Suspicious Unemployment Insurance Payments During the Pandemic*

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Abstract

This paper studies the amount and nature of suspicious Unemployment Insurance (UI) payments during the period of expanded UI programs in 2020 and 2021. Using administrative tax data, we establish six key results: (1) suspicious UI payments were very large ($214 billion, equal to 24% of all UI payments); (2) the Pandemic Unemployment Assistance program featured a particularly high amount of suspicious UI payments ($124 billion, 45% of all PUA payments); (3) 46% of suspicious UI payments could have been identified ex-ante if more information were made available to state UI agencies; (4) the amount of suspicious UI benefits in a state is strongly related to the pre-pandemic level of UI fraud; (5) suspicious UI benefits are more highly concentrated in certain ZIP codes than non-suspicious UI benefits; and (6) suspicious UI benefits appear across a range of 2019 income levels, though they are concentrated in tax returns with no income. Motivated by these results, we consider counterfactual policies and show that several alternative approaches could have simultaneously provided better insurance against large income losses, provided benefits to individuals more quickly, lowered the amount of suspicious payments, and reduced administrative costs.

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1 Introduction

When designing and administering welfare and social insurance programs, governments attempt to establish benefit eligibility criteria that maximize timely benefit receipt among "deserving" individuals (however defined), minimize benefit receipt among non-deserving individuals, and limit program costs. Achieving these criteria is difficult because governments lack complete information about individuals' circumstances, and there can be a trade off between these goals. For example, a policy reform that reduces the number of criteria used to assess eligibility can accomplish the goal of increasing the share of deserving recipients that get timely benefits, while also leading to the undesirable outcomes of higher benefit receipt among non-deserving recipients and higher program costs.

One of the most striking examples of this policymaking challenge came during 2020. Employment in the U.S. fell by over 20 million jobs in March and April because of the pandemic and government-imposed shutdowns. This abrupt halt in the economy translated into an enormous increase in the number of people who were in need of assistance. In providing benefits directly to individuals, Congress relied on two very different types of programs.[1] Economic Impact Payments (EIPs), also known as stimulus checks, provided $814 billion in benefits based on a simple function of individuals' adjusted gross income, tax filing status, and number of dependents. A second key program was Unemployment Insurance (UI). Congress provided around $653 billion in additional UI funding during the pandemic beyond the amount available through regular UI programs, which in combination totaled $857 billion. As part of this UI expansion, Congress created the Pandemic Unemployment Assistance (PUA) program, which gave benefits to a much broader range of individuals who were not eligible for regular UI, such as those who were self-employed. UI program rules were also relaxed, as in-person identity verification requirements were dropped and job search requirements were loosened.

EIPs were easier to administer, as the criteria used to determine EIP benefits were largely ob-

[1] These programs constituted two of the three largest components of the economic response, with the third program being the $793 billion Paycheck Protection Program, which sought in part to provide indirect assistance to individuals via employers.

served on previously-filed tax returns. Nonetheless, policymakers directed resources towards the UI program because of concerns about job loss and the desire to target benefit payments to individuals who experienced large income losses. However, the expanded eligibility criteria and relaxed verification processes for UI benefits raise the possibility that many UI dollars went to unintended recipients. Understanding the extent of potentially improper payments and the degree to which pandemic UI programs protected individuals against large income losses is important not only for understanding the extraordinary efforts made during this period, but also for informing how policymakers should design emergency benefit programs, whether for future pandemics, natural disasters, or even recessions. There is little comprehensive evidence on these questions, largely because of the challenge of simultaneously measuring potentially improper payments, income losses, and other characteristics of individuals.

This paper uses administrative tax data to provide a comprehensive analysis of suspicious UI payments 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 suspicious UI payments by matching provisions of UI program rules to conditions observed in the data. For example, we flag a UI payment as suspicious if the intended recipient is deceased according to Social Security Administration records. We use several other criteria that depend on taxpayers' demographics, 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 improper or fraudulent, and we use the word "suspicious" 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 (i.e., there are truly suspicious payments that we miss and truly not-suspicious payments that we identify as suspicious).

Our analysis of the tax data yields six key results. First, suspicious UI payments in 2020 and 2021 were very large. We identify $214 billion of suspicious UI payments, which amounts to 24%

of all UI payments during this period. The most important explanations for suspicious payments are that individuals received benefits even though they experienced no decrease in earned income and were likely employed, had no earned income in the year before or the year of UI receipt, and received benefits from states for which there is no record of them living or working there.

Second, suspicious UI payments were especially common in the PUA program. We identify a total of $274 billion in PUA payments, with $124 billion in suspicious payments likely made through the program, which means that 45% of all UI payments made through PUA are suspicious. PUA accounts for 58% of all suspicious UI payments, which is over three times as large as its share of non-suspicious UI payments.

Third, a sizable share of suspicious UI 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. We identify ex-ante suspicious 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, or someone not connected to the state making the UI payment via place of residence or work. All of these variables reflect outcomes in 2019 or earlier, which means that they were knowable to a substantial degree as of March 2020. We estimate that 46% of all suspicious UI payments made in 2020 were suspicious ex-ante ($50 billion). This result underscores the potential gains from reforms to improve data sharing between the federal and state governments.

Fourth, the amount of suspicious UI benefits is larger in states with higher amounts of UI fraud in the pre-pandemic period as measured by the Department of Labor. This result holds when examining the amount of suspicious UI payments per working age individual and the share of UI payments that are suspicious. In contrast, there is a much weaker relationship between the amount of suspicious UI benefits and pre-pandemic measures of UI benefit generosity and the timeliness of benefit payments.

Fifth, suspicious UI benefits are especially concentrated in certain ZIP codes. The top 1%

of ZIP codes account for 22% of all suspicious UI payments and 50% of UI payments that are suspicious because the government-intended UI recipient was deceased. By comparison, the top 1% of ZIP codes account for 13% of non-suspicious UI payments and 8% of total population. These results are consistent with concentrated fraudulent activity driving part of the suspicious UI payments we identify.

Sixth, suspicious UI benefits are associated with a wide range of individuals and concentrated in those with lower amounts of 2019 earned income. We estimate at least $3 billion in suspicious UI payments in each vingtile of the 2019 earned income distribution. About $35 billion of suspicious UI benefits occur on records where the individual had no earned income, and $58 billion of suspicious UI benefits are associated with individuals that experienced an increase in earned income from 2019 to 2020 and have no indication of non-employment during 2020.

Motivated by these results, we consider whether counterfactual policies could have simultaneously lowered suspicious UI payment rates, provided better insurance against earnings losses, and sped up the disbursement of money (via an EIP-like program). Focusing on 2020, we estimate that 25% 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. When eliminating suspicious UI payments, this share rises only slightly to 25.3%, which is consistent with suspicious payments being concentrated among those that saw earned income gains. We estimate that a counterfactual scenario that eliminates all suspicious UI payments, redistributes the funds to individuals with the lowest amounts of 2019 earned income, and provides benefits equal to the smaller of individuals' 2019 earned income and $15,000, would reduce the net share of people with a large income drop to 20.1%. This redistribution schedule is effective in our setting because individuals with lower earned income in 2019 had larger proportional income drops, the size of the potential earnings drop is bounded from above by 2019 earnings, and a cap of $15,000 in benefits ensures that benefits are available for more people. While eliminating all suspicious UI payments was not a feasible policy, we find that eliminating PUA and redistributing the resulting money in the same manner would achieve a similar improvement; this reform would lower the share of people with

a large income drop by 5.1 percentage points (20% of the actual amount). Counterfactuals with even smaller, but more broadly distributed, EIP-level payments also see improved outcomes along the dimensions we examine. Thus, our results suggest that alternative policies could have lowered suspicious UI payments, provided better insurance against lost earnings, provided benefits to individuals more quickly, lowered administrative costs, and removed any distortionary impacts of UI on labor supply.

This paper contributes to several strands of research on program design and attempts to understand the nature of improper payments in benefit programs. Theoretical models analyze the government's goals of ensuring high benefit receipt rates among the truly deserving and low benefit receipt rates among the non-deserving (e.g., Akerlof, 1978; Nichols and Zeckhauser, 1982; Kleven and Kopczuk, 2011). We contribute to this work by providing empirical evidence on the amount and nature of suspicious UI transfers, tradeoffs involved in limiting such payments, and the performance of counterfactual policies. Much of the empirical work in this area focuses on incomplete take-up of benefits among eligible individuals (Currie, 2006), and our study of improper benefits is complementary.[2] Finally, several government organizations have estimated the amount of improper and fraudulent payments in the pandemic UI programs (U.S. Department of Labor, 2023*a*; U.S. Department of Labor Office of Inspector General, 2023; U.S. Government Accountability Office, 2023). Our estimate of the overall amount of improper payments is similar to theirs (but higher), and our study, among other things, goes further in analyzing the characteristics most commonly associated with improper payments and considering counterfactual payment programs, leading to deeper insights.

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,

[2] An important exception is that several papers analyze the receipt of Earned Income Tax Credit (EITC) benefits among ineligible individuals (Liebman, 2000; McCubbin, 2000; Blumenthal, Erard and Ho, 2005).

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 equally urgent and large policy response, and the U.S. government authorized around $5 trillion in spending that went to businesses, individuals, hospitals and local governments.

