Social Insurance with Imperfect Eligibility Screening: Theory and Evidence from Pandemic UI*

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Abstract

This paper studies social insurance with imperfect eligibility screening, focusing on Unemployment Insurance (UI) during its expansion in 2020 and 2021. We study the extent of imperfect screening by identifying anomalous payments using administrative tax data and UI policies, finding $214 billion in potentially-improper payments—concentrated in the Pandemic Unemployment Assistance (PUA) program—with approximately half detectable ex-ante through improved federal-state data sharing. There is substantial geographic variation, and a border design shows this is partly due to policy decisions made by states. To assess the implications for optimal policy, we first conduct simulations that replace PUA with means-tested, lump-sum transfers, finding that these transfers would have better insured against income losses at lower administrative cost. Second, we develop a model of opt-in versus automatic transfers that shows the targeting advantage of opt-in programs can reverse when ineligible recipients pass the benefit screen. Calibrated to 2020 UI, the model implies that shifting toward automatic transfers would have increased social welfare.

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1 Introduction

The U.S. government has invested considerable resources into identifying and eliminating "fraud, waste, and abuse" for over 150 years.[1] The Government Accountability Office (GAO) and Inspector General offices routinely estimate how much government spending is fraudulent or improper. Politicians and members of the public also regularly express concerns about wasteful spending.[2] Despite the public attention paid to this topic, canonical research on public benefit design devotes little attention to the issue of improper benefit receipt and its effect on optimal government policy (e.g., Currie, 2006; Ko and Moffitt, 2022).

This paper combines administrative data and theory to study benefit receipt among likely ineligible individuals in the context of expanded Unemployment Insurance (UI) in the United States in 2020 and 2021. We use comprehensive linked tax administrative data and UI program rules to first provide new evidence on the size and nature of "anomalous" UI payments—those going to likely ineligible individuals—and their relationship with state UI policies. Then, we analyze the targeting properties (i.e., how well benefits reach individuals with the greatest need) of expanded UI by studying how effective UI was at preventing large income losses relative to counterfactual automatic payments made to individuals with low levels of 2019 income. Finally, we develop a model to study how benefit receipt among ineligibles affects the optimal government allocation of resources to programs that require individuals to opt-in (like UI) versus automatic transfers. We calibrate this model using our administrative records and other data we collect to measure the welfare consequences of shifting resources away from UI during this period.

We study one of the most dramatic expansions of government benefit programs in recent history. In response to the pandemic and government-imposed shutdowns in 2020, Congress allocated over $650 billion for new UI spending. In addition to increasing benefits available through the reg-

[1] The False Claims Act was passed in 1863 to eliminate fraud during the Civil War and is still used for so-called "whistleblower" claims.

[2] For example, respondents to a 2011 Gallup poll reported that on average 51 cents of every tax dollar spent by the federal government is wasted, with little difference by respondents' political affiliation. See `https://news.gallup.com/poll/149543/americans-say-federal-gov-wastes-half-every-dollar.aspx`, accessed November 11, 2025.

ular UI program, Congress created the Pandemic Unemployment Assistance (PUA) program to provide benefits to a broader range of individuals who were not eligible for regular UI, such as those who were self-employed. UI program rules, including in-person identity verification and job search requirements, were also relaxed. Moreover, the American Rescue Plan (ARP) Act of 2021 excluded up to $10,000 of UI income from federal taxes in 2020, leading to fewer incentives for victims to report UI fraud. Supporters argued that these policy changes were necessary for addressing clear economic hardship, but some members of Congress have since described fraud in these UI programs as "the greatest theft of taxpayer dollars in American history" (U.S. Congress, House Committee on Ways and Means, 2023). Congress also provided automatic payments to individuals via Economic Impact Payments (EIPs), known as stimulus checks. The EIP benefit amount did not depend on income losses during 2020. Because EIP eligibility was straightforward to determine, there was little scope for these benefits to be paid to ineligible individuals. These program features raise the possibility that expanded UI programs more effectively replaced lost income than EIPs at the cost of higher payments to ineligible individuals.

To shed light on these issues, we start by using tax data to provide a comprehensive analysis of UI payments going to likely ineligible recipients in 2020 and 2021. Our data include Form 1099-G reports from state governments on UI payments associated with each taxpayer identification number (TIN, which in most cases is a Social Security number), as well as administrative records on earnings and place of residence and work. We identify anomalous UI payments by matching provisions of UI program rules to conditions observed in the data. For example, we flag a UI payment if the intended recipient is deceased according to Social Security Administration records. We use several other criteria that depend on taxpayers' TIN type, age, incarceration status, history of working or living in a state issuing a UI payment, and history of income and employment. Administrative tax data do not allow us to perfectly assess whether a UI payment is fraudulent or improper, and we use the words "anomalous" and "likely ineligible" to indicate a payment that is questionable from the standpoint of the government making the UI payment. Our approach surely leads to misclassified payments, though this misclassification occurs in both directions.

We estimate that \$214 billion of UI payments went to likely ineligible individuals, amounting to 24% of all UI payments during this period. Many UI payments went to individuals lacking any earned income in 2019 and 2020, experiencing no disruption in employment or decrease in their earned income in 2020, and not having a history of working or living in the state that paid benefits. Approximately half of all likely ineligible payments could have been identified before funds were disbursed if state UI agencies had timely access to tax data or similar information available in nationwide records. Moreover, anomalous UI payments are disproportionately concentrated in the PUA program, with 45% of all payments made through the PUA program being anomalous. By comparison, the rate of anomalous payments in the regular UI program is considerably smaller, at 15%, suggesting that the regular UI program performed relatively well despite the 10-fold increase in claims during the peak of the pandemic.

Our data also allow us to describe how likely ineligible UI benefits are distributed across individuals and geography.[3] Anomalous UI payments are associated with a wide range of individuals, but concentrated in people with lower amounts of 2019 earned income. Moreover, likely ineligible UI payments are concentrated in certain ZIP codes, with the top 1% of ZIP codes accounting for 22% of all such payments. By comparison, the top 1% of ZIP codes account for 13% of non-anomalous UI payments and 8% of total population. These results are consistent with concentrated fraudulent activity driving part of the anomalous UI payments we identify.

Likely ineligible UI benefits vary widely across states, which have considerable leeway in setting UI rules and procedures. For example, total anomalous UI benefits in 2020 and 2021 per working age individual were \$1,197 in Massachusetts and \$231 in New Hampshire, and the share of all UI payments classified as anomalous in these two contiguous states is 20% vs. 13%. To help isolate the role of state UI policies from that of state economic conditions, we use a cross-state border design that compares outcomes in ZIP codes on opposite sides of a state border, which face similar conditions but different UI policies. We find that each dollar of non-anomalous UI benefits leads to an \$0.90 increase in anomalous UI benefits in the PUA program, suggesting

[3]Tax data allow us to identify the intended recipient of UI benefits from a state's perspective. The actual recipient may differ in cases of identity theft.

that states struggled to distinguish legitimate from illegitimate PUA claims. In contrast, there is no significant relationship between non-anomalous and anomalous benefits in the regular UI program, where states have long-established procedures for assessing claims. We also find that the share of PUA payments that are likely ineligible is strongly increasing in states' pre-pandemic UI fraud rate and the percentage of UI claims that were approved during the pandemic—highlighting important roles for states' program integrity and operational decisions.

Assessing the effectiveness of expanded UI programs requires a broader analysis beyond the size of payments going to likely ineligible individuals. To that end, we measure the extent to which likely eligible UI payments acted as insurance (replacing lost earnings relative to 2019) versus a transfer (increasing total income relative to 2019). We find that while the regular UI program functioned primarily as insurance, the PUA program was primarily an income transfer, with most likely eligible payments increasing income in 2020 relative to 2019. To evaluate targeting more systematically, we study how effective UI was at preventing large income losses relative to a counterfactual set of automatic transfers not specifically targeted to individuals who experienced earnings losses. Focusing on 2020, we estimate that 25.2% of the individuals in our data with positive 2019 earned income experienced, net of any UI benefits associated with their TIN, a decrease in earnings of 10% or more. In a counterfactual scenario that eliminates all likely ineligible UI payments, redistributes the funds to individuals with the lowest amounts of 2019 earned income (in absolute value), and provides benefits equal to the smaller of individuals' 2019 earned income and $10,000, the share of people with a large income loss would fall to 19.5%. While eliminating all anomalous UI payments was not a feasible policy, eliminating PUA and redistributing the resulting money in the same manner would achieve a similar improvement. These counterfactuals also increase the total amount of dollars that replace income lost between 2019 and 2020. Counterfactuals with smaller, but more broadly distributed, EIP-level payments also see improved outcomes. Thus, our results suggest that alternative policies, including those more easily administered through the Internal Revenue Service (IRS), could have lowered improper UI payments and at the same time provided better insurance against lost earnings. Moreover, such policies could have provided benefits to individuals more quickly, lowered administrative costs, and reduced distortionary impacts of UI on labor supply.

In the final part of the paper we develop a theoretical model to formalize how improper payments change the optimal allocation of resources to programs that provide automatic benefits (as with EIPs) or require individuals to apply (as with UI) for a government that cannot perfectly observe individuals' eligibility for opt-in benefits. We consider a budget-neutral reform that lowers the UI benefit amount and redistributes the saved funds via automatic transfers. Improper benefits have two distinct effects in this model. First, they can change the targeting consequences of shifting resources from UI to automatic transfers. For example, the presence of ineligible UI recipients who are better-off provides an incentive for shifting resources away from UI to automatic transfers. Second, the government can directly care about the overall amount of UI benefits paid to ineligible individuals. The net effect of these two forces is ambiguous and depends on empirical moments.

Our calibration of the model implies that it would have been welfare-enhancing to reduce UI benefits in 2020. This occurs because UI benefits in 2020 were very generous, leading UI recipients to have lower marginal utilities of consumption than the general population. The welfare gain from lowering UI benefits is increasing in the government's distaste for payments to ineligible recipients. For example, when calibrating this distaste based on responses from the senior staff responsible for UI issues in the House of Representatives and Senate, we find that the welfare gain from a marginal decrease in UI is 62% larger under the Republican distaste for improper UI than the Democratic distaste.

This paper contributes to three related areas of research. First, a large literature studies what types of people receive opt-in benefits and how take-up depends on program features (e.g., Currie, 2006; Ko and Moffitt, 2022; Rafkin, Solomon and Soltas, 2024), including recent studies of how application costs affect the take-up of benefits among eligible individuals and the resulting targeting efficiency (e.g., Deshpande and Li, 2019; Finkelstein and Notowidigdo, 2019). We contribute to this literature by providing comprehensive empirical evidence on the extent and distribution of payments to likely *ineligible* recipients in the context of the important pandemic UI programs. We also provide evidence on the targeting performance of counterfactual policies that shift resources from opt-in to automatic transfers.

Second, our model contributes to the theoretical literature studying opt-in benefit programs in settings where the government has imperfect information about applicants. One important strand of this work emphasizes that opt-in programs with costly applications can dominate automatic transfers if they incentivize more needy eligible individuals to apply (e.g., Nichols and Zeckhauser, 1982; Besley and Coate, 1992). A second strand recognizes that, because the government cannot perfectly verify eligibility, opt-in programs will inevitably attract some ineligible applicants, and analyzes how costly application requirements can minimize this (Kleven and Kopczuk, 2011).[4] Our model takes imperfect eligibility verification as given and provides a unified analysis of how ineligible receipt interacts with self-targeting. We show that the targeting advantage of opt-in programs is weakened when a sufficient share of benefits accrues to ineligible, less needy recipients. Moreover, quantifying our model requires a small number of statistics that are intuitive and readily estimable. We provide evidence on the sole exception—policymakers' attitudes toward ineligible payments—using a survey connected to our theory. The framework is applicable to evaluating opt-in versus automatic transfer trade-offs across a wide range of safety net programs beyond pandemic UI.

Finally, we contribute to the growing literature on fraud and improper payments in government programs. Several recent papers study how monitoring technology and screening requirements affect fraud and administrative costs, including in healthcare (Shi, 2024; Eliason et al., 2025) and the Paycheck Protection Program (Aman-Rana, Gingerich and Sukhtankar, 2026). Khetan et al. (2024) use a novel dataset of high frequency debit card transactions to identify UI fraud. Moreover, several government organizations have estimated the amount of improper and fraudulent UI payments during the pandemic (U.S. Department of Labor, 2023*a*; U.S. Department of Labor Office of Inspector General, 2023; U.S. Government Accountability Office, 2023). Much of this literature focuses on how to reduce fraud within a given type of program. Our model instead analyzes

[4] Fuller, Ravikumar and Zhang (2015) study how to deter UI benefit receipt among employed individuals using a combination of monitoring and taxes and benefits that vary over time.

the optimal allocation of resources to opt-in vs. automatic transfers when ineligible recipients are present. Our empirical results show how payments to likely ineligible recipients vary with features of state UI systems and quantify the relationship between payments received by likely ineligible and eligible individuals. We find that several counterfactual policies could have reduced anomalous UI payments, while simultaneously lowering administrative costs and improving insurance against income losses.

2 Background: Unemployment Insurance during the Pandemic

The spread of COVID-19 and accompanying stay-at-home orders in 2020 brought an unprecedented halt to the global economy. The U.S. unemployment rate increased to 14.8% in April 2020, the highest since the Great Depression, and remained higher than pre-pandemic levels until early 2022. The suddenness and depth of the crisis prompted an urgent and large policy response, and the U.S. government authorized around $5 trillion in spending that went to individuals, businesses, hospitals, and local governments.

One of the most important responses was the expansion of UI, a joint state-federal program that provides financial assistance to individuals who lose a job though no fault of their own. The federal government mandates a minimum set of program parameters and provides some funding, but states set their own benefit amount generosity and eligibility criteria. Most states replace between 30% and 60% of prior wages, for up to 26 weeks. All states require individuals to accumulate sufficient work history with an employer and to look and be available for work. Hence, individuals who are self employed or have little attachment to the labor market are generally not eligible for regular UI. Finally, each state administers their own UI program, leading to variation in application and approval processes.

The Coronavirus Aid, Relief, and Economic Security (CARES) Act of March 2020 changed UI significantly. First, unemployed workers became eligible for an additional $600—later this became $300—in weekly benefits under the new Federal Pandemic Unemployment Compensation (FPUC) program, bringing the replacement rate to above 100% for many low-wage workers (Ganong, Noel and Vavra, 2020). Second, those who had exhausted their benefits became eligible for an additional 13 weeks of benefits under the new Pandemic Emergency Unemployment Compensation (PEUC) program. Third, the government created the Pandemic Unemployment Assistance (PUA) program, which provided unemployment benefits to some individuals who were not eligible under the regular UI program, such as employees who did not meet the work history requirement, self-employed individuals, and those who quit their job as a direct result of COVID-19. Importantly, PUA was only available to individuals who experienced a decrease in earned income (including job loss), and thus required individuals to have worked prior to the pandemic.[5] Exceptions to this rule were only for individuals unable to start a previously accepted job because of the pandemic or individuals who were not working but whose primary worker in the household died because of COVID-19. Finally, the American Rescue Plan (ARP) Act of 2021 changed the tax treatment of UI. UI income generally is subject to federal income tax, which incentivizes taxpayers who get a 1099-G indicating fraudulent UI payments made in their name to report the identity theft.[6] The 2021 ARP excluded up to $10,000 of UI income from federal taxes in 2020 for taxpayers with adjusted gross income of $150,000 or less, resulting in lower incentives to report fraudulent payments.

The depth of the economic crises and changes in UI benefits and eligibility generated a surge in UI claims that overwhelmed many states. This led to increased risk of improper payments, defined by the Department of Labor (DOL) as any payment that should not have been made or was made in the incorrect amount, which includes but is not limited to fraud. The increase in benefit levels made it more valuable for individuals and organized crime to target and exploit the UI program. The risk of improper payments was particularly high for PUA because eligibility could frequently be self-certified and much of the required application documentation could be easily falsified. States had limited ability to implement anti-fraud measures to verify UI claims due to the large increase in

[5]Being unemployed because the pandemic made it difficult to find a job was not sufficient for gaining eligibility under PUA (DOL UI Program Letter No. 16-20, Attachment I).

[6]Even if they do not receive a 1099-G, taxpayers will likely learn about the UI payments from an Automated Underreporter notice sent by the IRS that indicates income may have been unreported on their tax return (as identified through document matching).

claims and limited data available for this purpose, especially for PUA (U.S. Department of Labor Office of Inspector General, 2023).

3 Measuring Likely Ineligible UI Payments

3.1 Data

We use administrative tax data from the Internal Revenue Service (IRS) for calendar years 2018–2021. We merge data from several tax forms. First, we use data from Form 1099-G (including any corrections), which includes information on yearly UI benefit payments from each state. Second, we use Form W-2 to measure wage and salary income. Third, we obtain data on various earned income sources from Form 1040, including Schedules C, F, and SE for self-employment. Fourth, we use data from Forms 1099-MISC, 1099-NEC, and 1099-K to obtain information on nonemployee or related compensation (e.g., income received as a contractor). Fifth, we use information on the address of the individual and employer or contractee, when applicable, from all of the above tax forms and Forms 1095-A, 1095-B, and 1095-C (which cover all individuals with health insurance). Sixth, we use Social Security data on date of birth, date of death, disability benefits, current immigration status, and valid Taxpayer Identification Number (TIN) status. Seventh, we use data from Form 1095-C to obtain monthly information on nonemployment spells. Employers with at least 50 full-time equivalent employees are required to provide this information to comply with provisions of the Affordable Care Act, and we impute nonemployment spells for individuals who work at smaller employers, as described below. Finally, we use data on all incarceration spells in state and federal prisons reported annually to the IRS by states and the federal government for the purpose of identifying tax fraud. We use a random 10% sample for all our analysis and obtain aggregate estimates by multiplying totals from our data by 10.

These data identify the TIN associated with a UI payment, but do not measure who actually received the payment. For example, if an individual's identity was stolen and used for a fraudulent UI application, that person would have a Form 1099-G UI payment associated with their TIN, even if they did not receive any money.[7] We interpret the results accordingly below.

Form 1099-G does not identify whether a UI payment is part of the regular UI program or PUA. To proxy for the UI payment type, we calculate the total amount of 2019 wage and salary income from Form W-2 and classify a UI payment as being made through the regular UI program if an individual's W-2 income exceeded the minimum amount of base period earnings required in each state to be eligible for the regular UI program as of January 2020.[8] UI payments made to individuals with earnings below this threshold are classified as being made through PUA.[9,10]

We use additional data sources to obtain information on state UI parameters and other characteristics. First, we use the maximum benefit amount in each state from Kuka and Stuart (2025). Second, we use state-level data from the DOL on the share of initial or all UI claims that are approved and the share of initial or all UI claims that are paid within 14 days. Third, we use state-level data on improper payments and fraud rates as measured in the BAM data. Finally, we use data on the number of working age individuals in each state from the Bureau of Labor Statistics (BLS).

3.2 Methodology

To identify likely ineligible UI, we use a set of criteria that follow from UI rules and are reasonably well-observed in tax data. In particular, we define a 2020 UI payment as anomalous if it is inconsistent with a person being able and available to work, is inconsistent with rules on earnings

[7] If a person in this situation reported UI fraud to the state UI agency, the 1099-G UI payment would be corrected to zero. We observe these corrections and use them to define likely ineligible UI payments.

[8] Laws regarding UI eligibility vary significantly across states, with differences in both the amount needed to qualify and how this amount must be distributed across quarters. For example, some states require a minimum amount of earnings in the base period (defined as the first four of the five quarters before job loss), some require a minimum amount in the highest-earning quarter during the base period, and one state (Washington) has a minimum hours requirement in the base period. We use the base period wage requirement because we have only annual earnings data. For states that only have quarterly wage requirements, we convert these requirements to an annual basis. For Washington, we convert the hours requirement into an earnings requirement by assuming that people earn the minimum wage.

[9] If anything, this approach may understate the amount of PUA UI recipients: individuals below this threshold are very likely to be PUA recipients, while some individuals above it could be PUA recipients even though they are classified as getting regular UI.

[10] For this exercise we add up all W-2 earnings from employers in the state issuing the UI payment. The alternative approach of adding up W-2 earnings from all states leads to little change in the share of UI recipients classified into the regular vs. PUA programs.

and residence history as well as multiple claiming, or is inconsistent with earnings or job loss. We describe each category in detail.

Person unable or unavailable to work. A 2020 UI payment is inconsistent with a person being able and available to work if it is associated with an individual who (1) does not have a valid SSN that is authorized for work, (2) died before 2020, (3) was born after 2010 or before 1920 (hence, less than 10 or more than 100 years old in 2020), (4) was incarcerated for all of 2020, or (5) received disability benefits in both 2019 and 2020 and had zero earnings in both 2019 and 2020.

Conditions 1–4 cover situations in which UI recipients do not meet basic eligibility criteria.[11] Condition 5 identifies individuals with no earned income in 2019 and 2020—from Forms W-2, 1040 (Schedules C, F, and SE plus wage, salary, and tip income), 1099-MISC, 1099-NEC, and 1099-K—who also received disability insurance benefits in 2019 and 2020. These individuals are especially unlikely to qualify for UI because they were determined by the disability insurance program to have experienced a career-limiting disability before 2020 and lacked any record of recently earned income.

Payment inconsistent with UI rules. A 2020 UI payment is inconsistent with UI rules if it is associated with an individual who (6) has no record on any Form 1040, W-2, 1095, 1099-MISC, 1099-NEC, or 1099-K between 2018 and 2020 of living or working in either the state disbursing the payment or the state of residence reported by the payer state on the Form 1099-G, (7) received UI from multiple states in 2020, or (8) the payment is amended to 0 in a corrected Form 1099-G.

Condition 6 follows the rule that individuals can only receive UI payments from a state in which they have worked or lived.[12] We use several tax forms and a wider time period of 2018 to 2020 to minimize instances where an individual's location is not recorded in tax data.[13,14] We adopt a

[11] UI benefits, including through PUA, were only available to people with legal work authorization.

[12] An individual can receive UI from a state in which they do not live. For example, if an individual is employed in Pennsylvania and lives in Delaware, Pennsylvania would pay any UI benefits.

[13] We use addresses from tax years 2018–2020 for Form 1040, on which taxpayers report their current address when filing taxes, and 2019–2020 for the information returns.

[14] For example, if an individual was initially self-employed in Pennsylvania in 2019, moved to Delaware in 2020 after filing 2019 taxes, continued their trade or business, filed for PUA in Delaware later in 2020, and then moved out

conservative approach by not imposing condition 6 whenever the state of residence reported by the UI agency on Form 1099-G matches a state of residence reported on any other tax form.

