



FEDERAL RESERVE BANK
OF MINNEAPOLIS

Community
Development
and Engagement

WORKING PAPER

Federal Oversight and Benefit Payment Accuracy: Evidence from the Unemployment Insurance System

October 2026

Ayushi Narayan

Federal Reserve Bank of Minneapolis

Keywords: Unemployment Insurance, Improper Payments, Job-Search Requirements

The views expressed herein are those of the author and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

**Federal Oversight and Benefit Payment Accuracy:
Evidence from the Unemployment Insurance System**

Ayushi Narayan*

Federal Reserve Bank of Minneapolis

October 2026

Abstract

States with high Unemployment Insurance (UI) improper payment rates measured by the Benefits Accuracy Measurement (BAM) statistical survey see increased federal oversight via corrective action plans. Using a regression discontinuity methodology comparing states with improper payment rates just above and below the threshold for increased federal scrutiny, I find that the BAM program and associated federal action have limited impact on future improper payments or work search related investigations. However, detections of earnings-related non-fraud rise in the immediate aftermath of having a high improper payment rate, and there is some evidence of processing delays and reduced reciprocity rates.

* Contact ayushi.narayan@mpls.frb.org. The views I express are my own and do not necessarily reflect the views of the Federal Reserve Bank of Minneapolis or the Federal Reserve System. I thank experts from the Minnesota Department of Employment and Economic Development for helpful feedback.

I. Introduction

Many public programs in the United States feature a joint federal state model under which the federal government defines certain eligibility and implementation parameters of the program and the state government defines the remaining parameters and implements the program. Sometimes the objectives and priorities of the federal government can differ from those of the state government, creating a principal agent problem (Holmstrom 1979), and federal oversight is required. For example, states may differ from the federal government in how they trade off limited funds and staff time between benefits disbursement and program integrity. A key focus area of federal oversight has been the prevention of improper payments (U.S. Government Accountability Office 2024). This paper studies the efficacy of federal oversight for improper payments in the unemployment insurance (UI) system.

The federal government uses the Benefits Accuracy Measurement (BAM) statistical survey to assess state UI payment accuracy. The BAM statistical survey reviews a sample of UI claims to check whether payments were made correctly. Improper payments include both overpayments and underpayments that occurred due to intentional and unintentional errors by applicants in their claims, errors by employers in their reporting of earnings and reasons for separation, and errors by state UI agencies. States with improper payment levels above 10 percent are deemed to have improper payment rates that require additional oversight via corrective action plans (U.S. Department of Labor 2012). High levels of improper payments in UI, measured through the BAM survey, are driven by issues with applicants meeting work search requirements and issues with applicants earning wages while receiving benefits, concerns that may now also be salient in other benefit programs such as SNAP and Medicaid, which have recently expanded work requirements (Bauer and East 2026; Diana et al. 2026).

Using a regression discontinuity methodology, this study assesses the effects of greater federal oversight via corrective action plans that state UI agencies experience when their improper payments cross the 10 percent threshold. It finds that the corrective action plans associated with crossing the 10 percent threshold have no impact on future improper payment rates, with standard errors suggesting that effect sizes greater than 2 percentage points would be unlikely.

I also observe that neither proactive determinations (either approvals or denials) regarding claimants' eligibility for benefits nor denials alone rise when states put in place corrective action plans. I detect no increase in total determinations and denials, those specific to non-separation issues and those even more specific to workers being able and available and actively seeking work are highly unlikely. The results suggest that state UI agencies are not increasing their scrutiny of incoming claims either as a whole or in relation to work search requirements after their improper payment rates exceed 10 percent.

However, the results suggest that increased oversight via corrective action plans leads states to increase their detection of non-fraud (unintentional mistake) cases through controllable means. For example, cases of non-fraud detected by using crossmatches that contain wages reported by employers rise after states experience high improper payments. These methods primarily relate to issues with worker earnings while receiving benefits; they have limited ability to detect overpayments related to work search or other issues. Detections of fraud cases (intentional misrepresentation) on the whole and non-fraud cases from non-controllable sources are unaffected by federal oversight for high improper payment rates.

