity of 0.33 across five states between 1978 and 1984, with estimates ranging from 0.04 to 0.82.[27] Earlier studies using difference-in-differences designs report elasticities between 0.07 and 0.53. Chetty (2008) estimates an elasticity of 0.53 by comparing liquidity-constrained and unconstrained households, while Meyer and Mok (2007) finds an elasticity of 0.35 by exploiting a large increase in New York's benefit cap. At the lower end, Solon (1985) reports an elasticity of 0.07 following Georgia's 1979 decision to tax UI benefits, comparing high- and low-income workers. Other studies exploiting cross-state and time variation in benefit generosity report elasticities between 0.36 and 0.82 (Kroft and Notowidigdo, 2016; Katz and Meyer, 1990).

One important distinction is that this literature is focused on how benefit generosity affects *unemployment duration*. However, for UI recipients, claim duration serves as a useful, but imperfect, proxy of unemployment duration. Many fo these previous studies tried to account for the differences between unemployment duration and claim duration. Recognizing that workers may move in and out of employment while on the same UI claim, several studies focus on the "initial spell," defined as the number of weeks from the initial claim until two or more consecutive weeks without claiming benefits. Others capture all weeks of unemployment—including unpaid "wait weeks" or skipped weekly claims—by counting the total weeks from the initial claim to the final payment.[28] Using these alternative measures does not substantially change the estimates. Moreover, workers are typically limited to 26 benefit payments, while unemployment can last considerably longer. To account for this, Schmieder and Von Wachter (2016) extrapolates from claim duration to unemployment duration using a constant hazard assumption and the observed share of recipients who exhaust their benefits. Although prior research recognized the limitations of using claim duration as a proxy, conditioning on benefit receipt introduces other potential issues.

pared to all recipients (13.7 weeks), likely reflecting our requirement that likely-eligible workers experience a sufficient reduction in hours between quarters, signaling a longer employment disruption.

[27] These states are Idaho, Louisiana, Missouri, New Mexico, and Washington.

[28] These definitions follow Spiegelman et al. (1992), as outlined in Landais (2015).

6.2 Potential Issues

The consistency of our estimates with previous work suggests external validity, and also raises the question of whether the relationship we document between benefit level and take-up was present in these previous settings. Engoenous take-up introduces two potential issues to previous work that conditions on benefit receipt.

First, this approach fails to account for take-up as a margin of response, which leads us to underestimate the cost of raising benefits. The effect on claim duration only captures the intensive margin response whereby more generous benefits lead claimants to remain on benefits longer. As demonstrated in the theoretical model, it is an incomplete measure of the fiscal externality if raising benefit levels leads more workers to claim UI. Furthermore, our empirical results indicate that take-up is a quantitatively significant margin of response. The relevant elasticity more than triples from 0.16 to 0.62 once we allow for endogenous take-up.

Second, endogenous take-up may introduce selection bias into estimates of the causal effect on claim duration. If take-up responds to the benefit level, then variation in benefit generosity is accompanied by corresponding changes in the sample of UI recipients. Specifically, in an RKD design, the concern is that the kink in take-up creates a corresponding kink in the composition of UI recipients. Similarly, in a differences-in-differences approach, the increase in benefits leads to a change in the composition of the treatment group across periods, confounding the causal effect with selection. Furthermore, the direction of this bias is ambiguous: higher benefits could attract workers expecting shorter unemployment spells, understating the effect on claim duration, or they could induce workers facing high application costs who plan minimal job search effort, inflating the estimated duration effect. In either scenario, endogenous take-up alters the composition of UI recipients, making it difficult to disentangle true effects on claim duration from changes in who claims benefits.

Previous research has recognized this potential issue. Card et al. (2015b) and Card et al. (2015a) identify a kink in the density of UI recipients previously employed in manufacturing, suggesting sample selection, and consequently drop these workers from their analysis. Landais (2015) notes that incomplete take-up may threaten the validity of an RKD if it generates a non-smooth relationship between the assignment variable and unobserved heterogeneity at the kink. Similarly, Chetty (2008) cautions that restricting the sample to UI recipients could introduce selection bias if take-up is endogenous, but argues this is less concerning if the elasticity of take-up is similar across treatment and control groups. Meyer and Mok (2007) contend that New York's sudden increase in the maximum benefit generates variation in generosity without affecting the composition of

UI recipients, though they emphasize this is context-specific and that the direction of potential selection bias remains unclear. Kroft and Notowidigdo (2016) highlight that the relationship between benefit levels and take-up in the SIPP may raise selection concerns but find minimal effects on observable characteristics.[29] Collectively, these studies take steps to mitigate selection bias when analyzing samples of UI recipients.

These issues motivate our use of a sample of likely-eligible workers instead of a sample of UI recipients. This approach illustrates the broader insight that assessing public benefit programs requires analyzing the entire eligible population rather than restricting to benefit recipients.

7 Welfare and Policy Implications

Using these empirical results, we assess the welfare and policy implications of incomplete and endogenous take-up. First, we calculate the optimal benefit level and show that endogenous take-up lowers this value by 29 percent, from \$633 to \$451. Next, we apply the marginal value of public funds (MVPF) framework to measure the effectiveness of each dollar the government spends to raise benefit levels. Our results indicate that endogenous take-up reduces the MVPF by 27 percent, from 0.90 to 0.66. Moreover, this result indicates that existing estimates overstate the cost-effectiveness of raising benefit levels. Increasing the weekly benefit may not be the most efficient use of funds; instead, resources could be directed toward other public benefit programs or other ways to improve the UI program.

7.1 Optimal Benefit Level

Using our theoretical framework and empirical estimates, we examine how behavioral responses affect the optimal benefit level. To do so, we evaluate the optimal policy condition derived in Section 2 and expressed in Equation 2. This expression equalizes the marginal gain for UI recipients from an increase in the benefit level b against the marginal cost borne by all workers.

We parameterize the left-hand side of the optimal policy condition, which represents the marginal utility gain from higher benefits. We assume that utility exhibits constant relative risk aversion (CRRA) with the functional form $u(c) = \frac{1}{1-\rho} \cdot c^{1-\rho}$ and risk param-

[29] Kroft and Notowidigdo (2016) further address this using a two-step estimator that predicts UI receipt and then estimates their main results on an expanded sample including non-recipients, yielding similar estimates.

eter $\rho = 2$. The marginal gain thus becomes

$$\frac{u'(w_L + b) - v'(w_H - \tau)}{v'(w_H - \tau)} = \left(\frac{w_H - \tau}{w_L + b}\right)^{\rho} - 1 \ .$$

We directly observe weekly after-tax income while employed, $(w_H - \tau)$, in our data. To estimate exogenous income during unemployment w_L, we leverage the finding from Ganong and Noel (2019) that UI recipients experience a 6 percent drop in consumption under the current benefits schedule. The value of w_L can then be identified using the consumption ratio

$$\frac{w_L + b_0}{w_H - \tau} = 1 - \%\Delta(c)$$

where b_0 represents the current weekly benefit level.

Next, we turn to the right-hand side of the optimal policy condition, which captures the fiscal externalities from more generous UI benefits. We use the estimate for the elasticity of benefit payments $\varepsilon_{\theta(1-e_1),b}$ from our empirical results. To calculate the elasticity of tax revenue $\varepsilon_{e,b}$, we first relate it to the elasticity of unemployment duration for the whole population $\varepsilon_{1-e,b}$ and then approximate this value by scaling the elasticity of unemployment duration for claimants $\varepsilon_{1-e_1,b}$ by the take-up rate θ so that

$$\varepsilon_{e,b} = \frac{e-1}{e} \cdot \varepsilon_{1-e,b} \approx \frac{e-1}{e} \cdot \theta \cdot \varepsilon_{1-e_1,b} \ .$$

This approximation relies on the notion that non-claimants are unlikely to adjust their search behavior substantially in response to marginal changes to UI payroll taxes. Furthermore, this term is scaled by the ratio of time workers spend unemployed relative to employed $\frac{1-e}{e}$. For values of e near one, such as our baseline assumption that $e = 0.95$, this term is much smaller in magnitude than the elasticity of benefit payments $\varepsilon_{\theta(1-e_1),b}$. As a result, this approximation does not significantly impact the optimal benefit calibration.

Combining these components, we obtain an expression for the optimal benefit level $b^\star$ with incomplete and endogenous take-up as

$$b^\star = (w_H - \tau) \cdot \left[1 + \varepsilon_{\theta(1-e_1),b} - \varepsilon_{e,b}\right]^{\frac{-1}{\rho}} - w_L \ .$$

We calculate the optimal benefit level under three counterfactuals. First, we assume there is no behavioral response such that the elasticity of benefit payments $\varepsilon_{\theta(1-e_1),b}$ and the elasticity of tax revenue $\varepsilon_{e,b}$ are both equal to zero. Second, we assume perfect take-up while allowing search effort to be endogenous so that $\theta = 1$ and $\varepsilon_{\theta,b} = 0$. In this case, the elasticity of benefit payments is then equal to the elasticity of claim duration $\varepsilon_{\theta(1-e_1),b} = \varepsilon_{1-e_1,b}$. Lastly, we assume take-up and search effort are both endogenous.

Table 5 presents the results. If there is no behavioral response, then it is optimal to provide a weekly benefit of $731 that achieves "full insurance." Introducing endogenous search effort decreases the optimal benefit level by 13 percent to $633. Lastly, endogenous take-up further reduces the optimal benefit level to $451—38 percent less than full insurance and 29 percent less than the optimal benefit under perfect take-up. The behavioral responses generate fiscal externalities without corresponding welfare gains, which lowers the optimal benefit level. In assessing the relative importance of these responses, endogenous take-up expands the wedge between full insurance and the optimal benefit level to $280, compared to $98 when we only consider endogenous search effort.

Figure 10 plots the current benefit level for our sample against the optimal benefit level in each of the three counterfactuals. In our sample, the weekly benefit is $653, which lies remarkably close to the optimal benefit level under perfect take-up—only 3 percent higher. However, this weekly benefit is 45 percent greater than the optimal benefit with endogenous take-up. If policymakers assume no take-up response, the current benefit level appears nearly optimal. However, accounting for endogenous take-up fundamentally alters this conclusion, indicating that benefits should be set considerably lower.

In Table A.9, we present estimates of the optimal benefit level under alternate assumptions about the risk parameter ρ or the consumption drop experienced by UI recipients. Ultimately, the relative importance of the take-up response remains consistent across assumptions. Higher risk aversion or a great drop in consumption upon job loss increases optimal benefit levels by raising the consumption-smoothing value of UI benefits. Nonetheless, when we compare the results under perfect take-up versus endogenous take-up, we find that endogenous take-up nearly triples the wedge between the optimal benefit level and full insurance.

7.2 Marginal Value of Public Funds

Next, we apply the marginal value of public funds (MVPF) framework from Hendren and Sprung-Keyser (2020) to measure the value created by additional spending to raise UI benefit levels. The MVPF is defined as the ratio of beneficiaries' willingness-to-pay (WTP) to the net cost to the government (G), representing the value generated per $1 of additional government spending on the policy.

For the UI program, the WTP is equal to the utility gain from receiving benefit b scaled by the share of workers who claim benefits θ and the duration of their unemployment $(1 -$

e_1). When we normalize the utility gain relative to an additional dollar in the employed state, this can be expressed

$$WTP = (1 - e_1) \cdot \theta \cdot \frac{u(w_L + b) - u(w_L)}{v'(w_H - \tau)} \quad .$$

To capture the marginal change in the WTP created by raising benefit levels, we take the partial derivative with respect to benefit b to obtain

$$\frac{\partial WTP}{\partial b} = (1 - e_1) \cdot \theta \cdot \frac{u'(w_L + b)}{v'(w_H - \tau)} \quad .$$

Next, we consider the net cost to the government (G) of providing UI benefits. This cost is equal to the benefit level b multiplied by the share of workers who claim benefits θ and their claim duration $1 - e_1$ minus the tax collected on workers during employment $e \cdot \tau$, and so can be expressed

$$G = (1 - e_1) \cdot \theta \cdot b - e \cdot \tau \quad .$$

Once again, to determine the marginal cost from raising benefit levels, we take the partial derivative of G with respect to benefit b, which yields

$$\frac{\partial G}{\partial b} = \underbrace{(1 - e_1) \cdot \theta}_{\text{Mechanical}} + \underbrace{(1 - e_1) \cdot b \cdot \frac{\partial \theta}{\partial b}}_{\text{Take-up}} - \underbrace{\theta \cdot b \cdot \frac{\partial e_1}{\partial b}}_{\text{Search Effort (Benefits)}} - \underbrace{\frac{\partial e}{\partial b} \cdot \tau}_{\text{Search Effort (Revenue)}} \quad .$$

As in the theoretical model, the cost of higher benefits can be decomposed into four distinct terms capturing the mechanical cost, the take-up response, extended claim durations, and shorter employment durations. In contrast to the theoretical model, the MVPF measures the value of additional spending, and so there is no corresponding change in tax τ necessary to maintain the balanced budget constraint.[30]

The MVPF for increasing benefits is the ratio of the partial derivative of the willingness-to-pay and the net cost to the government with respect to benefit level b

$$MVPF = \frac{\partial WTP / \partial b}{\partial G / \partial b} = \frac{u'(w_L + b) \;/\; v'(w_H - \tau)}{1 + \varepsilon_{\theta(1-e_1),b} + \varepsilon_{1-e_1,b} \cdot (\tau/b)} \quad .$$

Following the same approach used in our optimal benefit calculations, the numerator

[30]This means that the change in search effort e can be simplified $\frac{\partial e}{\partial b} = \theta \cdot \frac{\partial e_1}{\partial b}$ since there is no change in search effort of non-claimants e_0.

can be calculated by assuming the CRRA utility function with risk parameter $\rho = 2$ and using the estimated consumption drop that UI recipients experience at the onset of unemployment. The elasticities in the denominator are identified in our empirical results. We impute the tax wedge ($^{\tau}/_{b}$) using the average effective tax rate of 31.5 percent so $\tau = 0.315 \cdot w_H$ and given that benefits replace half of a worker's wage so $b = 0.5 \cdot w_H$, following Schmieder and Von Wachter (2016). This approach captures the lost tax revenue to both state and federal governments.[31]

As before, we consider three scenarios when calculating the MVPF: no behavioral responses so that $\varepsilon_{\theta(1-e_1),b} = \varepsilon_{e,b} = 0$); endogenous search with perfect take-up so that $\theta = 1$; and both search effort and take-up endogenous. Table 6 summarizes our results. If there is no behavioral response, then raising benefit levels has an MVPF of 1.13 as more generous benefits smooth consumption for workers through their unemployment while the cost of providing an additional \$1 is only the mechanical effect. Allowing for endogenous search effort creates a fiscal externality and reduces the MVPF by 20 percent from 1.13 to 0.90. Accounting for endogenous take-up further drives up the cost of providing additional benefits and reduces the MVPF by an additional 27 percent from 0.90 to 0.66. These differences are driven entirely by behavioral responses that amplify the cost, as the willingness-to-pay remains constant across scenarios. Fiscal externalities transform what appears to be a cost-effective policy that generates \$1.13 in social value for each dollar spent into one that produces only \$0.66 in welfare gains per dollar spent.

In Table A.10, we consider the robustness of these results to different assumptions about the risk parameter ρ and the change in consumption upon unemployment. The willingness-to-pay increases when workers are more risk-averse or experience a greater drop in consumption, which raises the MVPF. However, the net cost to the government does not change across these parameter choices. While these assumptions affect the MVPF estimates, they do not change our finding that endogenous search effort and take-up substantially reduce the policy's effectiveness.

This result suggests that existing MVPF estimates overstate the gains from raising benefit levels by ignoring the take-up response. Hendren and Sprung-Keyser (2020) computes the MVPF using estimates of the duration elasticity from prior work, and Figure 11 plots these estimates and their confidence intervals.[32] All previous MVPF estimates

[31] Alternatively, if we are only focused on cost and revenue for the UI program, then we would use the UI payroll tax of 3 percent so $\tau = 0.03 \cdot w_H$. Under this assumption, the tax wedge ($^{\tau}/_{b}$) is much smaller and so the effect of extended unemployment durations on the MVPF is less impactful.

[32] We estimate these MVPFs using the elasticity of claim duration shown in Figure A.19, following the process outlined in this paper. We follow Hendren and Sprung-Keyser (2020) to calculate 95 percent confidence intervals. Our estimates differ slightly from those in Hendren and Sprung-Keyser (2020) because we use the consumption drop from Ganong and Noel (2019) rather than Gruber (1997) (adjusted per Hendren

rely solely on the elasticity of claim duration and assume no take-up response. However, accounting for the take-up response lowers our MVPF by 27 percent, implying that these other estimates should be revised downward as well. This issue likely extends beyond weekly benefits: Hendren and Sprung-Keyser (2020) also evaluates extending the maximum UI duration using results from Katz and Meyer (1990) and Johnston and Mas (2018), but these estimates may similarly overstate policy effectiveness if longer durations induce additional take-up.

Accounting for endogenous take-up may shift a policy-maker's priorities. Figure 12 plots the MVPF under perfect versus endogenous take-up alongside estimates for spending on other policies, such as providing health insurance for adults, disability insurance, housing vouchers, Supplement Security Income, and direct cash transfers. If we assume perfect take-up, then raising UI benefit levels is the most cost-effective policy, but when we account for endogenous take-up, it becomes the least cost-effective among these different options. Even if the policymaker is committed to enhancing the UI program, it is not the most effective use of resources. McQuillan and Moore (2025b) shows that expanding eligibility to lower-income workers yields a much higher MVPF of 2.57, as receiving benefits only minimally delays re-employment for these workers while improving their re-employment outcomes in the medium-term.

8 Conclusion

This paper examines the incomplete and endogenous take-up of UI benefits. Theoretically, take-up is a potential margin by which workers may respond to changes in policy. Specifically, we consider whether more generous UI benefits increase the likelihood that eligible workers claim benefits, in addition to the well-documented effect whereby UI recipients extend their claim duration. Using a sample of likely-eligible workers, we identify the effect of benefit level on take-up and the number of benefit payments by exploiting nonlinearities in the benefits schedule with an RKD. Our results suggest that a 10 percent increase in the weekly benefit leads to a 4.7 percent increase in take-up, which then drives a 6.2 percent increase in the number of benefit payments.