One of the most important responses was the expansion of the UI program. UI is a joint state-federal program that provides financial assistance to individuals that lost 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 (Ganong, Noel and Vavra, 2020), for up to 26 weeks. Moreover, most states require individuals to have had sufficient work history with an employer and to be looking and available to work. Hence, individuals who are self employed or have very 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 the complexity of the application process.

The Coronavirus Aid, Relief, and Economic Security (CARES) Act of March 2020 led to significant changes to the UI program. 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 that had exhausted their benefits became eligible for an additional 13 weeks of benefits under the new Pandemic Emergency Unemployment Compensation (PEUC) program. Third, and most importantly, the government created the Pandemic Unemployment Assistance (PUA) program, which provided unemployment benefits to some individuals who were not not eligible under the regular UI program, such as self-employed individuals, those who quit their job because of COVID-19 symptoms, and individuals who did not meet the standard work history requirement. Importantly, PUA was only available to individuals who experienced a decrease in earned income (including job loss) or were unable to

start a previously-accepted job because of the pandemic.[3] Eligibility for PUA was determined on a weekly basis, so an individual who was diagnosed with COVID-19 would only be eligible for PUA benefits during the weeks when they continued to have symptoms or test positive for the disease.

The depth of the economic crises jointly with the increase in UI benefit generosity and expansion of UI eligibility led to a surge in UI claims for which many states were unprepared. This led to increased risk of improper payments, defined by the U.S. Department of Labor (DOL) as any payment that should have not 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, given that much of the required application documentation could be self-certified or easily falsified. And the large volume of claims and the urgency of the crises limited states' ability to implement anti-fraud measures to verify UI claims, to the extent they even possessed such data, which was generally not the case for PUA (U.S. Department of Labor Office of Inspector General, 2023).

Improper payments are a perennial concern of the federal government, which regularly attempts to monitor and measure them. DOL uses data from the Benefit Accuracy Measurement (BAM) program to measure improper UI payments and fraud, and has estimated improper payments to be around 20% since the beginning of the pandemic, peaking at 25% in the last quarter of 2021 (U.S. Department of Labor, 2023*a*). Unfortunately, BAM did not collect data in the 2nd quarter of 2020 due to the pandemic or on any PUA claims. Moreover, while these estimates are valuable, they do not answer several important questions, such as the characteristics most commonly associated with suspicious payments and how alternative policies would have performed.

[3]Being unemployed because the pandemic made it difficult to find a job was not sufficient for gaining eligibility under PUA, so individuals who were re-entering the labor market after an extended absence were not generally eligible for PUA benefits.

3 Measuring Suspicious 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 filing status and various income sources from Form 1040, including Schedules C, F, and SE. 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). These tax forms also provide information on the address of the individual and employer (or contractee), when applicable, which we supplement with Forms 1095-A, 1095-B, and 1095-C that cover all insured individuals. Fifth, we use Social Security data on date of birth, date of death, disability benefits, current immigration status, and valid Taxpayer Identification Numbers (TINs). Sixth, 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 current prisoners reported periodically by states and the federal government to the Internal Revenue Service 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. We interpret the results accordingly below.

Form 1099-G does not identify whether a UI payment was through the regular UI program or PUA. To proxy for the type of UI payment that was made, 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 earnings amount required by each state. Payments made to individuals with earnings below this threshold are classified as being made through PUA.[4]

We use additional data sources to obtain information on state UI parameters and other characteristics. First, we use state measures of UI generosity obtained from Kuka and Stuart (2021), such as the maximum benefit amount, the average benefit amount, and the average replacement rate, measured as benefits as a share of earnings. Second, we use state-level data from the DOL on the share of initial or all UI claims that are paid within a certain time frame (such as 14, 21, or 28 days) and the share of initial or all UI claims that are denied. Third, we use state-level data on UI 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 suspicious 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 suspicious if it satisfies at least one of the following criteria, which are organized in roughly descending order of our confidence that a given payment is suspicious:

1. It was associated with an individual with an invalid TIN.
2. It was associated with an individual who died prior to 2020 or an individual born after 2010 or before 1920, hence less than 10 or more than 100 years old in 2020.
3. It was associated with an individual incarcerated for all of 2020.
4. It was associated with an individual who has no record from 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

[4]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.

Form 1099-G.[5]

5. It was amended to 0 in a corrected Form 1099-G.
6. It was associated with an individual who received UI from multiple states in 2020.
7. It was associated with an individual who received disability benefits in both 2019 and 2020 and had zero earnings in both 2019 and 2020.
8. It was associated with an individual who had zero earnings in both 2019 and 2020, and the individual was not estimated to have accepted a job offer and not start the job because of COVID-19.
9. It was associated with an individual who had nonzero earnings in 2020 that were at least as large as their earnings in both 2018 and 2019, and Form 1095-C data do not indicate any month of non-employment in 2020.

Criteria 1–3 specify that an individual needs a valid TIN to receive UI benefits, must be alive, and remotely of working age and not in prison. All of these are necessary conditions for proper UI receipt and are well-measured in administrative data.[6]

Criteria 4 identifies a UI payment as suspicious if we have no record of the individual ever living or working in that state. Individuals can only receive UI payments from a state in which they have worked or lived.[7] 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.[8]

Criteria 5 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

[5]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.

[6]UI benefits, including through PUA, were only available to (real) individuals with legal work authorization. One potential concern with the flag for an invalid TIN is that a TIN might be entered incorrectly on a tax form. However, we also use corrections to Form 1099-G, so if a state becomes aware of such an error and fixes it, we will not misclassify such cases. Moreover, states can use the IRS TIN Matching System to ensure this does not happen.

[7]An individual can receive UI from a state in which they do not currently live. For example, if an individual is employed in Pennsylvania and lives in Delaware, that person will receive UI from Pennsylvania.

[8]For example, if an individual was self-employed in Pennsylvania in 2019, moved to Delaware in 2020 (after filing 2019 taxes), filed for PUA in 2020, and then moved out of Delaware before being tied to the state on any tax form, then we might misclassify a Delaware UI payment as suspicious. Data from the Census Survey of Income and Program Participation (SIPP) suggest that such moves are extremely rare.

states' assessment of whether a UI payment was appropriate.[9]

Criteria 6 follows the rule that individuals do not receive UI from multiple states at the same time. Individuals *can* receive UI benefits based on work history from multiple states. For example, if an individual has jobs in Pennsylvania and Delaware and is laid off from both jobs, they can file a combined wage claim in one state that is based on earnings from both jobs. However, the UI payment only comes from the state in which the individual initiated 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.

Criteria 7–8 cover individuals with no earned income in 2019 and 2020 from Forms W-2, 1040 (from Schedules C, F, and SE or wage, salary, and tip income), 1099-MISC, 1099-NEC, and 1099-K. Criteria 7 separately identifies individuals with no earnings who 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. Criteria 8, which is broader, starts by considering all individuals with no earnings in 2019 and 2020. This is motivated by the rule that individuals generally had to be employed before the pandemic and lose income because of the pandemic to qualify for UI benefits.

We adjust Criteria 8 to account for the limited exceptions that were provided in the CARES Act. First, PUA benefits were available to individuals who had 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 are flagged as having suspicious UI by Criteria 8 but may have had a rescinded job offer. We remove Criteria 8 suspicious UI flags for a random subset of individuals.[10] Second, it is possible that individuals (improperly) received no information return indicating

[9] 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 suspicious.

[10] 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

earnings and reported zero earned income on their 2019 and 2020 tax returns, even though they had earned income, and these individuals might have been eligible to receive UI through PUA. 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 Criteria 8 suspicious UI flags for a random subset of individuals.[11] Third, we remove the Criteria 8 flag for anyone whose spouse died between March and December 2020 because the CARES Act made benefits available to individuals who are unemployed because a spouse died because of COVID-19. In total, these three exceptions reduce the number of individuals with a Criteria 8 flag by about 12%.

Criteria 9 identifies individuals who had nonzero earnings in 2020 and did not have a decrease in their earnings from 2018 to 2020 or 2019 to 2020. This mirrors the UI rule that pandemic 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 misclassification because of within-year earnings volatility.[12] 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 all employees' health insurance and employment status in each month. For people who work at these firms, which employ the majority of the workforce, we can use Form 1095-C to identify whether they are employed in each month of 2020, and we remove the Criteria 9 suspicious UI flag

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 suspicious UI payments) because (1) it assumes that the entire decrease in the rate of entry into employment in April 2020 is due to job offers being rescinded and (2) it assumes that all individuals with rescinded job offers applied for and received UI.

[11] 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 and 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 suspicious 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 but also an amount to maximize the EITC) that are determined to have none by these audits; it is not implausible that these individuals may have been inclined to also improperly claim UI.

[12] 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.

for individuals with at least 1 month of non-employment in 2020.[13] For people who do not work for these 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 Criteria 9 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 Criteria 9 flag for a randomly chosen subset of individuals for whom Form 1095-C data are not available.