Condition 7 follows the rule that individuals may not receive UI from multiple states concurrently. Individuals *can* receive UI benefits based on work history from multiple states. However, the UI payment only comes from the state in which the individual initiates the UI claim. As a result, given the extended benefit weeks that were available to all UI recipients in 2020, it is unlikely that individuals could have legitimately received UI in one state, re-established eligibility in another state, and then filed a UI claim in that other state.

Condition 8 identifies UI payments that appeared in the original Form 1099-G and were later zeroed out in corrected forms. States usually send corrected forms if the original form displayed incorrect UI information, likely in the event of detected UI fraud. As a result, this criteria relies on states' assessment of whether a UI payment was appropriate.[15]

Payment inconsistent with earnings or job loss. A 2020 UI payment is inconsistent with the recipient experiencing an earnings or job loss if it is associated with (9) an individual with zero earnings in both 2019 and 2020 who is not estimated to have qualified for one of the few potential exceptions or (10) an individual with nonzero earnings in 2020 that were at least as large as their earnings in both 2018 and 2019 who does not have any record of non-employed months during 2020 from Form 1095-C.

Condition 9 covers individuals with no earned income in 2019 and 2020 from Forms W-2, 1040 (Schedules C, F, and SE plus wage, salary, and tip income), 1099-MISC, 1099-NEC, and 1099-K. This is motivated by the rule that individuals generally had to be employed before the pandemic and lose income to qualify for UI benefits. We adjust condition 9 to account for the limited exceptions that were provided in the CARES Act. First, PUA benefits were available to

of Delaware before being tied to the state on any tax form, then we might misclassify the Delaware UI payment as anomalous. Data from the Census Survey of Income and Program Participation (SIPP) suggest that such moves are extremely rare. Note even in this example, the state linkage to Delaware could be observed from a Form 1095 for someone with non-group or Medicaid health insurance who switched insurance plans when moving across states.

[15] If a state issues a correction to Form 1099-G that does not zero out the UI payment, we do not use this correction to identify a payment as anomalous.

individuals who accepted a job offer that was rescinded because of COVID-19. To address this, we use the Current Population Survey (CPS) to estimate the number of people who would be flagged as having likely ineligible UI by condition 9 but may have had a rescinded job offer. Based off of this estimate, we accordingly remove condition 9 anomalous UI flags for a random subset of individuals.[16] Second, it is possible that individuals with earned income improperly received no information return indicating earnings and reported zero earned income on their 2019 and 2020 tax returns; these individuals might have been eligible to receive UI. To address this, we use the results of IRS National Research Program randomized audits from 2010 to 2017 to estimate the number of people who had zero earned income according to tax data but actually had nonzero earnings. We remove condition 9 likely ineligible UI flags for a random subset of individuals.[17] Third, the CARES Act made benefits available to individuals who are not employed if their spouse died of COVID-19. We account for this by removing the condition 9 flag for anyone whose spouse died (of any cause) between March and December 2020. In total, these three exceptions reduce the number of individuals with a condition 9 flag by about 12%.[18]

Condition 10 identifies individuals with nonzero earnings in 2020 who did not have a decrease in their earnings in 2020 relative to either 2018 or 2019. This reflects the rule that pandemic

[16] In particular, we use the monthly CPS to identify people with zero earned income in 2019 (based on the March 2020 ASEC) who appear in the CPS from January to April of 2020. We calculate the share of these individuals who are not employed in January through March and employed in April. This gives us a starting estimate of the share of people with no earned income in 2019 and 2020 who started a job in April (right after the pandemic began). This number is 0.27%. We calculate the same number for the previous year, which is 0.63%. Taking the difference yields an estimate that 0.37% of people with no earned income would have started a job in April 2020 but had their offer rescinded. We multiply 0.37% times the number of people in the tax data with no earned income in 2019 and 2020 to arrive at our adjustment. This approach is conservative—in the sense of removing a higher amount of anomalous UI payments—because (i) it assumes that the entire decrease in the rate of entry into employment in April 2020 is due to job offers being rescinded and (ii) it assumes that all individuals with rescinded job offers applied for and received UI.

[17] In particular, we analyze the results of randomized audits for non-married tax filers who did not have any earned income from a Form W-2 or 1099 and reported no wage or self-employment income on Form 1040. About 0.5% of these tax returns are revised to have wage or self-employment income. We multiply 0.5% times the number of people in the tax data with no earned income in 2019 and 2020. This approach is conservative—in the sense of removing a higher amount of anomalous UI payments—because it assumes that all these individuals applied for UI, effectively reporting to their state their tax evasion, and received UI, even though there is ambiguity over whether a state would grant such a request. We also take a conservative approach by not making a downward adjustment for the fact that three times as many individuals report earned income on their tax return (typically negative self-employment income or otherwise an amount at the first kink point of the EITC schedule to receive the maximum tax credit) that are determined to have none by these audits; these individuals might appear to receive non-anomalous UI payments in the tax data even though they have no true earnings.

[18] We also remove the condition 10 flag for people who meet these exceptions.

UI benefits were generally only available to individuals who lost income because of the pandemic. However, using annual data to measure earnings changes could generate misclassifications because of within-year earnings volatility.[19] To address this issue, we use monthly employment reports from Form 1095-C. Employers with at least 50 full-time equivalent employees are required to report employees' health insurance and employment status for each month. For people who work exclusively at these firms, which employ the majority of the workforce, we use Form 1095-C to identify whether they are employed in each month of 2020, and we remove the condition 10 anomalous UI flag for individuals with at least 1 month of non-employment in 2020.[20] For people who do not work exclusively for these large employers, we use an imputation approach. First, we use the observed Form 1095-C data to estimate the share of individuals in each 2019 earned income vingtile who have a condition 10 UI flag removed because of these employment measures. We allow this share to be a flexible function of 2019 earned income to account for the fact that income volatility is higher among lower-income individuals. Then, we remove the condition 10 flag for a randomly chosen subset of individuals for whom Form 1095-C data are not available.

Measuring likely ineligible UI payments in other years. For 2021, we apply similar criteria, with the reference year for each condition shifted forward.[21] However, we add one important criterion: if an individual received anomalous UI in 2020 and also received UI in 2021, we identify the 2021 payments as likely ineligible as well.[22] We also measure likely ineligible payments in 2019 to facilitate a comparison to BAM measures and study changes over time. We use the same conditions 1–10 above, though we use only W-2 earnings for earned income and do not adjust conditions 9 and 10 to account for CARES Act exceptions. We make these choices because only

[19]For example, someone might have gotten a better job in January 2020 such that their pay from January to March 2020 exceeded their pay in 2019 and 2018.

[20]The Form 1095-C data provide complete monthly employment data for individuals when the number of Forms 1095-C is as large as the number of Forms W-2. Any month without a Form 1095-C record of employment therefore reflects genuine non-employment rather than a gap in data coverage. For these individuals, we remove the condition 9 anomalous UI flag if there is at least one month of non-employment during the year. Among people where the number of Forms 1095-C is less than the number of Forms W-2, we use the imputation approach described next.

[21]For condition 4, we use years 2019–2021 for all tax forms. For 2021, when removing the condition 8 flag because of a spousal death, we allow for spousal deaths between March 2020 and August 2021.

[22]For individuals with non-anomalous UI in 2020, we classify their 2021 UI as anomalous only based on conditions 2, 3, 4, 8, and 10 (applied to 2021).

regular UI benefits were available in 2019 and the CARES Act was not effective.

4 Size and Distribution of Likely Ineligible UI Payments

In this section we describe the size of anomalous UI payments in 2020 and 2021 and their distribution across programs and people.

4.1 Total Amount of Likely Ineligible UI Payments

Table 1 contains our estimates of the total amount of UI benefits that were paid out (column 1) and the total number of UI recipients (column 4). As shown in Panel A, the government disbursed \$559 billion of UI payments to 45 million individuals in 2020. Panel B shows that these totals for 2021 are \$325 billion and 26 million recipients. We quantify the total amount of likely ineligible UI payments by sequentially imposing the criteria listed in each row of the table. The last rows of each panel contain the total amount that we classify as anomalous according to any of the conditions described in Section 3.2. We identify \$108 billion in likely ineligible UI payments in 2020 and \$106 billion in 2021, for a total of \$214 billion—equal to 24% of all UI payments disbursed. These anomalous payments went to 11 million recipients in 2020 and 10 million recipients in 2021, with an average payment per recipient of about \$10,000. Importantly, Appendix Table A.1 shows that likely ineligible payments were only 11% of all UI in 2019, suggesting that the high anomalous rate we estimate during the pandemic is not an artifact of our measurement and is driven by changes to the UI program that occurred during this period. As a point of comparison, the BAM program estimates a UI overpayment rate of 9.4% for 2019, as well as a fraud rate of 2.9%.

These likely ineligible UI payments are very large. For example, the \$214 billion in anomalous UI payments is almost 20% larger than all USDA spending on food and nutrition programs (SNAP, WIC, etc.) in 2022, almost four times as large as all EITC benefits paid out that year, and about 10 times as large as the amount of regular UI benefits paid out in 2022.

Our estimates of likely ineligible UI payments are somewhat larger than existing estimates of improper and fraudulent payments and based on much larger and more representative samples. The

DOL Inspector General estimated an improper payment rate of 21.5% in pandemic UI programs between April 2020 and September 2022, for a total of at least $191 billion of improper UI payments (U.S. Department of Labor Office of Inspector General, 2023).[23] The GAO estimated that fraudulent UI payments, which are a subset of improper payments, were at least $100–135 billion between April 2020 and May 2023 (U.S. Government Accountability Office, 2023).[24] Our analysis benefits from much larger samples and linkages across different tax forms, which are especially valuable for PUA given the lack of other data on this program. At the same time, the DOL and GAO estimates benefit from audits of selected UI payments that verify eligibility according to both earnings history and other job search requirements and they possess information on applications made through suspicious IP addresses. Therefore the estimate of interest differs across all of these methodologies, and we do not expect the numbers to agree perfectly. We view the general similarity between our estimates and those of DOL and GAO as reassuring evidence that our measure of likely ineligible UI payments is reasonable.

Which conditions account for the largest share of UI payments flagged as likely ineligible? Since the results in Table 1 depend on the stacking order in which conditions are applied, Appendix Table A.2 reports complementary evidence on 2020 anomalous UI payments where each condition is met (irrespective of whether another condition is also met). The largest contributor was condition 10; $56 billion in UI payments were linked to records for individuals who experienced no decrease in earnings between 2018–2020 and 2019–2020 and had no indication of non-employment. The second largest contributor was condition 9; $37 billion of UI payments were associated with records for individuals who had zero earnings in 2019 and 2020 and are not estimated to have possibly qualified for an exemption. The third largest contributor was condition 6; $14 billion in UI payments were tied to individuals lacking a connection, via place of work or

[23]The DOL arrived at this estimate by multiplying $888 billion in total federal and state UI payments from April 2020 through September 2022 by the estimated improper payment rate of 21.5%. This improper payment rate is derived from Benefit Accuracy Measurement (BAM) program audits, which cover regular (non-PUA) UI claims outside of the 2nd quarter of 2020 (when reporting was suspended). This estimate also includes Puerto Rico and the U.S. Virgin Islands, which are excluded from our analysis.

[24]GAO based their estimate of the fraud rate in the PUA program on a nonrandom sample of 2,540 payments from 26 states.

residence, to the state issuing the payment or the state-agency-reported state of residence of the payee. These three conditions flag the largest shares of potentially ineligible payments, whether applying them sequentially as in Table 1 or independently as in Appendix Table A.2. Turning to likely ineligible UI payments in 2021, around 45% were issued to individuals flagged as likely ineligible in 2020. Among newly anomalous UI payments in 2021, the primary drivers are the lack of a state match and no decrease in earnings from 2019–2021 and 2020–2021. The high share and magnitude of likely ineligible UI payments in 2021 are particularly notable because federal and state governments publicly discussed their intention to limit improper payments after reports of fraudulent activity in 2020. This pattern is consistent with ineligible recipients having little incentive to discontinue their claims (even as eligible recipients exited UI as the economy recovered) and social learning about program integrity vulnerabilities within the UI system.

These results suggest that a substantial amount of likely ineligible UI payments could have been identified before issuance. To explore this further, we identify ex-ante anomalous UI payments made in 2020 as those associated with an invalid TIN, a dead individual, an individual below age 10 or above age 100, an individual incarcerated at the beginning of 2020 without a scheduled release date in that year, someone with zero earned income in 2019, someone not connected to the state making the UI payment via place of residence or work in 2019, or someone receiving benefits from another state.[25] All of these characteristics refer to outcomes in 2019 or earlier, which means that they were largely knowable as of March 2020.[26] We identify $60 billion of UI payments made in 2020 as likely ineligible based on these ex-ante characteristics.[27] This is equal to 46% of all likely ineligible UI payments made in 2020. This figure grows to 55% when looking across 2020 and 2021. The two ex-ante conditions that identify the largest amounts of anomalous UI payments are no earned income in 2019 and no match to the state issuing the UI payment. An improved

[25] If the only ex-ante anomalous condition associated with an individual is that they received UI from multiple states, we treat $(S-1)/S$ percent of their total UI benefits as anomalous ex ante, where S is the number of states from which they received UI benefits. This approximates the idea that the first state's UI benefits might not be caught if states are double-checking cases where an individual receives UI from multiple states.

[26] This is only approximately true, as our ex-ante definition uses information from income tax returns, some of which had not been filed by March 2020. Information reports for 2019 were available by this time.

[27] Of this amount, $50 billion remains classified as anomalous after incorporating all 10 conditions described in Section 3.2.

data-sharing environment could provide state UI agencies with this information so that they could review these circumstances prior to paying out funds.

4.2 Distribution of Likely Ineligible UI Payments Across Programs

Table 1 also provides a breakdown of likely ineligible UI payments that were made through the regular and PUA programs. In total, $274 billion was distributed through the PUA program, and we estimate that $124 billion of this was anomalous (45%).[28] A smaller 15% of the $609 billion in UI benefits distributed through the regular UI program was likely ineligible. This means that PUA accounts for 58% of all anomalous UI payments and 22% of all non-anomalous UI payments. The clear picture that emerges is that likely ineligible UI payments were much larger under PUA, which is consistent with the fact that regular UI payments are subject to greater scrutiny and depend on inputs that are more readily verifiable with existing UI data systems.

Table 1 also shows systematic differences in the sources of likely ineligible UI payments in the PUA program. Across 2020 and 2021, almost $8 billion in PUA payments were disbursed to individuals who had an invalid TIN, were dead at the time, were below age 10, or were above age 100. The amount of regular UI payments flagged by these issues is much smaller, at $400 million. PUA accounts for all anomalous UI payments going to individuals with no match in terms of place of work or place of residence to the state issuing benefits and individuals with no earned income in 2019 and 2020.[29]

4.3 Distribution of Likely Ineligible UI Payments Across People

We next examine features of individual tax returns to better understand where likely ineligible UI payments were concentrated. Panel A of Figure 1 displays the total amount of anomalous 2020 UI

[28] As a point of comparison, DOL released an estimate for improper payments in PUA, suggesting that at least 18.5% of PUA claims were improperly claimed. However, DOL could not determine the validity of another 17.4% of benefits paid, leading to large uncertainty regarding the true PUA improper payment rate (U.S. Department of Labor, 2023*b*).

[29] If an individual has no connection to a state, then by definition they do not have W-2 income earned in the state, and so do not qualify for regular UI according to our classification. Likewise, individuals with no earned income in 2019 do not meet the regular UI minimum work history threshold.

payments associated with tax returns with zero earned income in 2019 (shown as a square) and for tax returns across vingtiles of the non-zero earned income distribution.[30] Panel B reports the share of UI payments that are likely ineligible. We find that anomalous UI payments are widespread, amounting to at least $3 billion in each vingtile of the 2019 earned income distribution and at least 10% of all UI payments. Individuals with no earned income in 2019 are clear outliers, accounting for $35 billion in anomalous UI (32% of all such payments) and for whom we estimate 79% of UI payments are likely ineligible. Moreover, we find that the share of UI payments that are likely ineligible decreases among individuals with higher earnings. One potential explanation for the finding that anomalous UI payments are higher for lower-income individuals is that such individuals are more likely to be victims of identity theft. However, Appendix Figure A.1 provides evidence from both IRS and National Crime Victimization Survey data that identity theft rates increase in individuals' income level. While not dispositive, this suggests that differences in identity theft victimization do not explain the income gradient.

Panels C and D of Figure 1 report analogous results based on categories of the 2019–2020 change in earned income. We find that $58 billion of likely ineligible UI benefits were associated with individuals with an increase in earned income from 2019 to 2020.

To better understand the amount of likely ineligible UI payments in comparison to the profile of likely eligible payments, we classify each dollar of a UI payment into one of three categories. Anomalous UI payments consist of payments made in one of the circumstances described in Section 3.2. When a UI payment is not anomalous, we classify the dollars that, combined with 2020 earned income, would replace an individual's 2019 earned income as insurance and the dollars beyond this amount as a transfer.[31]

Panel A of Figure 2 reports the share of all 2020 UI dollars in each category for different levels of 2019 earned income. Among all individuals, we estimate that insurance accounts for 48% of UI

[30] Individuals with negative earned income are included in the lowest vingtile, which also has some individuals with positive earned income. We focus this analysis on anomalous payments in 2020 because this makes it easier to interpret the role of 2019 earned income.

[31] For example, if an individual not flagged as receiving a anomalous UI payment made $50,000 in 2019 and $40,000 in 2020, and received $15,000 of UI benefits, we would classify $10,000 as insurance and $5,000 as a transfer.

payments and transfers account for 33%, with the remaining 19% coming from likely ineligible payments.[32] Moreover, we find that the share of UI payments that are insurance increases with income, which is a natural consequence of higher-income individuals having more income to be insured combined with the supplements from FPUC that are unrelated to prior earnings. Panel B reports the same decomposition of UI benefits separately for individuals who likely qualified under regular UI benefits (by virtue of having 2019 Form W-2 income above the state threshold) or PUA (everyone else). For regular UI benefits, we estimate that 57% of benefits were insurance, 31% of benefits were transfers, and 12% of benefits were anomalous. For PUA, we find the opposite: 24% of benefits were insurance, 38% of benefits were transfers, and 38% of benefits were anomalous.[33]

We also can identify the ZIP code associated with each UI payment from Form 1099-G. For legitimate UI recipients, this ZIP code generally reflects individuals' place of residence. For fraudulent UI claims, this ZIP code may or may not reflect the place of residence of the recipient (who might differ from the person whose name was used on the UI application). This information allows us to examine the extent of spatial concentration in likely ineligible UI payments, which is informative about their underlying source.

We first quantify the degree to which likely ineligible payments are concentrated in certain ZIP codes. We begin in Table 2 by reporting the share of total population in the 1% and 5% of ZIP codes that are largest (by population). The top 1% of ZIP codes account for 8% of total U.S. population. By comparison, 14% of all UI payments are in the top 1% of ZIP codes (where ZIP codes now are ranked by total UI payments). The concentration of non-anomalous UI payments is similar. In contrast, likely ineligible UI payments are much more concentrated: the top 1% share for all anomalous UI payments is 22%, and it reaches 50% for UI payments that are anomalous because the recipient was dead, younger than 10, or older than 100, and 85% for UI payments that

[32] These numbers differ slightly from those in Table 1 because we focus on individuals above age 18 for this analysis.

[33] The low rate of insurance in PUA is unlikely to be an artifact of income underreporting by self-employed recipients for several reasons. First, replacing reported income with imputed true income for the self-employed using NRP random audits and vingtiles of the reported self-employment income distribution yields effectively no change in the share of benefits that replace lost income. Second, reported earnings losses are actually *greater* for the self-employed than for other UI recipients. Instead, much of the reason for the pattern is that PUA was available to workers with wages too low to qualify for regular UI who (i) had very low baseline earnings, (ii) received benefits that often exceeded their 2019 earnings, and (iii) experienced much smaller earnings reductions than the self-employed or regular UI recipients.

are zeroed out in a corrected Form 1099-G.

To understand whether some ZIP codes saw particularly widespread instances of likely ineligible UI and where they are located, Table 3 looks for ZIP codes that have at least 100 residents and are in the top 1% in terms of per capita UI payments that are anomalous according to conditions 1–4, 6, and 8, which are most closely related to fraudulent activity.[34] Among the 62 such ZIP codes, we report aggregated statistics for the 40 ZIP codes with the highest amount of total anomalous UI payments. For example, the first row shows that there are $154 million of likely ineligible UI payments in 2020 associated with a ZIP code in Detroit, Michigan, which amounts to $2,710 of anomalous UI per capita.[35] The first 10 rows of the table are ZIP codes in Detroit, and more generally most ZIP codes in this table are in the Detroit and Los Angeles metropolitan areas. The high level of spatial concentration of anomalous UI, especially for conditions that are more likely to reflect fraudulent activity, is consistent with concentrated efforts by criminal organizations or social learning among individuals who are improperly claiming benefits.

5 Likely Ineligible UI Payments and State UI Programs

States have substantial leeway in determining UI policies and procedures, and there are many accounts of how states handled UI payments differently in 2020 and 2021. Motivated by these features and the geographic concentration documented above, we examine how likely ineligible UI payments vary across states.

5.1 Relationship between Anomalous and Non-Anomalous UI Payments

We start by examining the relationship between the amount of anomalous and non-anomalous UI payments made by a state. We are interested in whether high amounts of likely ineligible UI pay-

[34] As noted above, we do not know whether UI payments were actually received by individuals living in a ZIP code, but only the ZIP code associated with the UI payment on Form 1099-G.

[35] There are about 57,000 residents in this ZIP code. For this ZIP code, $12 million of UI payments is associated with individuals who were incarcerated for all of 2020, despite no prison being located in this ZIP code. Moreover, $42 million is associated with individuals who did not have a connection to Michigan, and $54 million is associated with individuals who received UI from multiple states.

ments are best understood as emerging alongside eligible payments, or whether distinct processes generated these two types of payments. Figure 3 plots anomalous UI against non-anomalous UI, both as total 2020 and 2021 payments per working-age person. For the regular UI program, each dollar of per capita non-anomalous UI is associated with an additional 13 cents of anomalous UI (Panel A). This relationship is over three times as strong for PUA (Panel B).