Finally, I examine whether the corrective action plans have an impact on UI reciprocity to assess whether the plans lead to states changing how they prioritize program integrity and

program disbursement. I find evidence that reciprocity rates fall after states put in place corrective action plans, consistent with results significant at the 10 percent level suggesting delays in processing first payments and determinations. The changes in reciprocity appear to correspond with some changes in the characteristics of UI recipients, namely an increase in the share of recipients who are White or female and a reduction in the share of recipients who broadly worked in low- and moderate-income occupations. I observe limited impact on the timeliness of continuing claims, the share of recipients who are of prime working age between 25 and 54, or the share of recipients who broadly worked in low- and moderate-income industries.

Taken together, my analysis suggests that increased federal oversight and associated corrective action plans stemming from the results of the BAM statistical survey do not appear to reduce future improper payment rates or increase proactive eligibility determination or denial decisions overall or for work search and related issues or raise detections of intentional fraud. However, the oversight does appear to encourage the use of tools such as wage crossmatches that increase detections of non-fraud cases associated with individuals taking jobs while receiving unemployment benefits. It also may affect who receives UI by creating processing delays. The results therefore suggest that in the case of UI, federal oversight stemming from statistical surveys may be ineffective in addressing issues with job search requirements but may have some influence on the usage of tools for detecting earnings-related non-fraud overpayments at the potential cost of reducing reciprocity rates.

The results presented in this paper pertain to high improper payment rates close to the 10 percent threshold. It is possible that the largest impacts of the BAM program come merely from its measurement of and spotlight on improper payments rather than the heightened oversight that occurs when improper payment rates exceed 10 percent, or it's possible that the federal

government focuses its oversight on states with improper payment rates much higher than 10 percent, so effects near the threshold are smaller than the overall effects. Still, the findings from this study suggest that the benefits of the BAM program may be limited, especially for issues surrounding work search requirements.

The BAM program costs states approximately one full-time equivalent worker for every 200 paid and denied claims reviewed, based on numbers from the state of Minnesota, which has five dedicated full-time equivalent workers who carry out BAM reviews. For context, the state of Minnesota receives roughly 3,000 to 13,000 initial claims every week. If the results of this study generalize to the BAM program as a whole, and the primary benefit of the BAM program is to encourage the use of tools like wage crossmatches, there may be more cost-effective ways for the federal government to achieve this benefit.

The potentially high cost-to-benefit ratio may have implications for recent policy proposals and actions. For example, there have been recent calls by the federal government for states to crack down on waste, fraud, and abuse based on data from the BAM program (U.S. Department of Labor 2026). The findings from this study suggest that plans focused on correcting high BAM improper payments may be generally ineffective given how BAM is implemented. Additionally, other joint federal-state programs such as Medicaid and SNAP have recently expanded their work requirements (Bauer and East 2026; Diana et al. 2026). The federal government may wish to increase its oversight of these work requirements, but the results from this analysis using the case study of UI suggest that doing so via a statistical survey like BAM may be costly and limited in efficacy.

In addition to having potential policy implications, the findings from this study add to two main academic literatures. First and most specifically, they contribute to a small but growing

causal literature on program administration in UI. Research in this space has examined topics such as stricter enforcement and verification of work search on UI reciprocity (Ashenfelter et al. 2005), identity verification and fraud in UI (Khetan et al. 2024), IT modernization and new hire directories on UI improper payments (Greer and Bullock 2018; Krause and Hong 2026), antiquated programming language and benefit disbursement delays (Navarrete 2024), the role of employers in UI claims and appeals (Lachowska et al. 2025), and inconvenience on UI take-up (Ebenstein and Stange 2009). Second and more broadly, this paper is related to a robust economics literature on monitoring for work search requirements in UI and related programs, as summarized in Marinescu (2017). That literature finds that basic job search monitoring can be enough to increase job finding, while reinforced job search monitoring does not increase job finding and that sanctions can push unemployed individuals to take lower quality jobs (Marinescu 2017). This paper adds to that literature by showing that corrective action plans do not cause states to put in place programs that reduce future work search issues that would increase associated job finding.

Altogether, the study adds to our understanding of how federal oversight relates to work search issues, improper payments, and take-up in UI. The paper proceeds as follows. Section II provides an overview of UI and the BAM program. Section III outlines my empirical strategy and evaluates its assumptions. Section IV presents the main empirical results. Section V concludes the paper.