The criteria above apply to 2020 UI payments. For 2021, we apply similar criteria, with the reference year for each condition shifted forward.[14] However, we add one important additional criterion: if an individual received suspicious UI in 2020 and also received payments in 2021, we identify the 2021 payments as suspicious as well.[15]

4 Evidence on Suspicious UI Payments

Result 1: Overall Amount of Suspicious 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 suspicious 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 suspicious according to any of the reasons listed in Section 3.2. We identify $108 billion in suspicious UI payments in 2020 and $106 billion in suspicious UI payments in 2021, for

[13]The Form 1095-C data provide complete monthly employment data for individuals when the number of Forms 1095-C is at least as large as the number of Forms W-2. In particular, in this situation we can distinguish between a month of non-employment at *any* firm and a month of non-employment at one firm but where the Form 1095-C information is missing for other firms who may or may not have employed the individual for that particular month. For these individuals, we remove the Criteria 9 suspicious 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.

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

[15]For individuals with non-suspicious UI in 2020, we classify their 2021 UI as suspicious only based on Criteria 2, 3, 5, and 9 (applied to 2021).

a total of $214 billion—equal to 24% of all UI payments disbursed. These suspicious payments went to 11 million recipients in 2020 and 10 million recipients in 2021. The average suspicious UI payment per recipient is about $10,000.

These suspicious UI payments are very large. For example, the $214 billion in suspicious 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 suspicious UI payments are somewhat larger than existing estimates of improper and fraudulent payments and based on much larger samples. The DOL Inspector General estimated an improper payment rate of 21.5% in pandemic UI programs between April 2020 through September 2022, for a total of at least $191 billion of improper UI payments (U.S. Department of Labor Office of Inspector General, 2023).[16] The Government Accountability Office (GAO) estimated that fraudulent UI payments, which are a subset of all improper payments, were at least $100–135 billion between April 2020 and May 2023 (U.S. Government Accountability Office, 2023).[17] Our analysis benefits from much larger samples and linkages across different tax forms, which are especially valuable for the PUA 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 so 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 suspicious UI payments is reasonable.

Where do suspicious UI payments come from? The results in Table 1 depend in the order in which criteria are applied, so Appendix Table A.1 reports complementary evidence on suspicious

[16]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 BAM audits, which cover regular (non-PUA) UI claims outside of the 2nd quarter of 2020. This estimate also includes Puerto Rico and the U.S. Virgin Islands, which are excluded from our analysis.

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

UI payments where each criteria is met (irrespective of whether another criteria is also met). The most important explanation for 2020 is that $56 billion of UI payments were paid on records for individuals who experienced no decrease in earnings between 2018–2020 and 2019–2020 and had no indication of non-employment (Criteria 9). The second most important explanation is that $37 billion of UI payments were based on records tied to individuals who had zero earnings in 2019 and 2020 and are not estimated to have had a job offer rescinded or failed to report the earnings (Criteria 8). The third most important explanation is that $14 billion of UI payments were based on records for individuals who did not have a connection, via place of work or residence, to the state issuing the payment (Criteria 4). These three explanations are the most important when stacking criteria as in Table 1 or looking at them separately as in Appendix Table A.1. Around 45% of suspicious UI payments in 2021 went to individuals who were flagged as suspicious in 2020. Among newly suspicious UI payments in 2021, the key explanations are the lack of a match to a state and no decrease in earnings from 2019–2021 and 2020–2021. The magnitude of suspicious UI payments in 2021 is especially noteworthy because federal and state governments focused on limiting improper payments after reports of fraudulent UI payments in 2020.

Result 2: Suspicious UI Payments in the PUA Program. Table 1 also provides a breakdown of suspicious UI payments that were likely 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 suspicious (45%).[18] By comparison, a smaller 15% of the $609 billion in UI benefits distributed through the regular UI program was suspicious. This means that PUA accounts for 58% of all suspicious UI payments and 22% of all non-suspicious UI payments. The clear picture that emerges is that suspicious UI payments were much larger under PUA, which is consistent with the fact that regular UI payments are subject to greater scrutiny and more verifiable with existing UI data systems.

[18] As a point of comparison, the 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 overpayment rate (U.S. Department of Labor, 2023*b*).

Table 1 also shows systematic differences in the sources of suspicious 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 suspicious 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.[19]

Result 3: Ex-Ante Suspicious UI Payments. Our baseline measure of suspicious UI payments described in Section 3.2 depends in part on outcomes that occurred in 2020 and 2021. While this approach yields a comprehensive ex-post evaluation, a separate question is how much of these suspicious payments could have been identified ex-ante. The magnitude of ex-ante suspicious UI payments informs the potential gains from better information sharing among government agencies.

We identify ex-ante suspicious 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.[20] All of these characteristics refer to outcomes in 2019 or earlier, which means that they were largely knowable as of March 2020.[21]

We identify $60 billion of UI payments made in 2020 as suspicious based on these ex-ante characteristics. Of this amount, $50 billion continues to be classified as suspicious after incorporating all of our indicators (yielding a relatively low type 2 error rate if the payments were held).

[19] 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 don't 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.

[20] If the only ex-ante suspicious 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 suspicious, 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.

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

This amount is equal to 46% of all suspicious UI payments made in 2020. The two ex-ante conditions that identify the largest amounts of suspicious UI payments are no earned income in 2019 and no match to the state issuing the UI payment. An improved data sharing environment could provide state UI agencies with both pieces of information so that they could review these suspicious circumstances before paying out funds.

Result 4: Variation in Suspicious UI Payments across States. We exploit variation in suspicious UI amounts across states to study whether pre-pandemic state UI program characteristics are associated with higher suspicious UI payments. Figure 1 shows the relationship between suspicious UI amounts in 2020 and 2021 and three state measures of pre-pandemic UI: the maximum weekly benefit amount in 2018, the share of payments paid within 14 days of claim filing from 2017–2019, and the share of payments classified as fraudulent in DOL BAM data from 2017–2019.[22] We relate each measure to both suspicious UI payments per working age individual and as a share of total UI disbursed.[23] The amount of suspicious UI payments per capita ranges from $113 (South Dakota) to $2,590 (Pennsylvania), while the share of UI payments that are suspicious ranges from 13% (New Hampshire) to 42% (Pennsylvania).

Panel A shows that states with more generous weekly benefit amounts in 2018 paid out more suspicious UI dollars per capita than less generous states. However, they disbursed less suspicious UI as a share of total UI (though the underlying slope coefficient is indistinguishable from zero). This is consistent with states offering higher UI payment amounts per recipient mechanically paying out more suspicious UI per capita, even though they might have been equally good at identifying and avoiding fraud. Panel B shows that states paying UI more promptly also disbursed less suspicious UI, though these relationships are not very precise. This suggests that states' pre-pandemic timeliness in processing claims was not strongly related to UI overpayments during the

[22]We use a single year of data for the first variable because it is a policy set by states and three years of data to construct the last two variables because they are based on measures with some noise. We exclude Nevada from this exercise, as it is an outlier in suspicious UI payments, with $4,667 of suspicious UI per working age individual and a share of suspicious UI among all UI disbursed of 84%. Appendix Table A.2 reports totals by state.

[23]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.

pandemic. Lastly, Panel C shows that the best predictor of suspicious UI—both per capita and as a share of total UI—is the state's pre-pandemic fraud rate. The pre-pandemic fraud rate can explain 19% of the cross-state variation in suspicious UI benefits per capita and 32% of the variation in the share of UI payments that were suspicious.[24]

Our finding that some states systematically struggled with UI payment accuracy before and during the pandemic highlights the potential value of improving UI performance in some states. Eighteen states had a suspicious UI payment rate of 20% or more. We consider a simple back of the envelope calculation in which the suspicious UI payment rate for these states is lowered to 20%, while nothing else changes. In this scenario, we estimate that more than $21 billion of suspicious UI payments would have been averted in 2020 alone. An important consideration for these results is that we are unable to observe the number of suspicious UI claims made in each state, which prevents us from assessing whether the states with high suspicious UI rates were simply overwhelmed by applications; however, isolating the role of applications is difficult because suspicious claims could have been targeted towards states with fewer safeguards in place.

Result 5: Variation in Suspicious UI Payments across ZIP Codes. We are able to 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 (or person whose name was used on the UI application). This information allows us to examine the extent of spatial concentration in suspicious UI payments, which is informative about their underlying source.

We begin by quantifying the degree to which suspicious 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 US population. By comparison, 14% of all UI payments are in the top 1% of ZIP codes (where ZIP

[24] Appendix Table A.3 presents results when we jointly analyze the relationship between suspicious UI and the three measures above as well as additional pre-pandemic measures of UI generosity, efficiency in claims processing, and overpayment rates, for overall UI as well as regular and PUA payments separately. The strongest predictor of suspicious UI remains states' pre-pandemic fraud rate.

codes now are ranked by total UI payments). The concentration of non-suspicious UI payments is similar. In contrast, suspicious UI payments are much more concentrated: the top 1% share for all suspicious UI payments is 22%, and it reaches 50% for UI payments that are suspicious because the recipient was dead, younger than 10, or older than 100, and 85% for UI payments that are zeroed out in a corrected Form 1099-G. The high level of spatial concentration of suspicious UI, especially for criteria 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.