By modeling the take-up decision, this paper takes a distinct approach from much of the previous work. Rather than solely focusing on benefit recipients and claim duration, we analyze a sample of likely-eligible workers in order to measure the take-up response. This broader perspective reveals a much larger cost than previously recognized. Our findings show that the fiscal externality more than triples when accounting for endogenous

(2017)) and do not apply the constant hazard approximation from Schmieder and Von Wachter (2016).

take-up. The policy implications are substantial: the optimal benefit level decreases by 29 percent and the effectiveness of spending to raise benefit levels decreases by 27 percent.

A key implication of our findings is that endogenous take-up makes it much more costly to raise benefit levels. However, this does not mean that UI fails to serve an important function or that other policy margins must face this same fiscal externality. First, other dimensions of benefit generosity may not induce the same take-up response. For example, while existing research shows that longer potential durations lead workers to remain on benefits longer (Katz and Meyer, 1990; Johnston and Mas, 2018), increasing the potential duration may not increase take-up to the same degree as increasing the weekly benefit, especially if workers are myopic about the hassle costs or overly optimistic about their job search. Similarly, McQuillan and Moore (2025b) shows it would be much more cost-effective to expand UI eligibility to workers marginally attached to the labor force, as UI receipt helps these workers find better and more stable re-employment opportunities. Second, there may be other factors driving incomplete take-up that warrant attention from policymakers. McQuillan and Moore (2025a) shows that targeted outreach to workers who recently lost their job can increase take-up, especially among low-income workers. Lachowska et al. (2025) provides evidence that employers discourage workers from claiming benefits by appealing their claims. Notably, higher take-up driven by removing these barriers may have vastly different welfare implications than take-up induced by more generous benefits. Understanding these distinctions across these different policy levers is critical for designing effective UI policy.

Alternatively, we may want to consider whether the hassle costs driving incomplete take-up are determined by features of the UI program. One limitation of our analysis is that we treat these costs as exogenous. If feasible, a social planner might even prefer to reduce hassle costs directly rather than increase the weekly benefit. Both policies generate welfare gains for inframarginal claimants while creating fiscal externalities through increased take-up by marginal claimants. However, reducing hassle costs may not yield the same mechanical cost or duration response as raising the weekly benefit. Relatedly, Kroft (2008) considers a social multiplier whereby these hassle costs are reduced when more workers claim benefits, which then further increases take-up. Our quasi-experimental estimates do not incorporate social learning mechanism, implying that take-up may rise even more in response to higher weekly benefits than our results suggest. In terms of welfare, the social multiplier would generate two counteracting effects: first, by underestimating the increase in take-up, we underestimate the fiscal cost; second, there would be an additional welfare gain to inframarginal claimants due to the lower hassle costs. Future research should explore hassle costs and the policy levers available to influence them, offering insight into another dimension of policy design.

Expanding the theoretical models and empirical analysis of UI benefits to account for incomplete and endogenous take-up opens promising avenues for future research. For instance, Kroft and Notowidigdo (2016) assesses whether the generosity of UI benefits should vary with the business cycle, measuring how the value of consumption smoothing and the elasticity of claim duration fluctuate over time. However, as shown in our optimal benefit condition, a missing component in this analysis is the elasticity of take-up itself. Future research could explore the responsiveness of take-up to macroeconomic conditions, which may exacerbate or dampen the cyclical variation in the fiscal externality. As another example, Mueller et al. (2021) shows that workers' beliefs about the length of their unemployment spell have strong predictive power for the actual duration, although workers tend to be overly optimistic. These privately held beliefs may also influence whether a worker decides to apply for UI benefits. Moreover, if workers who correctly believe they will experience short unemployment spells are disproportionately induced to take up benefits by more generous benefit levels, this selection would introduce a downward bias to estimates of the elasticity of claim duration that condition on benefit receipt. Future research on the UI program that accounts for incomplete and endogenous take-up will provide a more complete picture of how to best design policy.

This paper advances our understanding of UI benefits by incorporating incomplete and endogenous take-up into the analysis of optimal benefit levels. Both theoretically and empirically, take-up proves to be an important margin of response for workers that has been largely overlooked. More broadly, this paper illustrates the value of a comprehensive approach to studying the UI program—and public benefits programs in general—that considers the entire eligible population rather than focusing solely on benefit recipients. The costs and benefits of these social insurance programs depends on who participates, who does not, and why.

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Tables and Figures

Table 1: Descriptive Statistics for Sample of Job Losses

	(1) All Job Losses	(2) Local Sample
Employment over Previous Year		
Total Earnings	$37,785	$54,443
Hours Worked	1,566	1,879
Hourly Wage	$23.10	$30.84
UI Utilization		
Submit Initial Claim	0.280	0.373
Receive UI benefits	0.207	0.316
Weekly Benefit Amount	$348	$578
Share with Min WBA	0.148	0.000
Share with Max WBA	0.152	0.337
Industry of Previous Employer		
Construction	0.086	0.173
Education and Health Services	0.158	0.192
Financial Activities	0.038	0.053
Government	0.020	0.032
Information	0.025	0.033
Leisure and Hospitality	0.135	0.046
Manufacturing	0.071	0.090
Natural Resources and Mining	0.088	0.024
Other Services	0.032	0.026
Professional and Business Services	0.150	0.168
Trade, Transportation, and Utilities	0.198	0.163
Number of Observations	3,378,829	611,063

Note: This table reports descriptive statistics for the sample of job losses described in Section 3. Column (1) shows statistics for the full sample, and Column (2) for observations local to the kink in the benefit schedule, defined as having a weekly wage within $400 of the kink.

Table 2: Main RKD Estimates on Benefit Receipt and Payments

Outcome (Y):	(1) Benefit Receipt	(2) Benefit Payments
Estimates:		
Intercept	32.4	5.4
	(0.12)	(0.02)
Weekly Wage (V)	0.0086	0.0016
	(0.0005)	(0.0001)
$\mathbb{1}[V \geq k] \cdot (V - k)$	-0.0116	-0.0026
	(0.0011)	(0.0002)
Avg. Value at k:	32.4	5.4
Marginal Effect:		
$100 \cdot \alpha_Y$	2.32 p.p.	0.51
	[1.90, 2.74]	[0.43, 0.60]
Elasticity:		
$\varepsilon_{Y,b}$	0.467	0.619
	[0.382, 0.553]	[0.520, 0.718]
Observations	610,115	610,115

Note: This table reports the main RKD estimates of Equation 5 for benefit receipt and payments. Coefficients for benefit receipt are reported in percentage points. The term $\mathbb{1}[V \geq k] \cdot (V - k)$ captures the kink in the outcome variable $\Delta Y'$. The marginal effect represents the change in the outcome for a \$100 increase in weekly benefits, calculated as $100 \cdot \alpha_Y = \Delta Y'/\kappa$, where $\kappa = -1/2$ is identified from the benefit schedule. The elasticity $\varepsilon_{Y,b}$ is given by $\varepsilon_{Y,b} = \alpha_Y \cdot b(V = k)/E[Y|V = k]$, using the weekly benefit at the kink of \$653. Standard errors are in parentheses while the 95 percent confidence intervals are in brackets.

Table 3: RKD Estimates on the Application Process

Outcome (Y):	(1) Initial Claim	(2) Waiting Week Claim	(3) Payable Weekly Claim
Estimates:			
Intercept	37.1	35.9	35.2
	(0.13)	(0.13)	(0.13)
Weekly Wage (V)	0.0024	0.0039	0.0046
	(0.0005)	(0.0005)	(0.0005)
$\mathbb{1}[V \geq k] \cdot (V - k)$	-0.0075	-0.0089	-0.0096
	(0.0011)	(0.0011)	(0.0011)
Avg. Value at k:	37.1	35.9	35.2
Marginal Effect:			
$100 \cdot \alpha_Y$	1.50 p.p.	1.79 p.p.	1.93 p.p.
	[1.06, 1.94]	[1.35, 2.22]	[1.49, 2.36]
Elasticity:			
$\varepsilon_{Y,b}$	0.264	0.324	0.357
	[0.186, 0.341]	[0.245, 0.403]	[0.277, 0.438]
Observations	610,115	610,115	610,115

Note: This table reports the main RKD estimates of Equation 5 for different stages of the application process. Coefficients are reported in percentage points. The term $\mathbb{1}[V \geq k] \cdot (V - k)$ captures the kink in the outcome variable $\Delta Y'$. The marginal effect represents the change in the outcome for a \$100 increase in weekly benefits, calculated as $100 \cdot \alpha_Y = \Delta Y'/\kappa$, where $\kappa = -1/2$ is identified from the benefit schedule. The elasticity $\varepsilon_{Y,b}$ is given by $\varepsilon_{Y,b} = \alpha_Y \cdot b(V = k)/E[Y|V = k]$, using the weekly benefit at the kink of \$653. Standard errors are in parentheses while the 95 percent confidence intervals are in brackets.

Table 4: RKD Estimates on Claim Duration

Sample:	(1) Job Loss Sample	(2) All UI Recipients
Estimates:		
Intercept	16.7	13.7
	(0.04)	(0.03)
Weekly Wage (V)	0.0007	0.0004
	(0.0002)	(0.0001)
$\mathbb{1}[V \geq k] \cdot (V - k)$	-0.0021	-0.0015
	(0.0004)	(0.0003)
Avg. Values at k:		
Claim Duration	16.7	13.7
Weekly Benefit	$648	$650
Marginal Effect:		
$100 \cdot \alpha_{1-e_1}$	0.42	0.29
	[0.28, 0.56]	[0.19, 0.40]
Elasticity:		
$\varepsilon_{1-e_1,b}$	0.161	0.139
	[0.107, 0.215]	[0.088, 0.190]
Observations	188,582	366,026

Note: This table reports the RKD estimates of Equation 5 on claim duration using a sample of benefit recipients. Column (1) uses the main sample of job losses, restricting to benefit recipients. Column (2) uses all benefit recipients over the sample period. The term $\mathbb{1}[V \geq k] \cdot (V - k)$ captures the kink in the outcome variable $\Delta Y'$. The marginal effect represents the change in the outcome for a $100 increase in weekly benefits, calculated as $100 \cdot \alpha_Y = \Delta Y'/\kappa$, where $\kappa = -1/2$ is identified from the benefit schedule. The elasticity $\varepsilon_{Y,b}$ is given by $\varepsilon_{Y,b} = \alpha_Y \cdot b(V = k)/E[Y|V = k]$, using the weekly benefit at the kink of $653. Standard errors are in parentheses while the 95 percent confidence intervals are in brackets.

Table 5: Calibrating the Optimal Benefit Level

	No Behavioral Response	Perfect Take-up, Endogenous Search	Endogenous Take-up and Search Effort
Optimal Benefit Level	\$731	\$633	\$451
Diff. from full insurance	\$0	-\$98	-\$280
Share of full insurance	1.00	0.87	0.62

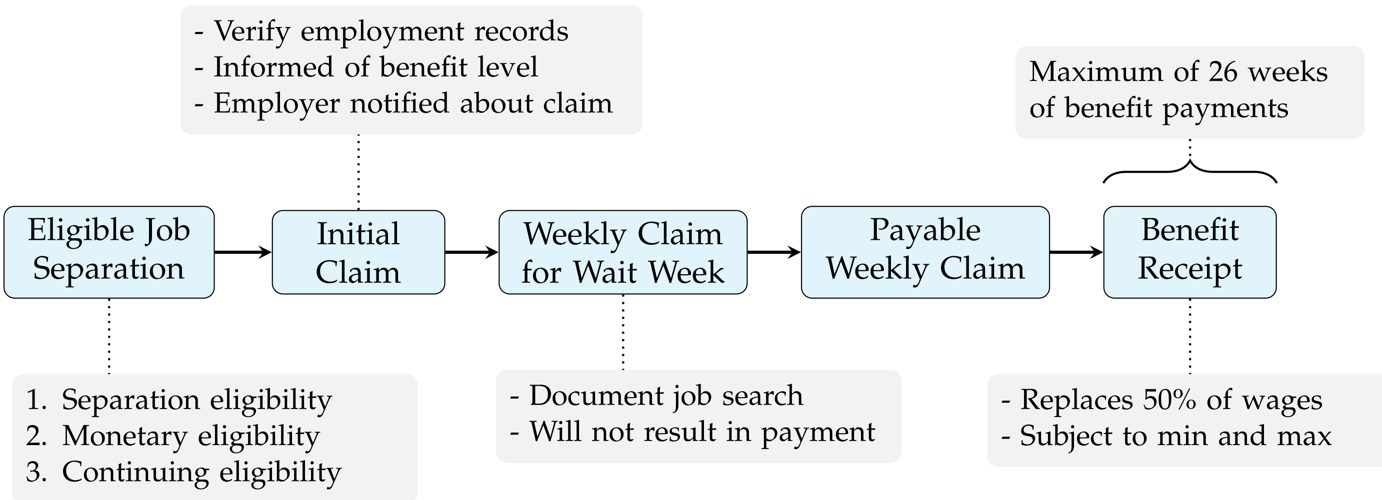
Note: This table reports the optimal benefit level across three counterfactuals. This calculation is described in detail in Section 7. Robustness to assumptions about the risk parameter ρ and change in consumption is shown in Table A.9.

Table 6: MVPF for Raising Benefit Levels

	No Behavioral Response	Perfect Take-up, Endogenous Search	Endogenous Take-up and Search Effort
MVPF	1.13	0.90	0.66
Willingness-to-pay	1.13	1.13	1.13
Cost to government	1.00	1.26	1.72

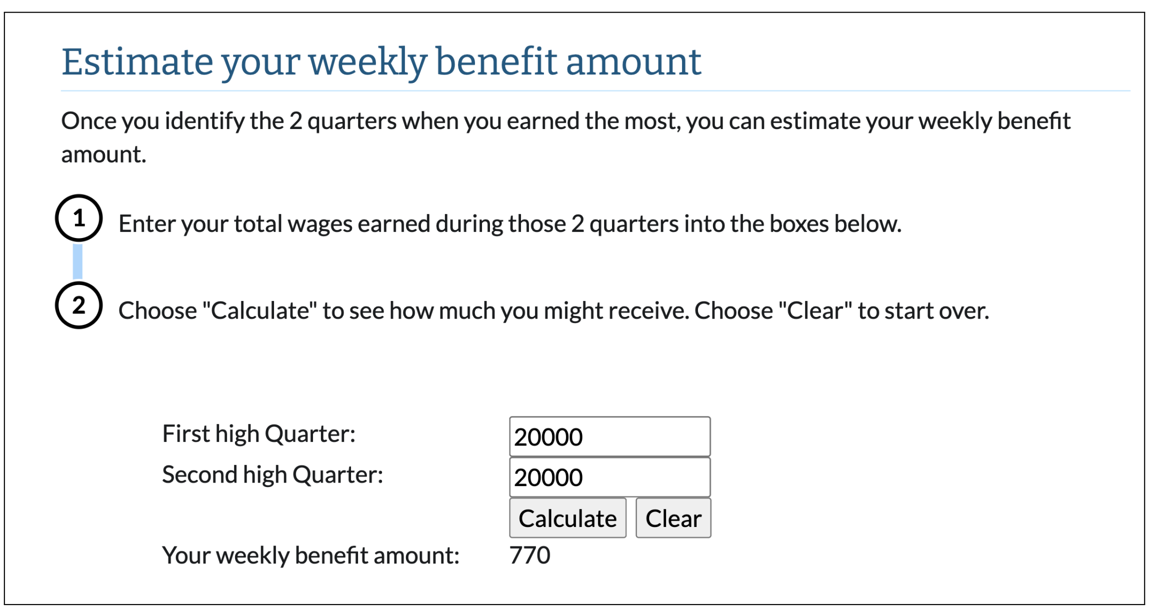
Note: This table reports the marginal value of public funds across three counterfactuals. This calculation is described in detail in Section 7. Robustness to assumptions about the risk parameter ρ and change in consumption is shown in Table A.10.

Figure 1: The Application Process for Unemployment Insurance



Note: This figure illustrates the key points in the application process with descriptions for each stage. This process is described in more detail in Section 3.

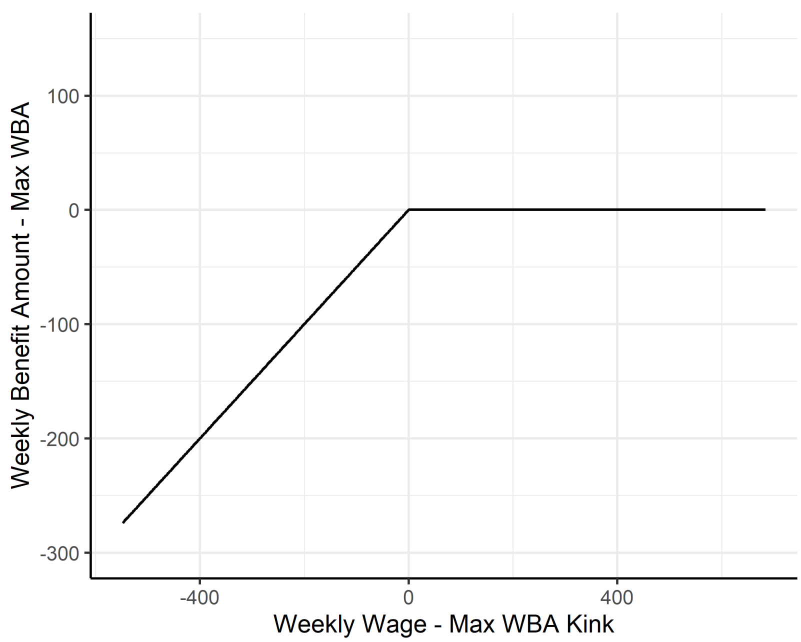
Figure 2: Benefit Estimation Tool



Note: This figure displays a screenshot of the benefit estimation tool on the website for Washington State's Employment Security Department.