II. Policy Overview

The joint federal-state UI system was created during the Great Depression under the Social Security Act of 1935. Since its inception, UI has aimed to provide temporary income

support to workers who have lost their jobs through no fault of their own (Price 1985). The federal government has provided some grant funding and broad standards for the program, but each state has defined its own detailed parameters and implemented its own program (Price 1985).

Oversight for payment accuracy in the UI program has evolved over time, as described in U.S. Department of Labor (1999). Federal oversight related to improper payments was limited during the initial years of the UI program (U.S. Department of Labor 1999). States could still conduct their own reviews, but it wasn't until the late 1970s that the UI program began intensive investigations of a sample of cases (U.S. Department of Labor 1999). After one study found that the existing measurement systems missed many errors, UI agencies began doing field verifications to supplement desk reviews to estimate UI payment errors (U.S. Department of Labor 1999). By 1984, 46 states operated Randomized Audit programs, the predecessor to the BAM program (U.S. Department of Labor 1999). The Benefits Quality Control (BQC) program was established by regulation in 1987, and after a series of modifications, including a renaming, became the BAM program in place today (U.S. Department of Labor 1999).

The current BAM program determines the accuracy of paid and denied claims in three major unemployment insurance programs: state unemployment insurance (UI), Unemployment Compensation for Federal Employees (UCFE), and Unemployment Compensation for Ex-SERVICE Members (UCX). This paper generally focuses on outcomes for the largest of the programs, state UI. The BAM program identifies and examines claims that were overpaid, underpaid, or improperly denied using a statistical sample to estimate accuracy rates. For erroneous claims, BAM determines the cause and the party responsible for the error, the point in the UI claims process at which the error was detected, and actions taken by the claimant, agency,

and employers prior to the error. BAM sampling occurs weekly, with sample sizes ranging from a total of 360 to 480 paid claims cases per state per year, with additional denied claims cases. BAM investigations are intensive, gathering information via various methods from claimants, employers, and third parties. (U.S. Department of Labor 2024)

In addition to being used for estimating payment accuracy, BAM is used as a tool by workforce agency staff to identify systemic errors and facilitate solutions (U.S. Department of Labor 2024). Improper payment rates derived from BAM are one of the core measures used for tracking UI performance today (U.S. Department of Labor 2021). Since 2012, these improper payment rates have been used to comply with the Improper Payments and Recovery Act of 2010, which requires states to develop corrective action plans if their improper payment rate exceeds the acceptable level of performance of 10 percent (Department of Labor 2012). This law relates to the Improper Payments Information Act (IPIA) of 2002, which put into place many of the requirements to review improper payments and report corrective actions to Congress, and to its successor, the Payment Integrity Information Act (PIIA) of 2019 (KPMG Government Institute 2020).

In 2024, work search issues were the largest cause of overpayments for states with high overpayment rates above 10 percent in terms of the total amount overpaid, and they were the most common top cause for overpayments among these states, as seen in Figure 1. The second largest cause was issues with benefit year earnings. This pattern differed somewhat in 2012 when corrective action plans were being introduced for states with high improper payment rates. In 2012, benefit year earnings and work search issues were more similar in their contributions to overpayments in high overpayment rate states. BAM data show that claimants are responsible for

the majority of overpayments, consistent with the growing emphasis on work search issues in improper payments (U.S. Department of Labor 2025a).

BAM has some key similarities with and differences from programs designed to measure improper payments in SNAP and Medicaid, two other large federal-state programs.¹ Under the SNAP quality control program, state agencies review about 50,000 cases each year, and the U.S. Department of Agriculture re-reviews about half of those cases. SNAP quality control assesses the accuracy of eligibility and benefit decisions by verifying data on household circumstances through a variety of sources and directly interviewing households to confirm case information. Unlike BAM, SNAP quality control does not interview employers or require third-party verification. States with high improper payment rates above 6 percent or the national improper payment rate are to be held financially liable if they do not work to address root causes and lower their future improper payment rates (U.S. Department of Agriculture 2025).