To understand whether some ZIP codes saw widespread instances of suspicious UI, 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 suspicious according to Criteria 1–5, which are most closely related to fraudulent activity. Among the 62 such ZIP codes, we list the 40 ZIP codes with the highest amount of total suspicious UI payments. For example, the first row shows that there are $154 million of suspicious UI payments in 2020 associated with ZIP code 48228 in Detroit, Michigan. There are 57,005 residents in this ZIP code, which amounts to $2,709 of suspicious UI per capita here.[25] For this ZIP code, $12 million of UI payments is associated with individuals who were incarcerated for all of 2020, $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.[26] The first 10 rows of the table are ZIP codes in Detroit, and more generally the vast majority of ZIP codes in this table are in the Detroit and Los Angeles metropolitan areas.

Result 6: Variation in Suspicious UI Payments across Individuals. We next examine features of individual tax returns to better understand where suspicious UI payments were concentrated. Panel A of Figure 2 displays the total amount of suspicious 2020 UI payments associated with tax returns with zero earned income in 2019 (shown as a square) and for tax returns across vingtiles of

[25] 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.

[26] There is no prison located in this zip code.

the non-zero earned income distribution.[27] Panel B reports the share of UI payments that are suspicious. We find that suspicious 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. Suspicious UI payments are somewhat larger for groups with lower amounts of 2019 earned income, with the clear outlier being individuals with zero earned income, who account for $35 billion (32% of all suspicious UI payments). Among individuals with no earned income in 2019, we estimate that 79% of UI payments are suspicious. Panels C and D report analogous results based on categories of the 2019–2020 change in earned income. We find that $58 billion of suspicious UI benefits were associated with individuals with an increase in earned income from 2019 to 2020.

To better understand the amount of suspicious UI payments, we classify each dollar of a UI payment into one of three categories. Suspicious UI payments consist of payments made in one of the circumstances described in Section 3.2. When a UI payment is not suspicious, we classify the dollars that, combined with 2020 earned income, would fully replace an individual's 2019 earned income as insurance and the dollars beyond this amount as a transfer.[28]

Panel A of Figure 3 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 payments and transfers account for 33%, with the remaining 19% coming from suspicious payments.[29] There are clear patterns by 2019 earned income level. The share of UI payments that are suspicious decreases among individuals with higher earnings, from 79% for people with no earned income in 2019 to 16% for people in the highest income vingtile. The share of UI payments that are insurance also increase with income, which is a natural consequence of higher-income individuals having more income to be insured. One potential explanation for the finding that suspicious 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

[27] 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 suspicious payments in 2020 because this makes it easier to interpret the role of 2019 earned income.

[28] For example, if an individual not flagged as receiving a suspicious 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 transfer.

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

from both IRS and National Crime Victimization Survey data that identity theft rates increase in individuals' income level.

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 suspicious. For PUA, we find the opposite: 24% of benefits were insurance, 38% of benefits were transfers, and 38% of benefits were suspicious.

5 The Effectiveness of Counterfactual Policies

So far, we have provided evidence of a sizable amount of suspicious UI payments under the reforms legislated by Congress. The existence of suspicious payments does not necessarily imply that a better policy was possible, as a reduction in suspicious payments might come at the cost of less insurance against income losses. In particular, while providing benefits to those that opt-in (with perhaps limited screening for eligibility) may increase suspicious payments, it may also provide effective targeting of legitimate benefits to those experiencing the largest of income drops. In this section, we compare the performance of the actual UI policy and counterfactual policies in mitigating income losses. For simplicity, we evaluate these policies based on the share of people with an income drop of at least 10% or 20%. The conclusions are similar when considering either income drop, which provides some reassurance that our results would be similar if we adopted a more complicated approach based on a social welfare function. We focus on individuals with a nonzero amount of earned income in 2019 for this analysis.

Panel A of Figure 4 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.[30] We estimate that 25% of individuals had an income

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

drop of at least 10% from 2019 to 2020.[31] If we exclude suspicious UI payments, this number rises only slightly to 25.3%, which is consistent with most suspicious UI payments being associated with individuals who did not experience a decrease in their earned income, as already seen.

The first counterfactual scenario we consider is one in which all suspicious UI payments are eliminated and the same amount is redistributed in a different manner, with earned income and non-suspicious UI payments not changed.[32] This is not an ex-ante feasible policy, but it serves as a useful benchmark. Because we focus on redistributing income to individuals with nonzero amounts of 2019 earned income, we also limit ourselves to removing UI payments from those with nonzero earned income in 2019 throughout this section. We consider three different redistribution schedules:

$$B_1 = \max\{0, 1800 - 0.10 \times \max\{0, Y_{2019} - 75,000\}\} \tag{1}$$

$$B_2 = \max\{0, 15,000 - 0.20 \times \max\{0, Y_{2019} - 50,000\}\} \tag{2}$$

$$B_3 = \min\{15,000, Y_{2019}\}, \tag{3}$$

where Y_{2019} is an individual's 2019 earned income amount. The first benefit schedule, B_1, is chosen to resemble the structure of the EIPs. This schedule pays a benefit of \$1,800 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_2, is more progressive, and pays \$15,000 to individuals with 2019 earned income below \$50,000, with a 20% phase-out rate. The third payment, B_3, equals the smaller of \$15,000 and 2019 earned income, which lowers the transfer amount to individuals with 2019 earned income below \$15,000. For all of these benefit schedules, we prioritize individuals with the lowest amount of 2019 earned income and make payments until the money available from eliminating suspicious UI payments is entirely spent.[33]

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

[32] Given the potential negative effect of UI on earnings through lowering the return to work, this will bias our counterfactuals against finding better targeting relative to actual UI.

[33] Note that an individual with a suspicious UI payment and a low amount of 2019 earned income can see a decrease in their 2020 income because of the removal of the suspicious UI payment and an increase in their 2020 income because of the redistribution.

We estimate that eliminating all suspicious UI payments and redistributing these dollars through one of the three benefit schedules described above would reduce the share of people with an income drop of at least 10%. Benefit schedule 3 provides the greatest increase in insurance against large income drops. Under this schedule, the share of people with an income drop of at least 10% falls to 20.1%, which is a decrease of 4.9 percentage points (20%) compared to the actual outcome. The less progressive schedule, B_1, does worse, at 21.6%, because the maximum benefit of $1,800 is not enough to offset large income losses. The more progressive schedule, B_2, is even worse, at 24.8% because it provides benefits to a smaller number of people. The general takeaway is that a simple benefit schedule equal to the smaller of individuals' 2019 earned income and $15,000 is effective because it balances the goals of providing a large enough benefit amount to offer a meaningful amount of insurance and providing benefits to many people.

We next consider counterfactuals that differ in which types of UI payments are eliminated and redistributed. First, we exclude ex-ante suspicious UI payments, as defined above in the discussion of Result 3. Second, we exclude UI payments where the predicted probability of being a suspicious payment exceeds 50%. To construct this probability, we estimate a logit regression where the dependent variable is an indicator for a person-by-state UI payment being suspicious, and the explanatory variables are based on outcomes observed from 2019 data.[34] This predicted probability of suspicious UI payments was not available in 2020, but it could be used in future episodes. 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 $15 billion, $17 billion, and $115 billion (compared to $71 billion of total suspicious UI payments).[35]

Two clear takeaways emerge from the analysis of these alternative scenarios. First, the relative ranking of the benefit payment schedules remains the same. We continue to see the greatest reduc-

[34]The explanatory variables are an indicator for being a likely PUA UI claimant; the likely PUA indicator interacted with 21 indicators for 2019 earned income and 26 indicators for 2019 industry of employment; the share of tax forms that match the state making the UI payment; indicators for each age; an indicator for filing taxes as a married individual; indicators for up to 5 dependents; and an indicator for filing a 2019 tax return.

[35]These numbers differ from those reported in Table 1 because we focus here on individuals age 18 and above with non-zero earned income in 2019. Appendix Table A.4 reports where in the 2019 earned income distribution redistributed funds are exhausted. These funds are exhausted much lower in the income distribution for benefit schedule 2.

tion in large income drops when setting benefits equal to the minimum of $15,000 and individuals' 2019 earned income. Second, eliminating PUA leads to smaller income drops than targeting suspicious UI payments in *any way*. When eliminating PUA and redistributing benefits according to B_3, we estimate that 19.9% of individuals would have had an income drop of at least 10%. Compared to the actual scenario, this is a decrease in the share of people with a large income drop of 5.1 percentage points (20%).

In Panel B of Figure 4 we evaluate these scenarios based on the share of individuals that experience a 20% decrease in income. The motivation for this exercise is that policymakers might be especially concerned about larger income drops. The takeaways from this exercise are similar to those when considering an income drop of 10%.

A complementary way of assessing these counterfactual scenarios is through the total amount of UI spending that goes to non-suspicious insurance or transfer payments. Figure 5 reports these numbers. We estimate that under the actual program, $267 billion of UI payments in 2020 was insurance (in the sense, described above, of replacing earnings lost in 2020) and $183 billion was a transfer. Eliminating suspicious UI payments and redistributing the funds according to the three benefit schedules we consider almost uniformly leads to an increase in the amount of insurance and transfers (with a relatively larger increase in the latter). For example, eliminating PUA and sending out payments according to B_3 would increase insurance spending by $1.5 billion and transfer spending by $105 billion.