However, these relationships do not isolate the role of state policies or procedures. For example, public health and economic conditions could drive both types of UI payments. To reduce the scope for such omitted variable bias, we follow Boone et al. (2021) and Jackson, Koustas and Garin (2024) in comparing outcomes across pairs of counties that are adjacent to each other but in neighboring states. In our main approach, we refine this comparison further by restricting the sample to ZIP codes whose centroids are at most 15 miles from the centroid of a ZIP code in the neighboring county of the county-border pair. The key equation of interest is:

$$\text{Anomalous UI}_z = \beta_0 + \beta_1 \text{Non-Anomalous UI}_z + X_z \beta_2 + \eta_{p(z)} + \epsilon_z, \tag{1}$$

where Anomalous UI_z is anomalous UI per 2019 worker in the ZIP code, Non-Anomalous UI_z is a similarly-constructed measure of non-anomalous UI per worker, X_z is a vector of controls, and $\eta_{p(z)}$ is a fixed effect for the county border pair associated with each ZIP code.[36]

The key advantage of the border pair design as implemented in equation (1) is an improved ability to control for hard-to-measure economic conditions or views about UI. Nonetheless, there is potential for omitted variable bias to remain. For example, there could be differences across ZIP codes within county border pairs in knowledge about UI or social norms about UI receipt that affect the amount of likely ineligible and eligible UI (e.g., Bertrand, Luttmer and Mullainathan, 2000; Chetty, Friedman and Saez, 2013). Alternatively, there could be differences across ZIP codes in economic conditions that affect one or both types of UI receipt. Moreover, this design might not isolate the role of differences in state UI policies or practices, which are of particular interest.

To address this set of concerns, we use an instrumental variable (IV) approach. Our IV is the amount of non-anomalous UI payments per capita in all counties within the same state as ZIP

[36] We construct the number of 2019 workers as the number of people with nonzero earned income. We use workers for this ZIP code-level analysis because this variable can be measured with minimal noise in the tax data.

code z, excluding the county of z. This leave-out-mean reflects common state-level factors that determine non-anomalous UI amounts. We view these state-level factors as primarily comprising (i) UI policies or practices and (ii) economic and social factors, like the depth of pandemic-induced recession. When combined with the border design, we view most of the remaining variation as being driven by UI policies and practices.

Table 4 presents results from these analyses, with separate panels for the regular and PUA UI programs. Column 1 reports OLS estimates of equation (1). An additional dollar of non-anomalous UI per capita in a ZIP code is associated with only a 1.5 cent increase in anomalous UI for the regular UI program, but 21.2 cents for the PUA program. These patterns are qualitatively similar to the broader state-level results in Figure 3, but smaller in magnitude. Column 2 reports estimates of the first stage equation, which show that an additional dollar of non-anomalous UI in the rest of the state predicts a 50–59 cent increase in non-anomalous UI benefits in a ZIP code. The first-stage F-statistics are above 50 for both programs.

Column 3 reports the "reduced-form" estimates, while column 4 reports the main IV estimates of interest. These estimates show that an additional dollar of non-anomalous UI benefits per capita in a ZIP code—as driven primarily by state-level UI policies and practices—leads to a 5 cent increase in anomalous UI benefits for the regular program and a 90 cent increase in anomalous UI benefits for PUA. In contrast to regular UI, the IV estimates for PUA are considerably larger in magnitude than the OLS estimates in column 1, which is consistent with policies that drive increases in non-anomalous UI benefits also having particularly large impacts on anomalous benefits in this program. Given baseline means, states expanding access to likely eligible PUA recipients experienced a disproportionately larger increase in payments to likely ineligible recipients.

We assess the robustness of these results in several ways. First, column 5 shows that the IV estimates are nearly identical when controlling for a range of ZIP code covariates.[37] Second, column 6 shows that there is little relationship between our IV variation in non-anomalous UI per

[37]These controls are the number of adults; mean earned income; the 10th, 25th, 50th, 75th, and 90th percentiles of the earned income distribution; the share of adults that worked; the share of individuals that filed a 1040; the share with a measure of wealth in the tax data (based on either mortgage deductions or the receipt of interest or capital gains); the mean number of dependents; the mean age; and the percent living in an urban area. All variables come from 2019.

capita and the UI receipt rate that is predicted by a ZIP code's 2019 industry composition and nationwide, industry-specific UI receipt.[38] This provides reassurance that our state border design and IV approach generate balance across ZIP codes in terms of key economic features that matter for UI receipt. Additionally, conclusions are similar when varying the minimum distance between ZIP codes in adjacent counties and when constructing the leave-out instrument using only other border counties (Appendix Table A.4).[39]

There are two key takeaways from these results. First, state policies that generated larger non-anomalous UI payments through the regular UI program led to minimal increases in anomalous UI payments in this program. Second, the PUA program shows a starkly different pattern: policies that increased non-anomalous PUA payments led to a nearly dollar-for-dollar increase in anomalous PUA payments. These results suggest that while states were well-positioned to screen applications and effectively administer the regular UI program, their ability to do the same for the PUA program was much more limited.

5.2 Relationship between Likely Ineligible Payments and State UI Policies

Next, we study the relationship between likely ineligible UI payments and specific dimensions of state UI policies and procedures. We focus on three state measures: the share of payments classified as fraudulent in DOL BAM data prior to the pandemic, the maximum weekly benefit amount prior to the pandemic, and the share of 2020 UI claims that were paid (i.e., not denied). The first two measures capture pre-pandemic characteristics of state UI systems, while the third also reflects state responses during the pandemic.[40]

Figure 4 shows the relationship between these state measures and the share of all UI payments

[38] In particular, the dependent variable in column 6 is the leave-out-ZIP, industry-predicted UI receipt rate. We calculate this as $\sum_k s_{z,k}$ UI Receipt$_{-z,k}$, where $s_{z,k}$ is the share of 2019 wage earners in ZIP code z employed in two-digit industry k and UI Receipt$_{-z,k}$ is the share of wage earners in industry k in 2019 who received UI in 2020 (excluding those living in ZIP code z).

[39] There is a standard bias-variance tradeoff when varying the minimum distance between ZIP codes in our sample. Our main leave-out instrument uses all other counties in the same state besides the county containing ZIP code z; we also use the subset of counties along other border segments because this comparison might do a better job of isolating policy differences between states.

[40] We use 2017–2019 to construct the first variable because it is based on measures with some noise and 2018 to construct the second variable because it is a policy set by states and not subject to measurement error.

in 2020 and 2021 that are likely ineligible, which ranges from 13% (New Hampshire) to 42% (Pennsylvania).[41] Appendix Figure A.2 relates these measures to likely ineligible UI per working-age individual, which ranges from \$113 (South Dakota) to \$2,590 (Pennsylvania). The strongest predictor of anomalous UI is the state's pre-pandemic fraud rate, which can explain 32% of the cross-state variation in the likely ineligible share (Panel A). States with more generous weekly benefit amounts in 2018 did not pay out a higher share of anomalous UI than less generous states (Panel B).[42] Lastly, Panel C shows that states which paid a higher share of submitted UI claims in 2020 disbursed a higher share of anomalous UI, though this can only explain 6% of the cross-state variation.

To better isolate the role of differences in state UI policies, we modify the border design described in equation (1), using a state policy variable as the key explanatory variable of interest instead of non-anomalous UI payments. The results are shown in Table 5. Column 2 reports the results of three separate regressions, corresponding to the three different explanatory variables of interest, where the dependent variable is the share of all UI payments made through the regular UI program that are likely ineligible. Column 3 reports the effect of a one standard deviation (SD) increase in each explanatory variable, divided by the dependent variable mean, to facilitate comparisons. Columns 4–5 contain results for the share of all PUA payments that are likely ineligible.

This table reveals significant relationships between the amount of likely ineligible PUA benefits and features of state UI systems. A one SD increase in the BAM fraud rate between 2017 and 2019 is associated with a 9% increase in the share of UI payments that are anomalous. A one SD increase in the share of 2020 UI claims that were paid is associated with an 11% increase in the share of UI payments that are likely ineligible.[43] These results suggest that anomalous PUA payments during

[41] We exclude Nevada from this exercise, as it is an outlier with 84% of all UI payments being likely ineligible. Appendix Table A.3 reports totals by state.

[42] However, Appendix Figure A.2 shows that states with more generous weekly benefits paid out more anomalous UI *dollars per capita*, consistent with states offering higher UI payment amounts per recipient mechanically paying out more anomalous UI per capita.

[43] When using the leave-out-ZIP, industry-predicted UI receipt rate as a placebo dependent variable (as is done in column 6 of Table 4), there is no significant relationship with these explanatory variables, which provides additional reassurance that our state border design and IV approach does an adequate job of holding economic conditions constant across neighboring ZIP codes.

the pandemic were higher in states with weaker anti-fraud practices in place beforehand and states that evaluated 2020 claims less carefully. In contrast, there is a much weaker relationship between likely ineligible UI payments and states' maximum weekly benefit amount, suggesting that higher UI benefits did not translate into relatively more anomalous UI. Finally, there is also a much weaker relationship between these state variables and the amount of anomalous UI payments made through the regular UI program, again pointing to pre-pandemic state policies across the board being better designed to administer the regular UI program relative to PUA. Conclusions are similar when looking at the amount of likely ineligible UI payments per capita (Appendix Table A.5).[44]

6 Effectiveness of Counterfactual Policies

So far, we have provided evidence of a sizable amount of likely ineligible UI payments under the reforms legislated by Congress. But the existence of anomalous payments does not necessarily imply that a better policy was possible (outside of operational changes within the program such as better data matching and/or better screening as suggested above), as a reduction in anomalous payments might come at the cost of less insurance against income losses. In particular, while expanding UI benefits may increase anomalous payments, it may also provide effective targeting of legitimate benefits to those experiencing larger income drops. In this section, we compare the performance of actual UI policy against specific counterfactual policies that would have required the same amount of government spending but replace opt-in payments with automatic ones.

We begin by assessing actual and counterfactual policies using three measures: the share of people who experience a large income drop (exceeding 10% or 20%), the amount of UI payments that replace lost income, and the amount that represents a transfer beyond lost income. We focus on these outcomes because they are easier to measure than—and provide an important foundation for understanding—impacts on welfare.

[44]As another measure of state UI policies, we also examined the share of payments paid within 14 days of claim filing from 2017–2019. The amount of anomalous UI payments is increasing in this measure of payment timeliness. We place less emphasis on this variable because it is less directly related to likely ineligible payments than the other variables.

Panel A of Figure 5 reports the share of people with an income drop from 2019 to 2020 of at least 10%. The top bar shows the realized change in income, which is calculated based on earned income and UI benefits in 2019 and 2020.[45] We estimate that 25.2% of individuals had an income drop of at least 10% from 2019 to 2020.[46] If we exclude likely ineligible UI payments, this number rises only slightly to 25.6%, which is consistent with most anomalous UI payments being associated with individuals who did not experience a decrease in their earned income, as already discussed.

We consider counterfactual scenarios that eliminate three different types of UI payments. First, we eliminate all likely ineligible UI payments. This is not an ex-ante feasible policy, but it serves as a useful benchmark. Second, we exclude ex-ante anomalous UI payments, as defined above in the discussion of Result 3. Third, we simply eliminate the PUA program, which clearly had the greatest scope for improper payments. The total amount of money available for redistribution under these three scenarios is \$107 billion, \$51 billion, and \$160 billion.[47]

We redistribute the amount of eliminated UI payments holding earned income and other UI payments fixed.[48] The redistributed payment amount, B, equals the smaller of \$10,000 and 2019 earned income, Y_{2019}:

$$B = \min\{10,000, Y_{2019}\}. \tag{2}$$

Capping the redistributed benefit amount at a person's 2019 earned income helps ensure that funds are spent on replacing lost income. We consider a maximum payment of \$10,000 because this is around the average amount of UI benefits received in our data. We redistribute funds to people with non-zero 2019 earned income, prioritizing those with the lowest amount of 2019 earned income in absolute value, and make payments until the money available from eliminating UI payments is entirely spent.[49]

[45] We exclude other forms of income throughout the analysis in this section.

[46] This estimate lines up closely with the estimate in Larrimore, Mortenson and Splinter (2022).

[47] These numbers differ slightly from those reported in Table 1 because we focus here on individuals age 18 and above in 2019.

[48] If we allowed earned income to adjust, then eliminating UI and replacing it with lump-sum transfers would tend to increase earnings and therefore increase the amount of insurance relative to what we report. This is because UI lowers the net return to working.

[49] Note that an individual with an anomalous UI payment and a low amount of 2019 earned income could simulta-

Panel A of Figure 5 shows that these counterfactual policies reduce the share of people with a large income drop. Eliminating all likely ineligible UI payments and redistributing these dollars would reduce the share of people with a large income drop to 19.5%, which is a decrease of 5.7 p.p. (23%) compared to the actual outcome. Cutting ex-ante anomalous UI payments lowers the share of people with a large income loss to 20.7%. The largest effect comes from replacing PUA with the lump-sum transfer; in this case, 19.3% of people would have an income loss of 10% or more. These results do not require the cut PUA benefits to be redistributed to people who are eligible for PUA (i.e., have 2019 wage and salary earnings below the state minimum earnings threshold and are thus not eligible for the regular UI program). The last bar in the figure shows the results when imposing this restriction, showing benefits that are slightly smaller, but still sizable.[50] Results are similar when examining the share of people with an income loss of 20% or more (Appendix Figure A.3, Panel B). We also find benefits of replacing these types of UI payments with different types of redistribution schedules (Appendix Figure A.3, Panels C–F).[51]

Panel B of Figure 5 shows that replacing these types of UI payments with lump-sum benefits *increases* the total amount of dollars that replace income lost between 2019 and 2020. The total amount of insurance payments rises by \$11.8 to \$34.6 billion (4–13%). This occurs because we consider eliminating UI payments that did not replace lost income to a substantial degree. By contrast, if we eliminated regular UI payments and redistributed them, the total amount of insurance payments would fall by \$103.7 billion (result not shown). The total amount of transfer payments

neously see a decrease in their 2020 income because of the removal of the UI payment and an increase in their 2020 income because of the counterfactual redistribution.

[50] Our baseline approach can take UI payments from individuals with zero earned income in 2019 even though funds are redistributed only to those with non-zero earned income. This is a natural approach because the UI payments were generally intended for individuals with prior labor market attachment (as discussed in Section 2). When only taking UI payments from individuals with non-zero earned income in 2019, results are similar (Appendix Figure A.5). Appendix Table A.6 reports the income levels that receive redistributed payments.

[51] In particular, we consider two other redistribution schedules:

$$B' = \max\{0, 1200 - 0.10 \times \max\{0, Y_{2019} - 75,000\}\} \tag{3}$$

$$B'' = \max\{0, 10,000 - 0.20 \times \max\{0, Y_{2019} - 50,000\}\}. \tag{4}$$

The first benefit schedule, B', resembles the structure of the 2020 EIP payment. This schedule pays a benefit of \$1,200 to individuals with 2019 earned income below \$75,000, and beyond that point is phased out at a 10% rate. We refer to this as the "less progressive" schedule. The second benefit, B'', is more progressive, and pays \$10,000 (approximately the average 2020 UI benefit amount per person) to individuals with 2019 earned income below \$50,000, with a 20% phase-out rate.

increases as well (Panel C).

In summary, the results in Figure 5 suggest that in the context of the pandemic and economic downturn in 2020, replacing PUA with a budget-neutral transfer equal to the minimum of individuals' 2019 earned income and $10,000 could have improved insurance against large income losses, reduced anomalous UI payments, and increased total insurance and transfer payments. Additionally, given the straightforward criteria and, in turn, availability of data needed to administer the counterfactuals, benefits could have been provided to individuals more quickly (via the IRS, for example) and at lower administrative costs.[52] This would have also removed the distortion resulting from the lowered net return to working imposed by UI eligibility criteria based on current earnings.

These results are driven by three key features of this context. First, there was a substantial amount of anomalous UI payments, which provides a large pool of funds to be redistributed. Second, anomalous UI payments were concentrated among individuals who saw increases in their income from 2019 to 2020. Finally, the recession in 2020 had particularly severe consequences for lower-income workers, so means-tested transfers do a reasonably good job of targeting income losses.

7 A Theoretical Model of Opt-in vs Automatic Transfers

The counterfactual analysis in the previous section shows that PUA payments were not particularly well-targeted to individuals with higher earnings losses and that simple lump-sum transfers could have done a better job than PUA of insuring against income losses. In this section, we develop a formal model to study the optimal allocation of government resources to opt-in vs. automatic transfers (e.g., UI vs. EIPs) in a setting where ineligible recipients can access the opt-in benefits. We study how the presence of ineligible benefit recipients changes the targeting properties of opt-in benefits and the optimal tradeoff between the two types of transfers. While the model

[52]Ninety-two percent of individuals potentially eligible for EIPs received them (Clark et al., 2023), and the improper payment rates was very low, at 2% (see `https://www.gao.gov/products/gao-22-106044`, accessed July 1, 2026).

below focuses on UI, it can also be applied to other safety net programs, such as SNAP, WIC, and Medicaid.

7.1 Set-up

People differ in their eligibility for UI, which is indicated by $e_i \in \{0, 1\}$. The government cannot perfectly observe each person's eligibility status. This asymmetric information generates the key challenge for the government in choosing optimal policy.

The main choice that individuals make is how much effort to put into their UI application. People choose a continuous amount of effort, which we normalize to equal the probability, p, that their UI claim is approved.[53] Individuals can choose to put no effort into their UI application. The cost of exerting effort is $\psi_i(p)$, which can vary across people for many different reasons, including preferences, the opportunity cost of time, stigma, and true or perceived eligibility status. We assume that $\partial\psi_i/\partial p > 0$ for all people.

We begin by treating individual earnings, w_i, as fixed. People with lower earnings have a higher marginal utility of consumption, and so are more likely to pursue UI benefits. Treating earnings as fixed simplifies the analysis and highlights how the government should respond to UI applications from people who are both eligible and ineligible for benefits. However, in the appendix we show how to extend the model to include individual decisions over labor supply.

After putting forth effort into their application, individuals' UI claim is either approved or rejected. If approved, individuals receive UI benefit b, and if rejected they receive no UI benefits. Individuals also receive a common lump-sum transfer t that does not depend on UI receipt. Given this set-up, an individual's indirect expected utility function is:

$$V_i(t, b) \equiv \max_p pu(w_i + t + b) + (1 - p)u(w_i + t) - \psi_i(p). \tag{5}$$

The government's problem is to maximize social welfare subject to its budget constraint by setting the lump-sum transfer amount, t, and UI benefit amount, $b > 0$. Social welfare is:

[53] This mirrors models in which individuals' choice over job search is parametrized as the probability they find a job (Chetty and Finkelstein, 2013).

$$W(t,b) = \sum_i \alpha_i V_i(t,b) - \delta B_{\neg e}, \tag{6}$$

which consists of individual indirect expected utility functions weighted by social welfare weights, α_i, and a direct distaste $\delta \geq 0$ for each UI dollar going to an ineligible individual. The expected amount of UI benefits going to ineligible individuals is $B_{\neg e} = \sum_{i:e_i=0} p_i(t,b)b$, where $p_i(t,b)$ is the probability that individual i gets UI given the lump-sum transfer t and UI benefit amount b. The government's budget constraint is

$$G \geq \sum_i [t + p_i(t,b)b], \tag{7}$$

where G is the total amount of money available to be spent on lump-sum transfers and UI benefits.

7.2 The Effect of Shifting from Opt-in Benefits to Automatic Transfers

We consider a budget-neutral reform where the UI benefit level is lowered for all UI recipients and the lump-sum transfer amount is increased. This captures the key tradeoff involved in a reform where UI benefits are reduced and EIP payments are increased (or lump-sum taxes are reduced). Appendix A.1 shows that the social welfare consequences of this reform are summarized by the following equation:

$$\frac{dW}{-db} = \underbrace{N_{UI}\left[\left(\frac{N_e}{N}\bar{\alpha}_e\bar{u}'_e + \frac{N_{\neg e}}{N}\bar{\alpha}_{\neg e}\bar{u}'_{\neg e}\right) - \left(\frac{N_{e,UI}}{N_{UI}}\bar{\alpha}_{e,UI}\bar{u}'_{e,UI} + \frac{N_{\neg e,UI}}{N_{UI}}\bar{\alpha}_{\neg e,UI}\bar{u}'_{\neg e,UI}\right)\right]}_{\text{Change in welfare due to differences in targeting}}$$
$$+ \underbrace{\frac{N_e\bar{\alpha}_e\bar{u}'_e + N_{\neg e}\bar{\alpha}_{\neg e}\bar{u}'_{\neg e}}{N}(N_{e,UI}\bar{\eta}^{p,b}_e + N_{\neg e,UI}\bar{\eta}^{p,b}_{\neg e})}_{\text{Change in welfare due to claiming responses}} + \underbrace{\delta N_{\neg e,UI}(1+\bar{\eta}^{p,b}_{\neg e})}_{\substack{\text{Change in welfare due to} \\ \text{lower ineligible UI}}}, \tag{8}$$

where subscripts reflect groups of individuals: all eligible individuals (e), all ineligible individuals ($\neg e$), eligible UI recipients (e, UI), and ineligible UI recipients ($\neg e, UI$). For each group k, N_k is the total number of individuals, $\bar{\alpha}_k$ is the average social welfare weight, $\bar{u}'_k$ is the average marginal utility of consumption (weighted by the social welfare weight), and $\bar{\eta}^{p,b}_k$ captures the sensitivity of application behavior as the average elasticity of benefit receipt with respect to benefit levels. The average value to society of transferring money to a person in group k is $\bar{\alpha}_k\bar{u}'_k$, which summarizes whether a transfer is well-targeted to a needy group. Finally, N represents the total number of individuals and N_{UI} the total number of UI recipients.

The first line of equation (8) isolates the core targeting tradeoff. The bracketed expression is the difference between two population-share-weighted averages of the social value of a dollar: the first bracket weights by population shares of eligible and ineligible individuals (N_e/N, $N_{\neg e}/N$), capturing the average benefit of the higher lump-sum transfer; the second weights by UI-recipient shares ($N_{e,UI}/N_{UI}$, $N_{\neg e,UI}/N_{UI}$), capturing the average loss to UI recipients from lower benefits. The term in front scales this per-dollar effect by the N_{UI} dollars that are redistributed as a lump-sum transfer when the UI benefit is cut by \$1. The second term represents the gain in welfare due to UI recipients' application response. When b decreases, UI claims fall by $N_{e,UI}\bar{\eta}_e^{p,b} + N_{\neg e,UI}\bar{\eta}_{\neg e}^{p,b}$. These funds are redistributed through the lump-sum transfer, which has an average value of $(N_e\bar{\alpha}_e\bar{u}'_e + N_{\neg e}\bar{\alpha}_{\neg e}\bar{u}'_{\neg e})/N$. Finally, the third term $\delta N_{\neg e,UI}(1 + \bar{\eta}_{\neg e}^{p,b})$ describes the gain in welfare that directly stems from a decrease in UI benefits paid to ineligible individuals.