The Payment Error Rate Measurement (PERM) program measures improper payments in Medicaid (Mathers et al. 2026). By 2029, the government will reduce federal Medicaid financial participation to states that exceed a 3 percent PERM eligibility error rate threshold (Mathers et al. 2026). Medicaid PERM focuses on improper payments that stem from providers along with improper payments originating from recipients and administrative staff (Mathers et al. 2026). The three key program components examined by PERM are fee-for-service claims, managed care capitation payments, and eligibility determinations (Mathers et al. 2026). Most improper payments are due to insufficient documentation (Mathers et al. 2026).

The UI BAM program is therefore unique in its focus on depth rather than breadth in investigations, its coverage of work search issues, its determination of what constitutes a high

¹ Statutory limitations prevent the Department of Health and Human Services from estimating and reporting TANF improper payment rates (U.S. Government Accountability Office 2026).

improper payment rate, and its definition of corrective action. These factors may all influence the efficacy of the program and the role of federal oversight in reducing improper payments.

III. Data and Methodology

To assess the impacts of the UI BAM program, I compile data from U.S. Department of Labor Employment and Training Administration (ETA) reports. First, to observe the state improper payment rates above and below the 10 percent threshold, I use July to June improper payment rates constructed for IPIA and PIIA reporting as is used by the Department of Labor when instructing states to create corrective action plans (U.S. Department of Labor 2025b). I merge those data with a two-year lag to annualized data on fraud and non-fraud overpayment detections from form ETA 227, determination and denial activities from form ETA 207, the timeliness of first payments, continuing payments, and determinations from forms ETA 9050, 9051, and 9052, respectively, and claimant characteristics from form ETA 203. I also add data on the number of initial and continuing UI claims from form ETA 5159 to use as control variables. I use data on reciprocity rates available from the Unemployment Insurance Chartbook.

My analysis centers on the 50 states and the District of Columbia, excluding data from Puerto Rico and the U.S. Virgin Islands. I drop outcomes after 2020 due to large changes in UI policies in response to the Covid-19 pandemic. When the outcomes data are disaggregated by UI program, I focus my analysis on the regular state UI program. I log count variables for ease of interpretation and to reduce the influence of outliers. Table 1 presents summary statistics for my main outcomes of interest for states with lagged improper payment rates above and below 10 percent. Although there are level differences in count variables potentially related to state size for the two groups, in general, states with high and low improper payment rates look similar.

Reciprocity rates, claimant characteristics, timing for receiving payments and determinations, and years are quite similar across the two groups.

I use these data in a regression discontinuity design methodology that assesses whether there were changes in UI outcomes for states whose lagged improper payment rates just exceeded the 10 percent threshold and necessitated corrective action plans. The main specification for my regression discontinuity strategy uses local linear regression and controls for state and year fixed effects as well as time varying (logged) counts of initial and continuing claims. The specification can be characterized by the following equation:

$$(1) \quad outcome_{s,t} = \gamma_0 + \gamma_1 \mathbf{1}\{ipr_{s,t-2} \geq T\} + \gamma_2 \{ipr_{s,t-2} - T\} + \gamma_3 \{ipr_{s,t-2} - T\} \times \mathbf{1}\{ipr_{s,t-2} \geq T\} + \nu X_{s,t} + \mu_s + \eta_t + v_{s,t}$$

Here, γ_1 represents my parameter of interest, which is the impact of crossing the threshold of $T = 0.1$. $ipr_{s,t-2}$ is the running lagged improper payments rate variable. $\mathbf{1}\{ipr_{s,t-2} \geq T\}$ is an indicator for whether the lagged improper payments rate exceeds $T = 0.1$. $X_{s,t}$ are the controls mentioned above, and μ_s and η_t are the state and year indicators. $v_{s,t}$ represents my error term.

I use the default bandwidth selection procedure from Calonico et al. (2017) based on the msrd one common MSE-optimal bandwidth selector with local linear regression for estimation ($p=1$) and local quadratic regression for bias correction ($q=2$). This MSE-optimal bandwidth I use is a data-driven window around the cutoff that balances bias and variance to minimize mean squared error loss. Because the bandwidth selection procedure introduces bias into the treatment effect estimation, I report bias-corrected estimates and robust standard errors from the estimation in my main figures (Calonico et al. 2014; Calonico et al. 2017). I provide the details of the estimation as well as conventional results in appendix tables. I also explore alternative bandwidths and time lags in robustness exercises.