Figure 3: Benefits Schedule

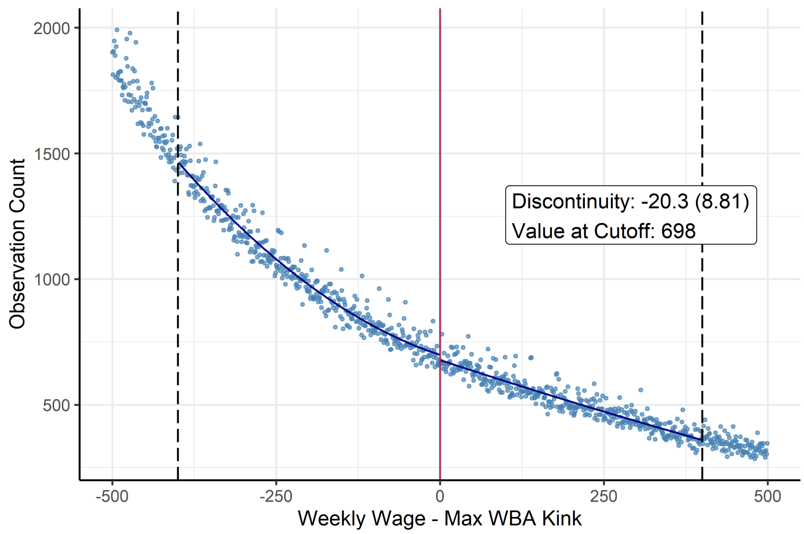
(a) Nominal



(b) Normalized

Note: This figure plots the benefit schedule as a function of a worker's weekly wage. Panel (a) shows the schedule by year, where increases in the maximum weekly benefit amount (WBA) generate different kink points. Panel (b) normalizes the schedules across years by subtracting the maximum WBA from both the weekly benefit amount and the weekly wage.

Figure 4: Testing for Manipulation of the Assignment Variable

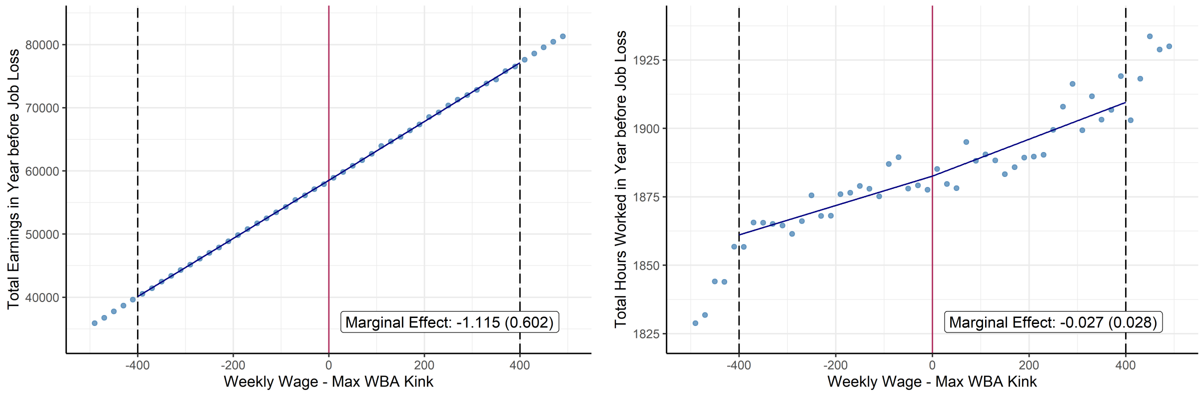


(a) Density

(b) Change in Density

Note: Panel (a) shows the density of the normalized weekly wage for observations within $500 of the kink in the benefit schedule, and Panel (b) shows the change in this density. Points represent $1 bins, the dark blue line is the fitted regression, the vertical red line marks the kink point, and the gray dotted lines indicate the regression bandwidths. The reported discontinuity at the kink is from the manipulation test of McCrary (2008), with the standard error in parentheses and the estimated value at the cutoff.

Figure 5: Covariate Balance in Employment History



(a) Annual Earnings

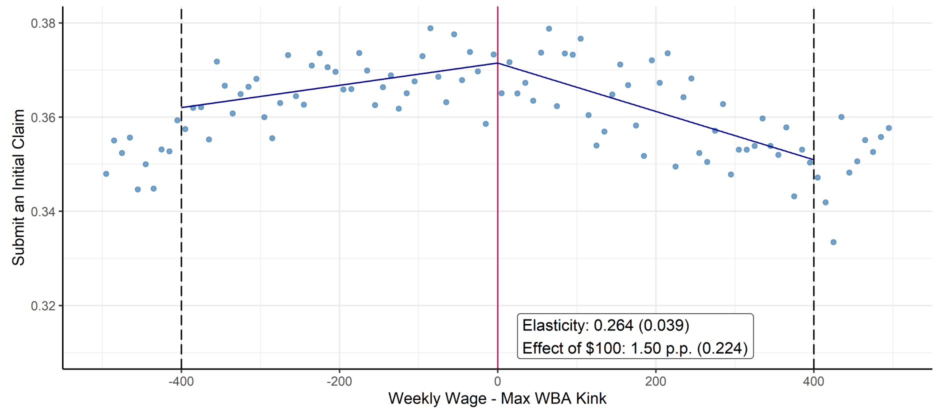
(b) Annual Hours Worked

Note: Panel (a) plots total earnings and Panel (b) hours worked in the year before job loss, by normalized weekly wage for observations within $500 of the kink in the benefit schedule. Points show averages for $20 bins, the dark blue line is the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect is calculated as described in Section 4.

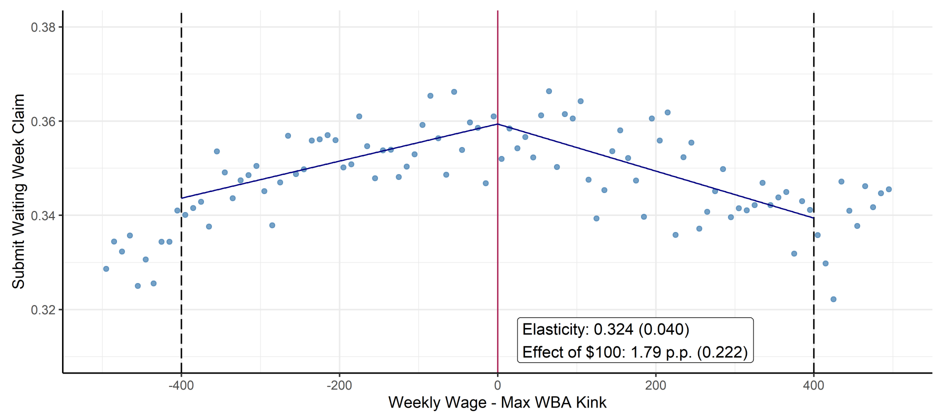
Figure 6: RKD Estimates on Benefit Receipt

Note: This figure plots benefit receipt by normalized weekly wage for observations within $500 of the kink in the benefit schedule. Points show averages for $20 bins, the dark blue line is the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect and elasticity are calculated as described in Section 4, with standard errors in parentheses.

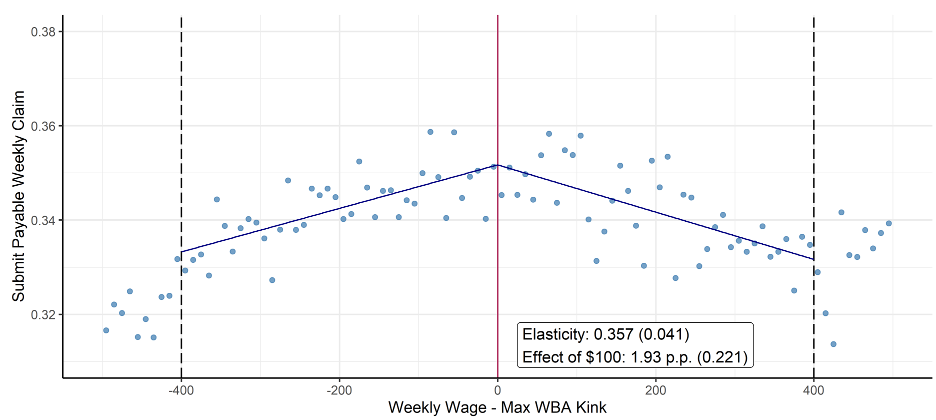
Figure 7: RKD Estimates on the Application Process



(a) Initial Claim



(b) Waiting Week Claim



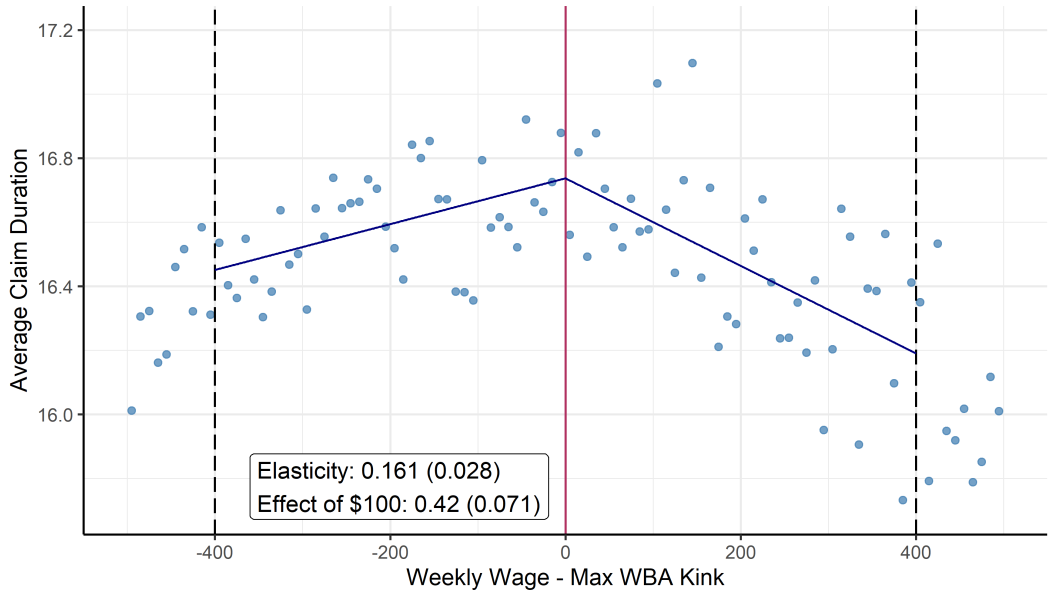
(c) Payable Weekly Claim

Note: This figure plots stages of the application process by normalized weekly wage for observations within $500 of the kink in the benefit schedule. Panel (a) shows the share filing an initial claim; Panel (b) the share filing a wait-week claim; and Panel (c) the share filing a payable claim. Points show averages for $20 bins, the dark blue line is the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines denote bandwidths. The marginal effect and elasticity are computed as described in Section 4, with standard errors in parentheses.

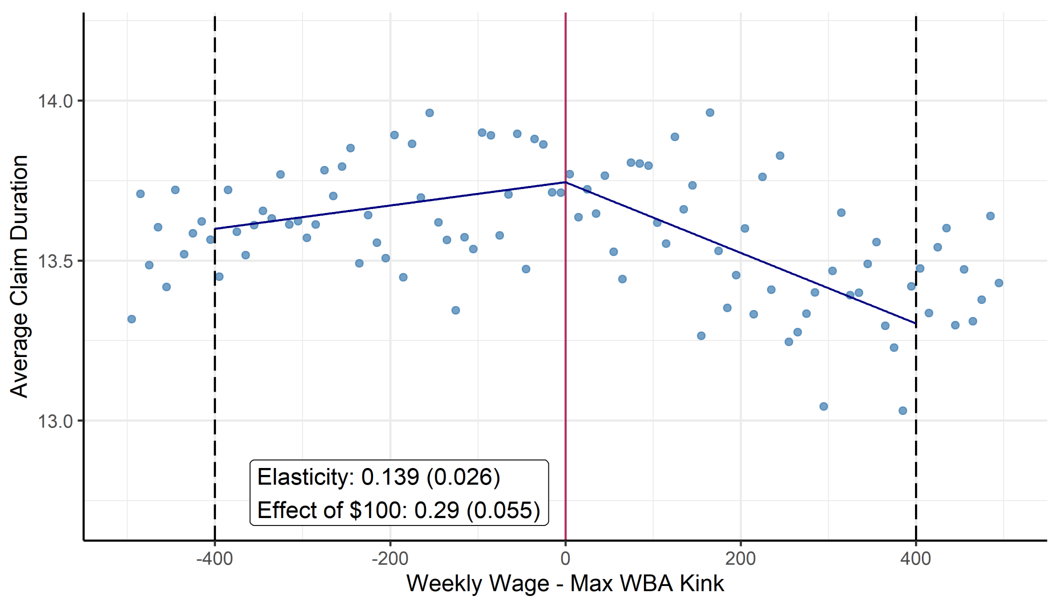
Figure 8: RKD Estimates on Benefit Payments

Note: This figure plots the number of benefit payments per job loss by normalized weekly wage for observations within $500 of the kink in the benefit schedule. Points show averages for $20 bins, the dark blue line is the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect and elasticity are calculated as described in Section 4, with standard errors in parentheses.

Figure 9: RKD Estimates on Claim Duration



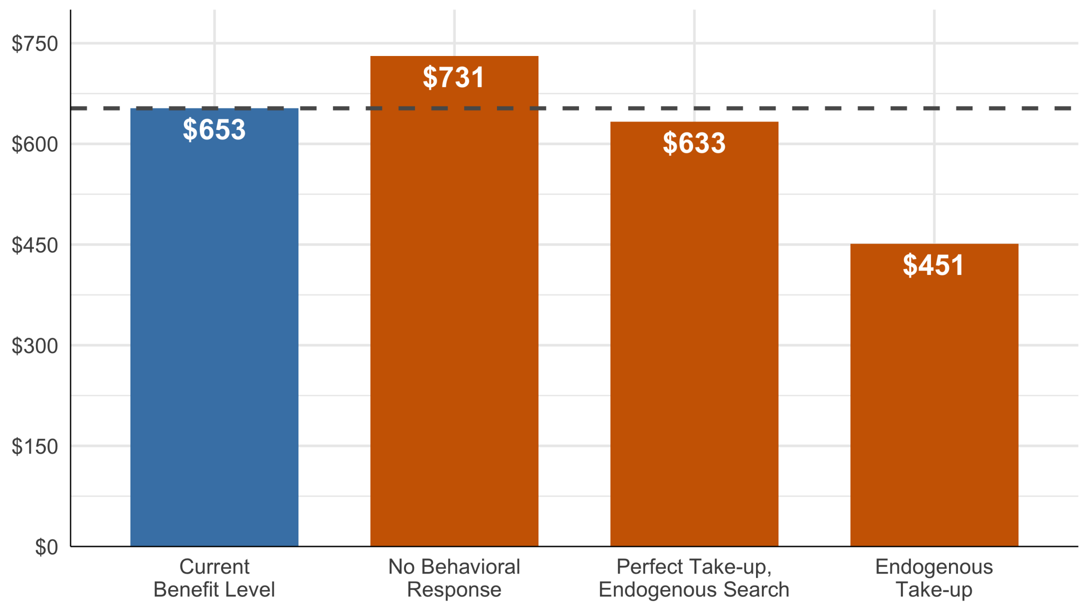
(a) UI Recipients in Main Sample



(b) All UI Recipients in Compensation Records

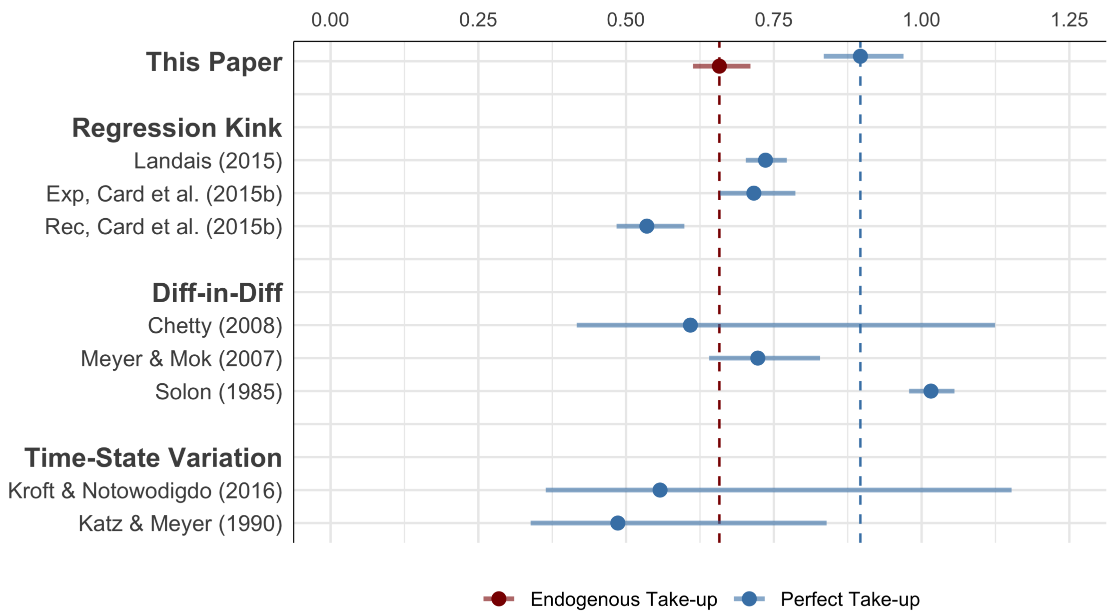
Note: This figure plots the average claim duration by normalized weekly wage for observations within $500 of the kink in the benefit schedule. Panel (a) uses the main sample of job losses, restricting to benefit recipients. Panel (b) uses all benefit recipients over the sample period.Points show averages for $20 bins, the dark blue line is the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect and elasticity are calculated as described in Section 4, with standard errors in parentheses.