A sufficient condition for the overall welfare effect in equation (8) to be positive is that the automatic transfer is better targeted than UI. The reform will increase social welfare if UI recipients are relatively advantaged—that is, if their marginal utility of income is lower than the population average—because the reform shifts funds from lower to higher marginal utility individuals.[54]

Accounting for the presence of ineligible recipients can change the welfare effects of the reform in two key ways. First, ineligible recipients change the targeting tradeoff. Because ineligible UI recipients likely have lower marginal utilities than eligible recipients (having not experienced an earnings loss), they pull down the UI-recipient average, making the targeting gap larger and the reform more attractive. Second, the model features a direct government distaste for UI benefits to ineligible recipients, measured through δ. This also makes the reform more attractive.

[54]Both the distaste for anomalous payments—which is always non-negative—and the claim response allow for a positive welfare effect even if UI recipients are more disadvantaged than transfer recipients. The larger the elasticity of UI claims to benefits, the more funds are available to transfer as a lump sum, increasing welfare even when transfer recipients are more advantaged.

7.3 Quantification

We quantify equation (8) to provide evidence on whether this type of reform redistributing from all UI recipients (both regular and PUA) would have been welfare-enhancing in 2020. For this exercise, we identify people as ineligible for UI if they either received anomalous UI benefits or did not receive UI benefits but satisfy any of the criteria described in Section 3.2 that do not depend on observed UI receipt (conditions 1–5 and 9–10). We focus on people age 18–64 with nonzero earned income in 2019 for this exercise, who were the primary intended recipients of UI, though results are not sensitive to this choice.[55]

We consider two different forms of social welfare weights. First, we give everyone the same α_i. In this approach, the government cares equally about everyone, but there still are social gains from transferring money to people with high marginal utilities of consumption. Second, we set $\alpha_i = 0$ for people who did not lose earned income between 2019 and 2020 while continuing to treat all earned income losers equally.[56,57] This approach implements a scenario where the government only cares about income losers, which is relevant given our focus on UI.

We assume that utility takes the CRRA form: $u(c) = c^{1-\gamma}/(1-\gamma)$, with $\gamma \in \{2, 4, 6\}$ (Landais and Spinnewijn, 2021). For 2020 consumption, we use either total earned income including actual UI benefits received or total earned income excluding UI. The former approach allows us to assess the welfare consequences of lowering UI benefits after the 2020 expansion was put in place, while the latter describes the welfare consequences of lowering UI benefits when starting from a situation with no UI benefits.[58] We set all claiming elasticities to equal zero for simplicity, which leads us

[55]Throughout, we assume that all UI payments were received by the individual associated with the UI record. This assumption is not true in cases of identity theft. However, it is possible to assess how results would change under different assumptions. To take one extreme case, if the government places zero social welfare weight on ineligible UI recipients (e.g., because the perpetrators of identity theft live outside of the US), then the change in welfare in equation (8) from lowering UI is unambiguously higher, which reinforces our main conclusion.

[56]We normalize the social welfare weights to have the same total in each case, which means that social welfare weights for people who lose earned income are higher in the second scenario than the first.

[57]Alternatively, we could have set $\alpha_i = 0$ for all people whose earned income plus UI in 2020 was weakly greater than 2019 earned income, which would reflect a scenario where the government only cares about income losers (after accounting for UI). This would increase the change in welfare in equation (8) compared to the case where $\alpha_i = 0$ only for those people whose earned income in 2020 weakly exceeds that in 2019, thus reinforcing our main conclusion.

[58]In practice, we set b equal to 1 dollar to avoid complications arising from corner solutions.

to under-estimate the welfare gains from the reform.[59]

The most difficult parameter to quantify in equation (8) is δ, which measures the government's distaste for each dollar of UI benefits going to ineligible individuals. The value of δ is most meaningful when considered in relation to the social welfare weights and the individual utility function. A natural approach is to specify δ as a multiple of the average social welfare weight times the average marginal utility of consumption: $\delta = \beta\bar{\alpha}\bar{u}'$, where $\beta \geq 0$ is a scaling factor. For example, $\beta = 0.5$ implies that the increase in social welfare due to a \$1 decrease in ineligible UI is half of the increase from a \$1 transfer to individuals. A higher value of β corresponds to a stronger distaste for ineligible UI payments relative to the value of transfers.

Appendix A.3 shows that β can be identified from the following thought experiment. Consider a policy change that lowers the private value of UI benefits by \$10 million. If someone only views this policy change as worthwhile if it also leads to a decrease in the amount of UI benefits going to ineligible recipients of at least \$10 million, then they think $\beta > 1$. Alternatively, if someone only views this policy change as worthwhile if the amount of UI benefits to ineligibles falls by at least \$100 million, then $\beta > 0.1$.

We asked the lead senior staff members responsible for UI issues from each political party in each chamber of Congress (i.e. from the majority and minority side of the House Committee on Ways and Means and the Senate Committee on Finance) to complete a short survey to help us understand policymaker preferences over improper payments in unemployment insurance. Following the model-based approach developed in Appendix A.3, the survey asks respondents the minimum decrease in benefits to ineligible recipients that would be necessary for the majority of members of Congress from their party to support a policy change that lowers the private value of UI by \$10 million. Out of four possible respondents (one Democrat and Republican in the House and Senate), we received complete responses from both Democrats and one Republican. The average of the Democrat staff members' responses leads to $\beta > 0.12$, and the Republican staff member's

[59] Estimates of the elasticity of UI benefits with respect to the UI benefit amount in Anderson and Meyer (1997) range from 0.39 to 0.95 (Table IV). We are unaware of estimates of the elasticity of UI benefits with respect to the UI benefit amount among ineligible individuals.

response implies a greater distaste for ineligible UI payments of $\beta > 1$.[60] While this evidence is novel and valuable, there remains uncertainty about the relevant value of δ. Given this, we present results for a range of values of β, from 0 to 3.

A final issue is that, because the level of equation (8) depends on the social welfare weights and utility function, it is difficult to interpret the resulting numbers and compare results across different parametrizations. To address this issue, we report the effect of the reform, $dW/-db$, divided by the effect of giving everyone an increase in the lump-sum transfer through an exogenous increase in the budget constraint.[61] This means that we report the change in social welfare from the UI reform as a share of the welfare gain from an exogenous \$1 increase in the lump-sum transfer to everyone.

7.4 Results

Targeting We begin by quantifying the targeting gap at the heart of equation (8). When setting social welfare weights to be the same for everyone and setting $\gamma = 2$, the change in welfare due to differences in targeting from equation (8) is:

$$38{,}924{,}990 \cdot \left[\underbrace{(0.57 \cdot 0.00036 + 0.43 \cdot 0.00012)}_{\substack{\text{Population-weighted} \\ \text{avg. social value} \\ = 0.00026}} - \underbrace{(0.80 \cdot 0.00021 + 0.20 \cdot 0.00013)}_{\substack{\text{UI-recipient-weighted} \\ \text{avg. social value} \\ = 0.00019}} \right] \tag{9}$$

While the scale is not directly meaningful (the units are utils), the expression clearly illustrates the targeting gap. The population-average social value of a dollar (0.00026) exceeds the UI-recipient-average social value (0.00019), so the reform is welfare-improving through the targeting channel. Ineligible UI recipients are less needy than eligible UI recipients (0.00013 vs. 0.00021), and the presence of these individuals among UI recipients lowers the social cost of reducing UI benefits compared to a world where only eligible individuals got UI benefits. This confirms that

[60]The Democrat staff members' individual responses imply $\beta > 0.1$ and $\beta > 0.133$. To protect respondent privacy, we do not report the chamber in which the Republican staff member works.

[61]This is: $\left.\frac{\partial W}{\partial t}\right|_b = \bar{\alpha}\bar{u}'$.

the presence of ineligible recipients lowers the targeting advantages of UI relative to an automatic transfer.

Total Welfare Effects Figure 6 displays the total welfare effects of the reform, allowing for non-zero δ. Social welfare weights are the same for everyone in Panel A and set to zero for people who did not lose income between 2019 and 2020 in Panel B. When including UI benefits in people's consumption (results shown in the top navy blue line), the welfare effects of the reform are always positive. In effect, UI benefits in 2020 were so high that people who received UI had lower marginal utilities of consumption on average than those who did not receive UI, generating a positive targeting gap (the first line of equation (8)). As a result, it is welfare-improving to slightly decrease UI benefits and increase the lump-sum transfer received by everyone. Notably, this result holds even when social welfare weights are zero for people who did not lose income between 2019 and 2020 (Panel B). Moreover, the size of the welfare gains are meaningful. For example, when the government does not have a direct distaste for UI benefits going to ineligible recipients ($\delta = 0$) and places positive social welfare weights on everyone (Panel A), the budget-neutral reform that lowers the UI benefit level by \$1 and redistributes funds to lump-sum transfers increases social welfare by 6% as much as a reform that exogenously increases the lump-sum transfer by \$1. This value grows with the government's distaste for UI benefits paid to ineligible recipients. For example, the welfare gain is 62% larger for the value of δ implied by the lower bound of Republican than Democratic survey responses.

In contrast, the reform can have negative effects when considering scenarios with less generous UI benefits, as long as the government's distaste for ineligible UI payments is not too large. We illustrate this by re-calculating marginal utilities after keeping only 35% of each person's UI benefit—motivated by the fact that the average UI benefit amount in 2019 is 35% as large as the average in 2020—and when excluding all UI benefits from consumption (results in green and maroon lines, respectively). This reversal occurs because, when lowering UI benefits by either of these amounts, the average marginal utilities of UI recipients rise, such that the targeting advantage reverses. When excluding all UI payments for the case where $\delta = 0$ and social welfare weights are positive for everyone, the reform lowers social welfare by 11% as much as an exogenous \$1 decrease in the lump-sum transfer. However, once $\beta \geq 2.5$, the welfare effect turns positive, as the distaste for ineligible UI payments outweighs the worse targeting properties that follow the reform.[62]

We also consider the welfare effects of this reform if all anomalous UI benefits were eliminated and redistributed according to equation (2) (results shown in the horizontal, short-dash navy line). This exercise provides another way to understand how the presence of anomalous UI payments shapes the optimal amount of UI. We find that eliminating anomalous UI decreases the welfare gains from reducing UI benefits at the margin. Intuitively, if there are no anomalous UI payments, then the targeting gap narrows. Most strikingly, when there are only positive social welfare weights on income losers (Panel B), the welfare effect of cutting UI flips from being positive to negative.

One final takeaway from these results is that the welfare consequences of shifting funds from UI to a lump-sum transfer depends on the size of the UI benefit level. A natural question is how much 2020 UI benefits would have had to be cut before the welfare effects of the reform turn negative. We examine this issue by proportionally cutting all UI receipients' benefit amount. When $\delta = 0$ and $\alpha_i > 0$ for everyone, the effects of the reform turn negative when UI benefits are cut by 35–40%. When $\alpha_i > 0$ only for income losers, the effects of the reform turn negative when UI benefits are cut by 10–15%.[63] This suggests that, according to this model, the welfare-maximizing level of UI benefits in 2020 might have been 10–40% lower than what was actually implemented.

Extensions This model can be extended in several ways. First, it is straightforward to modify social welfare weights to depend on individuals' eligibility status. For example, a government may want to ignore the welfare losses that ineligible UI recipients experience from the reduction in UI benefits. When social welfare weights are the same for everyone and $\delta = 0$, the overall welfare

[62]The results in Figure 6 use a utility function parametrization of $\gamma = 2$ following the evidence in Landais and Spinnewijn (2021). When using higher values of γ, the pattern of results is similar, but the welfare effects of the reform are more positive (Appendix Figure A.6).

[63]For comparison, the third line from the top in Figure 6 cuts UI benefits by 65%.

gain of the reform rises by 39% when ignoring ineligibles' welfare loss from lower UI, underscoring how much the presence of ineligible recipients shapes the targeting comparison.[64] Second, in Appendix A.2 we extend the model to allow for labor supply responses. In this extension, individuals face an exogenous *weekly* wage and choose how many weeks to work, but they can only receive UI benefits if they do not work. The effects of the reform include changes in labor supply and income taxes. However, the conclusion from this model is qualitatively similar to that from our baseline approach. Finally, the model also could be extended to allow for heterogeneity in the type of UI and lump-sum transfer that people receive. This would facilitate the analysis of policies that cut PUA vs. regular UI benefit amounts separately and redistribute funds to particular groups of people.

8 Conclusion

This paper uses administrative tax data to provide a comprehensive analysis of likely ineligible UI payments during the expansion of 2020 and 2021. We estimate that \$214 billion in UI payments—24% of all payments during this period—were anomalous, and that these payments were disproportionately concentrated in the PUA program. Approximately half of likely ineligible payments could have been identified before disbursement with improved federal-state data sharing. While anomalous payments appear across the income distribution, they are concentrated among individuals with no 2019 earned income and exhibit significant geographic clustering, with the top 1% of ZIP codes accounting for 22% of all such payments. Using a state border design, we find that states with higher pre-pandemic fraud rates and higher 2020 claim approval rates experienced substantially more anomalous PUA payments. The scale of anomalous UI payments likely reduced the true revenue cost of the 2021 ARP provision that excluded up to \$10,000 of UI benefits from income, while that same exclusion also relieved identity theft victims of the burden of proving fraudulent payments to the IRS.

[64] Follow-up interviews with our Congressional staff respondents indicated that Democrats may ignore the welfare losses for individuals who are knowingly ineligible, whereas Republicans may disregard welfare losses for all ineligible recipients, regardless of their intent.

Our counterfactual analysis demonstrates that alternative policy designs could have achieved better outcomes. Replacing PUA with means-tested, lump-sum transfers—providing benefits equal to the smaller of individuals' 2019 earned income and $10,000—would have reduced the share of individuals experiencing large income losses by nearly 6 percentage points while eliminating a substantial source of likely ineligible payments. A calibrated theoretical model further suggests that shifting expenditures from UI to automatic transfers in 2020 would have increased social welfare, primarily driven by the high generosity of UI benefits during this period.

More broadly, our results highlight a fundamental tradeoff in social insurance design: programs with complex eligibility criteria require robust verification systems. When such systems are lacking, automatic transfers—though less precisely targeted in theory—may outperform opt-in programs that cannot effectively screen out ineligible recipients.

References

Aman-Rana, Shan, Daniel Gingerich, and Sandip Sukhtankar. 2026. "Screen Now, Save Later? The Trade-Off between Administrative Ordeals and Fraud." Working paper.

Anderson, Patricia M., and Bruce D. Meyer. 1997. "Unemployment Insurance Takeup Rates and the After-Tax Value of Benefits." *Quarterly Journal of Economics*, 112(3): 913–937.

Bertrand, Marianne, Erzo F. P. Luttmer, and Sendhil Mullainathan. 2000. "Network Effects and Welfare Cultures." *Quarterly Journal of Economics*, 115(3): 1019–1055.

Besley, Timothy, and Stephen Coate. 1992. "Workfare versus Welfare: Incentive Arguments for Work Requirements in Poverty-Alleviation Programs." *American Economic Review*, 82(1): 249–261.

Boone, Christopher, Arindrajit Dube, Lucas Goodman, and Ethan Kaplan. 2021. "Unemployment Insurance Generosity and Aggregate Employment." *American Economic Journal: Economic Policy*, 13(2): 58–99.

Chetty, Raj, and Amy Finkelstein. 2013. "Social insurance: Connecting theory to data." In *Handbook of public economics*. Vol. 5, 111–193. Elsevier.

Chetty, Raj, John N. Friedman, and Emmanuel Saez. 2013. "Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings." *American Economic Review*, 103(7): 2683–2721.

Clark, Leah R., Adam J. Cole, Amanda Eng, Ben S. Meiselman, Nikolas Pharris-Ciurej, Kevin Pierce, and John Voorheis. 2023. "The Demographics of the Recipients of the First Economic Impact Payment." U.S. Census Bureau CES Working Paper CES-23-24.

Currie, Janet. 2006. "The Take-Up of Social Benefits." In *Public Policy and Income Distribution*. ed. Alan J. Auerbach, David Card and John M. Quigley, 80–148. New York: Russell Sage

Foundation.
Deshpande, Manasi, and Yue Li. 2019. "Who Is Screened Out? Application Costs and the Targeting of Disability Programs." *American Economic Journal: Economic Policy*, 11(4): 213–248.
Eliason, Paul, Riley League, Jetson Leder-Luis, Ryan C McDevitt, and James W Roberts. 2025. "Ambulance Taxis: The Impact of Regulation and Litigation on Health-Care Fraud." *Journal of Political Economy*, 133(5): 1661–1702.
Finkelstein, Amy, and Matthew J Notowidigdo. 2019. "Take-Up and Targeting: Experimental Evidence from SNAP." *Quarterly Journal of Economics*, 134(3): 1505–1556.
Fuller, David L., B. Ravikumar, and Yuzhe Zhang. 2015. "Unemployment Insurance Fraud and Optimal Monitoring." *American Economic Journal: Macroeconomics*, 7(2): 249–290.
Ganong, Peter, Pascal Noel, and Joseph Vavra. 2020. "US unemployment insurance replacement rates during the pandemic." *Journal of public economics*, 191: 104273.
Jackson, Emilie, Dmitri Koustas, and Andrew Garin. 2024. "Effects of Unemployment Insurance for Self-Employed and Marginally-Attached Workers."
Khetan, Umang, Jetson Leder-Luis, Jialan Wang, and Yunrong Zhou. 2024. "Unemployment Insurance Fraud in the Debit Card Market." National Bureau of Economic Research Working Paper 32527.
Kleven, Henrik Jacobsen, and Wojciech Kopczuk. 2011. "Transfer Program Complexity and the Take-Up of Social Benefits." *American Economic Journal: Economic Policy*, 3(1): 54–90.
Ko, Wonsik, and Robert A Moffitt. 2022. "Take-up of Social Benefits." National Bureau of Economic Research Working Paper 30148.
Kuka, Elira, and Bryan A. Stuart. 2025. "Racial Inequality in Unemployment Insurance Receipt." *Journal of Public Economics*, 247: 105401.
Landais, Camille, and Johannes Spinnewijn. 2021. "The Value of Unemployment Insurance." *The Review of Economic Studies*, 88(6): 3041–3085.
Larrimore, Jeff, Jacob Mortenson, and David Splinter. 2022. "Earnings shocks and stabilization during COVID-19." *Journal of Public Economics*, 206: 104597.
Nichols, Albert L., and Richard J. Zeckhauser. 1982. "Targeting Transfers through Restrictions on Recipients." *American Economic Review*, 72(2): 372–377.
Rafkin, Charlie, Adam Solomon, and Evan J Soltas. 2024. "Self-Targeting in US Transfer Programs."
Shi, Maggie. 2024. "Monitoring for waste: Evidence from medicare audits." *The quarterly journal of economics*, 139(2): 993–1049.
U.S. Congress, House Committee on Ways and Means. 2023. *The Greatest Theft of Taxpayer Dollars: Unchecked Unemployment Fraud.* Washington, DC: U.S. Government Publishing Office. Hearing before the Committee on Ways and Means, House of Representatives, 118th Congress, 1st Session, February 8, 2023.
U.S. Department of Labor. 2023*a*. "Benefit Accuracy Measurement Payment Integrity Information Act, State Data Summary Performance Year 2022."
U.S. Department of Labor. 2023*b*. "PUA Improper Rate Report."
U.S. Department of Labor Office of Inspector General. 2023. "The Greatest Theft of American Tax Dollars: Unchecked Unemployment Fraud." Testimony before the U.S. House of Representatives Committee on Ways and Means.
U.S. Government Accountability Office. 2023. "Unemployment Insurance: Estimated Amount of Fraud during Pandemic Likely Between $100 Billion and $135 Billion." *Highlights of GAO-*

23-106696, a report to congressional requesters.

Table 1: UI Payments Flagged as Anomalous, By Reason

	Total (Billions $)			Recipients (Millions)		
	All	Regular	PUA	All	Regular	PUA
Panel A: UI in 2020						
Total Disbursed	558.6	396.7	161.9	45.35	33.69	11.65
Anomalous						
Invalid TIN	0.6	0.3	0.4	0.06	0.02	0.04
+ dead, below age 10, or above age 100	1.4	0.3	1.1	0.13	0.03	0.10
+ incarcerated all year	5.0	1.5	3.4	0.41	0.13	0.28
+ no state match from 2017–2019	18.0	1.5	16.5	1.51	0.13	1.38
+ Form 1099-G amended to 0	26.5	9.1	17.3	2.18	0.71	1.46
+ UI from multiple states	35.3	12.9	22.4	2.92	1.04	1.88
+ got DI in 2019 & 2020 and no earnings in 2019 & 2020	36.5	12.9	23.6	3.01	1.04	1.97
+ no earnings in 2019 & 2020	57.8	12.9	44.9	4.38	1.04	3.35
+ no decrease in earnings in 2020 and no indication of non-employment	108.2	46.0	62.2	11.13	6.27	4.85
Panel B: UI in 2021						
Total Disbursed	324.5	212.7	111.8	26.43	18.60	7.83
Anomalous						
Flagged as anomalous in 2020	47.1	19.3	27.8	4.06	1.94	2.12
Anomalous in 2021						
+ invalid TIN	51.4	19.3	32.0	4.08	1.94	2.14
+ dead, below age 10, or above age 100	53.9	19.4	34.6	4.08	1.94	2.14
+ incarcerated all year	54.3	19.5	34.8	4.12	1.96	2.16
+ no state match from 2019–2021	63.4	19.5	44.0	4.53	1.96	2.58
+ Form 1099-G amended to 0	63.8	19.8	44.1	4.57	1.99	2.59
+ UI from multiple states	66.7	21.1	45.6	4.86	2.11	2.75
+ got DI in 2020 & 2021 and no earnings in 2020 & 2021	66.9	21.1	45.8	4.88	2.11	2.77
+ no earnings in 2020 & 2021	69.7	21.1	48.6	5.10	2.11	2.99
+ no decrease in earnings in 2021 and no indication of non-employment	105.8	43.6	62.2	9.86	5.58	4.28

Notes: This table reports the amount of UI benefits and number of UI recipients that meet the specified criteria. Anomalous UI criteria are added sequentially, so that the bottom row of each panel reports the total amount of anomalous UI.
Source: Authors' analysis of de-identified IRS data.