To assess the validity of my approach, I examine whether there is any bunching around the 10 percent threshold that might indicate state manipulation of improper payment rates of some sort. Manipulation may be less likely in this setting since states have limited control both over various sources of improper payments and over the sampling that occurs year-round, but it is still important to check for bunching. Figure 2 presents a density plot testing for manipulation based on Cattaneo, Jansson, and Ma (2018) and a local linear estimator. The associated p-value for the manipulation test is 0.19, failing to reject the null. It thus appears that the regression discontinuity methodology is likely valid for estimating the impacts of greater federal oversight via corrective action plans for states with improper payment rates exceeding 10 percent.

IV. Results

Figure 3 assesses the effect of having an improper payment rate just exceeding 10 percent on future improper payment rates. Details of the estimates as well as related conventional estimates are provided in Appendix Table 1. The top row estimate uses the baseline specification and finds that crossing the high improper payment rate threshold is associated with just a 0.1 percentage point reduction in future improper payment rates. The 95 percent confidence interval suggests effects much larger than 2 percentage points would be unlikely. Using an alternative bandwidth selection procedure, the `cerd` one common CER-optimal bandwidth selector, which is optimal in terms of coverage error, likewise yields a null result. Dropping controls has basically no impact on the point estimate, but the estimation is noisier, so the confidence interval includes values as large as 5 percentage points in both directions.

If I exclude observations where the lagged improper payment rate was between 9.75 and 10.25 to avoid any potential effects of manipulation just around the threshold, I continue to

observe a null effect on future improper payments. Estimates using a three-year lag likewise suggest a null impact on future improper payments. Restricting the sample to all years of data including the Covid-19 pandemic and the years that followed continues to yield a null result.

Figure 4 examines the effects of having a high improper payment rate on future fraud and non-fraud cases. These cases are those that are detected by UI agencies as part of their standard processes rather than those detected by the BAM statistical survey. The top row shows the estimate for total fraud and non-fraud cases, showing a somewhat noisy null effect of about 5 log points. The second row focuses on fraud cases, those cases in which individuals knowingly misrepresented information. It continues to show a noisy null effect of about negative 5 log points. Non-fraud cases, cases where no false information was knowingly provided, which make up the majority of overpayment cases, saw an insignificant 5 log point increase, in line with the total fraud and non-fraud estimate.

The subsequent rows explore more carefully the means through which the fraud and non-fraud cases were detected. They show that controllable sources, such as wage crossmatches, were responsible for statistically significant increases in non-fraud cases. Controllable non-fraud cases rose by a statistically significant 37 log points, with a large and significant increase in controllable cases detected by wage crossmatches. New hire directory use did not appear to be affected by corrective action plans during my study period. Controllable fraud cases and both fraud and non-fraud cases from non-controllable sources saw relatively small effects, and the standard errors suggest effect sizes as large as those for non-fraud controllable sources would be unlikely.

Taken together, the fraud and non-fraud estimates suggest that states increase their use of wage crossmatches to detect non-fraud overpayments, but they do not appear to detect or

necessarily reduce other sources of overpayments. This interpretation is consistent with the results presented in Figure 5 on determinations and denials, which are proactive decisions UI agencies make as they disburse payments. The figure shows that total determinations – which include both approvals and denials– and denials had no significant changes following high improper payment rates. The pattern is similar for determinations and denials specific to non-separation issues and for those specific to issues related to recipients being able and available and actively seeking work, which all saw null or even significantly negative effects. It thus appears that increased oversight via corrective action plans for states having high overpayment rates exceeding 10 percent does not lead states to exercise increased proactive scrutiny over issues related to work search, the most common cause of BAM overpayments.