Figure 10: Optimal Benefit Level



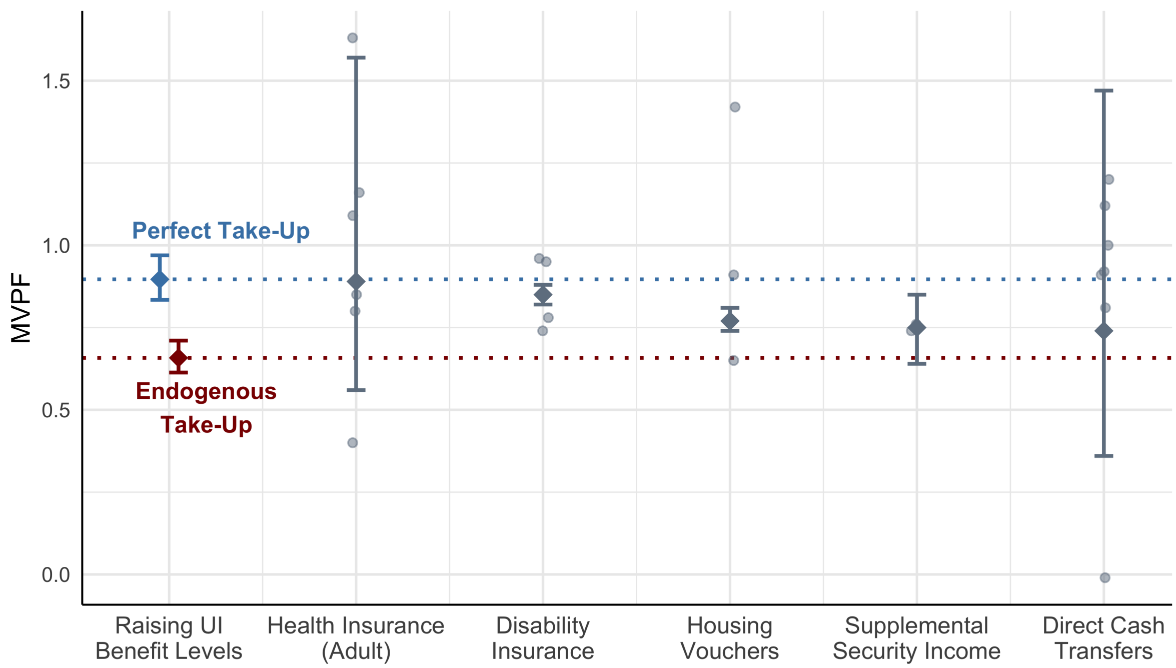
Note: This figure plots the optimal benefit level across three counterfactuals, as reported in Table 6, relative to the weekly benefit at the kink ($653). Details of the calculation are provided in Section 7.

Figure 11: MVPF Estimates for Raising Benefit Levels



Note: This figure plots the marginal value of public funds under perfect and endogenous take-up, as reported in Table 6. Details of the calculation are provided in Section 7. For comparison, we include estimates from Hendren and Sprung-Keyser (2020) based on duration elasticities from prior studies, using the same assumptions for risk aversion and consumption drop. Error bars show 95 percent confidence intervals, while the dotted line marks the estimates from this paper.

Figure 12: MVPF: Raising UI Benefits versus Alternative Policies



Note: This figure plots the marginal value of public funds under perfect and endogenous take-up, as reported in Table 6, alongside MVPF estimates for other policies from Hendren and Sprung-Keyser (2020). Transparent points show individual MVPF estimates, diamonds show category averages, error bars indicate 95 percent confidence intervals, while the dotted line marks the estimates from this paper..

Appendix

Table A.1: Reasons for Not Claiming Unemployment Insurance

	Share	**N**
Cost-Benefit Considerations	0.352	539
Don't need money/benefits too small	0.281	430
Too much work/hassle	0.071	109
Expecting Re-employment	0.272	416
Expect to get new job	0.175	268
Expect to be recalled	0.097	148
Information	0.107	164
Didn't know benefits existed	0.057	87
Didn't know where/how to apply	0.033	51
Employer gave no info	0.018	26
Stigma	0.058	89
Feels like welfare	0.047	72
Worried about future job	0.011	17
Access and Support	0.042	64
Application too confusing	0.013	20
No transportation	0.012	18
Couldn't get help with application	0.008	12
No phone/computer/internet	0.004	6
Phone/internet system not working	0.003	5
Not available in their language	0.001	2
Other	0.223	341
Other reason	0.138	211
Plan to file soon	0.085	130

Note: This table reports the self-reported reasons for not claiming benefits from the 2018 Current Population Survey's Unemployment Insurance Nonfilers Supplement. The sample includes 1,532 workers who did not claim benefits and is restricted to individuals who would have been eligible based on their responses.

Table A.2: RKD Estimates on Benefit Receipt by Year

Outcome (Y): Benefit Receipt	FY 2011	FY 2012	FY 2013	FY 2014	FY 2015	FY 2016	FY 2017	FY 2018
Estimates:								
Intercept	37.5	34.6	35.8	31.9	29.9	29.8	29.1	29.1
	(0.35)	(0.34)	(0.35)	(0.34)	(0.34)	(0.34)	(0.34)	(0.39)
Weekly Wage (V)	0.007	0.008	0.010	0.008	0.010	0.011	0.009	0.010
	(0.0015)	(0.0014)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0016)
$\mathbb{1}[V \geq k] \cdot (V-k)$	-0.015	-0.017	-0.016	-0.012	-0.006	-0.009	-0.003	-0.015
	(0.0030)	(0.0029)	(0.0031)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0034)
Marginal Effect:								
$100 \cdot \alpha_\theta$	3.05 p.p.	3.42 p.p.	3.17 p.p.	2.35 p.p.	1.27 p.p.	1.87 p.p.	0.68 p.p.	2.92 p.p.
	[1.87, 4.23]	[2.27, 4.57]	[1.94, 4.39]	[1.17, 3.53]	[0.1, 2.44]	[0.7, 3.04]	[-0.49, 1.85]	[1.61, 4.24]
Average Values at k:								
Benefit Receipt	37.5	34.6	35.8	31.9	29.9	29.8	29.1	29.1
Weekly Benefit b	$583	$604	$624	$637	$664	$681	$713	$749
Elasticity:								
$\varepsilon_{\theta,b}$	0.474	0.598	0.552	0.470	0.282	0.427	0.166	0.753
	[0.291, 0.658]	[0.396, 0.8]	[0.339, 0.764]	[0.234, 0.705]	[0.023, 0.542]	[0.159, 0.695]	[-0.121, 0.453]	[0.414, 1.091]
Observations	83,491	84,780	77,308	77,359	77,080	75,541	75,646	58,910

Note: This table reports RKD estimates on benefit receipt for each year. Coefficients are reported in percentage points. The marginal effect and elasticity are calculated as described in Section 4. Standard errors are in parentheses while the 95 percent confidence intervals are in brackets.

Table A.3: RKD Estimates on Benefit Payments by Year

Outcome (Y): Benefit Payments	FY 2011	FY 2012	FY 2013	FY 2014	FY 2015	FY 2016	FY 2017	FY 2018
Estimates:								
Intercept	6.9	6.1	6.2	5.4	4.8	4.0	4.8	4.7
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)
Weekly Wage (V)	0.001	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
$\mathbb{1}[V \geq k] \cdot (V-k)$	-0.004	-0.003	-0.003	-0.003	-0.002	-0.002	-0.001	-0.003
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)
Marginal Effect:								
$100 \cdot \alpha_{\theta(1-e_1),b}$	0.70	0.69	0.63	0.64	0.34	0.35	0.23	0.52
	[0.45, 0.95]	[0.46, 0.93]	[0.38, 0.87]	[0.41, 0.86]	[0.12, 0.56]	[0.15, 0.54]	[0.01, 0.46]	[0.27, 0.77]
Average Values at k:								
Benefit Payments	6.9	6.1	6.2	5.4	4.8	4.0	4.8	4.7
Weekly Benefit b	$583	$604	$624	$637	$664	$681	$713	$749
Elasticity:								
$\varepsilon_{\theta(1-e_1),b}$	0.593	0.680	0.631	0.747	0.468	0.595	0.348	0.823
	[0.384, 0.802]	[0.449, 0.911]	[0.385, 0.876]	[0.478, 1.017]	[0.166, 0.771]	[0.262, 0.929]	[0.017, 0.679]	[0.428, 1.219]
Observations	83,491	84,780	77,308	77,359	77,080	75,541	75,646	58,910

Note: This table reports RKD estimates on benefit payments for each year. The marginal effect and elasticity are calculated as described in Section 4. Standard errors are in parentheses while the 95 percent confidence intervals are in brackets.

Table A.4: RKD Estimates on Benefit Receipt in Mass Layoff Sample

	Baseline	Mass Layoff Sample		
		$\geq$ 5% contraction	$\geq$ 15% contraction	$\geq$ 30% contraction
Estimates:				
Intercept	32.4	31.8	31.4	27.4
	(0.12)	(0.17)	(0.21)	(0.26)
Weekly Wage (V)	0.0086	0.0087	0.0084	0.0047
	(0.0005)	(0.0007)	(0.0009)	(0.0011)
$\mathbb{1}[V \geq k] \cdot (V-k)$	-0.0116	-0.0135	-0.0143	-0.0099
	(0.0011)	(0.0015)	(0.0018)	(0.0023)
Benefit Receipt at k:	32.4	31.8	31.4	27.4
Marginal Effect:				
$100 \cdot \alpha_\theta$	2.32 p.p.	2.70	2.86	1.98
	[1.90, 2.74]	[2.11, 3.30]	[2.14, 3.58]	[1.10, 2.86]
Elasticity:				
$\varepsilon_{\theta,b}$	0.467	0.555	0.592	0.469
	[0.382, 0.553]	[0.433, 0.677]	[0.444, 0.741]	[0.260, 0.679]
Observations	610,115	306,310	207,291	126,781

Note: This table reports RKD estimates on benefit receipt for the mass layoff samples. The marginal effect and elasticity are calculated as described in Section 4 while construction of the mass layoff sample is explained in Section 5. Standard errors are in parentheses while the 95 percent confidence intervals are in brackets.

Table A.5: RKD Estimates on Benefit Payments in Mass Layoff Sample

	Baseline	Mass Layoff Sample		
		$\geq$ 5% contraction	$\geq$ 15% contraction	$\geq$ 30% contraction
Estimates:				
Intercept	5.4	5.3	5.2	4.5
	(0.02)	(0.03)	(0.04)	(0.05)
Weekly Wage (V)	0.0016	0.0017	0.0016	0.0010
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
$\mathbb{1}[V \geq k] \cdot (V - k)$	-0.0026	-0.0030	-0.0031	-0.0022
	(0.0002)	(0.0003)	(0.0003)	(0.0004)
Benefit Payments at k:	5.4	5.3	5.2	4.5
Marginal Effect:				
$100 \cdot \alpha_{\theta(1-e_1),b}$	0.51	0.59	0.61	0.43
	[0.43, 0.60]	[0.48, 0.71]	[0.48, 0.75]	[0.27, 0.61]
Elasticity:				
$\varepsilon_{\theta(1-e_1),b}$	0.619	0.729	0.763	0.626
	[0.520, 0.718]	[0.589, 0.870]	[0.593, 0.934]	[0.386, 0.867]
Observations	610,115	306,310	207,291	126,781

Note: This table reports RKD estimates on benefit payments for the mass layoff samples. The marginal effect and elasticity are calculated as described in Section 4 while construction of the mass layoff sample is explained in Section 5. Standard errors are in parentheses while the 95 percent confidence intervals are in brackets.

Table A.6: RKD Estimates by Previous UI Experience

	Never Applied Before	Previously Applied
Benefit Receipt:		
Marginal Effect	1.42 p.p.	1.76 p.p.
	[0.75, 2.10]	[0.29, 3.23]
Average Value at k	0.228	0.502
Elasticity	0.441	0.247
	[0.231, 0.650]	[0.040, 0.453]
Benefit Payments:		
Marginal Effect	0.29	0.45
	[0.17, 0.41]	[0.17, 0.73]
Average Value at k	3.5	7.5
Elasticity	0.577	0.417
	[0.331, 0.823]	[0.156, 0.679]
Observations	189,990	57,729
Share of sample	76.7%	23.3%

Note: This table reports RKD estimates on benefit receipt benefit payments based on whether a worker had previously applied for UI benefits. The marginal effect and elasticity are calculated as described in Section 4 while determining whether a worker previously applied for benefits is further explained in Section 5. Standard errors are in parentheses while the 95 percent confidence intervals are in brackets.

Table A.7: RKD Estimates on Benefit Receipt by Industry

Outcome Variable (Y): Benefit Receipt	Natural Resources and Mining	Construction	Manufacturing	Trade, Transportation and Utilities	Information	Financial Activities
Marginal Effect:						
$100 \cdot \alpha_Y$	2.06 p.p.	5.12 p.p.	2.77 p.p.	0.26 p.p.	1.89 p.p.	1.76 p.p.
	[-1.06, 5.18]	[4.04, 6.20]	[1.27, 4.27]	[-0.78, 1.31]	[-0.37, 4.15]	[-0.09, 3.60]
Average Values at k:						
Benefit Receipt	38.1	54.5	39.9	27.9	32.8	30.8
Weekly Benefit b	$653	$653	$651	$651	$649	$652
Elasticity:						
$\varepsilon_{Y,b}$	0.353	0.614	0.452	0.061	0.374	0.371
	[-0.182, 0.889]	[0.484, 0.743]	[0.207, 0.698]	[-0.183, 0.306]	[-0.073, 0.821]	[-0.019, 0.761]
Observations	14,510	105,582	54,920	99,384	20,253	32,097

	Professional and Business Service	Education and Health Services	Leisure and Hospitality	Other Services	Government
Marginal Effect:					
$100 \cdot \alpha_Y$	1.74 p.p.	-0.89 p.p.	2.55 p.p.	0.36 p.p.	-0.44 p.p.
	[0.73, 2.76]	[-1.59, -0.18]	[0.43, 4.66]	[-2.39, 3.11]	[-2.46, 1.59]
Average Values at k:					
Benefit Receipt	34.1	12.8	24.5	29.0	19.7
Weekly Benefit b	$653	$655	$656	$650	$649
Elasticity:					
$\varepsilon_{Y,b}$	0.334	-0.453	0.684	0.081	-0.143
	[0.140, 0.529]	[-0.812, -0.094]	[0.117, 1.251]	[-0.536, 0.698]	[-0.809, 0.522]
Observations	102,648	117,321	27,994	15,758	19,644

Note: This table reports RKD estimates on benefit receipt based on the industry of the previous employer. The marginal effect and elasticity are calculated as described in Section 4. Standard errors are in parentheses while the 95 percent confidence intervals are in brackets.

Table A.8: RKD Estimates on Benefit Payments by Industry

Outcome Variable (Y): Benefit Payments	Natural Resources and Mining	Construction	Manufacturing	Trade, Transportation and Utilities	Information	Financial Activities
Marginal Effect:						
$100 \cdot \alpha_Y$	0.35	1.11	0.45	0.13	0.43	0.61
	[-0.25, 0.95]	[0.89, 1.32]	[0.15, 0.76]	[-0.08, 0.33]	[-0.03, 0.90]	[0.24, 0.98]
Average Values at k:						
Benefit Payments	6.2	8.8	6.8	4.7	5.8	5.5
Weekly Benefit b	$653	$653	$651	$651	$649	$652
Elasticity:						
$\varepsilon_{Y,b}$	0.367	0.825	0.437	0.179	0.487	0.718
	[-0.264, 0.998]	[0.666, 0.984]	[0.146, 0.728]	[-0.106, 0.465]	[-0.031, 1.004]	[0.281, 1.154]
Observations	14,510	105,582	54,920	99,384	20,253	32,097

	Professional and Business Service	Education and Health Services	Leisure and Hospitality	Other Services	Government
Marginal Effect:					
$100 \cdot \alpha_Y$	0.43	-0.05	0.47	0.21	0.01
	[0.23, 0.63]	[-0.19, 0.08]	[0.05, 0.88]	[-0.34, 0.75]	[-0.40, 0.42]
Average Values at k:					
Benefit Payments	5.7	2.2	4.2	5.0	3.6
Weekly Benefit b	$653	$655	$656	$650	$649
Elasticity:					
$\varepsilon_{Y,b}$	0.491	-0.161	0.731	0.267	0.020
	[0.264, 0.718]	[-0.564, 0.242]	[0.078, 1.384]	[-0.440, 0.975]	[-0.724, 0.763]
Observations	102,648	117,321	27,994	15,758	19,644

Note: This table reports RKD estimates on benefit payments based on the industry of the previous employer. Average benefit receipt is expressed in percentage points. The marginal effect and elasticity are calculated as described in Section 4. Standard errors are in parentheses while the 95 percent confidence intervals are in brackets.

Table A.9: Robustness of Optimal Benefit Level to Parameter Assumptions

	Baseline	Risk Parameter		Consumption Drop		
		$\rho = 1.5$	$\rho = 2.5$	3%	10%	15%
No Behavioral Response	$731	$731	$731	$692	$784	$849
Diff. from full insurance	$0	$0	$0	$0	$0	$0
Share of full insurance	1.00	1.00	1.00	1.00	1.00	1.00
Perfect Take-up	$633	$602	$652	$594	$685	$751
Diff. from full insurance	-$98	-$129	-$79	-$98	-$98	-$98
Share of full insurance	0.87	0.82	0.89	0.86	0.88	0.88
Endogenous Take-up	$451	$371	$502	$412	$503	$568
Diff. from full insurance	-$280	-$360	-$230	-$280	-$280	-$280
Share of full insurance	0.62	0.51	0.69	0.59	0.64	0.67

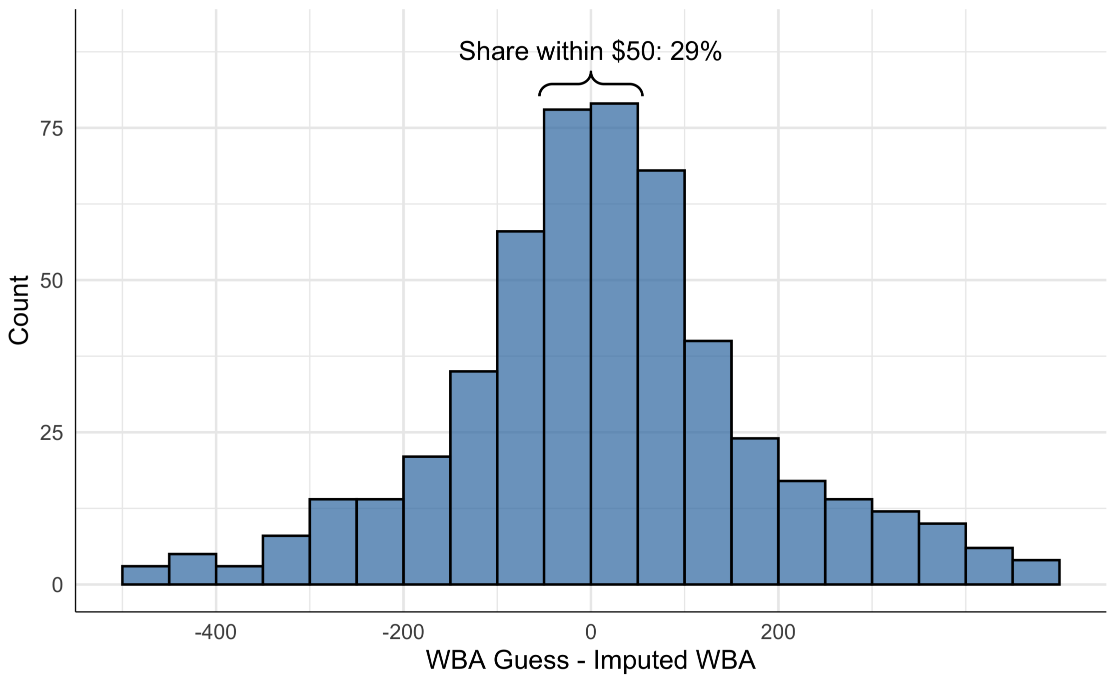
Note: This table reports the optimal benefit level across three counterfactuals, varying assumptions on the risk parameter ρ and the consumption drop following job loss. Details of the calculation are in Section 7.