In summary, the results in Figure 4 suggest that in the context of the pandemic and economic downturn in 2020 policymakers could have achieved better insurance against large income losses, reduced suspicious UI payments, and increased total insurance and transfer payments while providing the same amount of benefits by replacing PUA with a transfer equal to the minimum of individuals' 2019 earned income and $15,000. Additionally, given the straightforward criteria and, in turn, availability of data needed to administer the counterfactuals, benefits could have generally been provided to individuals more quickly (via the IRS, for example) and at lower administrative costs. This would have also removed any 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 suspicious UI payments, which provides a large pool of funds to be redistributed. Second, suspicious 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 that means-tested transfers do a reasonably good job of targeting income losses.

6 Conclusion

This paper uses administrative tax data to establish six main results on suspicious UI payments during the pandemic: (1) suspicious UI payments were very large, amounting to $214 billion; (2) suspicious UI payments were particularly common in the PUA program, which accounts for 58% of all suspicious UI payments; (3) almost one-half of suspicious UI payments could have been identified ex-ante if more information were made available to state UI agencies; (4) the amount of suspicious UI benefits in a state is most strongly related to the pre-pandemic level of UI fraud; (5) suspicious UI benefits are more concentrated in certain ZIP codes than non-suspicious benefits; and (6) suspicious UI benefits appear across a range of 2019 income levels, though they are concentrated among those with no income. Motivated by these results, we consider counterfactual policies and show that several alternative approaches could have simultaneously provided better insurance against large income losses and lowered the amount of suspicious payments. Most strikingly, eliminating the PUA program, redistributing the funds to individuals with the lowest amounts of 2019 earned income, and providing benefits equal to the smaller of individuals' 2019 earned income and $15,000 would have lowered the share of people with a large income drop by 5.1 percentage points (20% of the actual amount).

More broadly, our results highlight the importance of designing social insurance programs for which eligibility criteria can be properly administered. While the pandemic posed enormous challenges in benefit administration, the techniques used by fraudulent claimants are likely to be

improved upon and used in the future. Consequently, the benefits of UI modernization efforts are likely to be important both for normal UI operations and during periods of acute tumult.

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Table 1: UI Payments Flagged as Suspicious, 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
Suspicious						
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 2018–2020	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
Suspicious						
Flagged as suspicious in 2020	47.1	19.3	27.8	4.06	1.94	2.12
Suspicious 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. Suspicious UI criteria are added sequentially, so that the bottom row of each panel reports the total amount of suspicious 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-suspicious UI	0.13	0.39
Suspicious 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 Suspicious UI Payments, Selected Categories

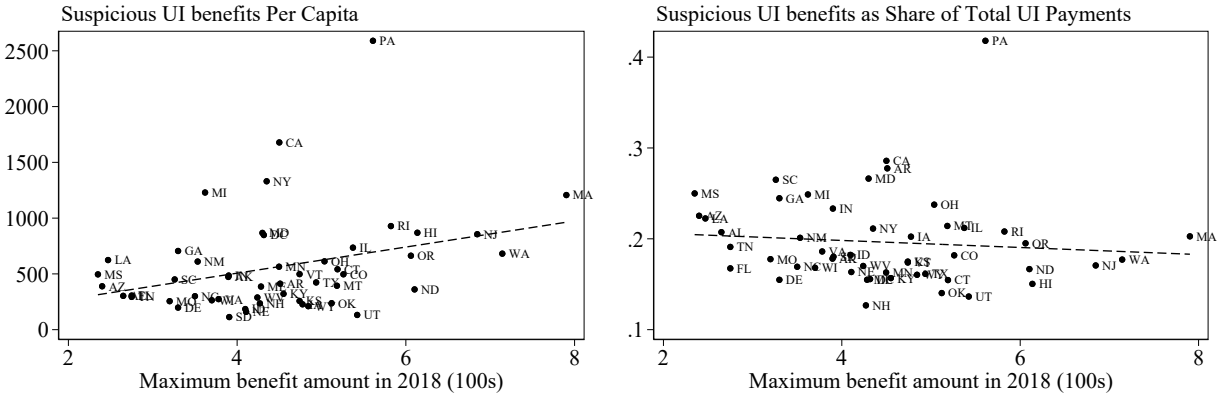
			Millions of dollars of suspicious UI payments						
ZIP (1)	ZIP name (2)	Population (3)	All reasons (4)	Invalid TIN (5)	Dead or Age (6)	Prison (7)	No state match (8)	Amended 1099-G (9)	Multiple UI states (10)
48228	Detroit, MI	57,005	154.44	0.27	2.30	12.44	41.70	1.69	53.98
48235	Detroit, MI	45,558	131.28	0.11	2.14	10.78	35.68	1.04	44.85
48227	Detroit, MI	39,974	128.84	0.05	3.09	8.75	34.52	0.70	45.77
48219	Detroit, MI	43,749	119.34	0.00	1.58	10.18	31.77	1.10	37.18
48224	Detroit, MI	38,824	117.23	0.09	2.59	10.04	24.27	1.39	41.00
48205	Detroit, MI	31,721	109.95	0.00	1.64	9.21	26.82	1.05	39.46
48234	Detroit, MI	33,555	89.11	0.00	1.59	6.29	20.87	0.64	29.65
48221	Detroit, MI	41,203	88.18	0.00	2.47	4.26	23.94	0.65	30.93
48238	Detroit, MI	24,927	78.74	0.00	1.44	6.54	23.59	0.83	28.73
48204	Detroit, MI	22,218	74.76	0.00	0.96	6.32	20.85	0.92	29.63
91601	North Hollywood, CA	34,786	74.36	0.55	1.55	1.64	36.43	0.02	15.72
91405	Van Nuys, CA	55,751	70.61	1.18	2.70	1.85	29.43	0.00	7.89
90028	Los Angeles, CA	29,887	67.90	0.52	0.72	2.27	32.26	0.13	14.87
90813	Long Beach, CA	56,420	66.30	0.86	3.97	1.32	23.92	0.00	8.61
90019	Los Angeles, CA	61,061	65.40	1.03	3.20	1.32	21.96	0.18	10.38
91606	North Hollywood, CA	43,381	64.85	0.75	2.66	0.61	29.45	0.00	6.28
90008	Los Angeles, CA	31,046	64.09	0.18	4.52	4.46	24.46	1.24	10.01
48213	Detroit, MI	20,900	61.71	0.24	2.49	5.83	15.41	0.64	20.86
48223	Detroit, MI	25,037	57.24	0.07	1.07	3.59	14.51	0.68	21.37
48203	Highland Park, MI	21,253	56.43	0.06	1.58	3.55	16.63	0.57	19.86
30315	Atlanta, GA	35,324	56.37	0.00	0.64	5.84	16.17	0.49	23.19
48141	Inkster, MI	25,849	55.07	0.00	1.00	4.31	17.11	0.59	14.86
90004	Los Angeles, CA	59,621	54.76	1.11	1.93	1.00	19.85	0.30	7.55
90804	Long Beach, CA	37,953	53.07	0.55	4.45	2.76	16.81	0.00	7.30
94804	Richmond, CA	43,346	51.03	0.66	1.34	1.94	17.57	0.00	7.90
90036	Los Angeles, CA	37,596	46.34	1.55	2.35	1.17	16.19	0.16	5.93
33605	Tampa, FL	16,139	42.31	0.00	0.00	2.05	17.40	0.00	21.18
33054	Opa Locka, FL	32,390	41.79	0.66	0.70	1.51	24.13	0.69	12.07
91042	Tujunga, CA	26,686	40.27	0.75	1.26	0.25	15.73	1.10	6.60
48206	Detroit, MI	15,271	40.23	0.05	0.88	3.45	11.69	0.68	16.31
48214	Detroit, MI	19,817	39.48	0.00	0.64	3.28	10.38	0.52	14.88
90017	Los Angeles, CA	28,433	37.01	0.62	1.71	0.87	18.64	0.52	7.13
10039	New York, NY	27,234	35.91	0.79	0.89	1.22	8.60	8.47	4.32
48207	Detroit, MI	20,142	34.61	0.00	0.64	1.98	9.68	0.27	14.10
91203	Glendale, CA	16,557	32.90	0.86	0.86	0.82	15.20	0.00	2.25
90005	Los Angeles, CA	36,910	32.72	0.78	1.54	1.05	13.18	0.00	3.44
48225	Harper Woods, MI	16,201	26.39	0.22	0.62	0.77	6.12	1.23	10.20
48202	Detroit, MI	15,029	26.06	0.00	0.26	2.54	8.52	0.29	8.55
48341	Pontiac, MI	18,921	25.91	0.00	0.28	5.11	6.17	0.03	6.47
90013	Los Angeles, CA	13,413	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 suspicious 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 suspicious UI payments among this sample. Column 4 reports the total amount of suspicious UI payments associated with each ZIP code for all reasons listed in Table 1. A UI payment can be classified as suspicious for multiple reasons and hence show up in more than one of the columns. Data cover 2020 UI payments only.