Still, states could make changes in their processing of UI claims that lead to delays for claimants and affect UI reciprocity. Figure 6 explores the effects of corrective action plans on recipient outcomes by examining the effect of crossing the 10 percent threshold on UI reciprocity rates, timing of UI payments, and the characteristics of UI recipients. The top row of the figure shows that the corrective actions plans led to a 3 percentage point reduction in the UI reciprocity rates (the Department of Labor estimate of the share of unemployed individuals in a state who are receiving UI benefits). In line with this fall in reciprocity rates, the figure also shows that the share of first payments and determinations that happened in 14 days declined by 2 to 4 percentage points, statistically significant at the 10 percent level. The timeliness of continuing claims appears unaffected.

The final rows of the figure show that the characteristics of UI recipients changed somewhat following high improper payment rates. The share of recipients who were female significantly increased by 2 percentage points, while the share who were White significantly

increased by 4 percentage points. I do not observe a change in the share of recipients who were prime-aged between 25 and 54. To aggregate claimant characteristics by various industries and occupations, I classify industries and occupations as low- or moderate-income if their 2024 wages in the Quarterly Workforce Indicators (QWI) or the Occupational Employment and Wage Statistics (OEWS) were less than 80 percent of the national average. I find that the share of recipients whose broad occupation would be considered low- or moderate-income significantly fell by 3 percentage points, though the share of recipients who would be considered low- or moderate-income based on their industry stayed flat.

V. Conclusion

Altogether, this paper finds that increased federal scrutiny on states with high BAM improper payment rates does not appear to change UI programmatic outcomes except for increasing the detection of non-fraud overpayments through controllable sources such as wage crossmatches, at the potential cost of reductions to UI reciprocity. Other policy levers could be more efficient in achieving greater use of these tools at lower monetary and program accessibility costs. More research is needed to better understand how to design efficient policy.

This paper uses a regression discontinuity design to understand the impacts of corrective action plans for states just exceeding the 10 percent improper payment threshold. It's possible that the effect of BAM and associated federal scrutiny occurs at much higher improper payment rates or across the entire distribution in ways my methodology would not detect. Additional analysis could help explain the ways through which BAM influences UI outcomes. Research on other quality control programs in SNAP or Medicaid could further shed light on how statistical

surveys and federal oversight can be used to improve programmatic outcomes. A comparison across programs could be particularly helpful in understanding the value of depth versus breadth in statistical surveys and whether financial sanctions tied to high improper payment rates help improve outcomes or simply reduce available resources.

Still, this analysis of the BAM statistical survey and related federal oversight provides evidence on the efficacy of corrective action plans associated with a program that focuses on depth rather than breadth and dives deep into work search issues. The study adds to literatures on UI administration and on work search monitoring, showing that corrective action plans associated with BAM have limited impact on UI payment accuracy outcomes for states with high improper payment rates near the 10 percent threshold, including on those outcomes associated with work search issues.

These results have potential policy implications. Building understanding of how the UI BAM program and associated federal oversight and corrective action plans impact improper payments might help in designing future UI quality control efforts. Moreover, because work search requirements have expanded in other federal-state programs, this analysis of UI BAM may also have implications for how the federal government considers future oversight related to improper payments in those programs.

References

- Ashenfelter, Orley, David Ashmore, and Olivier Deschenes. 2005. "Do Unemployment Insurance Recipients Actively Seek Work? Evidence from Randomized Trials in Four U.S. States." *Journal of Econometrics* 125:53-75.
- Bauer, Lauren, and Chloe East. 2026. "A Primer on SNAP Work Requirements." The Hamilton Project.
- Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik. 2014. "Robust Non-Parametric Confidence Intervals for Regression Discontinuity Designs." *Econometrica* 82(6): 2295-2326.
- Calonico, Sebastian, Matias D. Cattaneo, Max H. Farrell, and Rocio Titiunik. 2017. "rdrobust: Software for Regression Discontinuity Designs." *Stata Journal* 17(2): 372-404.
- Cattaneo, Matias D., Michael Jansson, and Xinwei Ma. 2018. "Manipulation Testing based on Density Discontinuity." *Stata Journal* 18(1): 234-261.
- Diana, Amaya, Jennifer Tolbert, Alisha Rao, and Sammy Cervantes. 2026. "A Look at the Intersection of SNAP and Medicaid as States Implement Medicaid Work Requirements." Kaiser Family Foundation.
- Ebenstein, Avraham, and Kevin Stange. 2009. "Does Inconvenience Explain Low Take-Up? Evidence from Unemployment Insurance." *Journal of Policy Analysis and Management* 29(1): 111-136.
- Greer, Robert A., and Justin B. Bullock. 2018. "Decreasing Improper Payments in a Complex Federal Program." *Public Administration Review* 78(1): 14-23.
- Holmstrom, Bengt. 1979. "Moral Hazard and Observability." *Bell Journal of Economics* 10(1): 74-91.