Table A.10: Robustness of MVPF to Parameter Assumptions

	Baseline	Risk Parameter		Consumption Drop		
		$\rho = 1.5$	$\rho = 2.5$	3%	10%	15%
No Behavioral Response	1.13	1.10	1.17	1.06	1.23	1.38
Willingness-to-pay	1.13	1.10	1.17	1.06	1.23	1.38
Cost to government	1.00	1.00	1.00	1.00	1.00	1.00
Perfect Take-up	0.90	0.87	0.92	0.84	0.98	1.10
Willingness-to-pay	1.13	1.10	1.17	1.06	1.23	1.38
Cost to government	1.26	1.26	1.26	1.26	1.26	1.26
Endogenous Take-up	0.66	0.64	0.68	0.62	0.72	0.80
Willingness-to-pay	1.13	1.10	1.17	1.06	1.23	1.38
Cost to government	1.72	1.72	1.72	1.72	1.72	1.72

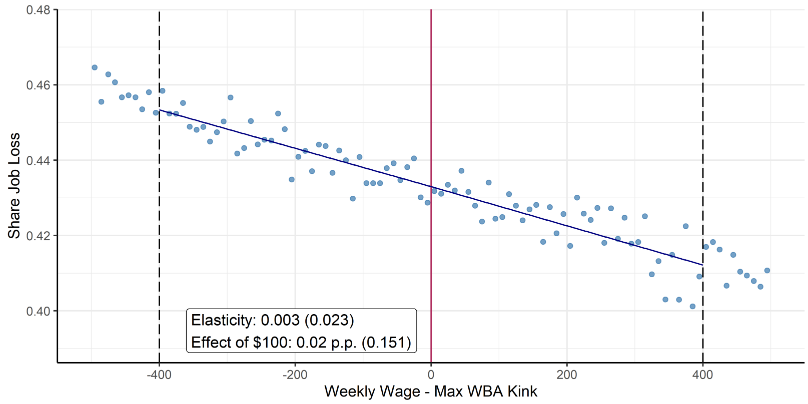
Note: This table reports the MVPF across three counterfactuals, varying assumptions about the risk parameter ρ and the consumption drop following job loss. Details of the calculation are in Section 7.

Figure A.1: Estimated Benefits in Survey of Non-Recipients

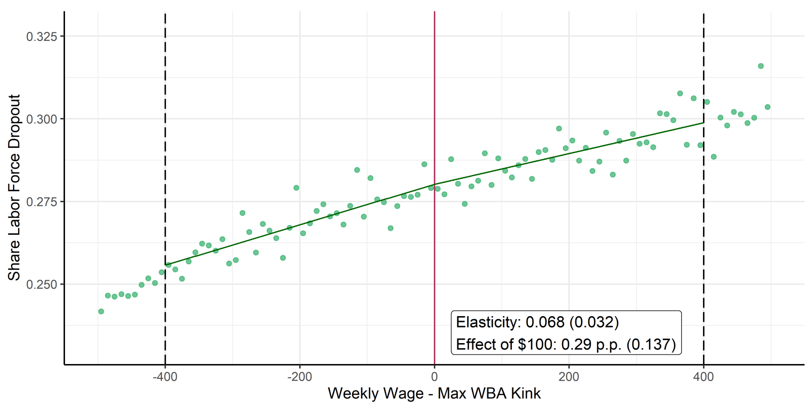


Note: This figure plots a histogram of workers' guess for their weekly benefit amount (WBA) minus their imputed WBA, calculated based on state of residence and reported earnings. The data are drawn from an online survey of 530 likely UI-eligible unemployed nonclaimants conducted as part of McQuillan and Moore (2025a). Bars represent counts in $50 bins.

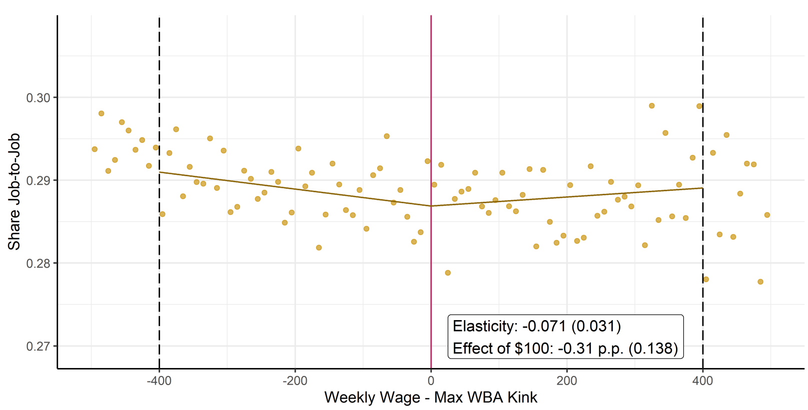
Figure A.2: Classification of Job Separations by Type



(a) Job Loss



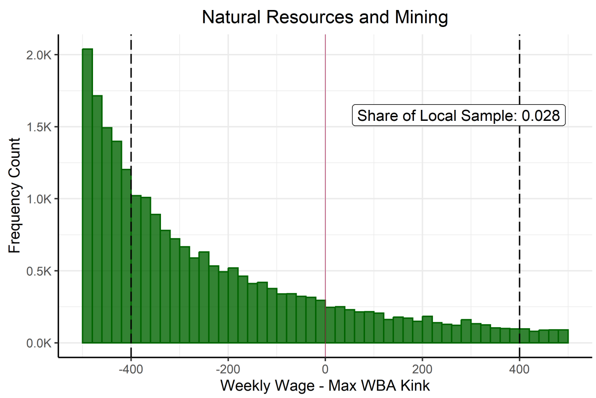
(b) Labor Force Dropout



(c) Job-to-Job Transition

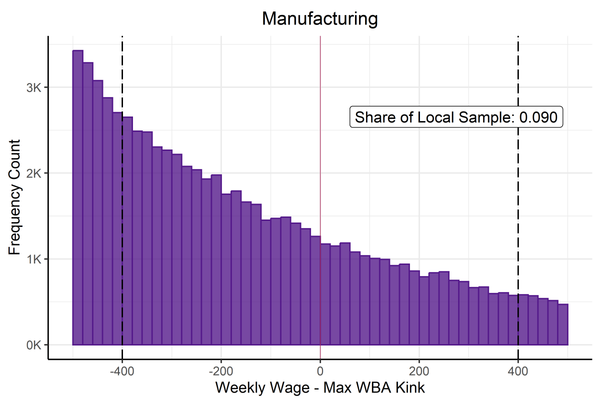
Note: This figure plots the share of job separations classified as a Job Loss in Panel (a), Labor Force Dropout in Panel (b), and Job-to-Job Transition in Panel (c) by normalized weekly wage for observations within \$500 of the kink in the benefit schedule. Points show averages for \$20 bins, the solid line shows the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect and elasticity are calculated as described in Section 4, with standard errors in parentheses.

Figure A.3: Distribution of Workers in Each Industry

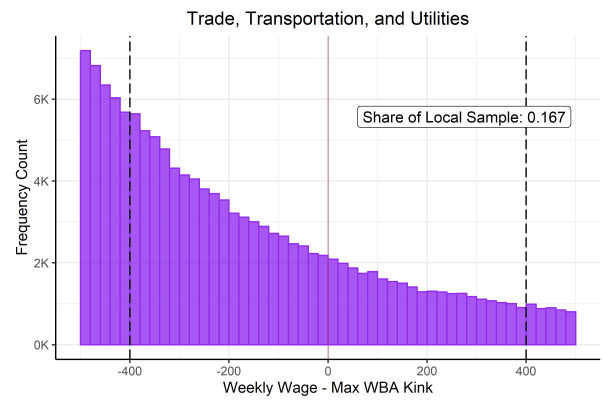


(a) Natural Resources and Mining

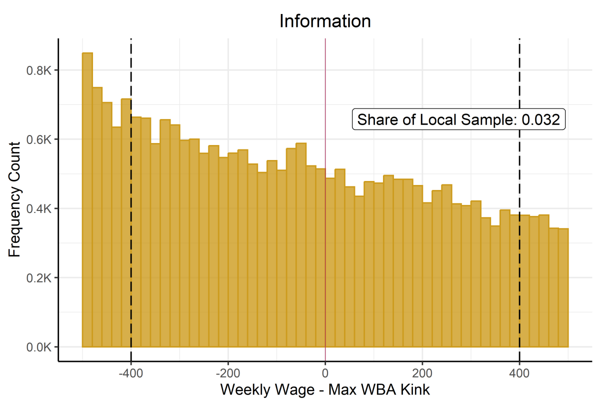
(b) Construction



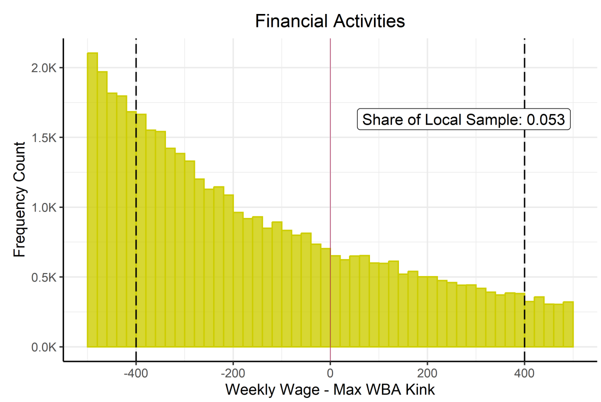
(c) Manufacturing



(d) Trade, Transportation, and Utilities

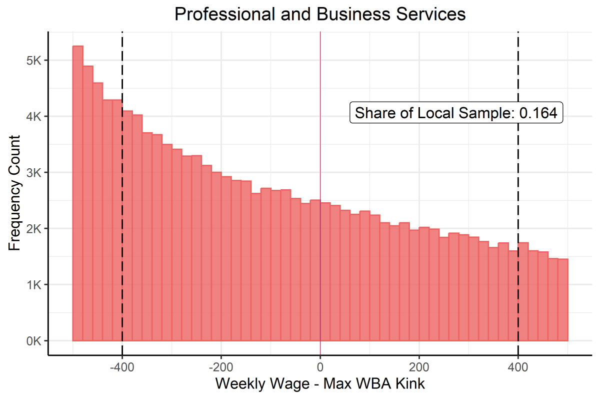


(e) Information

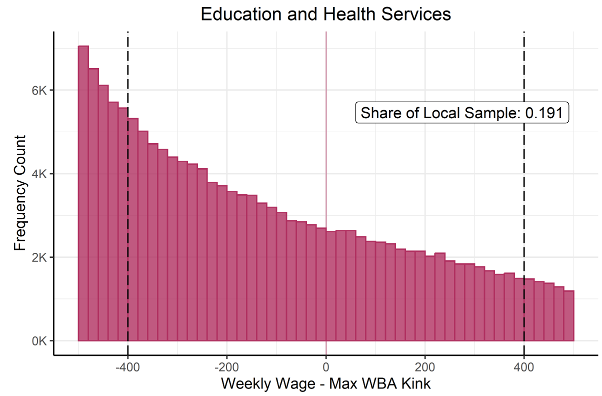


(f) Financial Activities

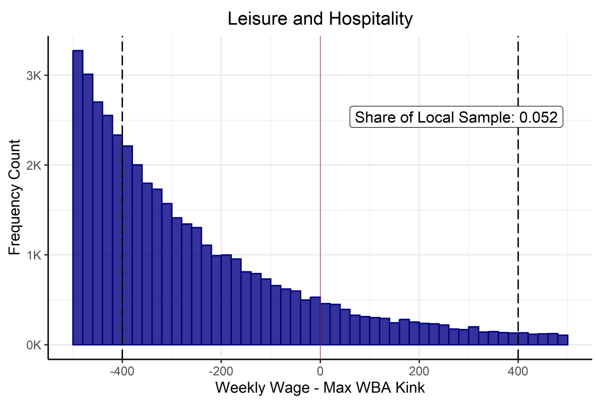
Figure A.3: Distribution of Workers in Each Industry (continued)



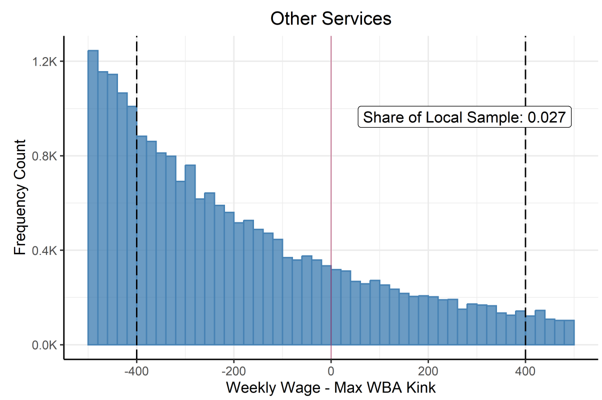
(g) Professional and Business Services



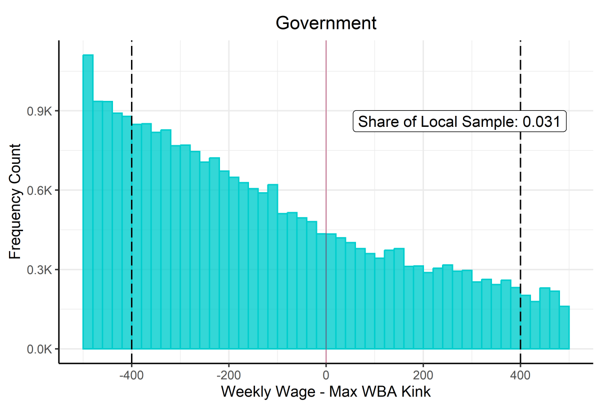
(h) Education and Health Services



(i) Leisure and Hospitality



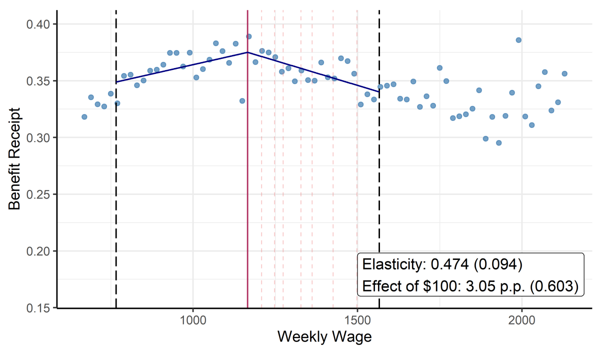
(j) Other Services



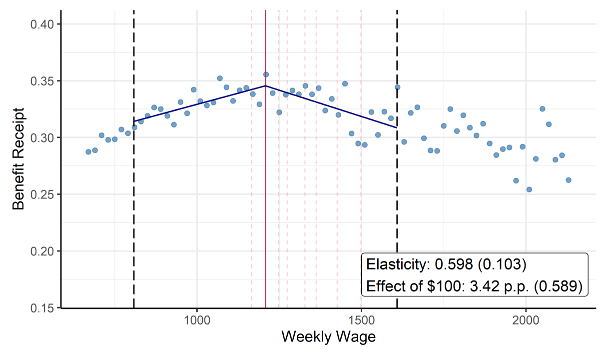
(k) Government

Note: This figure plots histograms of job loss by normalized weekly wage, separately by the workers' previous industry. Each panel reports the share of the local sample employed in that industry prior to job loss. Bars represent counts in $20 bins. The red line marks the kink, and dotted lines indicate bandwidths.