Table 2: Concentration of Population and 2020 UI Payments in Top 1% and 5% of ZIP Codes

	Share of total in	
	Top 1% (1)	Top 5% (2)
Population	0.08	0.27
Total UI	0.14	0.40
Non-anomalous UI	0.13	0.39
Anomalous UI	0.22	0.50
Invalid TIN	0.43	0.97
Dead or age	0.50	0.86
Prisoner	0.28	0.62
No state match	0.39	0.73
1099-G amended to 0	0.85	0.96
UI from multiple states	0.29	0.60
No earned income in 2019 and 2020	0.29	0.63
Positive earned income, no decrease from 2019 to 2020	0.14	0.40

Notes: This table reports the share of the total amount of population or 2020 UI payments that are concentrated in the top 1% or top 5% of ZIP codes. Statistics are calculated across 32,394 ZIP codes with positive population, which means that there are about 323 ZIP codes in the top 1% and 1,615 ZIP codes in the top 5%.
Source: Authors' analysis of de-identified IRS data.

Table 3: ZIP Codes with Particularly Large Amounts of Anomalous UI Payments, Selected Categories

		Anomalous	Millions of dollars of anomalous UI payments						
Area (1)	Population (2)	UI dollars per capita (3)	All reasons (4)	Invalid TIN (5)	Dead or Age (6)	Prison (7)	No state match (8)	Amended 1099-G (9)	Multiple UI states (10)
Detroit, MI	57,000	2,710	154.44	0.27	2.30	12.44	41.70	1.69	53.98
Detroit, MI	46,000	2,854	131.28	0.11	2.14	10.78	35.68	1.04	44.85
Detroit, MI	40,000	3,221	128.84	0.05	3.09	8.75	34.52	0.70	45.77
Detroit, MI	44,000	2,712	119.34	0.00	1.58	10.18	31.77	1.10	37.18
Detroit, MI	39,000	3,006	117.23	0.09	2.59	10.04	24.27	1.39	41.00
Detroit, MI	32,000	3,436	109.95	0.00	1.64	9.21	26.82	1.05	39.46
Detroit, MI	34,000	2,621	89.11	0.00	1.59	6.29	20.87	0.64	29.65
Detroit, MI	41,000	2,151	88.18	0.00	2.47	4.26	23.94	0.65	30.93
Detroit, MI	25,000	3,149	78.74	0.00	1.44	6.54	23.59	0.83	28.73
Detroit, MI	22,000	3,398	74.76	0.00	0.96	6.32	20.85	0.92	29.63
North Hollywood, CA	35,000	2,125	74.36	0.55	1.55	1.64	36.43	0.02	15.72
Van Nuys, CA	56,000	1,261	70.61	1.18	2.70	1.85	29.43	0.00	7.89
Los Angeles, CA	30,000	2,263	67.90	0.52	0.72	2.27	32.26	0.13	14.87
Long Beach, CA	56,000	1,184	66.30	0.86	3.97	1.32	23.92	0.00	8.61
Los Angeles, CA	61,000	1,072	65.40	1.03	3.20	1.32	21.96	0.18	10.38
North Hollywood, CA	43,000	1,508	64.85	0.75	2.66	0.61	29.45	0.00	6.28
Los Angeles, CA	31,000	2,067	64.09	0.18	4.52	4.46	24.46	1.24	10.01
Detroit, MI	21,000	2,939	61.71	0.24	2.49	5.83	15.41	0.64	20.86
Detroit, MI	25,000	2,290	57.24	0.07	1.07	3.59	14.51	0.68	21.37
Highland Park, MI	21,000	2,687	56.43	0.06	1.58	3.55	16.63	0.57	19.86
Atlanta, GA	35,000	1,611	56.37	0.00	0.64	5.84	16.17	0.49	23.19
Inkster, MI	26,000	2,118	55.07	0.00	1.00	4.31	17.11	0.59	14.86
Los Angeles, CA	60,000	913	54.76	1.11	1.93	1.00	19.85	0.30	7.55
Long Beach, CA	38,000	1,397	53.07	0.55	4.45	2.76	16.81	0.00	7.30
Richmond, CA	43,000	1,187	51.03	0.66	1.34	1.94	17.57	0.00	7.90
Los Angeles, CA	38,000	1,220	46.34	1.55	2.35	1.17	16.19	0.16	5.93
Tampa, FL	16,000	2,644	42.31	0.00	0.00	2.05	17.40	0.00	21.18
Opa Locka, FL	32,000	1,306	41.79	0.66	0.70	1.51	24.13	0.69	12.07
Tujunga, CA	27,000	1,491	40.27	0.75	1.26	0.25	15.73	1.10	6.60
Detroit, MI	15,000	2,682	40.23	0.05	0.88	3.45	11.69	0.68	16.31
Detroit, MI	20,000	1,974	39.48	0.00	0.64	3.28	10.38	0.52	14.88
Los Angeles, CA	28,000	1,322	37.01	0.62	1.71	0.87	18.64	0.52	7.13
New York, NY	27,000	1,330	35.91	0.79	0.89	1.22	8.60	8.47	4.32
Detroit, MI	20,000	1,731	34.61	0.00	0.64	1.98	9.68	0.27	14.10
Glendale, CA	17,000	1,936	32.90	0.86	0.86	0.82	15.20	0.00	2.25
Los Angeles, CA	37,000	884	32.72	0.78	1.54	1.05	13.18	0.00	3.44
Harper Woods, MI	16,000	1,650	26.39	0.22	0.62	0.77	6.12	1.23	10.20
Detroit, MI	15,000	1,737	26.06	0.00	0.26	2.54	8.52	0.29	8.55
Pontiac, MI	19,000	1,363	25.91	0.00	0.28	5.11	6.17	0.03	6.47
Los Angeles, CA	13,000	1,877	24.40	0.35	0.89	1.06	8.24	0.43	2.57

Notes: The starting point for this table is 62 ZIP codes that have at least 100 residents and have at least 3 appearances in the top 1% in terms of per capita UI payments that are anomalous according to the reasons listed in columns 5–10 of the table. We then select the 40 ZIP codes with the highest amount of total anomalous UI payments among this sample. Numbers in column 2 are rounded to the nearest thousand. Column 4 reports the total amount of anomalous UI payments associated with each ZIP code for all reasons listed in Table 1. A UI payment can be classified as anomalous for multiple reasons and hence show up in more than one of columns 5–10. Column 3 is the ratio of columns 4 and 2, converted from millions of dollars into dollars. Data cover 2020 UI payments only.

Source: Authors' analysis of de-identified IRS data; Population data from American Community Survey.

Table 4: Relationship Between Non-Anomalous and Anomalous UI Payments, Results from State Border Pair Design

	OLS	First stage	Reduced form	IV	IV controls	Placebo
	Dependent variable:					
	Anomalous UI per cap. (1)	Non-Anomalous UI per cap. (2)	Anomalous UI per cap. (3)	Anomalous UI per cap. (4)	Anomalous UI per cap. (5)	Industry-predicted UI receipt (6)
Panel A: Regular UI Program						
Non-anomalous UI	0.015			0.052	0.052	
	(0.005)			(0.037)	(0.034)	
Non-anomalous UI, leave-out state mean		0.503	0.026			-0.011
		(0.067)	(0.019)			(0.012)
Panel B: PUA UI Program						
Non-anomalous UI	0.212			0.897	0.893	
	(0.047)			(0.098)	(0.097)	
Non-anomalous UI, leave-out state mean		0.592	0.531			-0.009
		(0.059)	(0.065)			(0.013)

Notes: This table reports estimates of ZIP code regressions from the state border pair research design, for the regular UI program (Panel A) and PUA (Panel B). Column 1 reports OLS estimates relating anomalous UI to non-anomalous UI. Column 2 reports first-stage estimates. Column 3 reports reduced-form estimates. Column 4 reports IV estimates. Column 5 reports IV estimates with ZIP code level controls measured in 2019: the number of adults; mean earned income; the 10th, 25th, 50th, 75th, and 90th percentiles of the earned income distribution; the share of adults that worked; the share of individuals that filed a 1040; the share with a measure of wealth in the tax data (based on either mortgage deductions or the receipt of interest or capital gains); the mean number of dependents; the mean age; and the percent living in an urban area. Column 6 reports the results from a placebo exercise where the dependent variable is the leave-out-ZIP, industry-predicted UI receipt rate, calculated as $\sum_k s_{z,k}$ UI $\text{Receipt}_{-z,k}$, where $s_{z,k}$ is the share of 2019 wage earners in ZIP code z employed in two-digit industry k and UI $\text{Receipt}_{-z,k}$ is the share of wage earners in industry k in 2019 who received UI in 2020 (excluding those living in ZIP code z). All regressions include fixed effects for the county border pair associated with each ZIP code. See text for additional details.

Source: Authors' analysis of de-identified IRS data.

Table 5: Relationship Between Anomalous Share of UI Payments and State UI Variables, Results from State Border Pair Design

		Share of UI Payments that are Anomalous			
		Regular UI		PUA	
	Explanatory variable mean (SD) (1)	Coef. (2)	1 SD effect as share of DV mean (3)	Coef. (4)	1 SD effect as share of DV mean (5)
BAM fraud rate, 2017–2019	0.029	0.017	0.002	1.893	0.091
	(0.017)	(0.123)		(0.405)	
Maximum weekly benefit amount, 2018	4.6	-0.001	-0.010	-0.003	-0.010
	(1.2)	(0.002)		(0.007)	
Share UI claims paid, 2020	0.75	-0.025	-0.040	0.197	0.105
	(0.19)	(0.016)		(0.034)	
Dependent variable mean		0.118		0.355	
Dependent variable SD		0.157		0.285	

Notes: This table reports estimates of ZIP code regressions from the county border pair research design. Column 1 reports means and SDs of the explanatory variables, calculated for the combined sample of ZIP codes. Column 2 reports coefficient estimates and robust standard errors of three separate regressions, where the dependent variable is the share of UI payments made through the regular UI program that are anomalous. Column 3 reports the product of the point estimate and the SD of the explanatory variable divided by the mean of the dependent variable. Columns 4 and 5 report analogous results for the PUA program. All regressions include fixed effects for the county border pair associated with each ZIP code.
Source: Authors' analysis of de-identified IRS data.

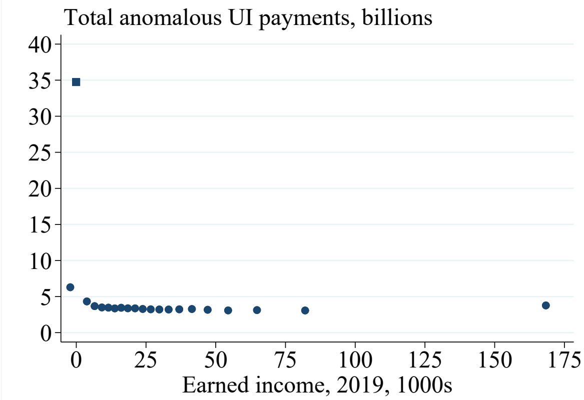
Table 6: Decomposition of Calibrated Welfare Effects of Reform that Marginally Lowers UI Benefits and Increases Lump-Sum Transfers

	Normalized change in welfare			
Relative value of decreasing anomalous payments, β (1)	Total (2)	Among eligibles (3)	Among ineligibles (4)	Due to lower ineligible UI (5)
Panel A: Consumption includes UI payments, positive social welfare weight for all				
0.0	0.059	0.035	0.023	0.000
1.0	0.104	0.035	0.023	0.046
Panel B: Consumption includes UI payments, positive social welfare weight for only income losers				
0.0	0.023	0.027	-0.004	0.000
1.0	0.069	0.027	-0.004	0.046
Panel C: Consumption excludes UI payments, positive social welfare weight for all				
0.0	-0.112	-0.115	0.003	0.000
1.0	-0.067	-0.115	0.003	0.046
Panel D: Consumption excludes UI payments, positive social welfare weight for only income losers				
0.0	-0.179	-0.169	-0.011	0.000
1.0	-0.134	-0.169	-0.011	0.046

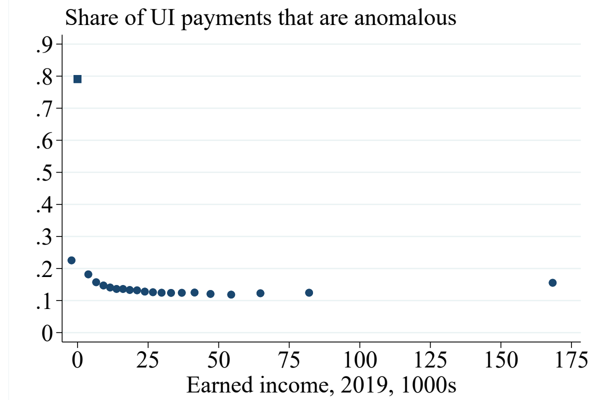
Notes: Table describes a decomposition of the welfare effect of a budget-neutral reform that lowers UI benefit levels by \$1 and increases lump-sum transfers, as a share of the welfare effect of an increase in lump-sum transfers by \$1 due to an exogenous increase in the government budget. Column 1 describes the degree to which the government has a direct distaste for UI benefits going to ineligible individuals. This is parametrized as $\delta = \beta\bar{\alpha}\bar{u}'$. Column 2 reports the total welfare effect, corresponding to the results shown in circles in Figure 6. Columns 3–5 decompose the total welfare effect into the welfare effect among people who are eligible for UI, people who are ineligible for UI, and the direct welfare effect of lowering UI payments to ineligible individuals. Only column 5 varies with β by construction. In Panel A, the social welfare weight, α_i, is the same positive constant for everyone. In Panel B, α_i is the same positive constant for people who lose earned income between 2019 and 2020 and 0 for everyone else. The parameter of relative risk aversion, γ, is 2.
Source: Authors' analysis of de-identified IRS data.

Figure 1: Anomalous UI Payments by 2019 Earned Income and Change in Income from 2019–2020

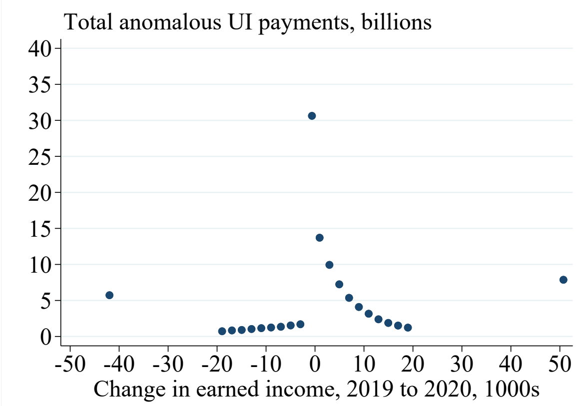
(a) Total Anomalous UI Payments by 2019 Earned Income



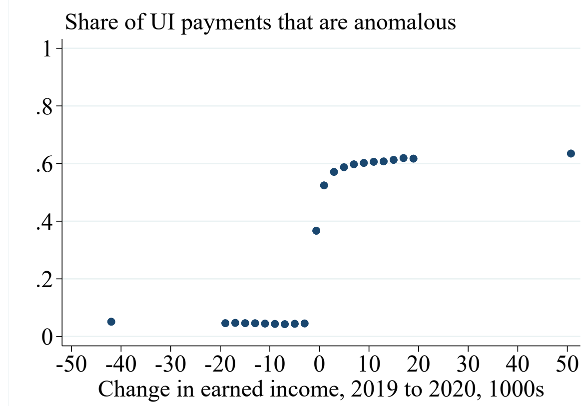
(b) Share of UI Payments that are Anomalous by 2019 Earned Income



(c) Total Anomalous UI Payments by 2019–2020 Change in Earned Income



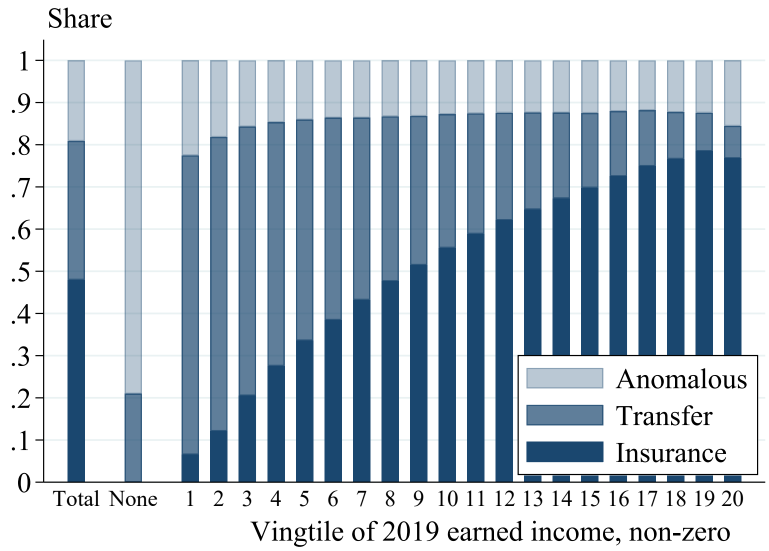
(d) Share of UI Payments that are Anomalous by 2019–2020 Change in Earned Income



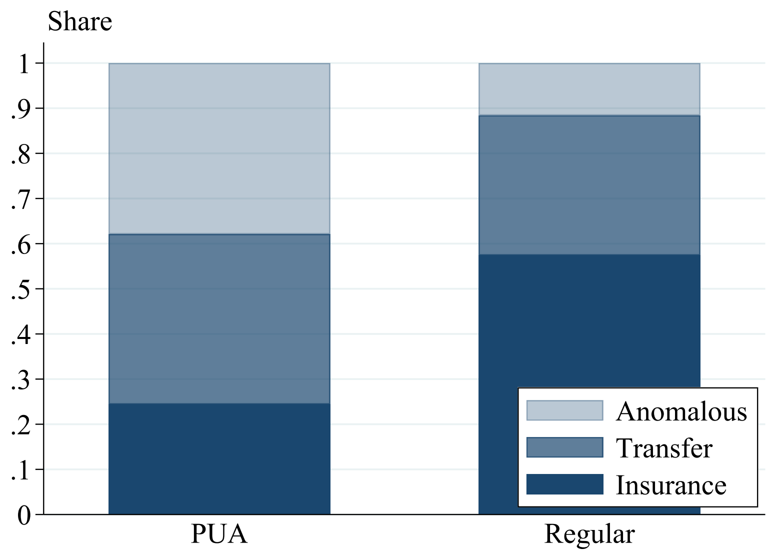
Notes: Panels A and C display the total amount of anomalous 2020 UI payments in billions of dollars. Panels B and D display the share of 2020 UI payments that are anomalous. In Panels A and B, the square symbol is for individuals with zero earned income in 2019, and the circles are for vingtiles of the non-zero earned income distribution. The location of each circle on the x-axis corresponds to the average earned income level within each vingtile. In Panels C and D, we report separate estimates for individuals with a 2019 to 2020 change in earned income that is less than −\$20,000, (−\$20,000, −\$18,000], ..., (\$18,000, \$20,000], and greater than \$20,000. The location of each circle on the x-axis corresponds to the average change in earned income within each category. The largest value in Panel B is for the earned income change in (−\$2,000, \$0].
Source: Authors' analysis of de-identified IRS data.

Figure 2: Share of UI Payments Classified as Income Replacement, Transfers, and Anomalous – By 2019 Earned Income and Regular/PUA Status

(a) Earned Income, 2019



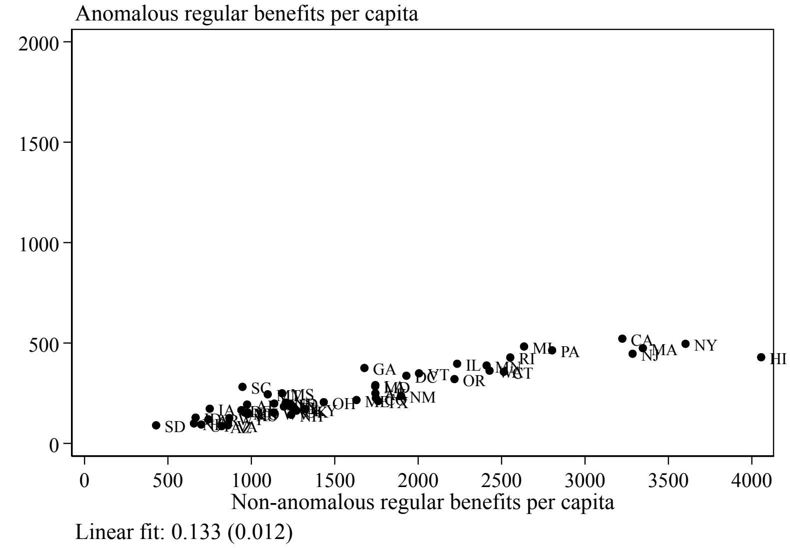
(b) Predicted Regular/PUA Eligibility Based on 2019 Earned Income



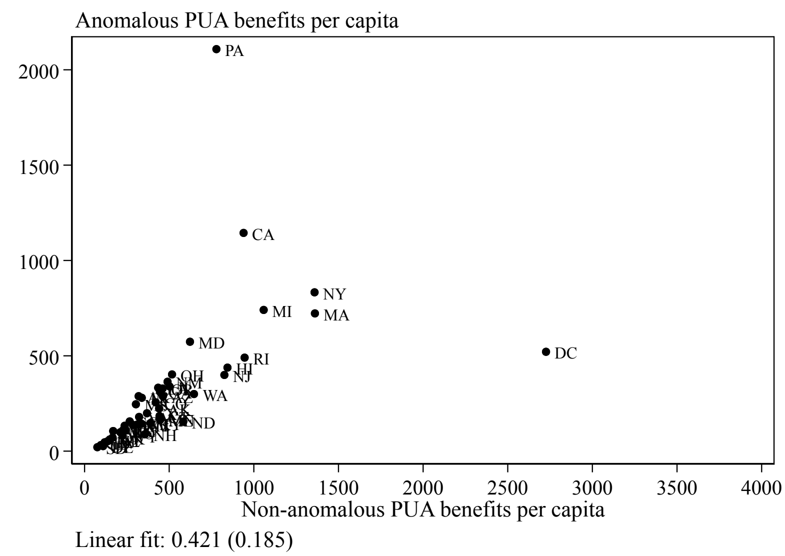
Notes: This figure displays the share of 2020 UI payments that are anomalous, a transfer (i.e., in excess of the decrease in earned income from 2019–2020), or income insurance (i.e., up to and including the decrease in earned income from 2019–2020). Panel A reports results for all individuals, individuals with no earned income in 2019, and individuals in each vingtile of the non-zero earned income distribution. Panel B reports results for individuals who likely only qualified for PUA benefits (because their 2019 Form W-2 wage and salary income was below each state's minimum earnings threshold for regular UI benefits) and everyone else.
Source: Authors' analysis of de-identified IRS data.