- Khetan, Umang, Jetson Leder-Luis, Jialan Wang, and Yunrong Zhou. 2024. “Unemployment Insurance Fraud in the Debit Card Market.” NBER Working Paper 32527.
- KPMG Government Institute. 2020. “Payment Integrity Information Act of 2019: A New Law to Identify and Reduce Government-Wide Improper Payments.” Issue Brief. Accessed from <https://kpmg.com/kpmg-us/content/dam/kpmg/pdf/2023/payment-integrity.pdf>.
- Krause, George A., and Ji Hyeun Hong. 2026. “Organizational Adaptation, Task Complexity, and Effective Administration of Unemployment Programs in the American States.” *Journal of Policy Analysis and Management* 45(2): e70024.
- Lachowska, Marta, Isaac Sorkin, and Stephen A. Woodbury. 2025. “Employers and Unemployment Insurance Take-Up.” *American Economic Review* 115(8): 2529-2573.
- Marinescu, Ioana E. 2017. “Job Search Monitoring and Assistance for the Unemployed.” IZA World of Labor.
- Mathers, Jessica, Elizabeth Hinton, and Robin Rudowitz. 2026. “A Look at the Medicaid Payment Error Rate Measurement (PERM) Program and Upcoming Changes and Impacts.” Kaiser Family Foundation.
- Navarrete, Michael A. 2024. “COBOLing Together UI Benefits: How Delays in Fiscal Stabilizers Affect Aggregate Consumption.” Hutchins Center Working Paper #98.
- Price, Daniel N. 1985. “Unemployment Insurance, Then and Now, 1935-85.” *Social Security Bulletin* 48(10): 22-32.
- U.S. Department of Agriculture. 2025. “SNAP Quality Control.” Web Article. Accessed from <https://www.fns.usda.gov/snap/qc>.
- U.S. Department of Labor. 1999. “UI Performs CY 1998 Annual Report.” Report. Accessed from https://oui.doleta.gov/unemploy/pdf/cy98_report.pdf.

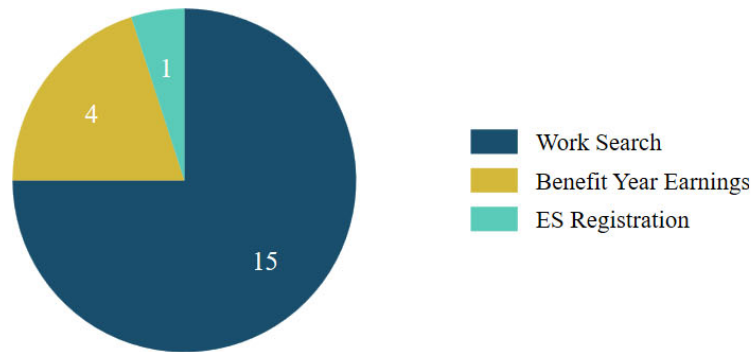
- U.S. Department of Labor. 2012. “Notice Requesting Public Comment on Two Proposed Unemployment Insurance (UI) Program Performance Measures to Meet Requirements in the Improper Payments and Recovery Act of 2010 (IPERA).” *Federal Register* 77(29): 7604-7609.
- U.S. Department of Labor. 2021. “UI PERFORMS Core Measures.” Report. Accessed from https://oui.doleta.gov/unemploy/pdf/Core_Measures.pdf.
- U.S. Department of Labor. 2024. “Benefit Accuracy Measurement Methodology and Program Description.” Report. Accessed from https://oui.doleta.gov/unemploy/bam/2024/PIIA_2024_Methodology_and_Program_Description.pdf.
- U.S. Department of Labor. 2025a. “Benefit Accuracy Measurement Payment Integrity Information Act State Data Summary Performance Year 2024.” Report. Accessed from https://oui.doleta.gov/unemploy/bam/2024/PIIA_2024_Benefit_Accuracy_Measurement_Annual_Report.pdf.
- U.S. Department of Labor. 2025b. “Additional Planning Guidance for the Fiscal Year (FY) 2026 Unemployment Insurance (UI) State Quality Service Plan (SQSP).” Program Letter No. 14-25. Accessed from <https://www.dol.gov/agencies/eta/advisories/uipl-14-25>.
- U.S. Department of Labor. 2026. “U.S. Department of Labor Demands Immediate Action from Governors on Unemployment Insurance Fraud.” News Release. Accessed from <https://www.dol.gov/newsroom/releases/eta/eta20260617>.
- U.S. Government Accountability Office. 2024. “Improper Payments: Key Concepts and Information on Programs with High Rates or Lacking Estimates.” Report. Accessed from <https://www.gao.gov/products/gao-24-107482>.