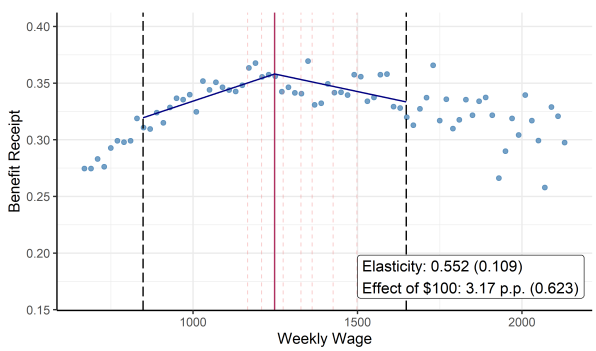
Figure A.4: Benefit Receipt by Year



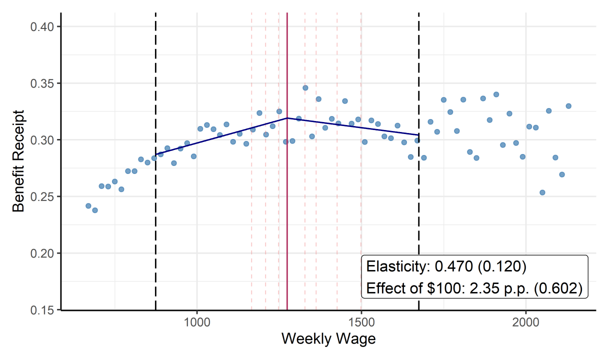
(a) FY 2011



(b) FY 2012

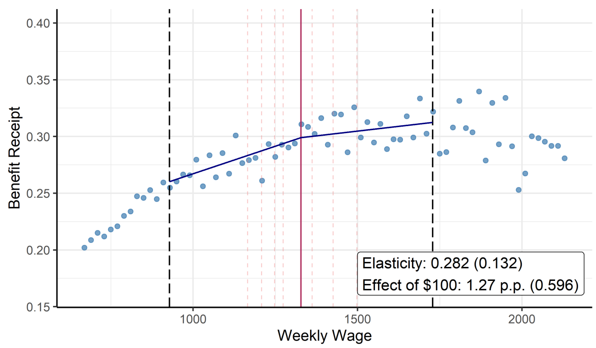


(c) FY 2013

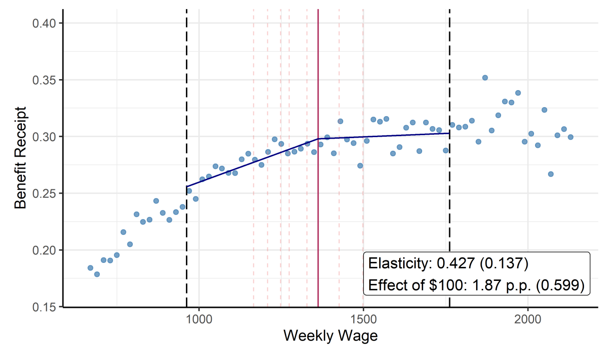


(d) FY 2014

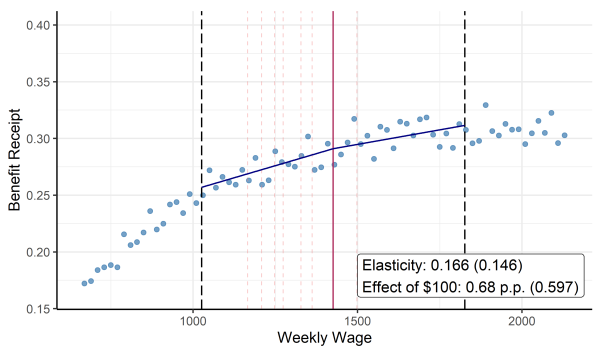
Figure A.4: Benefit Receipt by Year (continued)



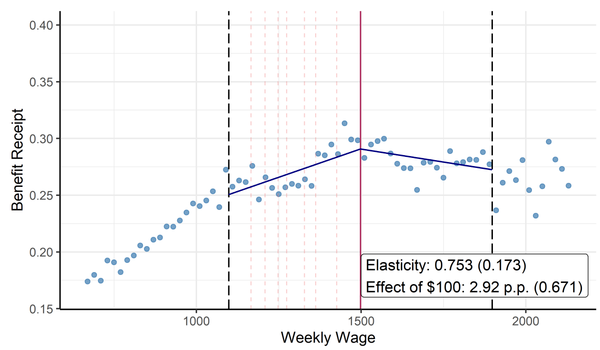
(e) FY 2015



(f) FY 2016



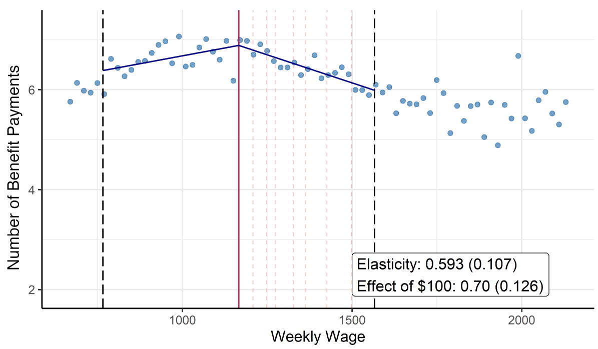
(g) FY 2017



(h) FY 2018

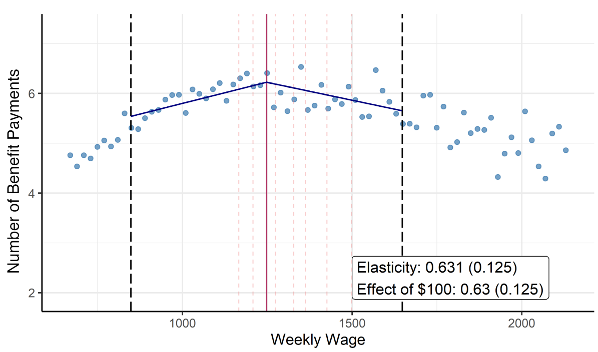
Note: This figure plots benefit receipt by normalized weekly wage for observations within $500 of the kink in the benefit schedule, separately for each year from 2011 to 2018. Points show averages for $20 bins, the dark blue line shows the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect and elasticity are calculated as described in Section 4, with standard errors in parentheses.

Figure A.5: Benefit Payments by Year

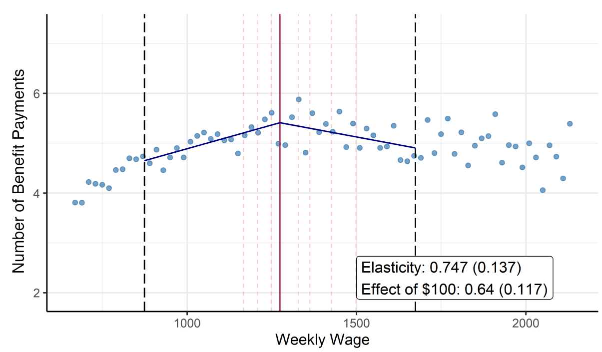


(a) FY 2011

(b) FY 2012

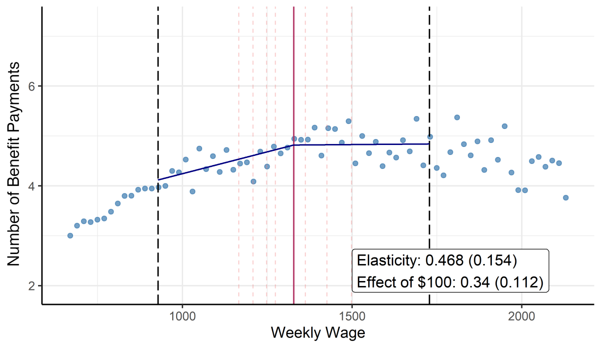


(c) FY 2013

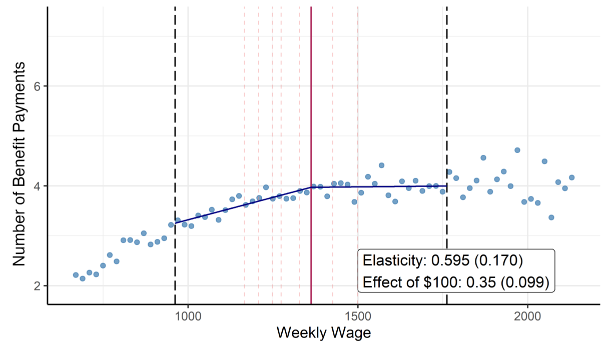


(d) FY 2014

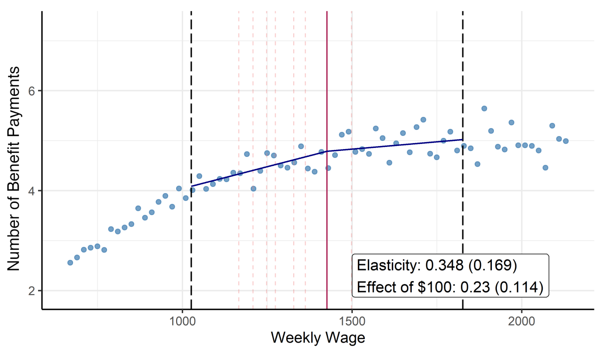
Figure A.5: Benefit Payments by Year (continued)



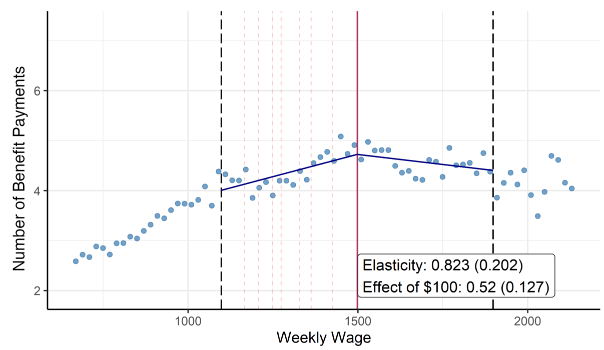
(e) FY 2015



(f) FY 2016



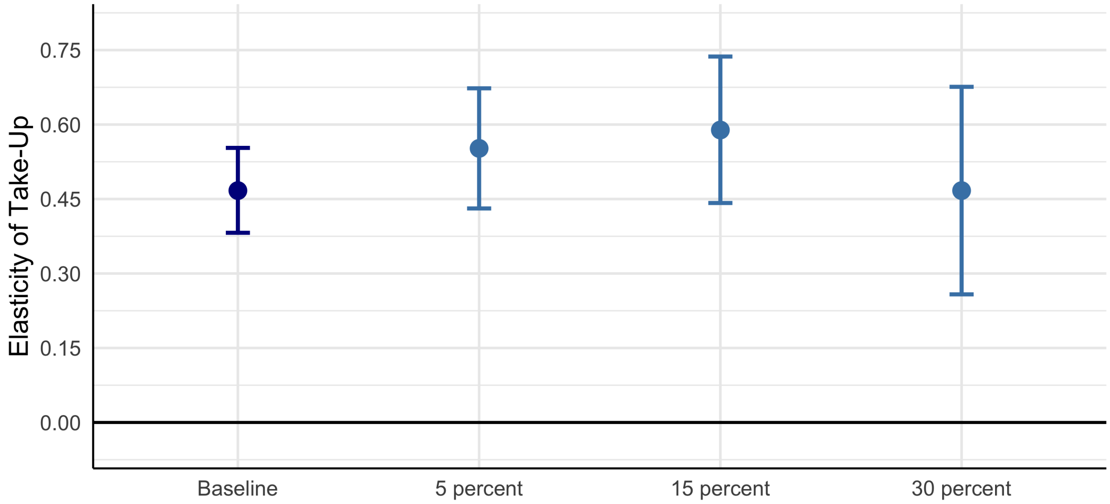
(g) FY 2017



(h) FY 2018

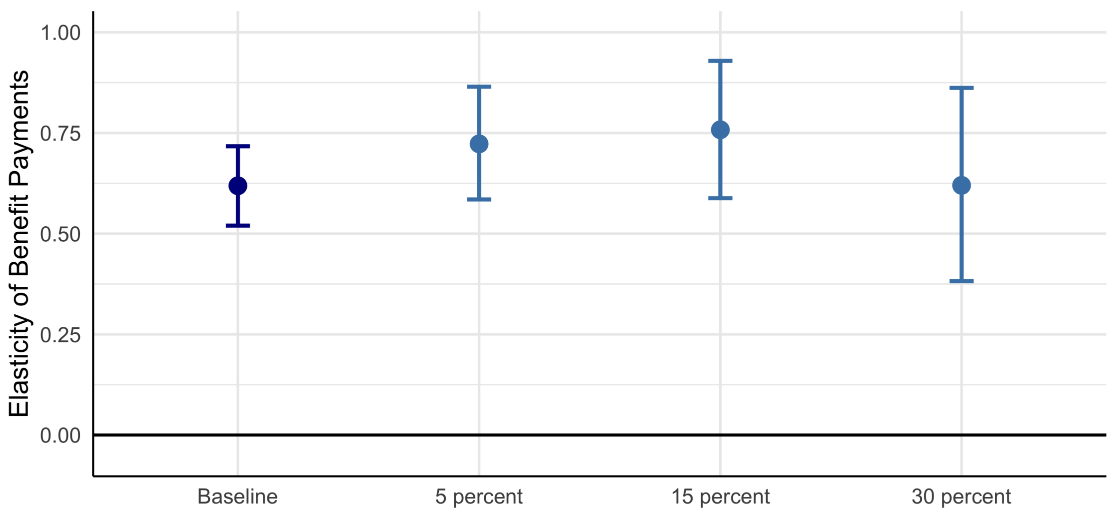
Note: This figure plots the number of benefit payments per job loss by normalized weekly wage for observations within $500 of the kink in the benefit schedule, separately for each year from 2011 to 2018. Points show averages for $20 bins, the dark blue line is the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect and elasticity are calculated as described in Section 4, with standard errors in parentheses.

Figure A.6: Elasticity of Take-up in Mass Layoff Samples



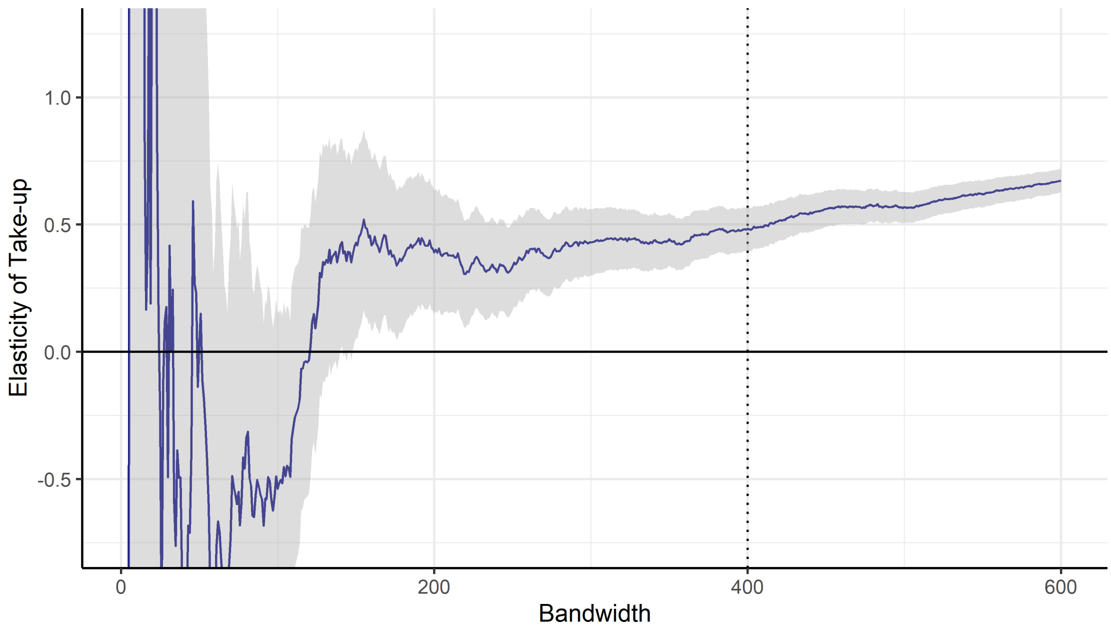
Note: This figure plots RKD estimates of the take-up elasticity in our baseline sample as well as in the mass layoff samples, varying the sufficient contract to be 5, 15, and 30 percent. Error bars represent 95 percent confidence intervals. The elasticity is calculated as described in Section 4, and construction of the mass layoff sample is detailed in Section 5.

Figure A.7: Elasticity of Benefit Payments in Mass Layoff Samples



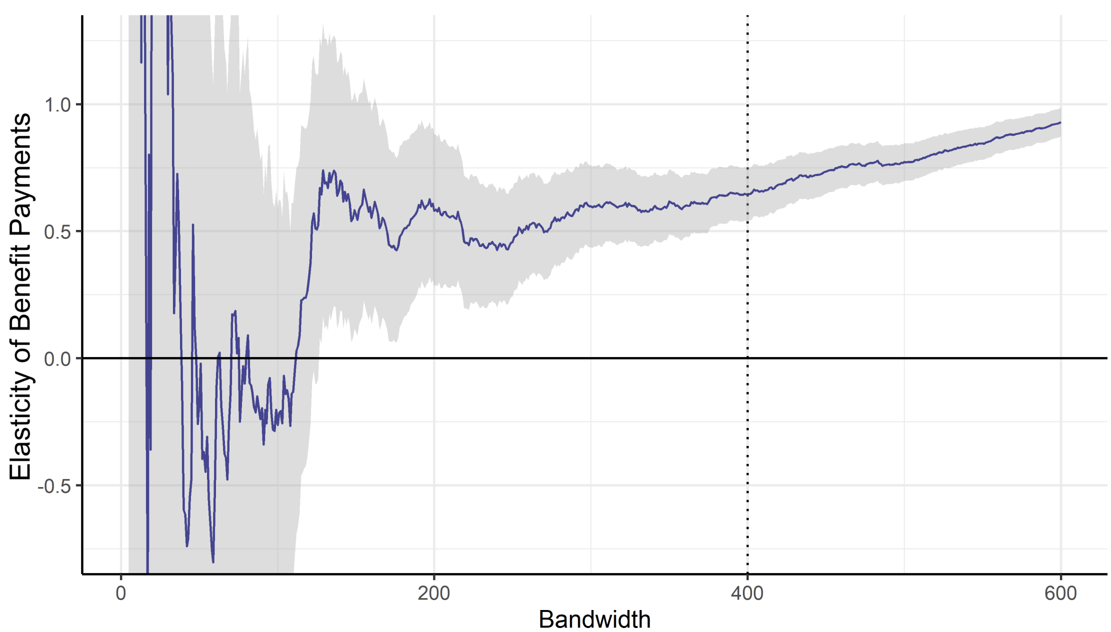
Note: This figure plots RKD estimates of the elasticity of benefit payments in our baseline sample as well as in the mass layoff samples, varying the sufficient contract to be 5, 15, and 30 percent. Error bars represent 95 percent confidence intervals. The elasticity is calculated as described in Section 4, and construction of the mass layoff sample is detailed in Section 5.

Figure A.8: Elasticity of Take-up by Bandwidth



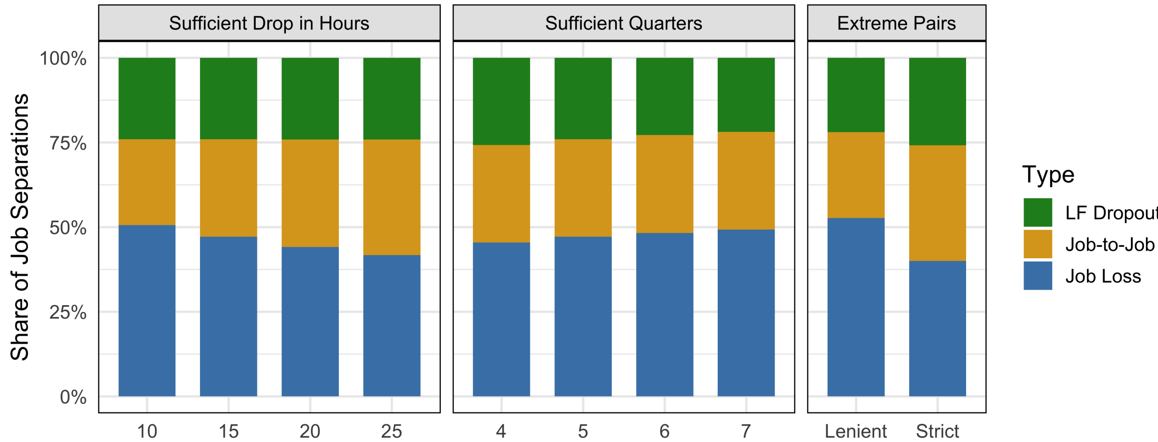
Note: This figure plots RKD estimates of the elasticity of take-up using bandwidths from \$5 to \$600. The shaded area represents the 95 percent confidence interval, and the dotted line marks the \$400 bandwidth used in our main estimates.