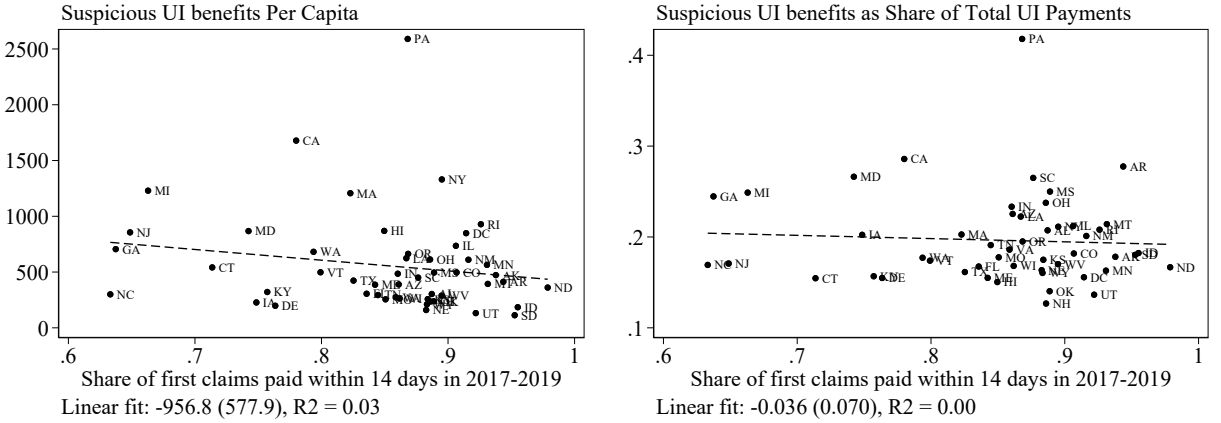
Source: Authors' analysis of de-identified IRS data; Population data from American Community Survey.

Figure 1: Relationship Between Suspicious UI and Pre-Pandemic State UI Characteristics

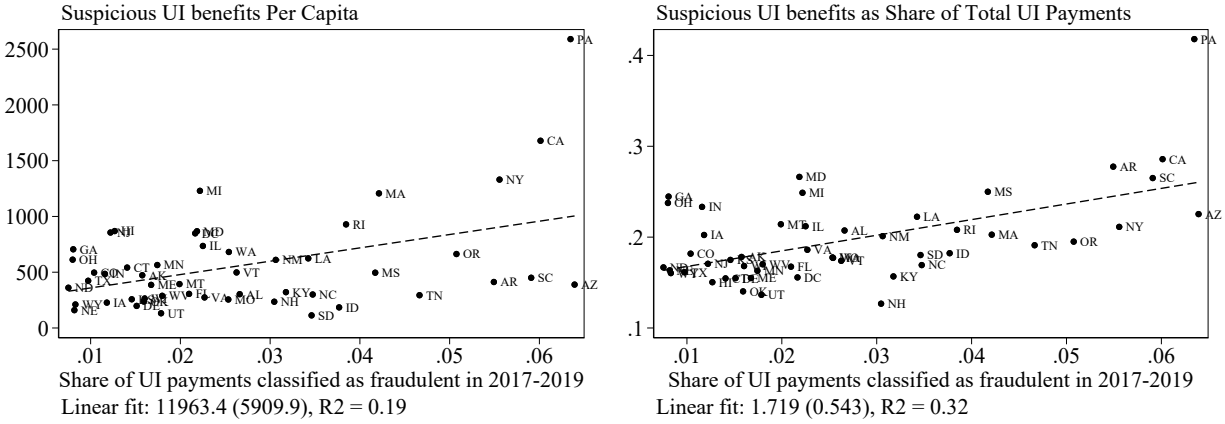
(a) Maximum Weekly Benefit Amount



(b) Share Payments Paid within 14 Days



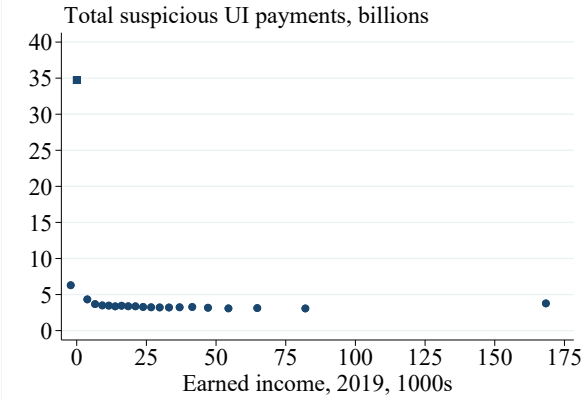
(c) BAM Fraud Rate



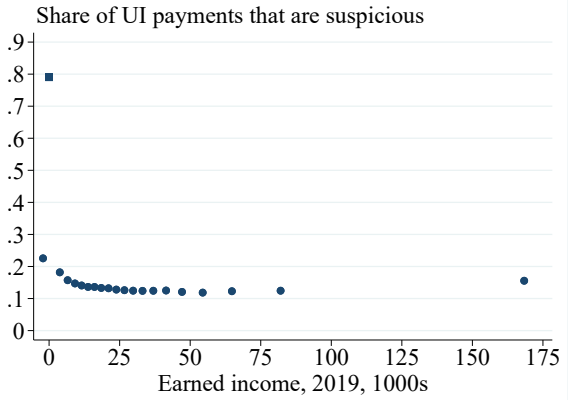
Notes: This figure plots the relationship between suspicious UI payments per working age individual (left column) and the share of UI payments that are suspicious (right column) against the characteristic of the state UI system indicated in each panel title. We exclude Nevada from this figure because it is an outlier in suspicious UI, with $4,667 of suspicious UI per working age individual and a share of suspicious 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 2: Suspicious UI Payments by 2019 Earned Income and Change in Income from 2019–2020

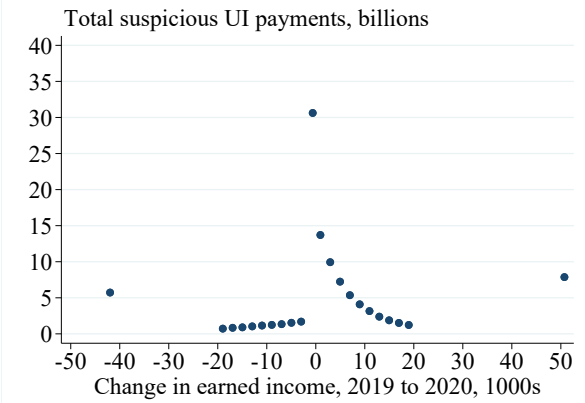
(a) Total Suspicious UI Payments by 2019 Earned Income



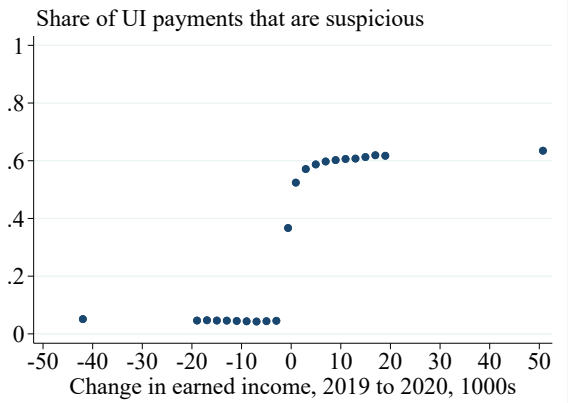
(b) Share of UI Payments that are Suspicious by 2019 Earned Income



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



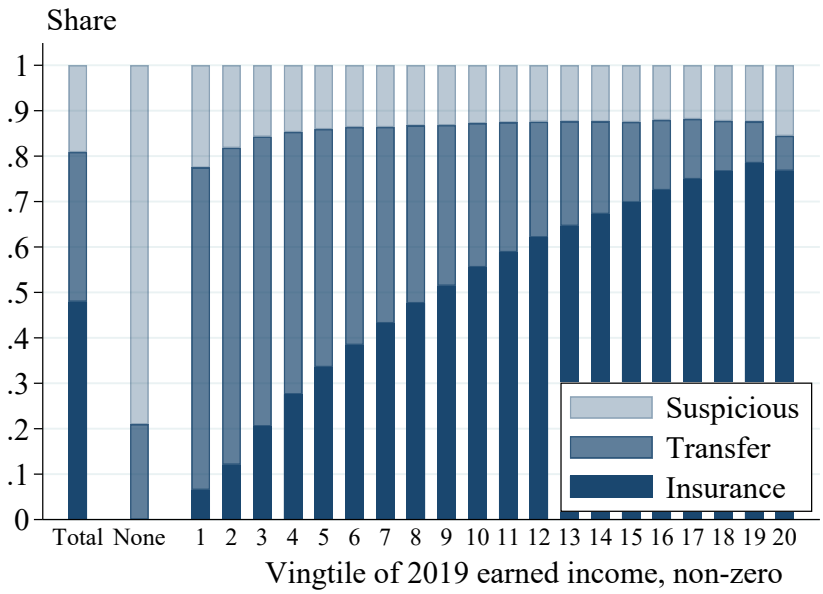
(d) Share of UI Payments that are Suspicious by 2019–2020 Change in Earned Income