Figure 3: Relationship Between Anomalous UI and Non-Anomalous UI

(a) Regular Payments



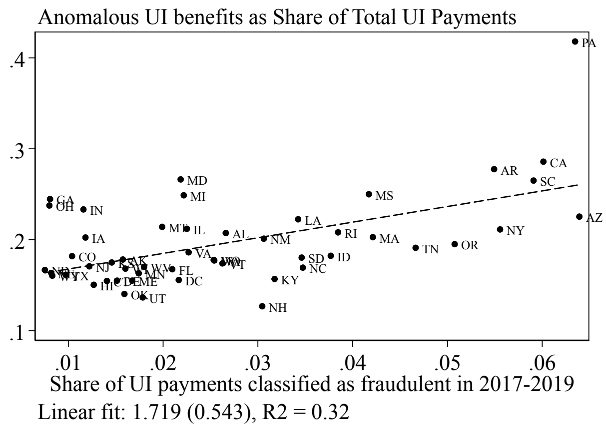
(b) PUA Payments



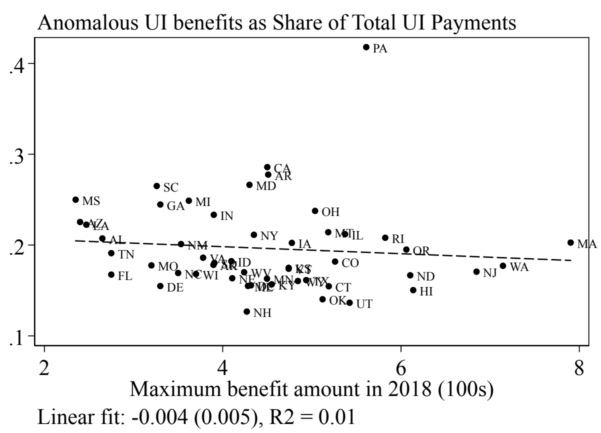
Notes: This figure plots the relationship between anomalous UI payments per working age individual against non-anomalous payments. We exclude Nevada from this figure because it is an outlier in anomalous UI, with \$4,667 of anomalous UI per working age individual and a share of anomalous UI among all UI disbursed of 84%. The estimated relationships are not sensitive to the inclusion of this outlier.
Source: Authors' analysis of de-identified IRS data.

Figure 4: Relationship Between Anomalous UI and Pre-Pandemic State UI Characteristics

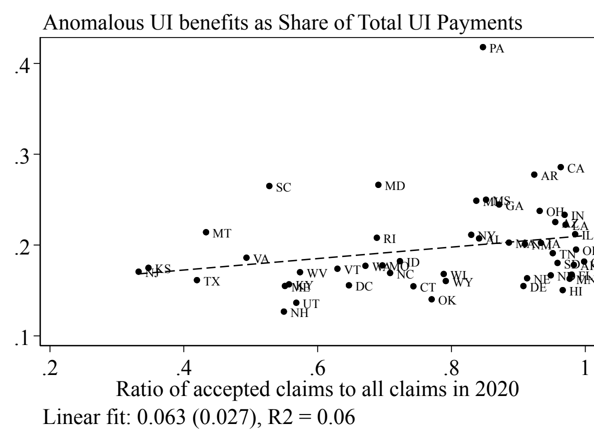
(a) BAM Fraud Rate, 2017–2019



(b) Maximum Weekly Benefit Amount, 2018

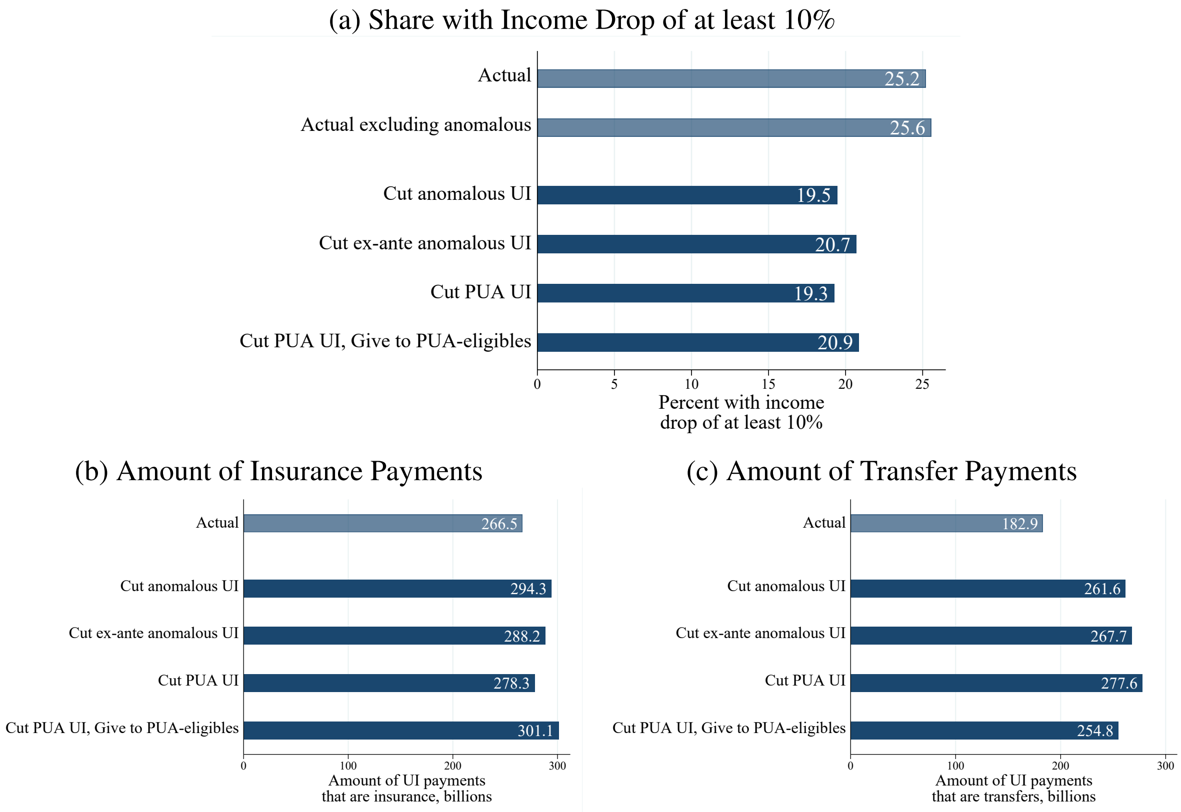


(c) Share Claims Paid, 2020



Notes: This figure plots the relationship between anomalous UI payments as a share of total payments against the characteristic of the state UI system indicated in each panel title. We exclude Nevada from this figure because it is an outlier in anomalous UI, with $4,667 of anomalous UI per working age individual and a share of anomalous UI among all UI disbursed of 84%. The estimated relationships are not sensitive to the inclusion of this outlier.
Source: Authors' analysis of de-identified IRS data.

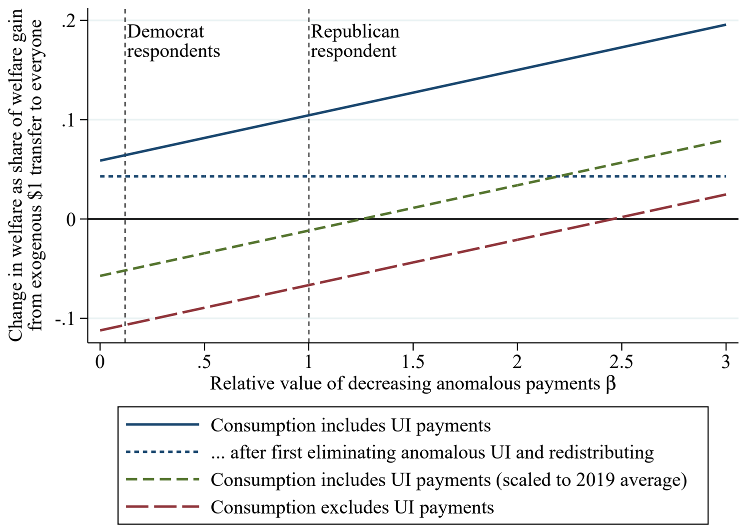
Figure 5: Income Losses, Insurance, and Transfer Payments under Actual and Counterfactual Scenarios



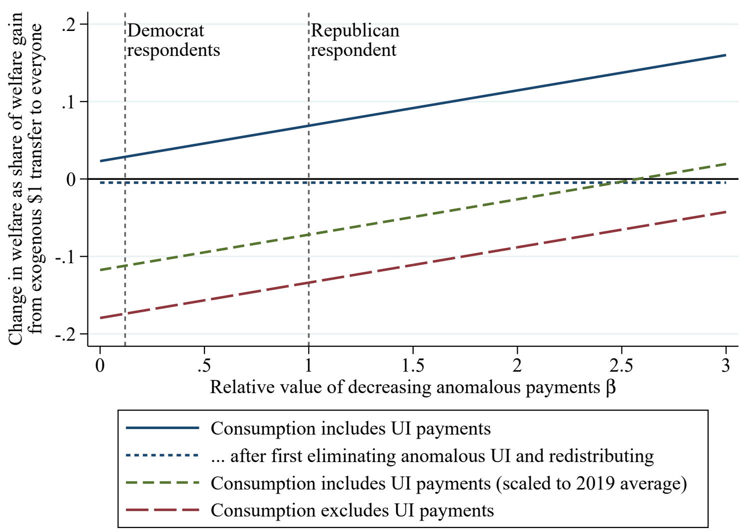
Notes: Panel A displays the share of individuals with non-zero 2019 earned income who experienced a decrease in their income (defined as earned income plus UI benefits) of at least 10% under the actual state of the world, with and without including anomalous UI payments. The figure also reports the share under counterfactual scenarios in which all anomalous UI payments are eliminated, ex-ante anomalous UI payments are eliminated, or PUA UI payments are eliminated. UI payments are redistributed to people with the lowest amounts of 2019 earned income (in absolute value) according to the redistribution function described in equation (2). The bottom bar shows results when UI payments are further restricted to individuals who would likely qualify for PUA because their 2019 wage and salary income was sufficiently low. Panels B and C display the amount of UI payments that are non-anomalous insurance (i.e., payments that replace income lost between 2019 and 2020) or transfers (payments exceeding the amount of lost income) under actual and counterfactual scenarios.
Source: Authors' analysis of de-identified IRS data.

Figure 6: Quantified Effects of Reform that Marginally Lowers UI Benefits and Increases Lump-Sum Transfers

(a) Positive social welfare weight α_i for everyone



(b) Positive social welfare weight α_i for only income losers



Notes: Figure displays the welfare effect of a budget-neutral reform that lowers UI benefit levels by $1 and increases lump-sum transfers, as a share of the welfare effect of an increase in lump-sum transfers by $1 due to an exogenous increase in the government budget. The x-axis shows the degree to which the government has a direct distaste for UI benefits going to ineligible individuals. This is parametrized as $\delta = \beta\bar{\alpha}\bar{u}'$. In Panel A, the social welfare weight, α_i, is the same positive constant for everyone. In Panel B, α_i is the same positive constant for people who lose earned income between 2019 and 2020 and 0 for everyone else. The top line includes 2020 UI benefits in consumption. The second line from the top reports results after anomalous UI payments are first eliminated and redistributed according to the benefit schedule in equation (2). The third line from the top reports results when only keeping 35% of each person's UI benefit, motivated by the fact that the average UI benefit amount in 2019 is 35% as large as the average in 2020. The bottom line excludes all UI benefits from consumption. The short-dashed blue line reports effects after anomalous UI payments are first eliminated and redistributed according to the benefit schedule in equation (2). The parameter of relative risk aversion, γ, is 2. The vertical lines indicate the lower bound of β implied by survey responses of two Democrat Congressional staffers (0.12) and one Republican Congressional staffer (1).
Source: Authors' analysis of de-identified IRS data.

Online Appendix

Table A.1: UI Payments in 2019 Flagged as Anomalous, By Reason

	Total (Billions)	Recipients (Millions)
Total Disbursed	28.94	6.76
Anomalous		
Invalid TIN	0.03	0.01
+ dead, below age 10, or above age 100	0.09	0.02
+ incarcerated all year	0.17	0.05
+ no state match from 2017–2019	0.18	0.05
+ Form 1099-G amended to 0	0.18	0.05
+ UI from multiple states	0.39	0.10
+ got DI in 2019 and no earnings in 2018–2019	0.39	0.10
+ no earnings in 2018–2019	0.46	0.11
+ no decrease in earnings in 2019 and no indication of non-employment	3.30	1.12

Notes: This table reports the amount of 2019 UI benefits and number of UI recipients that meet the specified criteria. Anomalous UI criteria are added sequentially, so that the bottom row reports the total amount of anomalous UI.

Source: Authors' analysis of de-identified IRS data.

Table A.2: UI Payments Flagged as Anomalous, Separately by Reason, 2020

	Total (Billions)			Recipients (Millions)		
	All	Regular	PUA	All	Regular	PUA
Total anomalous	108.2	46.0	62.2	11.13	6.27	4.85
By reason, without stacking						
Invalid TIN	0.6	0.3	0.4	0.06	0.02	0.04
Dead, below age 10, or above 100	1.4	0.3	1.1	0.13	0.03	0.10
Incarcerated all year	3.6	1.2	2.4	0.28	0.10	0.18
No match to states from 2019–2021	14.0	0.0	14.0	1.20	0.00	1.20
1099-G amended to 0	9.1	7.6	1.5	0.73	0.59	0.14
Received UI from multiple states	12.9	3.9	9.0	1.10	0.34	0.77
Got DI in 2020, no 2019–2020 earnings	1.9	0.0	1.9	0.15	0.00	0.15
No 2019–2020 earnings	36.8	0.0	36.8	2.68	0.00	2.68
No 2020 decrease in earnings, no non-employment	56.3	34.5	21.8	7.32	5.42	1.90

Notes: This table reports the amount of UI benefits and number of UI recipients that meet the specified criteria. Anomalous UI criteria are considered on a case-by-case basis, which distinguishes this table from Table 1.
Source: Authors' analysis of de-identified IRS data.

Table A.3: Total and Anomalous UI Payments by State, 2020–2021

State	Total UI, billions \$ (1)	Anomalous UI, billions \$ (2)	Share Anomalous (3)	Anomalous UI per Capita (4)
AK	1.45	0.26	0.178	474
AL	5.72	1.19	0.207	299
AR	3.45	0.96	0.278	408
AZ	9.39	2.12	0.225	374
CA	181.72	51.94	0.286	1666
CO	12.15	2.21	0.182	482
CT	10.19	1.58	0.155	540
DC	3.06	0.48	0.156	858
DE	0.99	0.15	0.155	192
FL	31.12	5.21	0.167	298
GA	23.35	5.71	0.245	688
HI	6.49	0.98	0.150	867
IA	2.78	0.56	0.202	225
ID	1.37	0.25	0.182	175
IL	35.15	7.45	0.212	736
IN	10.86	2.53	0.233	478
KS	3.29	0.57	0.175	255
KY	7.18	1.12	0.157	319
LA	10.06	2.24	0.222	623
MA	33.89	6.87	0.203	1197
MD	15.71	4.18	0.266	858
ME	2.78	0.43	0.155	381
MI	39.66	9.87	0.249	1223
MN	15.30	2.49	0.163	556
MO	6.89	1.22	0.178	253
MS	4.53	1.13	0.250	496
MT	1.55	0.33	0.214	384
NC	14.25	2.41	0.169	293
ND	1.28	0.21	0.167	358
NE	1.45	0.24	0.163	157
NH	2.08	0.26	0.127	231
NJ	36.66	6.26	0.171	846
NM	4.97	1.00	0.201	601
NV	13.17	11.01	0.836	4476
NY	102.06	21.56	0.211	1329
OH	23.89	5.68	0.238	608
OK	5.07	0.71	0.140	234
OR	11.44	2.23	0.195	649

continued

Table A.3: Total and Anomalous UI Payments by State, 2020–2021

State	Total UI, billions $ (1)	Anomalous UI, billions $ (2)	Share Anomalous (3)	Anomalous UI per Capita (4)
PA	64.36	26.90	0.418	2572
RI	3.96	0.82	0.208	919
SC	6.71	1.78	0.265	438
SD	0.42	0.08	0.180	111
TN	8.22	1.57	0.191	287
TX	56.27	9.08	0.161	410
UT	2.23	0.31	0.136	126
VA	9.82	1.83	0.186	270
VT	1.52	0.26	0.174	493
WA	22.86	4.05	0.177	662
WI	7.27	1.22	0.168	260
WV	2.47	0.42	0.170	291
WY	0.59	0.09	0.160	209

Notes: Columns 1 and 2 report the amount of all UI and anomalous UI payments issued by a state in 2020 and 2021. Column 3 reports the share of payments that are anomalous. Column 4 reports the amount of anomalous UI payments per working age individual.

Table A.4: Relationship Between Non-Anomalous and Anomalous UI Payments, Results from State Border Pair Design, Robustness to Sample and Instruments

Dependent variable: Anomalous UI per capita IV estimate, coefficient on non-anomalous UI	UI program	
	Regular (1)	PUA (2)
Panel A: Sensitivity to Distance		
5	-0.098	1.261
	(0.092)	(0.299)
10	0.001	1.030
	(0.047)	(0.145)
15 (baseline)	0.052	0.897
	(0.037)	(0.098)
20	0.040	0.784
	(0.030)	(0.072)
25	0.028	0.767
	(0.026)	(0.063)
30	0.034	0.778
	(0.024)	(0.060)
Panel B: Sensitivity to Counties Used in Leave-Out Instrument		
All other counties in same state (baseline)	0.052	0.897
	(0.037)	(0.098)
Subset of counties along other border segments	0.019	1.041
	(0.041)	(0.136)

Notes: This table reports estimates of ZIP code regressions from the county border pair research design. All coefficients are IV estimates from regressions where the dependent variable is the amount of anomalous UI per capita and the independent variable of interest is the amount of non-anomalous UI per capita. Column 1 reports results for the regular UI program, and column 2 reports results for the PUA UI program. In Panel A, we vary the sample by adjusting the maximum allowable distance between ZIP codes in adjacent states and counties; our baseline sample contains ZIP codes that are at most 15 miles from a ZIP code in the other county of the county border pair. In Panel B, we vary the construction of the instrument. Our baseline approach uses the amount of non-anomalous UI payments per capita in all counties within the same state as ZIP code z, excluding the county of z. We also report results when constructing an instrument based on the subset of these counties that also belong to a different county border pair than the one that contains ZIP code z.
Source: Authors' analysis of de-identified IRS data.

Table A.5: Relationship Between Anomalous UI Payments and State UI Variables, Results from State Border Pair Design

		Anomalous UI per capita			
		Regular UI		PUA	
	Explanatory variable mean (SD)	Coef.	1 SD effect as share of DV mean	Coef.	1 SD effect as share of DV mean
	(1)	(2)	(3)	(4)	(5)
BAM fraud rate, 2017–2019	0.029	1022.1	0.08	36,320.9	0.63
	0.017	(479.0)		(8317.4)	
Maximum weekly benefit amount, 2018	4.6	18.7	0.10	23.1	0.03
	1.2	(9.1)		(110.1)	
Share UI claims paid, 2020	0.75	41.0	0.04	2805.3	0.54
	0.19	(49.7)		(710.3)	
Dependent variable mean		215.9		985.3	
Dependent variable SD		425.3		2098.2	
Observations		10,185		9,868	

Notes: This table reports estimates of ZIP code regressions from the county border pair research design. Column 1 reports means and SDs of the explanatory variables, calculated for the combined sample of ZIP codes. Column 2 reports coefficient estimates and robust standard errors of three separate regressions, where the dependent variable is the amount of anomalous UI per capita. Column 3 reports the product of the point estimate and the SD of the explanatory variable divided by the mean of the dependent variable. Columns 4 and 5 report analogous results for the PUA program. All regressions include fixed effects for the county border pair associated with each ZIP code.

Source: Authors' analysis of de-identified IRS data.

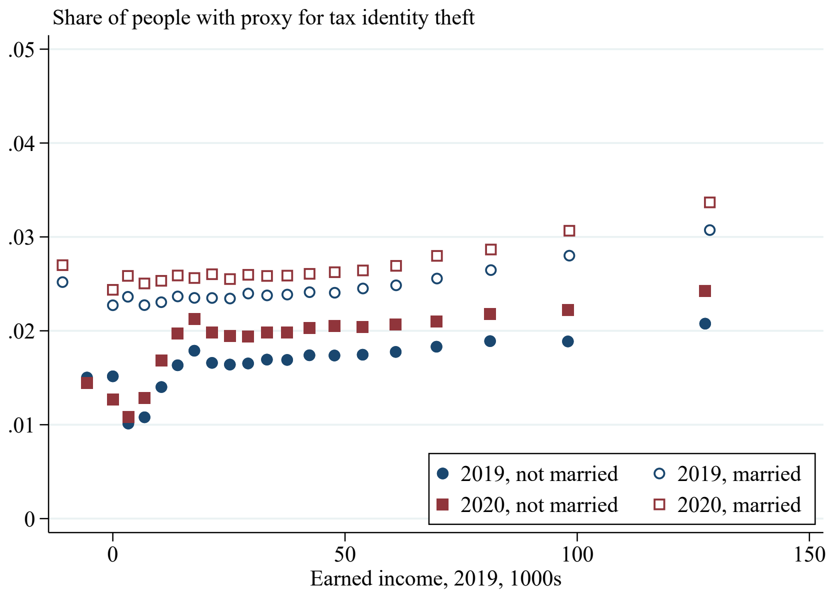
Table A.6: Location in 2019 Earned Income Distribution where Redistributed UI Benefits Are Exhausted in Main Counterfactual Exercises

Counterfactual exercise		
UI payments removed	Payment schedule	Maximum 2019 earnings of redistributed UI recipient
All anomalous	Less progressive	29,869
	More progressive	1,742
	Min($10,000, 2019 earnings)	8,074
Ex-ante anomalous	Less progressive	11,358
	More progressive	646
	Min($10,000, 2019 earnings)	5,266
PUA	Less progressive	54,635
	More progressive	3,001
	Min($15,000, 2019 earnings)	10,185

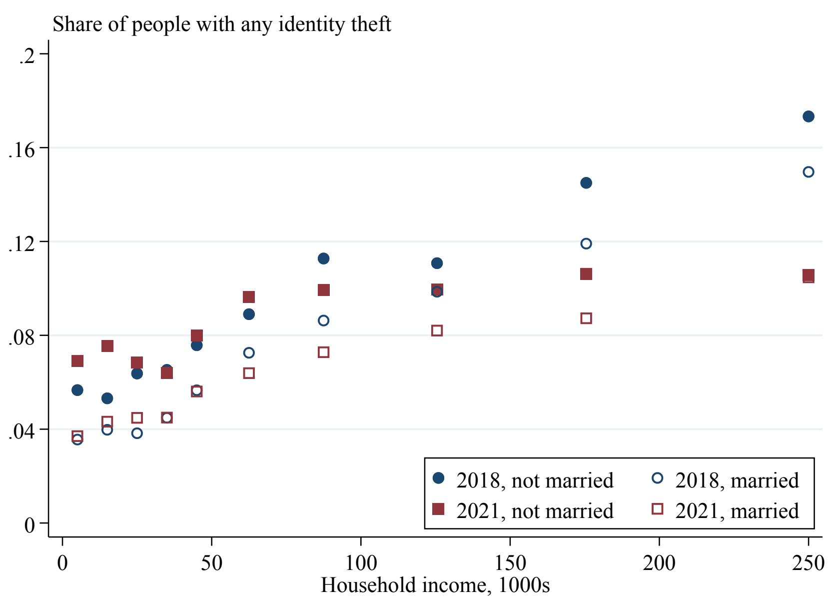
Notes: This table reports where in the 2019 earned income distribution we exhaust the redistributed UI benefits under the indicated counterfactual exercises. For each counterfactual, redistributed benefits are first provided to individuals with the lowest absolute value of 2019 earned income, and then benefits are provided up the earned income distribution (in absolute value terms) until all funds are exhausted.
Source: Authors' analysis of de-identified IRS data.