Figure A.9: Elasticity of Benefit Payments by Bandwidth



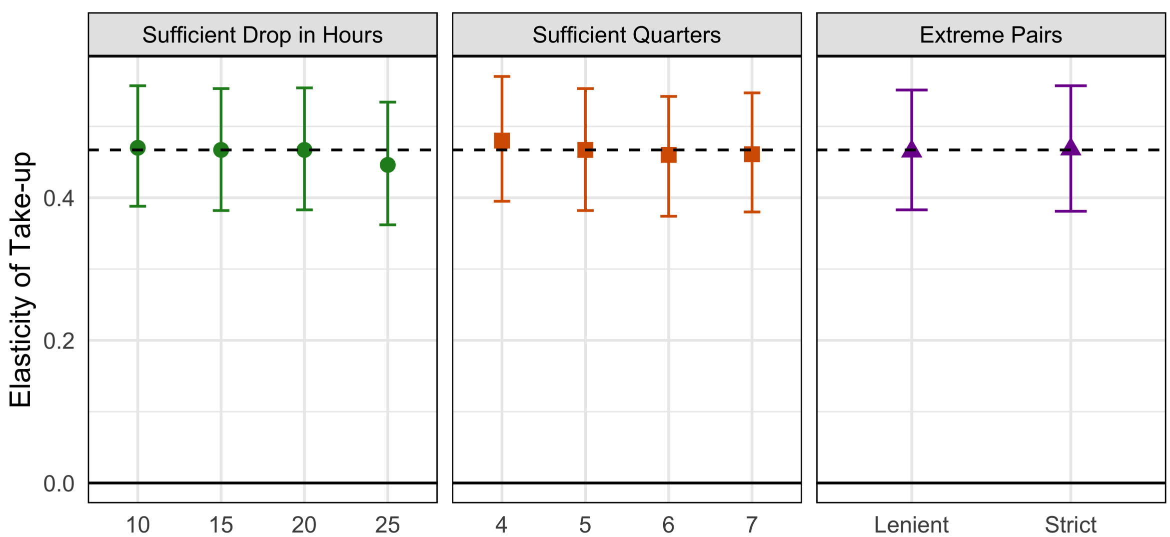
Note: This figure plots RKD estimates of the elasticity of benefit payments using bandwidths from \$5 to \$600. The shaded area represents the 95 percent confidence interval, and the dotted line marks the \$400 bandwidth used in our main estimates.

Figure A.10: Composition of Separations Across Job Loss Definitions



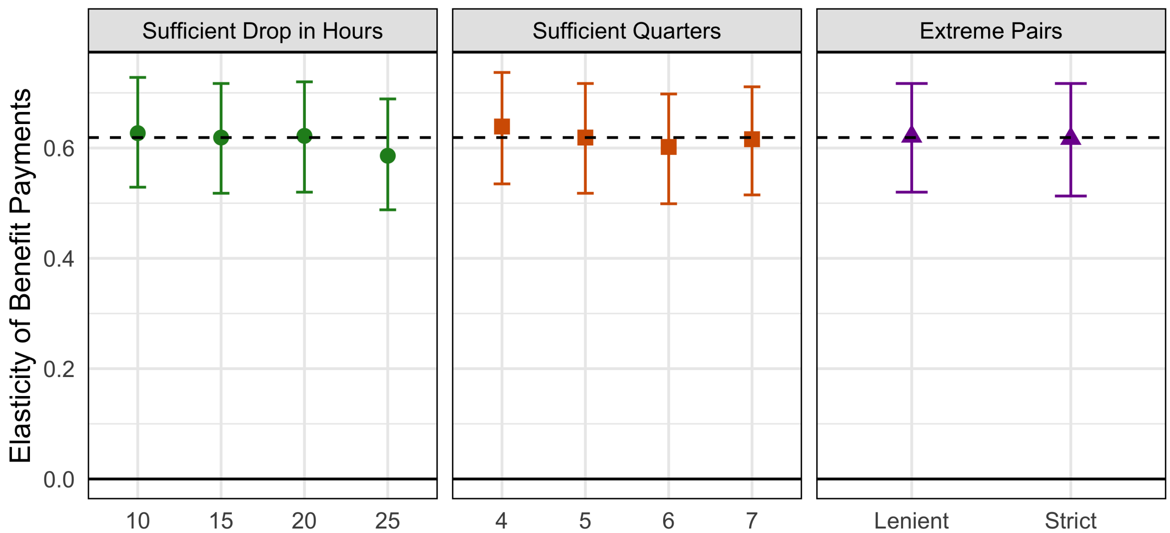
Note: This figure plots the share of job separations classified as a Job Loss, Job-to-Job Transition, and Labor Force Dropout while varying the parameters that define these classifications. Details on these parameters are provided in Section 5.

Figure A.11: Elasticity of Take-up Across Job Loss Definitions



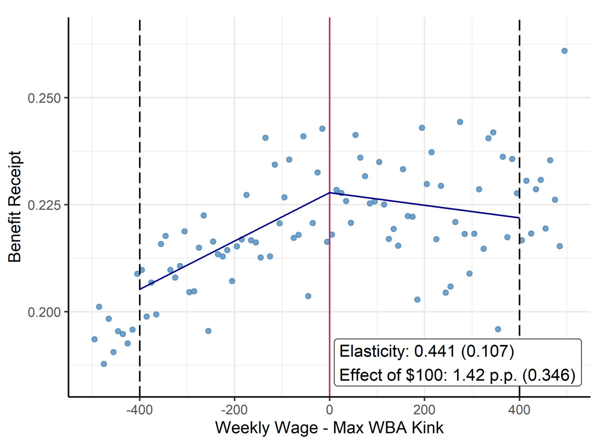
Note: This figure plots RKD estimates for the take-up elasticity while varying the parameters that define a job loss. Details on these parameters are provided in Section 5.

Figure A.12: Elasticity of Benefit Payments Across Job Loss Definitions

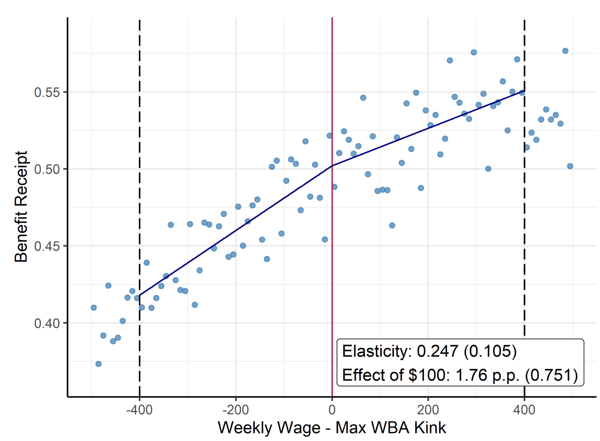


Note: This figure plots RKD estimates for the elasticity of benefit payments while varying the parameters that define a job loss. Details on these parameters are provided in Section 5.

Figure A.13: Benefit Receipt by Previous UI Experience



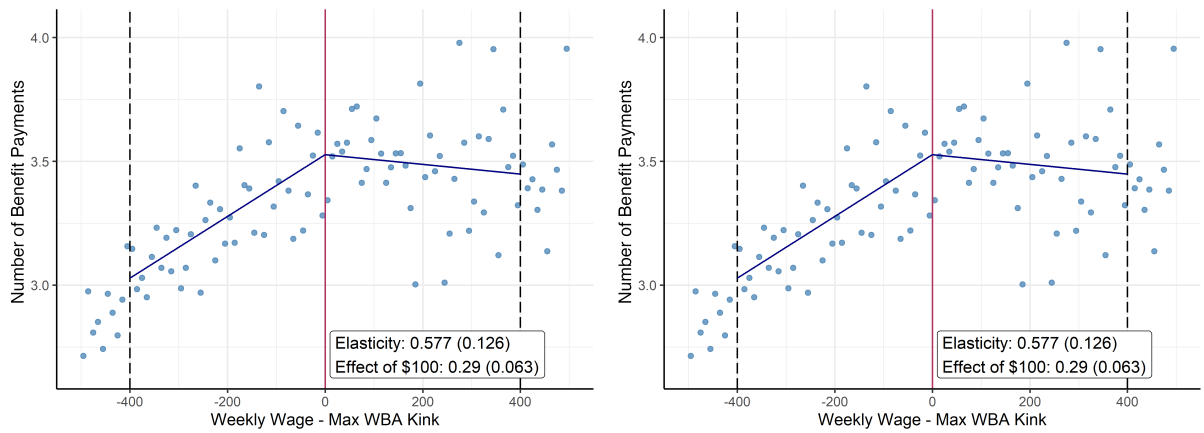
(a) Never applied before



(b) Previously applied

Note: This figure plots benefit receipt by normalized weekly wage for observations within $500 of the kink in the benefit schedule, separately by whether the worker had previously applied for UI benefits. Details on how we define previous UI experience are provided in Section 5. Points show averages for $20 bins, the dark blue line shows the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect and elasticity are calculated as described in Section 4, with standard errors in parentheses.

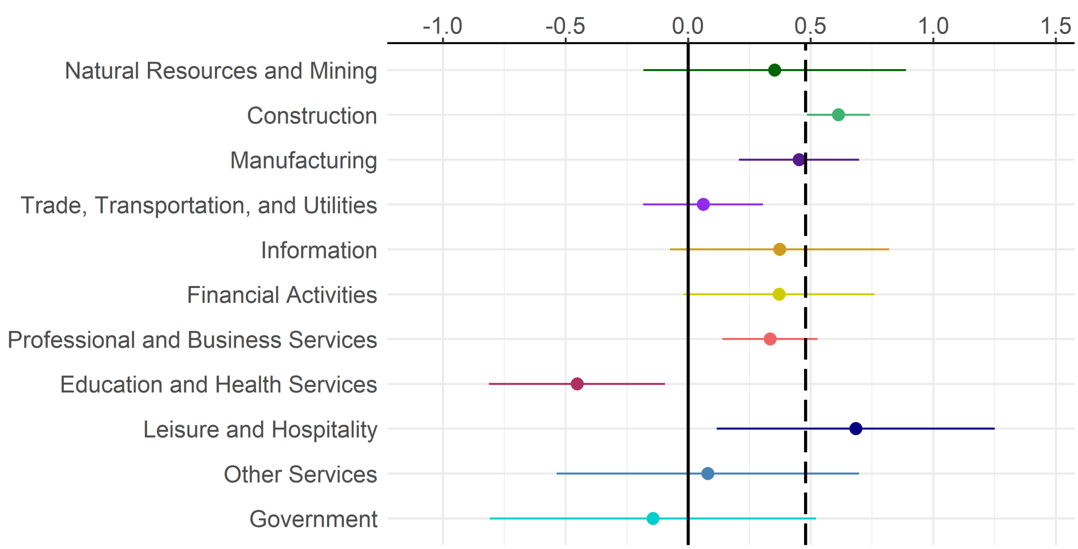
Figure A.14: Benefit Payments by Previous UI Experience



(a) Never applied before (b) Previously applied

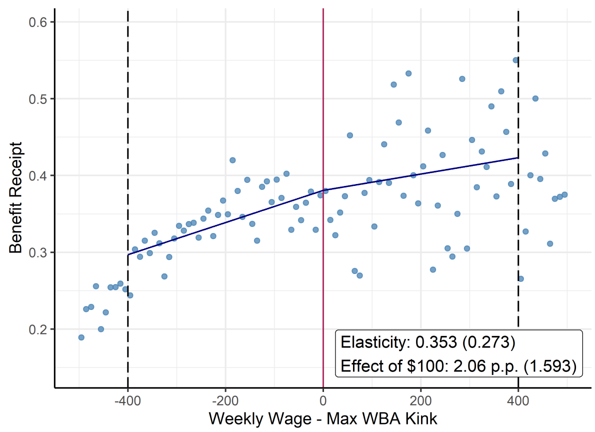
Note: This figure plots benefit receipt by normalized weekly wage for observations within $500 of the kink in the benefit schedule, separately by whether the worker had previously applied for UI benefits. Details on how we define previous UI experience are provided in Section 5. Points show averages for $20 bins, the dark blue line shows the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect and elasticity are calculated as described in Section 4, with standard errors in parentheses.

Figure A.15: Elasticity of Benefit Receipt by Industry

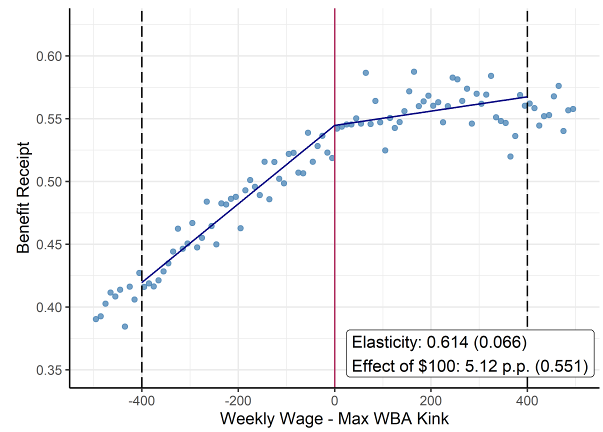


Note: This figures plots the RKD estimates for the take-up elasticity based on the industry of the previous employer. The elasticity is calculated as described in Section 4. Error bars represent 95 percent confidence intervals.

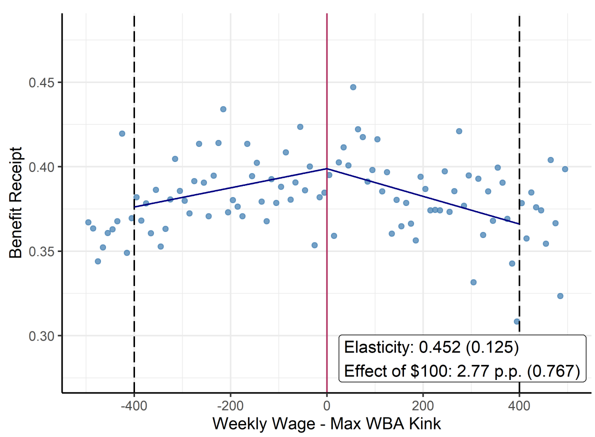
Figure A.16: Benefit Receipt by Industry



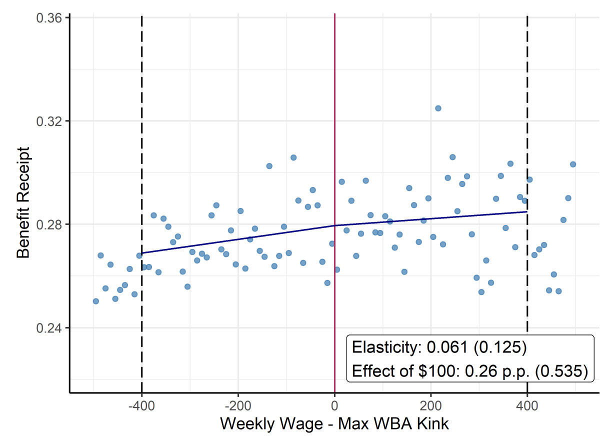
(a) Natural Resources and Mining



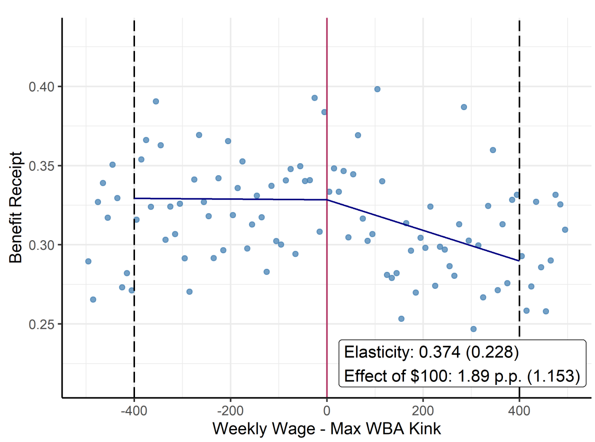
(b) Construction



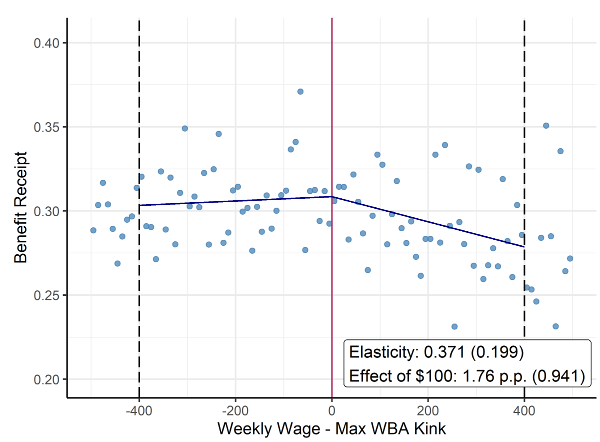
(c) Manufacturing



(d) Trade, Transportation, and Utilities

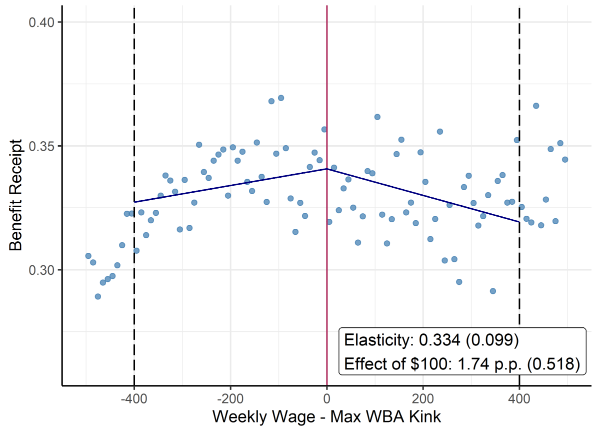


(e) Information

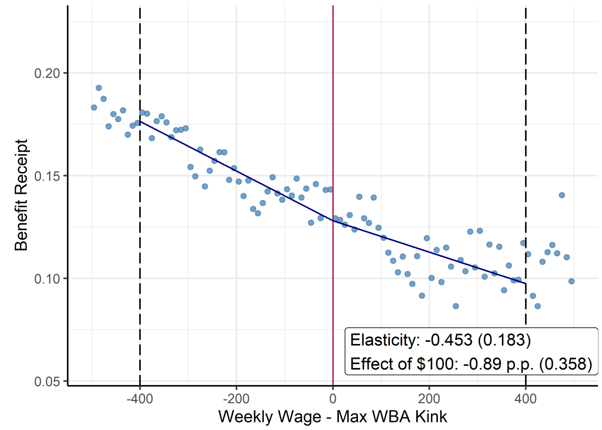


(f) Financial Activities

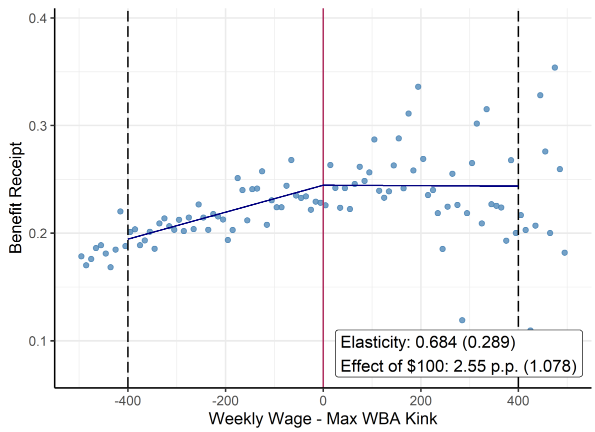
Figure A.16: Benefit Receipt by Industry (continued)