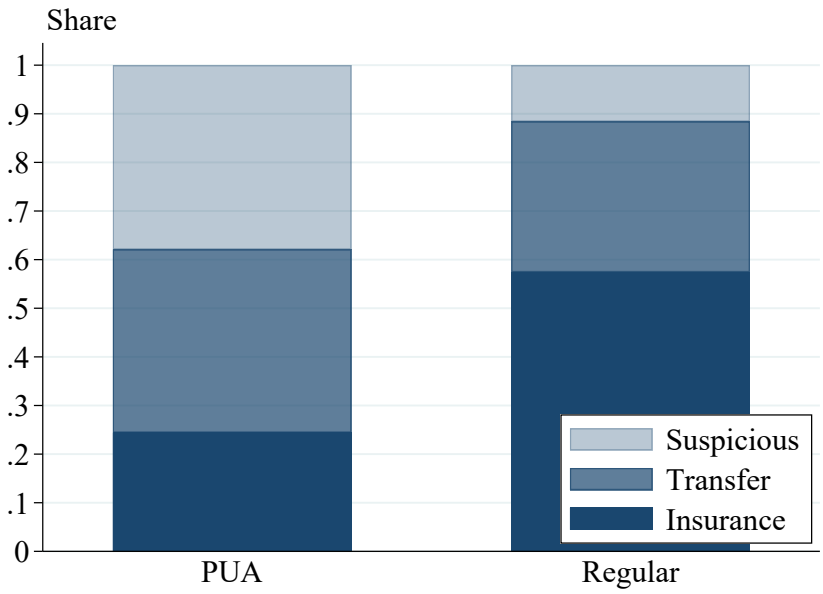
Notes: Panels A and C display the total amount of suspicious 2020 UI payments in billions of dollars. Panels B and D display the share of 2020 UI payments that are suspicious. In Panels A and B, the square symbol is for individuals with zero earned income in 2019, and the circles are for vingtiles of 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 3: Share of UI Payments Classified as Income Replacement, Transfers, and Suspicious, by 2019 Earned Income and Regular/PUA Status

(a) Earned Income, 2019



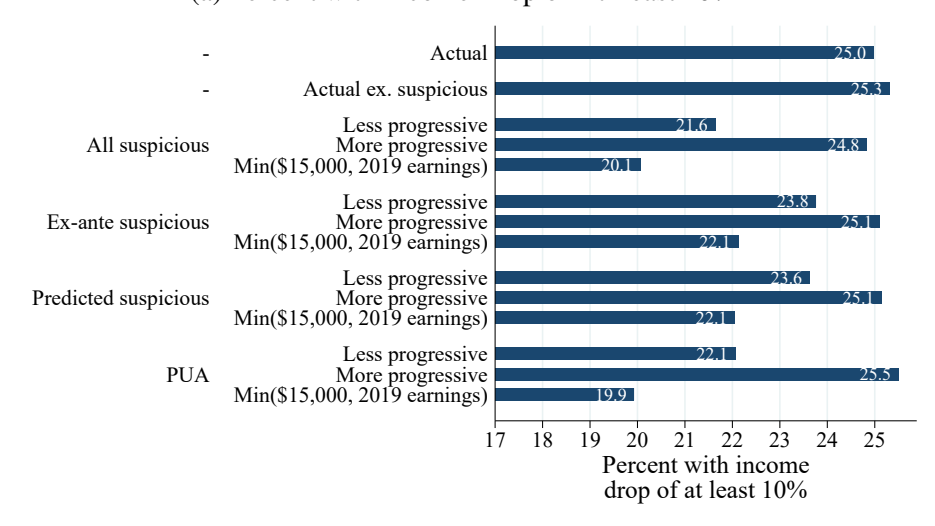
(b) Predicted Regular/PUA Eligibility Based on 2019 Earned Income



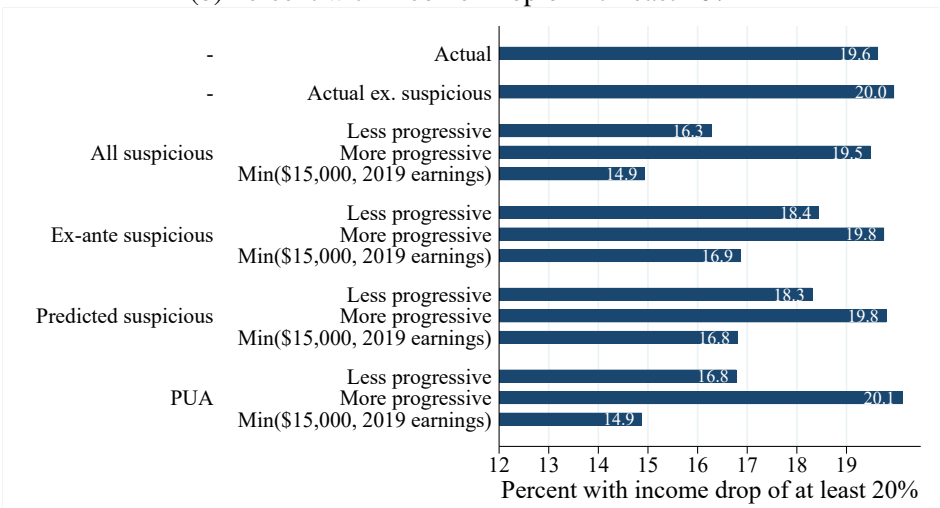
Notes: This figure displays the share of 2020 UI payments that are suspicious, a transfer (i.e., in excess of the decrease in earned income from 2019–2020), or income insurance (i.e., up to and including the decrease in earned income from 2019–2020). Panel A reports results for all individuals, individuals 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 4: Percent of People with a 2019–2020 Income Drop of At Least 10% or 20%, Actual Outcomes and Counterfactual Outcomes

(a) Percent with Income Drop of At Least 10%



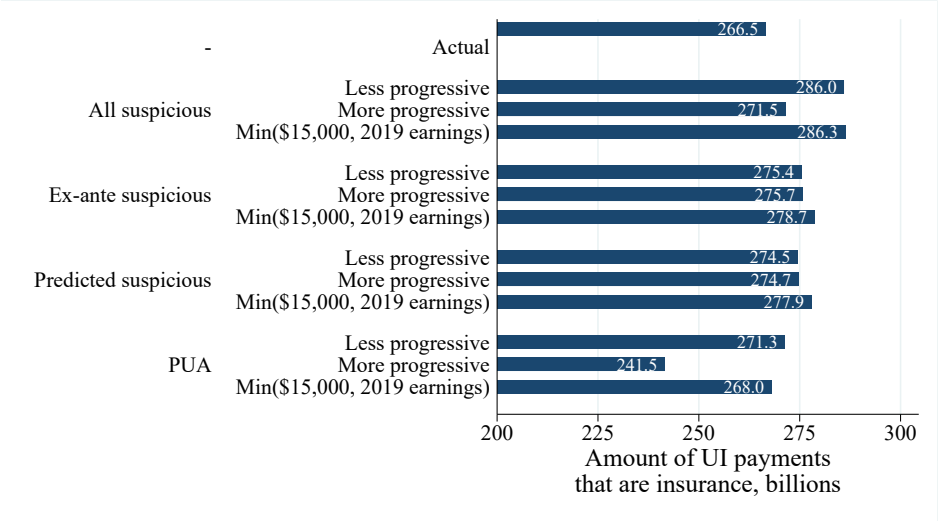
(b) Percent with Income Drop of At Least 20%



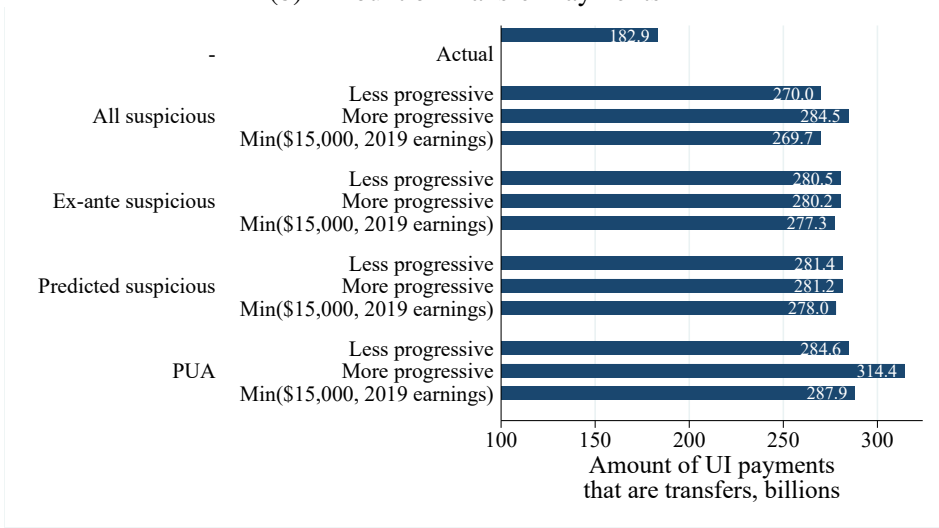
Notes: This figure reports the share of individuals with positive 2019 earned income who experienced a decrease in their income of at least 10% (Panel A) or 20% (Panel B). See text for details.
Source: Authors' analysis of de-identified IRS data.

Figure 5: Amount of UI Payments That Are Insurance or Transfers

(a) Amount of Insurance Payments



(b) Amount of Transfer Payments



Notes: This figure displays the amount of UI payments that are transfers or insurance under various actual and counterfactual scenarios. See text for details.
Source: Authors' analysis of de-identified IRS data.