Figure A.1: Relationship between Income and Identity Theft

(a) Tax-Related Identity Theft (IRS)



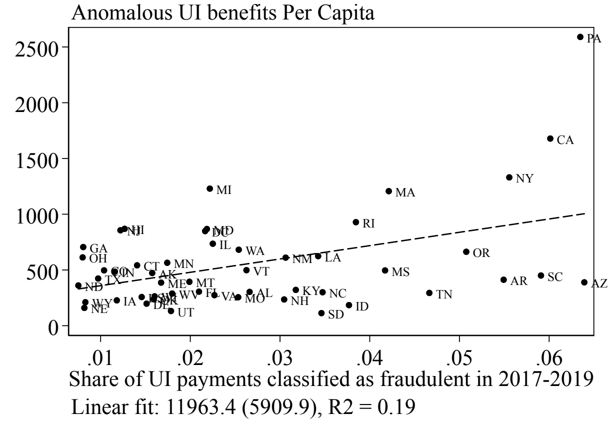
(b) All Identity Theft (NCVS)



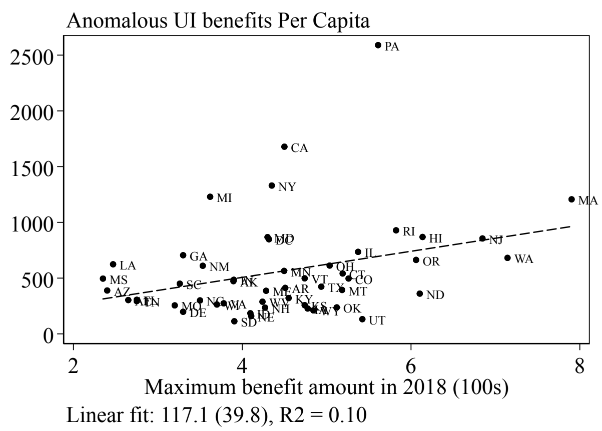
Notes: Panel A displays the share of people that were issued an identity protection PIN by the IRS in 2019 and 2020. The IRS issues identity protection PINs to taxpayers after cases of confirmed tax-related identity theft to mitigate improper tax filing. We calculate this share separately for married and non-married individuals because the PIN applies to the tax filing unit, which consists of both individuals if married filing jointly. For each year and marital status, we calculate the share separately by vingtiles of the 2019 earned income distribution. We omit the highest vingtile (95% and above) from this figure to focus on lower-income levels. Panel B reports the share of people who report being a victim of identity theft from the National Crime Victimization Survey.
Source: Authors' analysis of de-identified IRS data and National Crime Victimization Survey data.

Figure A.2: Relationship Between Anomalous UI and Pre-Pandemic State UI Characteristics

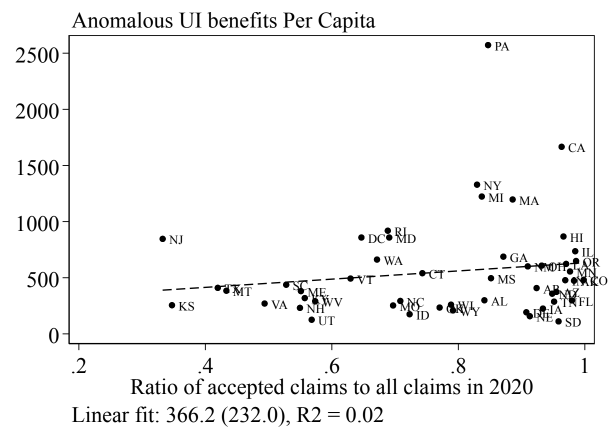
(a) BAM Fraud Rate, 2017–2019



(b) Maximum Weekly Benefit Amount, 2018



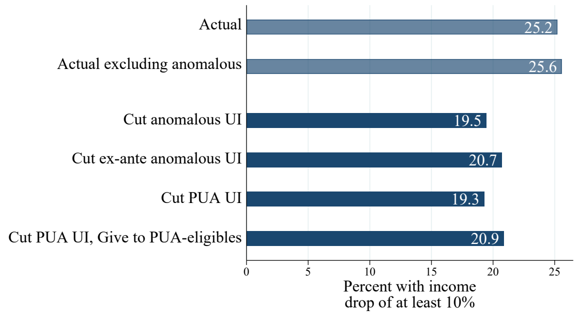
(c) Share Claims Paid, 2020



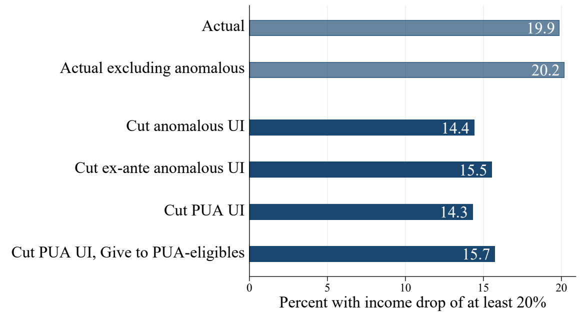
Notes: This figure plots the relationship between anomalous UI payments per working age individual against the characteristic of the state UI system indicated in each panel title. The number of working age individuals in each state is the civilian noninstitutional population aged 16 and above. We calculate this using averages from 2017 to 2019 of the number of employed individuals and the employment-population ratio in each state from the BLS. We exclude Nevada from this figure because it is an outlier in anomalous UI, with $4,667 of anomalous UI per working age individual and a share of anomalous UI among all UI disbursed of 84%. The estimated relationships are not sensitive to the inclusion of this outlier.
Source: Authors' analysis of de-identified IRS data.

Figure A.3: Share with Income Drop of at least 10% or 20% under Actual and Counterfactual Scenarios, Comparison of Results from Different Payment Schedules

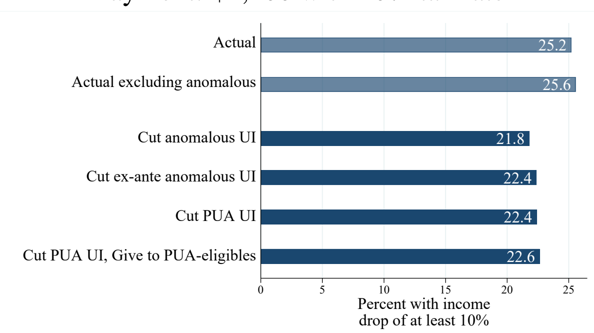
(a) Income Drop of at least 10%
Payment: Min($10,000, 2019 earnings)



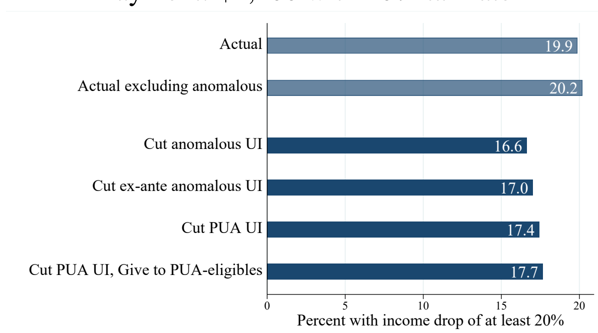
(b) Income Drop of at least 20%
Payment: Min($10,000, 2019 earnings)



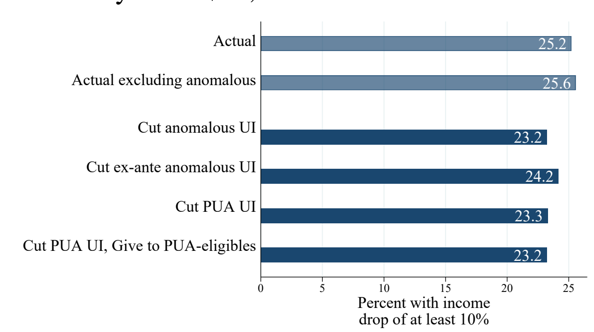
(c) Income Drop of at least 10%
Payment: $1,200 with 10% tax rate



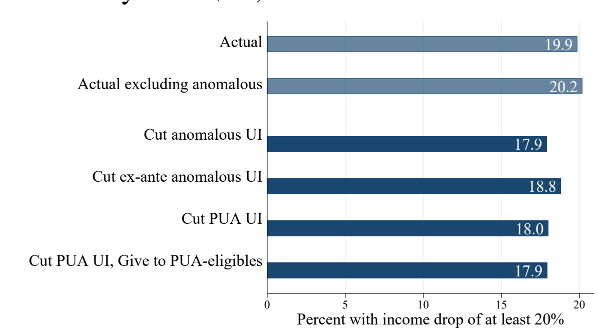
(d) Income Drop of at least 20%
Payment: $1,200 with 10% tax rate



(e) Income Drop of at least 10%
Payment: $10,000 with 20% tax rate

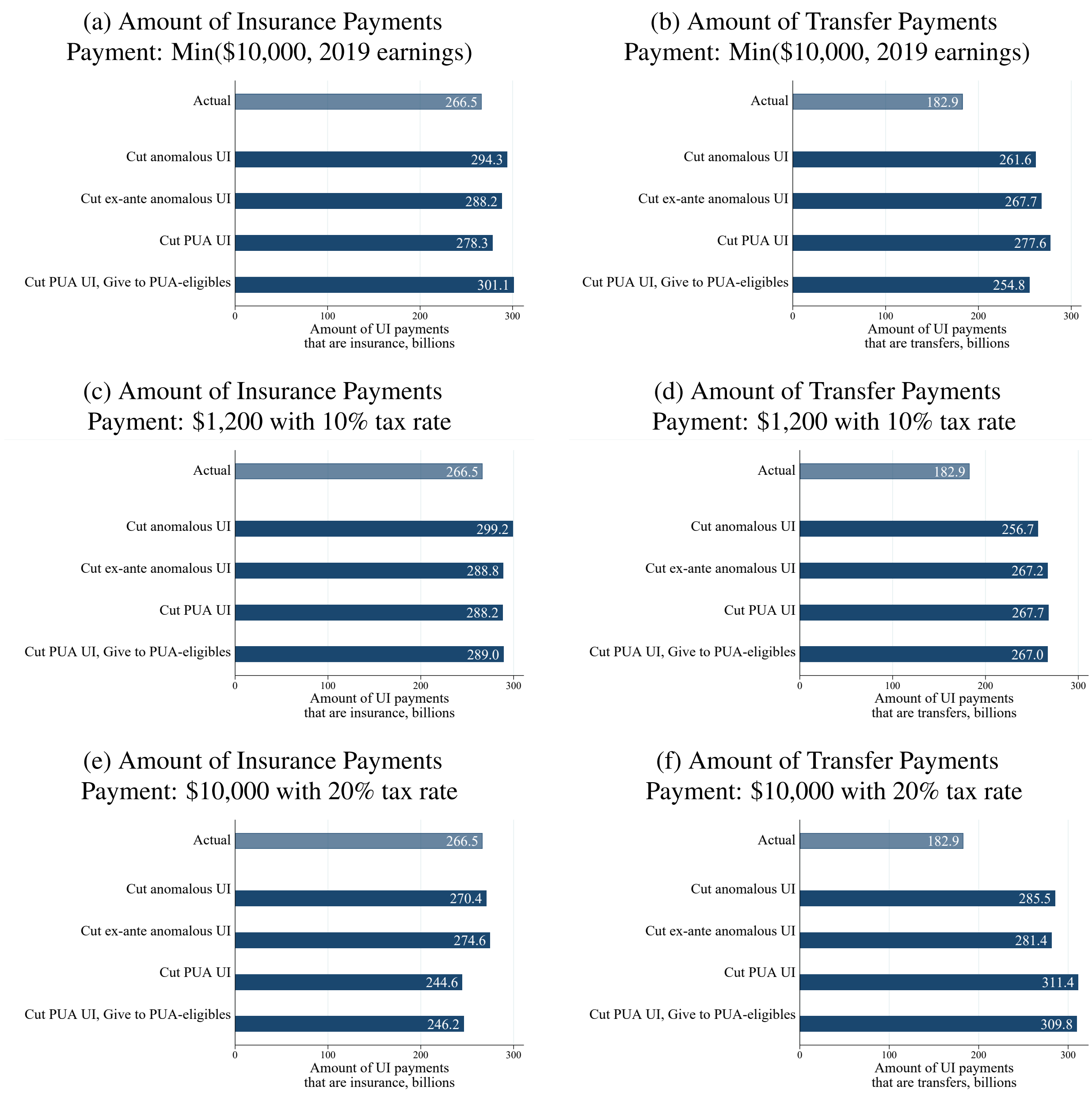


(f) Income Drop of at least 20%
Payment: $10,000 with 20% tax rate



Notes: Figure displays the share of individuals with non-zero 2019 earned income who experienced a decrease in their income (defined as earned income plus UI benefits) of at least 10% (Panels A, C, E) or at least 20% (Panels B, D, F) under the actual state of the world, with and without including anomalous UI payments. The figure also reports the share under counterfactual scenarios in which all anomalous UI payments are eliminated, ex-ante anomalous UI payments are eliminated, or PUA UI payments are eliminated. UI payments are redistributed to people with the lowest amounts of 2019 earned income (in absolute value). The bottom bar shows results when UI payments are further restricted to individuals who would likely qualify for PUA because their 2019 wage and salary income was sufficiently low. Panels A and B use the redistribution function described in equation (2). Panels C and D use the redistribution function described in equation (3). Panels E and F use the redistribution function described in equation (4).
Source: Authors' analysis of de-identified IRS data.

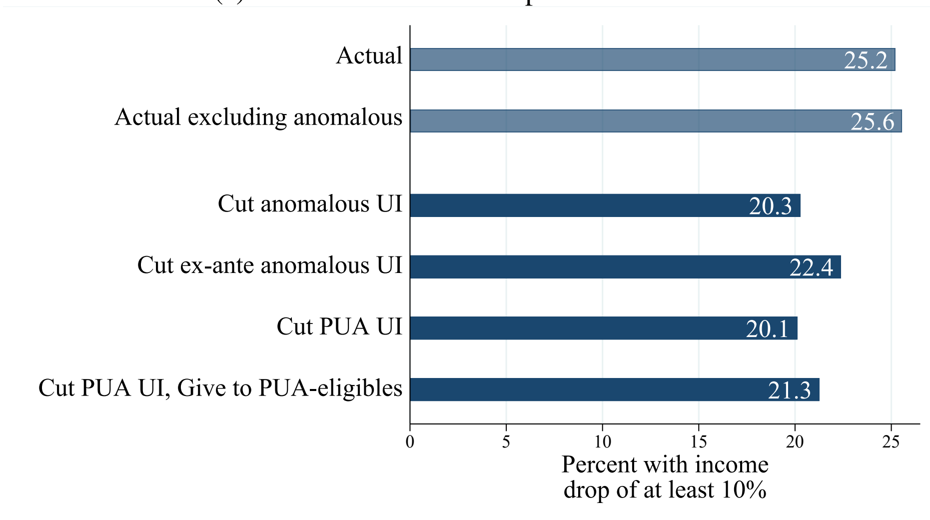
Figure A.4: Amount of Insurance and Transfer Payments under Actual and Counterfactual Scenarios, Comparison of Results from Different Payment Schedules



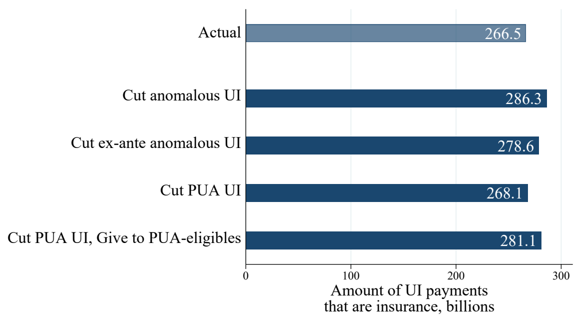
Notes: Figure displays the amount of UI payments that are non-anomalous insurance (i.e., payments that replace income lost between 2019 and 2020) or transfers (payments exceeding the amount of lost income) under the actual state of the world. The figure also reports the share under counterfactual scenarios in which all anomalous UI payments are eliminated, ex-ante anomalous UI payments are eliminated, or PUA UI payments are eliminated. UI payments are redistributed to people with the lowest amounts of 2019 earned income (in absolute value). The bottom bar shows results when UI payments are further restricted to individuals who would likely qualify for PUA because their 2019 wage and salary income was sufficiently low. Panels A and B use the redistribution function described in equation (2). Panels C and D use the redistribution function described in equation (3). Panels E and F use the redistribution function described in equation (4).
Source: Authors' analysis of de-identified IRS data.

Figure A.5: Income Losses, Insurance, and Transfer Payments under Actual and Counterfactual Scenarios, Only Removing UI Payments from People with Non-zero Earned Income in 2019

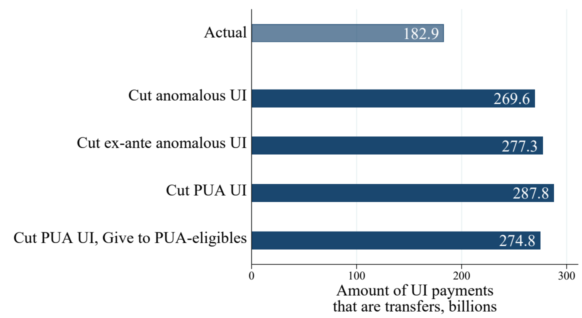
(a) Share with Income Drop of at least 10%



(b) Amount of Insurance Payments

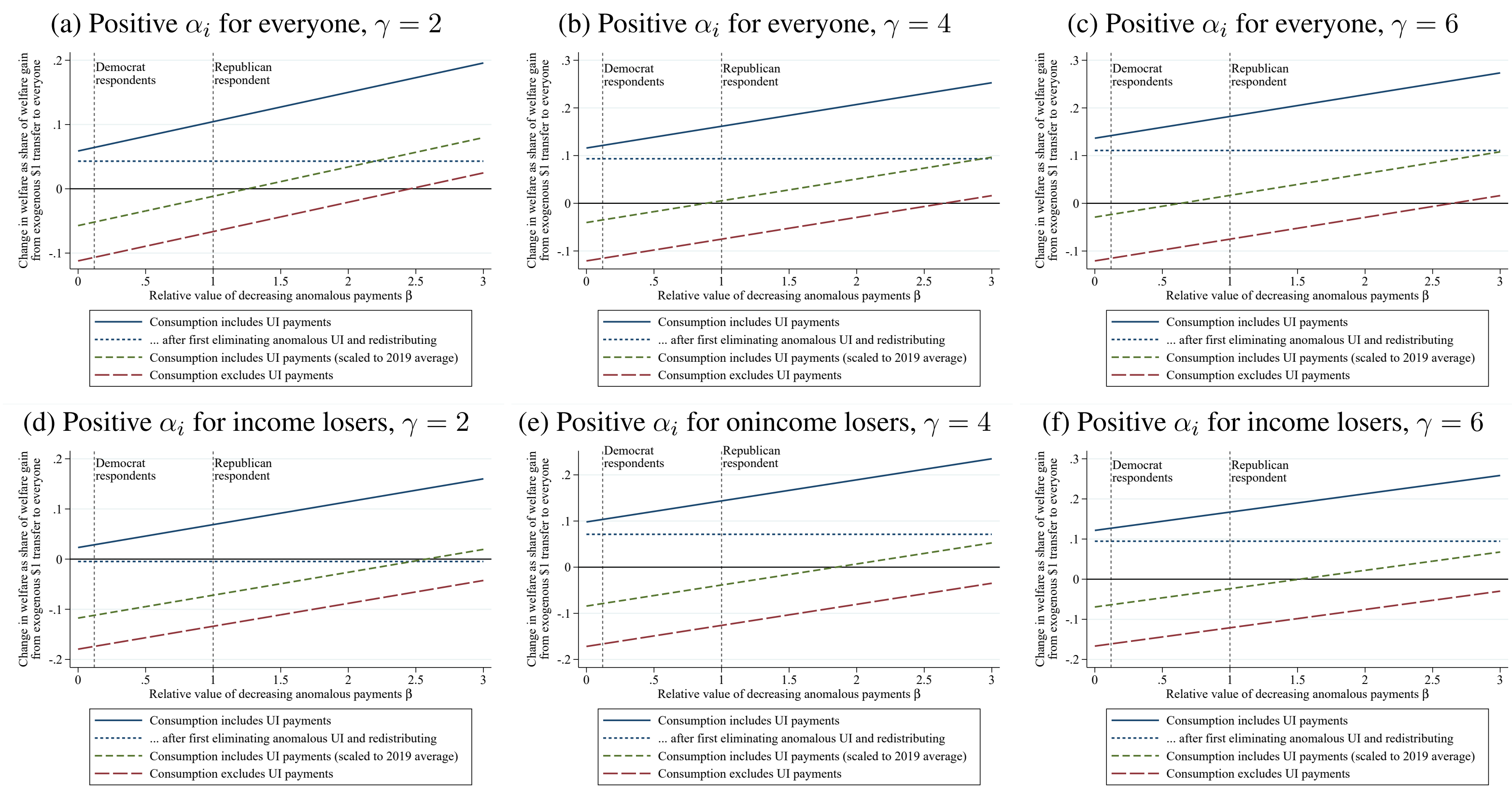


(c) Amount of Transfer Payments



Notes: Panel A displays the share of individuals with non-zero 2019 earned income who experienced a decrease in their income (defined as earned income plus UI benefits) of at least 10% under the actual state of the world, with and without including anomalous UI payments. The figure also reports the share under counterfactual scenarios in which all anomalous UI payments are eliminated, ex-ante anomalous UI payments are eliminated, or PUA UI payments are eliminated. For this figure, UI payments are only taken from individuals with non-zero 2019 earned income. UI payments are redistributed to people with the lowest amounts of 2019 earned income (in absolute value) according to the redistribution function described in equation (2). The bottom bar shows results when UI payments are further restricted to individuals who would likely qualify for PUA because their 2019 wage and salary income was sufficiently low. Panels B and C display the amount of UI payments that are non-anomalous insurance (i.e., payments that replace income lost between 2019 and 2020) or transfers (payments exceeding the amount of lost income) under actual and counterfactual scenarios.
Source: Authors' analysis of de-identified IRS data.