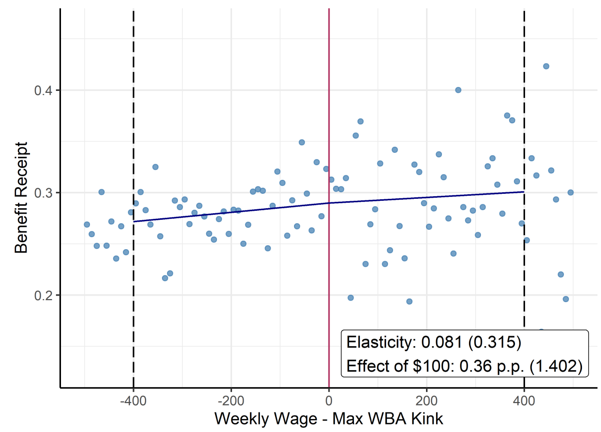
(g) Professional and Business Services



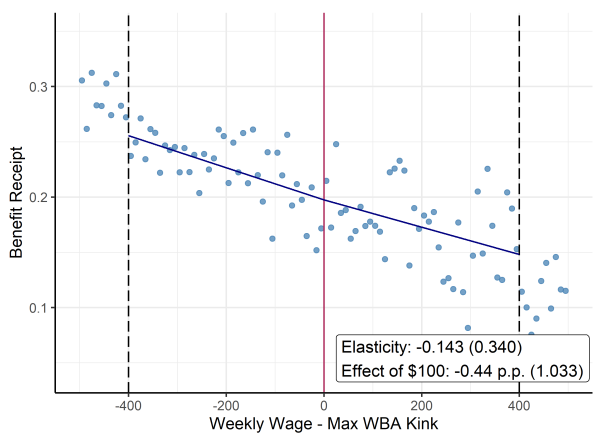
(h) Education and Health Services



(i) Leisure and Hospitality



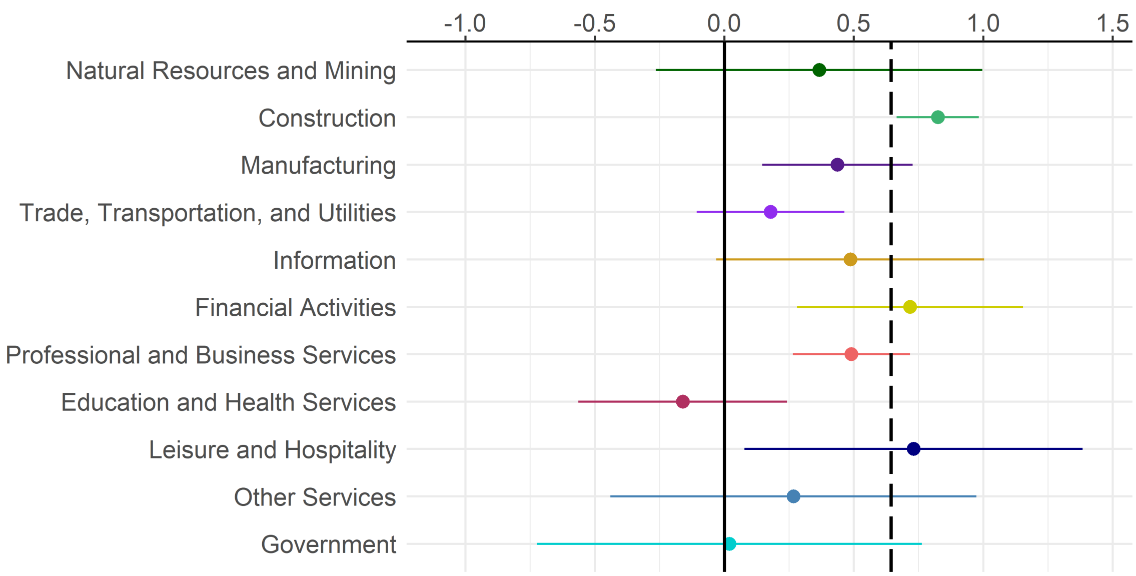
(j) Other Services



(k) Government

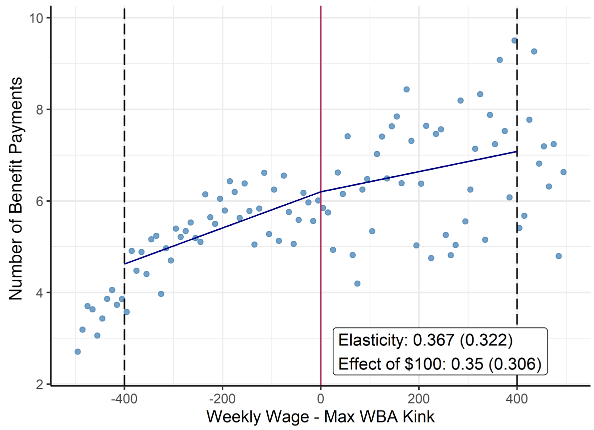
Note: This figure plots benefit receipt by normalized weekly wage for observations within $500 of the kink in the benefit schedule, separately by the industry of the worker's previous employer. Points show averages for $20 bins, the dark blue line shows the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect and elasticity are calculated as described in Section 4, with standard errors in parentheses.

Figure A.17: Elasticity of Benefit Payments by Industry

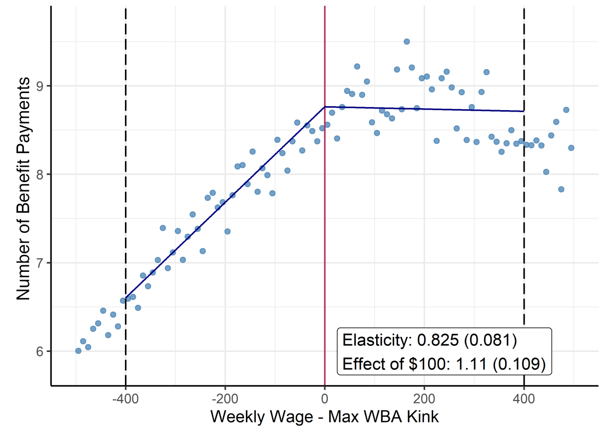


Note: This figures plots the RKD estimates for the elasticity of benefit payments based on the industry of the previous employer. The elasticity is calculated as described in Section 4. Error bars represent 95 percent confidence intervals.

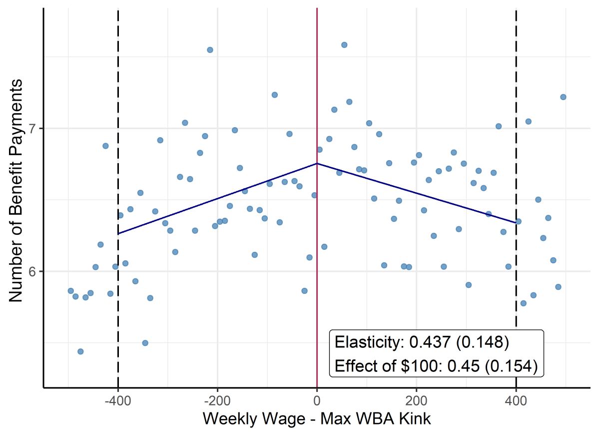
Figure A.18: Benefit Payments by Industry



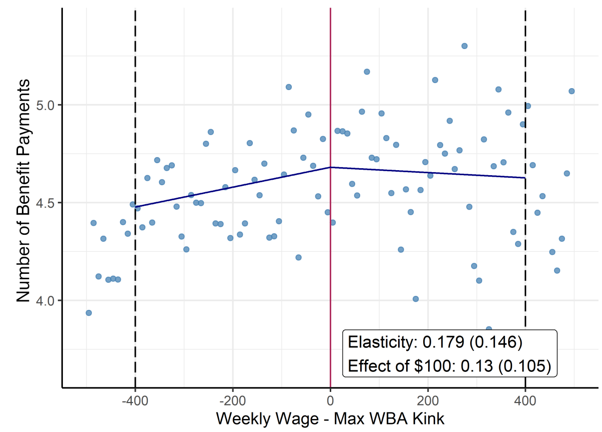
(a) Natural Resources and Mining



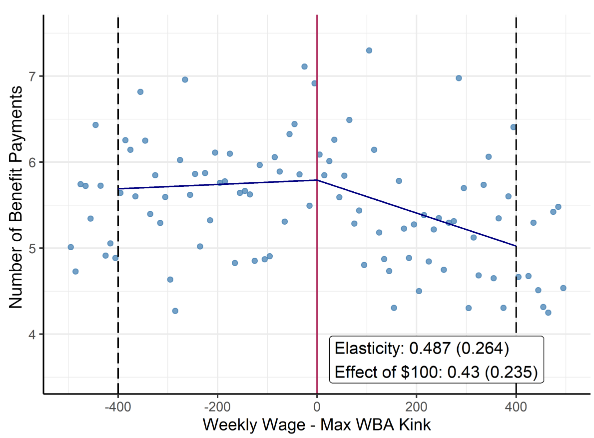
(b) Construction



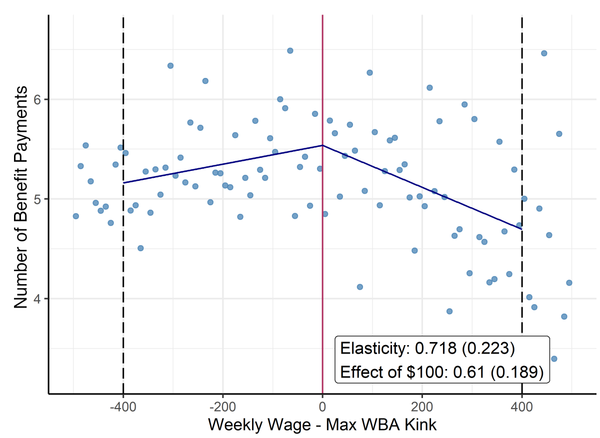
(c) Manufacturing



(d) Trade, Transportation, and Utilities

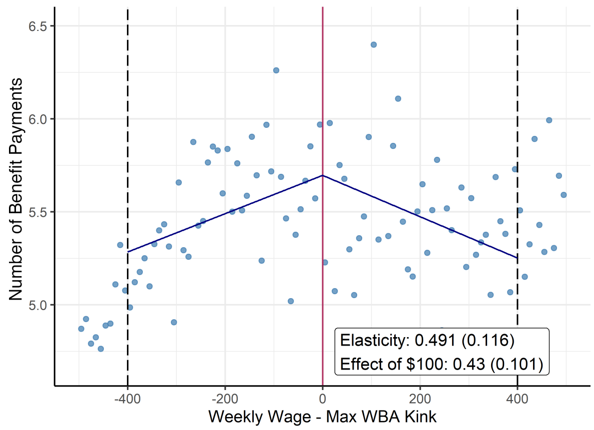


(e) Information

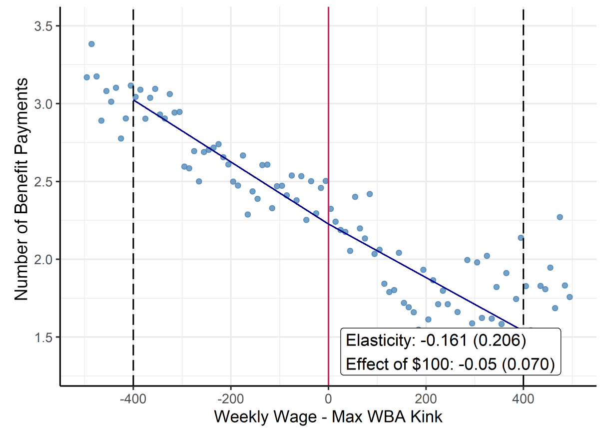


(f) Financial Activities

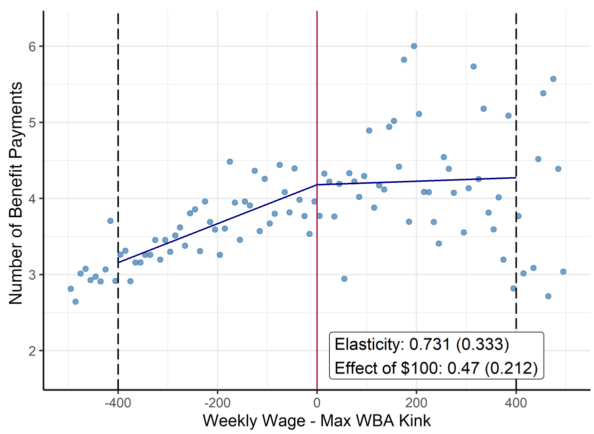
Figure A.18: Benefit Payments by Industry (continued)



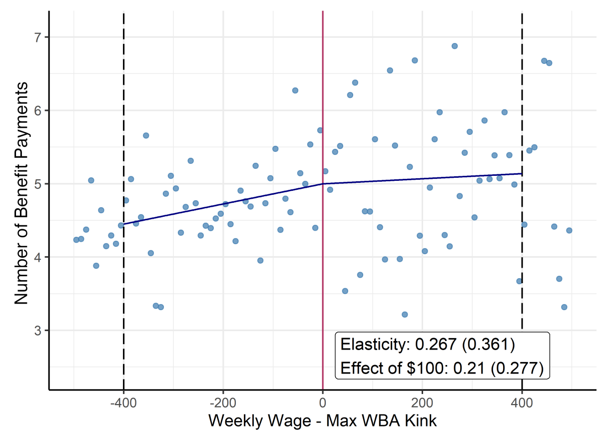
(g) Professional and Business Services



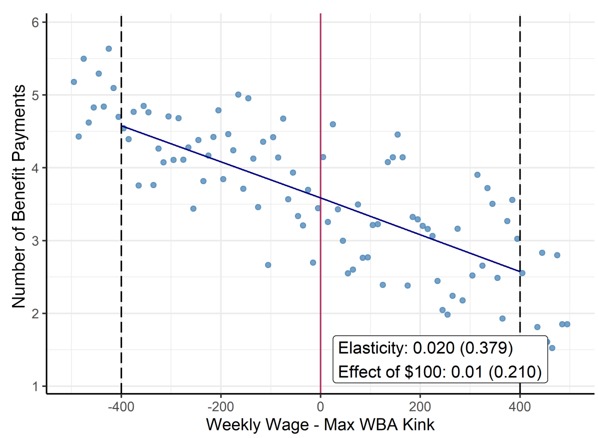
(h) Education and Health Services



(i) Leisure and Hospitality



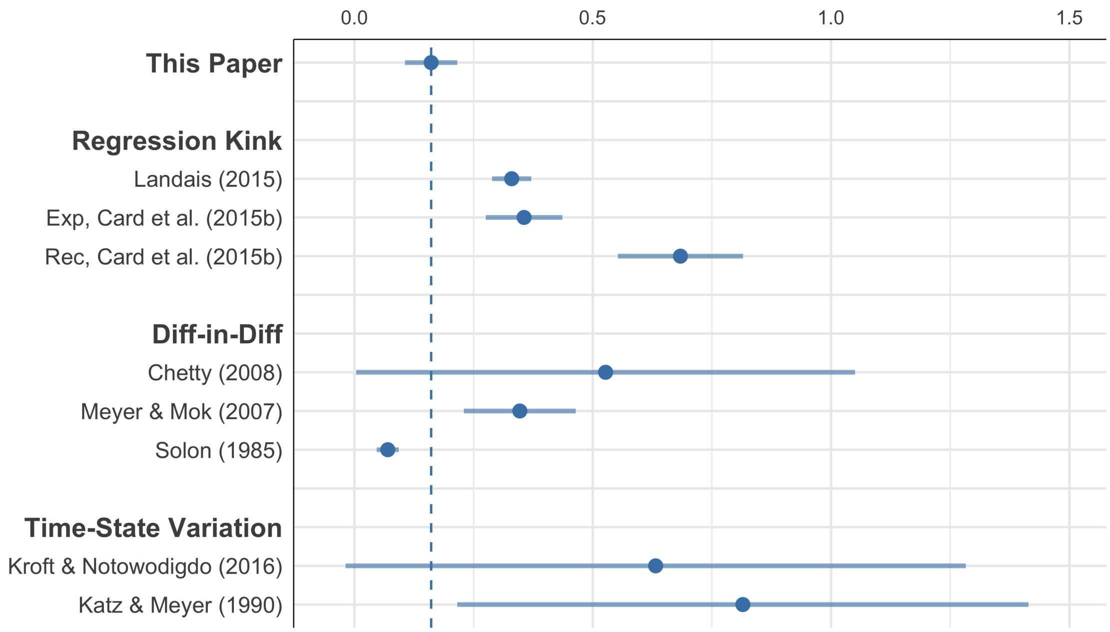
(j) Other Services



(k) Government

Note: This figure plots benefit payments by normalized weekly wage for observations within \$500 of the kink in the benefit schedule, separately by the industry of the worker's previous employer. Points show averages for \$20 bins, the dark blue line shows the fitted regression from Equation 5, the red line marks the kink, and gray dotted lines indicate bandwidths. The marginal effect and elasticity are calculated as described in Section 4, with standard errors in parentheses.

Figure A.19: Estimates of the Elasticity of Claim Duration



Note: This figure plots the elasticity of claim duration estimated in this paper alongside existing estimates from other papers and reported in Hendren and Sprung-Keyser (2020). Error bars represent 95 percent confidence intervals, while the dotted line marks the estimate from this paper.