Online Appendix

Table A.1: UI Payments Flagged as Suspicious, Separately by Reason

	Total (Billions)			Recipients (Millions)		
	All	Regular	PUA	All	Regular	PUA
Panel A: UI in 2020						
Total suspicious	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 age 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 state match from 2018–2020	14.0	0.0	14.0	1.20	0.00	1.20
Form 1099-G amended to 0	9.1	7.6	1.5	0.73	0.59	0.14
UI from multiple states	12.9	3.9	9.0	1.10	0.34	0.77
Got DI in 2019 & 2020 and no earnings in 2019 & 2020	1.9	0.0	1.9	0.15	0.00	0.15
No earnings in 2019 & 2020	36.8	0.0	36.8	2.68	0.00	2.68
No decrease in earnings in 2020 and no indication of non-employment	56.3	34.5	21.8	7.32	5.42	1.90
Panel B: UI in 2021						
Total suspicious	105.8	43.6	62.2	9.86	5.58	4.28
By reason, without stacking						
Flagged as suspicious in 2020	47.1	19.3	27.8	4.06	1.94	2.12
Suspicious in 2021						
Invalid TIN	4.5	0.2	4.3	0.03	0.01	0.02
Dead, below age 10, or above age 100	2.6	0.0	2.5	0.01	0.00	0.00
Incarcerated all year	1.7	0.8	0.9	0.14	0.06	0.08
No state match from 2019–2021	11.7	0.0	11.7	0.42	0.00	0.42
Form 1099-G amended to 0	0.5	0.3	0.2	0.05	0.04	0.01
UI from multiple states	6.0	2.0	4.0	0.53	0.18	0.35
Got DI in 2020 & 2021 and no earnings in 2020 & 2021	0.4	0.0	0.4	0.04	0.00	0.04
No earnings in 2020 & 2021	15.0	0.0	15.0	0.68	0.00	0.68
No decrease in earnings in 2021 and no indication of non-employment	47.6	26.5	21.1	6.01	4.07	1.94

Notes: This table reports the amount of UI benefits and number of UI recipients that meet the specified criteria. Suspicious 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.2: Total and Suspicious UI Payments by State, 2020–2021

State	Total UI, billions $ (1)	Suspicious UI, billions $ (2)	Share Suspicious (3)	Suspicious 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.2: Total and Suspicious UI Payments by State, 2020–2021

State	Total UI, billions $ (1)	Suspicious UI, billions $ (2)	Share Suspicious (3)	Suspicious 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 suspicious UI payments issued by a state in 2020 and 2021. Column 3 reports the share of payments that are suspicious. Column 4 reports the amount of suspicious UI payments per working age individuals.

Table A.3: Relationship Between Suspicious UI and Pre-Pandemic State UI Characteristics

	Suspicious UI per Capita			Suspicious UI as Share of Total		
	All	Regular	PUA	All	Regular	PUA
Measures of Benefit Generosity						
Max Weekly Benefit Amount (100s)	105.12*	33.08**	72.03	0.01	0.00	0.00
	(57.24)	(12.74)	(50.49)	(0.01)	(0.00)	(0.02)
Sim. Weekly Benefit Amount (100s)	-212.27	-107.22*	-105.05	-0.03	-0.02	-0.05
	(262.73)	(60.04)	(234.63)	(0.04)	(0.02)	(0.11)
Sim. Replacement Rate	2613.63	1121.69**	1491.94	0.12	0.09	0.45
	(1572.12)	(477.06)	(1231.36)	(0.22)	(0.15)	(0.48)
Measures of Administration Efficiency						
Share of first claims paid in 14 days	-1270.28	68.42	-1338.70	-0.50*	-0.31**	-0.25
	(2087.22)	(641.16)	(1541.74)	(0.25)	(0.14)	(0.60)
Share of first claims paid in 21 days	-3187.95	-3107.03	-80.91	0.82	0.74	-0.69
	(7309.71)	(2038.55)	(5750.96)	(0.84)	(0.45)	(2.07)
Share of first claims paid in 28 days	4914.62	3239.95	1674.67	-0.04	-0.30	1.16
	(7347.86)	(2131.91)	(5840.66)	(0.79)	(0.42)	(1.91)
Ratio of denied to initial claims	1128.00**	259.12	868.89**	0.06	-0.03	0.11
	(523.99)	(199.02)	(385.06)	(0.06)	(0.05)	(0.18)
Ratio of denied to all claims	-7951.52*	-1995.07	-5956.45*	-0.28	0.43	-0.57
	(3962.87)	(1401.07)	(3087.10)	(0.45)	(0.38)	(1.32)
Measures of Suspicious Activity						
Share of UI classified as overpayments	844.49	243.67	600.82	0.08	0.02	-0.02
	(1139.33)	(374.60)	(844.98)	(0.11)	(0.05)	(0.21)
Share of UI classified as fraudulent	16107.38**	2662.88**	13444.50**	2.26***	0.48	3.50**
	(6307.83)	(1068.11)	(5738.37)	(0.69)	(0.37)	(1.30)

Notes: Table reports results from state-level regressions of the indicated dependent variable against all explanatory variables. Sample excludes Nevada because it is an outlier in the amount of suspicious UI payments. Heteroskedasticity-robust standard errors are in parentheses.

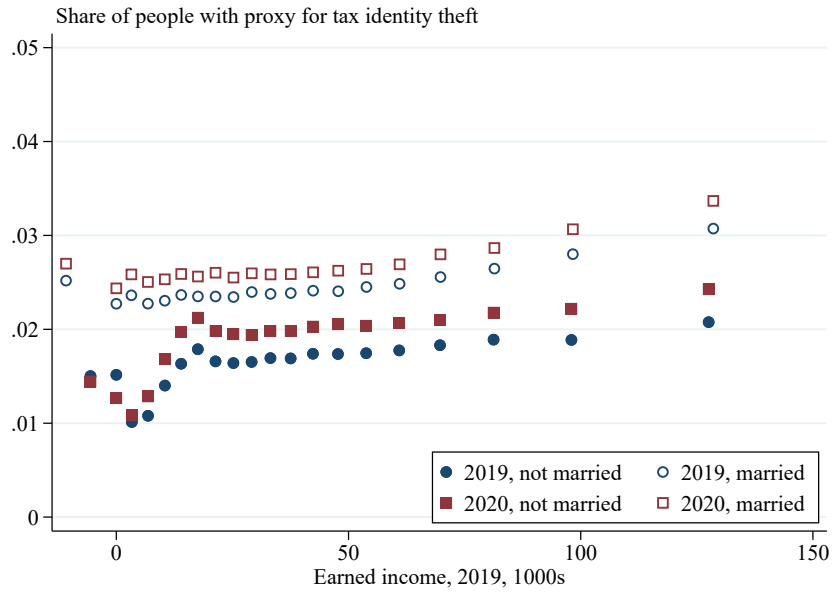
Table A.4: Location in 2019 Earned Income Distribution where Redistributed UI Benefits Are Exhausted in Counterfactual Exercises

Counterfactual exercise		
UI payments removed	Payment schedule	Maximum 2019 earnings of redistributed UI recipient
All suspicious	Less progressive	10,357
	More progressive	141
	Min($15,000, 2019 earnings)	6,501
Ex-ante suspicious	Less progressive	780
	More progressive	-12,331
	Min($15,000, 2019 earnings)	2,689
Predicted suspicious	Less progressive	936
	More progressive	-10,929
	Min($15,000, 2019 earnings)	2,829
PUA	Less progressive	19,639
	More progressive	615
	Min($15,000, 2019 earnings)	8,583

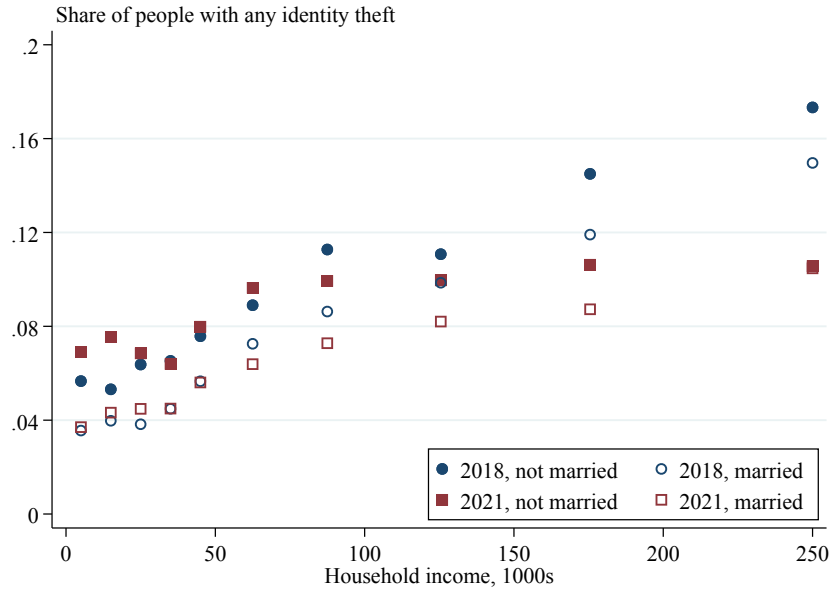
Notes: This table reports where in the 2019 earned income distribution we exhaust the redistributed UI benefits under the indicated counterfactual exercises. For each counterfactual, redistributed benefits are first provided to individuals with the lowest amount of 2019 earned income, and then benefits are provided up the earned income distribution 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.