Figure A.6: Quantified Effects of Reform that Marginally Lowers UI Benefits and Increases Lump-Sum Transfers, Robustness to Utility Function Parametrization



Notes: Figure displays the welfare effect of a budget-neutral reform that lowers UI benefit levels by \$1 and increases lump-sum transfers, as a share of the welfare effect of an increase in lump-sum transfers by \$1 due to an exogenous increase in the government budget. The x-axis shows the degree to which the government has a direct distaste for UI benefits going to ineligible individuals. This is parametrized as $\delta = \beta\bar{\alpha}\bar{u}'$. In Panels A–C, the social welfare weight, α_i, is the same positive constant for everyone. In Panels D–F, α_i is the same positive constant for people who lose earned income between 2019 and 2020 and 0 for everyone else. The top line includes 2020 UI benefits in consumption. The second line from the top reports results after anomalous UI payments are first eliminated and redistributed according to the benefit schedule in equation (2). The third line from the top reports results when only keeping 35% of each person's UI benefit, motivated by the fact that the average UI benefit amount in 2019 is 35% as large as the average in 2020. The bottom line excludes all UI benefits from consumption. The parameter of relative risk aversion, γ, is 2 in Panels A and D, 4 in Panels B and E, and 6 in Panels C and F. The vertical lines indicate the lower bound of β implied by survey responses of two Democrat Congressional staffers (0.12) and one Republican Congressional staffer (0.1).
Source: Authors' analysis of de-identified IRS data.

A Theoretical Derivations

A.1 Reform: Decrease benefit levels

This appendix derives equation (8), the social welfare effect of a budget-neutral reform that lowers the UI benefit b by \$1 and raises the lump-sum transfer t accordingly.

Notation. For any group g of individuals, let $N_g \equiv |g|$ denote the number of individuals in the group, $N_{g,UI} \equiv \sum_{i \in g} p_i$ the expected number of UI claimants, and $\bar{\eta}_g^{p,b} \equiv \frac{1}{N_{g,UI}} \sum_{i \in g} p_i \eta_i^{p,b}$ the claim-weighted average elasticity of UI receipt with respect to the benefit level, where $\eta_i^{p,b} \equiv (dp_i/db)(b/p_i)$. Let $c_i^{UI} \equiv w_i + b + t$ and $c_i^{\neg UI} \equiv w_i + t$ be consumption with and without UI benefits, and define the welfare-weighted averages of marginal utility

$$N_g \bar{\alpha}_g \bar{u}'_g \equiv \sum_{i \in g} \alpha_i \left[p_i u'(c_i^{UI}) + (1 - p_i) u'(c_i^{\neg UI}) \right], \tag{A.1}$$

$$N_{g,UI} \bar{\alpha}_{g,UI} \bar{u}'_{g,UI} \equiv \sum_{i \in g} \alpha_i p_i u'(c_i^{UI}). \tag{A.2}$$

We apply this notation to the eligibility groups $g \in \{e, \neg e\}$, with $N = N_e + N_{\neg e}$ and $N_{UI} = N_{e,UI} + N_{\neg e,UI}$.

Derivation. The change in welfare from a \$1 decrease in b is

$$\frac{dW}{-db} = -\sum_i \alpha_i \frac{dV_i}{db} + \delta \frac{dB_{\neg e}}{db}. \tag{A.3}$$

By the envelope theorem,

$$\frac{dV_i}{db} = p_i u'(c_i^{UI}) + \left[p_i u'(c_i^{UI}) + (1 - p_i) u'(c_i^{\neg UI}) \right] \frac{dt}{db}. \tag{A.4}$$

Differentiating $B_{\neg e} = \sum_{i:e_i=0} p_i b$ and using the elasticity definition gives

$$\frac{dB_{\neg e}}{db} = \sum_{i:e_i=0} \left(p_i + p_i \eta_i^{p,b} \right) = N_{\neg e,UI} \left(1 + \bar{\eta}_{\neg e}^{p,b} \right). \tag{A.5}$$

The same calculation applied to the budget constraint $G = Nt + \sum_i p_i b$ yields

$$-\frac{dt}{db} = \frac{1}{N} \sum_i \left(p_i + p_i \eta_i^{p,b} \right) = \frac{1}{N} \left[N_{UI} + N_{e,UI} \bar{\eta}_e^{p,b} + N_{\neg e,UI} \bar{\eta}_{\neg e}^{p,b} \right]. \tag{A.6}$$

Substituting equations (A.4) and (A.5) into (A.3), and splitting the resulting sums by eligibility, gives

$$\frac{dW}{-db} = \left(-\frac{dt}{db} \right) \left[N_e \bar{\alpha}_e \bar{u}'_e + N_{\neg e} \bar{\alpha}_{\neg e} \bar{u}'_{\neg e} \right] - \left[N_{e,UI} \bar{\alpha}_{e,UI} \bar{u}'_{e,UI} + N_{\neg e,UI} \bar{\alpha}_{\neg e,UI} \bar{u}'_{\neg e,UI} \right]$$
$$+ \delta N_{\neg e,UI} \left(1 + \bar{\eta}_{\neg e}^{p,b} \right). \tag{A.7}$$

Plugging in $-dt/db$ from equation (A.6) and rearranging the terms,

$$
\begin{aligned}
\frac{dW}{-db} &= N_e\left[\frac{N_{UI}}{N}\bar{\alpha}_e\bar{u}'_e - \frac{N_{e,UI}}{N_e}\bar{\alpha}_{e,UI}\bar{u}'_{e,UI}\right] + N_{\neg e}\left[\frac{N_{UI}}{N}\bar{\alpha}_{\neg e}\bar{u}'_{\neg e} - \frac{N_{\neg e,UI}}{N_{\neg e}}\bar{\alpha}_{\neg e,UI}\bar{u}'_{\neg e,UI}\right] \\
&\quad + \frac{N_e\bar{\alpha}_e\bar{u}'_e + N_{\neg e}\bar{\alpha}_{\neg e}\bar{u}'_{\neg e}}{N}\left(N_{e,UI}\bar{\eta}^{p,b}_e + N_{\neg e,UI}\bar{\eta}^{p,b}_{\neg e}\right) + \delta N_{\neg e,UI}\left(1 + \bar{\eta}^{p,b}_{\neg e}\right), \\
&= \underbrace{N_{UI}\left[\left(\frac{N_e}{N}\bar{\alpha}_e\bar{u}'_e + \frac{N_{\neg e}}{N}\bar{\alpha}_{\neg e}\bar{u}'_{\neg e}\right) - \left(\frac{N_{e,UI}}{N_{UI}}\bar{\alpha}_{e,UI}\bar{u}'_{e,UI} + \frac{N_{\neg e,UI}}{N_{UI}}\bar{\alpha}_{\neg e,UI}\bar{u}'_{\neg e,UI}\right)\right]}_{\text{Change in welfare due to differences in targeting}} \\
&\quad + \underbrace{\frac{N_e\bar{\alpha}_e\bar{u}'_e + N_{\neg e}\bar{\alpha}_{\neg e}\bar{u}'_{\neg e}}{N}(N_{e,UI}\bar{\eta}^{p,b}_e + N_{\neg e,UI}\bar{\eta}^{p,b}_{\neg e})}_{\text{Change in welfare due to claiming responses}} + \underbrace{\delta N_{\neg e,UI}(1 + \bar{\eta}^{p,b}_{\neg e})}_{\substack{\text{Change in welfare due to} \\ \text{lower ineligible UI}}},
\end{aligned} \tag{A.8}
$$

which is equation (8).

A.2 Extension: Allow labor supply responses

In this section, we extend the model to feature choices over both UI application effort and labor supply. The set-up is similar to the main model, but with a few key differences. First, individuals now face an exogenous *hourly* wage, instead of an annual one. Individuals choose the optimal share of time to work in the scenarios where they do or do not receive UI. Second, UI benefit receipt depends on labor supply and on whether the government can fully observe labor supply, as the government does not pay out UI benefits if it thinks a person is working. Finally, labor income is taxed, which yields an additional set of fiscal consequences of the policy reform.

The indirect expected utility function is:

$$
V_i(t, b) \equiv \max_p \quad p\left[u(c_i^{UI}) - \eta_i^{UI}(h_i^{UI})\right] + (1-p)\left[u(c_i^{\neg UI}) - \eta_i^{\neg UI}(h_i^{\neg UI})\right] - \psi_i(p), \tag{A.9}
$$

where c_i^{UI} and $c_i^{\neg UI}$ are consumption for individuals who get or do not get UI, respectively, and $h_i^{UI}, h_i^{\neg UI} \in [0, 1]$ are the optimal share of time that individuals work, if they get or do not get UI.

Consumption among individuals who get or do not get UI is equal to the following:

$$
c_i^{UI} \equiv (1-\tau)w_i h_i^{UI} + b(1 - \gamma h_i^{UI}) + t \tag{A.10}
$$

$$
c_i^{\neg UI} \equiv (1-\tau)w_i h_i^{\neg UI} + t, \tag{A.11}
$$

where τ is the linear income tax, w_i is the hourly wage, and h_i^{UI} and $h_i^{\neg UI}$ are the optimal labor supply choices as above. Individuals who apply and receive UI receive b in benefits, but benefits are only paid for the share of time that the government observes the individual as not working. Governments may not fully observe individuals' work choices, and the parameter γ provides a simple way to parametrize the government's knowledge.[65] All individuals get transfer t independent of their UI status.

The government's problem is to maximize the social-welfare-weighted average of individuals' indirect expected utility, net of the welfare cost of UI payments going to people with a high income realization, subject to the budget constraint. We write t as a function of b: the government will choose b, and this then pins down t through the budget constraint.

[65] For example, if the parameter is zero, individuals can conceal all their work hours from the government. If the parameter is 0.5 they can conceal half of their work. If the parameter is one, they cannot conceal their work at all.

$$\max_b W(b) \equiv \sum_i \alpha_i V_i(t(b), b) - \delta B_{\neg e} \tag{A.12}$$

$$\text{s.t. } G + \sum_i \tau w_i [p_i(b, t(b)) h_i^{UI} + (1 - p_i(b, t(b))) h_i^{\neg UI}]$$

$$= \sum_i [t(b) + p_i(b, t(b)) b(1 - \gamma h_i^{UI})] \tag{A.13}$$

$$B_{\neg e} = \sum_{i:e_i=0} p_i(b, t(b)) b(1 - \gamma h_i^{UI})) \tag{A.14}$$

Notation. We extend the notation of Appendix A.1. For any group g, let $\bar{h}_g^{UI} \equiv N_{g,UI}^{-1} \sum_{i \in g} p_i h_i^{UI}$ be the application-weighted average hours worked by group-G UI recipients. Let $\bar{B}_g \equiv N_{g,UI}^{-1} \sum_{i \in g} p_i b(1 - \gamma h_i^{UI})$ be average benefit payments per recipient in group g. Define the *marginal benefit payout rate*:

$$\Phi_g \;\equiv\; \frac{d\bar{B}_g}{db} = (1 + \eta^{p,b})(1 - \gamma \bar{h}_g^{UI}) - \gamma \eta^{h,b} \bar{h}_g^{UI}, \tag{A.15}$$

which collapses to $1 + \eta^{p,b}$ when $\gamma = 0$. Define the welfare-weighted average marginal utility *net of work*:

$$N_{g,UI} \bar{\alpha}_{g,UI} \widetilde{u}'_{g,UI} \;\equiv\; \sum_{i \in g} \alpha_i \, p_i \, u'(c_i^{UI})(1 - \gamma h_i^{UI}) \;=\; N_{g,UI} \bar{\alpha}_{g,UI} \big(\bar{u}'_{g,UI} - \gamma \, \overline{u' h}_{g,UI}^{UI}\big), \tag{A.16}$$

where $\overline{u' h}_{g,UI}^{UI}$ is the $\alpha_i p_i$-weighted average of $u'(c_i^{UI}) \, h_i^{UI}$ within group g. This replaces $\bar{u}'_{g,UI}$ because a dollar of UI benefits is received only while not working. Finally, define the tax-revenue adjustment from behavioral responses:

$$\mathcal{T} \;\equiv\; \frac{\tau}{bN} \Big[\eta^{p,b} \sum_i p_i w_i (h_i^{UI} - h_i^{\neg UI}) + \eta^{h,b} \sum_i p_i w_i h_i^{UI} \Big]. \tag{A.17}$$

Derivation. *Envelope theorem.* Since h_i^{UI} and $h_i^{\neg UI}$ are chosen optimally, the envelope theorem gives:

$$\frac{dV_i}{db} \;=\; p_i \, u'(c_i^{UI})(1 - \gamma h_i^{UI}) + \big[p_i \, u'(c_i^{UI}) + (1 - p_i) \, u'(c_i^{\neg UI}) \big] \frac{dt}{db}. \tag{A.18}$$

Budget constraint. Differentiating $G + \tau \sum_i w_i [p_i h_i^{UI} + (1 - p_i) h_i^{\neg UI}] = Nt + \sum_i p_i b(1 - \gamma h_i^{UI})$ with respect to b, using $\eta^{h^{\neg UI},b} = 0$ and common elasticities $\eta^{p,b}$, $\eta^{h,b}$:

$$-\frac{dt}{db} \;=\; \frac{1}{N} \sum_{g \in \{e, \neg e\}} N_{g,UI} \, \Phi_g \;-\; \mathcal{T}. \tag{A.19}$$

The first term is the elasticity-adjusted budget cost of UI; $\mathcal{T}$ adjusts for the change in income-tax revenue when labor supply responds.

Ineligible UI payments. Differentiating $B_{\neg e} = b \sum_{i:\, e_i=0} p_i(1-\gamma h_i^{UI})$:

$$\frac{dB_{\neg e}}{db} \;=\; N_{\neg e,UI}\,\Phi_{\neg e}. \tag{A.20}$$

Social welfare. Substituting (A.18)–(A.20) into $dW/(-db) = -\sum_i \alpha_i(dV_i/db) + \delta\,(dB_{\neg e}/db)$, and writing $\Phi_G = 1 + (\Phi_G - 1)$ to separate the terms that directly parallel equation (8):

$$\begin{aligned}\frac{dW}{-db} = {} & \underbrace{N_{UI}\left[\left(\frac{N_e}{N}\bar{\alpha}_e\bar{u}'_e + \frac{N_{\neg e}}{N}\bar{\alpha}_{\neg e}\bar{u}'_{\neg e}\right) - \left(\frac{N_{e,UI}}{N_{UI}}\bar{\alpha}_{e,UI}\widetilde{u}'_{e,UI} + \frac{N_{\neg e,UI}}{N_{UI}}\bar{\alpha}_{\neg e,UI}\widetilde{u}'_{\neg e,UI}\right)\right]}_{\text{Change in welfare due to differences in targeting}} \\ & + \underbrace{\frac{N_e\bar{\alpha}_e\bar{u}'_e + N_{\neg e}\bar{\alpha}_{\neg e}\bar{u}'_{\neg e}}{N}\sum_{g\in\{e,\neg e\}} N_{g,UI}\big(\Phi_g - 1\big)}_{\text{Change in welfare due to claiming and labor supply responses}} \\ & - \underbrace{\big(N_e\bar{\alpha}_e\bar{u}'_e + N_{\neg e}\bar{\alpha}_{\neg e}\bar{u}'_{\neg e}\big)\,\mathcal{T}}_{\text{Change in welfare due to tax revenue responses}} + \underbrace{\delta\, N_{\neg e,UI}\,\Phi_{\neg e}}_{\substack{\text{Change in welfare due to} \\ \text{lower ineligible UI}}},\end{aligned} \tag{A.21}$$

where $\Phi_g - 1 = \eta^{p,b}(1-\gamma\bar{h}_g^{UI}) - \gamma(1+\eta^{h,b})\bar{h}_g^{UI}$. When $\gamma = 0$, $\eta^{h,b} = 0$, and individuals work the same hours regardless of UI status (i.e., $h_i^{UI} = h_i^{\neg UI}$ for all i, as in the baseline model of Appendix A.1 where labor supply is fixed), we have $\Phi_g = 1 + \eta^{p,b}$, $\widetilde{u}'_{g,UI} = \bar{u}'_{g,UI}$, and $\mathcal{T} = 0$, so equation (A.21) reduces exactly to equation (8).

Like equation (8), the first line of (A.21) captures the change in welfare due to differences in targeting: it is the difference between the population-weighted average social value of the lump-sum transfer and the UI-recipient-weighted average social value of the UI benefit. The key modification is that the latter is now valued at $\bar{\alpha}_{g,UI}\widetilde{u}'_{g,UI} = \bar{\alpha}_{g,UI}(\bar{u}'_{g,UI} - \gamma\overline{u'h}^{UI}_{g,UI})$ per dollar rather than $\bar{\alpha}_{g,UI}\bar{u}'_{g,UI}$, because benefits are received only while not working.

The second line captures behavioral responses. The term $\Phi_g - 1 = \eta^{p,b}(1-\gamma\bar{h}_g^{UI}) - \gamma(1+\eta^{h,b})\bar{h}_g^{UI}$ has two parts: the application-margin response (lower benefits reduce UI applications, generating savings that can be redistributed as transfers, but only for the time recipients are not working) and the labor-supply response (lower benefits induce more work among UI recipients, further reducing UI outlays available for redistribution).

The first part of the third line adjusts for the change in income-tax revenue: lower benefits lead both marginal applicants and existing UI recipients to work more, raising tax revenue and expanding the transfer budget. The second part of the third line is the distaste for ineligible-payments term, now scaled by $\Phi_{\neg e}$ to account for the fact that ineligible recipients may work part of the time.

While equation (A.21) is more complex than (8), our main conclusion that transfers become relatively more attractive from a social welfare standpoint in the presence of anomalous payments remains.

A.3 Quantifying δ

This appendix describes how we quantify δ, which measures the government's distaste for each dollar of UI benefits going to ineligible recipients. We specify δ as a multiple of the average social welfare weight times the average marginal utility of consumption: $\delta = \beta\bar{\alpha}\bar{u}'$, where $\beta \geq 0$. Thus, the key parameter we need to quantify is β.

Using equation (6), the change in social welfare when moving from UI benefit amount b_0 to b_1 while adjusting the lump-sum transfer to keep the total amount of government spending constant is:[66]

$$\sum_i \alpha_i[V_i(b_1) - V_i(b_0)] - \delta[B_{\neg e}(b_1) - B_{\neg e}(b_0)].$$

The first term is the change in the private value of UI, and the second term is the social cost of UI benefits that go to ineligible recipients. The same expression can be written in dollar units as:[67]

$$\frac{1}{\bar{\alpha}\bar{u}'}\left[\sum_i \alpha_i[V_i(b_1) - V_i(b_0)] - \delta[B_{\neg e}(b_1) - B_{\neg e}(b_0)]\right].$$

This conversion is helpful because it allows us to ask a survey question in terms of dollars.

Without loss of generality, we assume that ineligible UI benefits are lower under b_1 than b_0 ($B_{\neg e}(b_1) < B_{\neg e}(b_0)$). All else equal, this raises social welfare. However, the private value of UI might also be lower under b_1, which creates a tradeoff. Using $\delta = \beta\bar{\alpha}\bar{u}'$, social welfare is higher under b_1 if:

$$\beta > \frac{\frac{1}{\bar{\alpha}\bar{u}'}\sum_i \alpha_i[V_i(b_1) - V_i(b_0)]}{B_{\neg e}(b_1) - B_{\neg e}(b_0)}. \tag{A.22}$$

The numerator is the change in the private value of UI when going from b_0 to b_1. The denominator is the change in benefits going to ineligible recipients. Both are measured in dollars.

We combine a novel survey with equation (A.22) to identify β. In particular, we tell survey respondents to consider a policy change that improves screening of UI applicants at no cost to the government and lowers the annual private value of UI from \$500 million to \$490 million.[68] This sets $\frac{1}{\bar{\alpha}\bar{u}'}\left[\sum_i \alpha_i[V_i(b_1) - V_i(b_0)]\right] = -10$. We ask respondents to tell us the minimum reduction in annual payments to ineligible recipients that would lead the majority of [Democrats/Republicans/politicians] in Congress to view this policy change as worthwhile. We interpret their answer as $B_{\neg e}(b_1) - B_{\neg e}(b_0)$. Using equation (A.22), this generates a lower bound on β.

For example, if someone reports that the policy change would have to reduce annual payments to ineligible recipients by at least \$10 million, we have $\beta > 1$. If someone says that the policy change would have to reduce ineligible payments by at least \$100 million, we have $\beta > 0.1$.

[66] We suppress the lump-sum transfer, t, throughout this appendix, as it is determined by b given the government budget constraint.

[67] To see this conversion, note that exogenously increasing the lump-sum transfer by \$1 per person, for a total expenditure of $\$N$, increases social welfare by $N\bar{\alpha}\bar{u}'$.

[68] We asked respondents to consider a policy change that improves screening instead of a policy change that lowers the weekly UI benefit amount because we thought this would be easier for them to interpret. Suppose that there is a hassle cost, κ, that the government can costlessly control such that $\partial\psi_i/\partial\kappa > 0$. It is straightforward to show that equation (A.22) also holds when considering a lower and higher level of hassle cost, $\kappa_0 < \kappa_1$.

Intuitively, a higher value of β indicates that the social cost of ineligible UI benefits is higher, which in turn means that a smaller reduction in ineligible payments is necessary for the policy to be worthwhile.