U.S. Government Accountability Office. 2026. “Payment Integrity: Agencies’ Estimated Improper Payments Increased to \$186 Billion in Fiscal Year 2025.” Report. Accessed from <https://www.gao.gov/assets/gao-26-108694.pdf>.

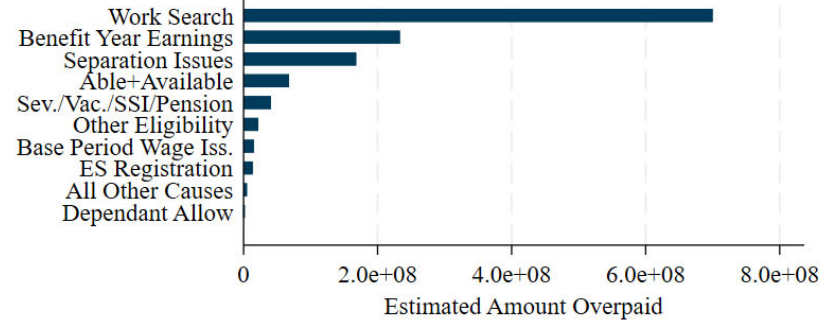
Figures and Tables

Figure 1. Overpayment Causes for States with High Overpayment Rates

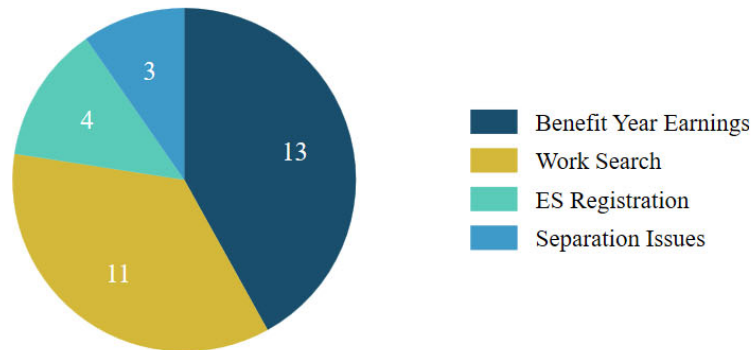
A. 2019 State Top Cause for Overpayments



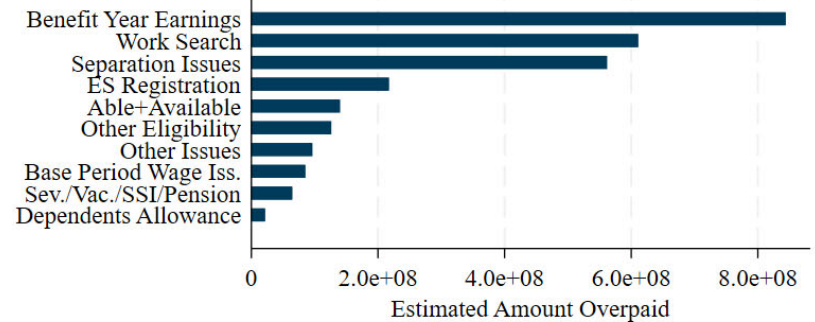
B. 2019 Total Amount Overpaid by Cause



C. 2012 State Top Cause for Overpayments



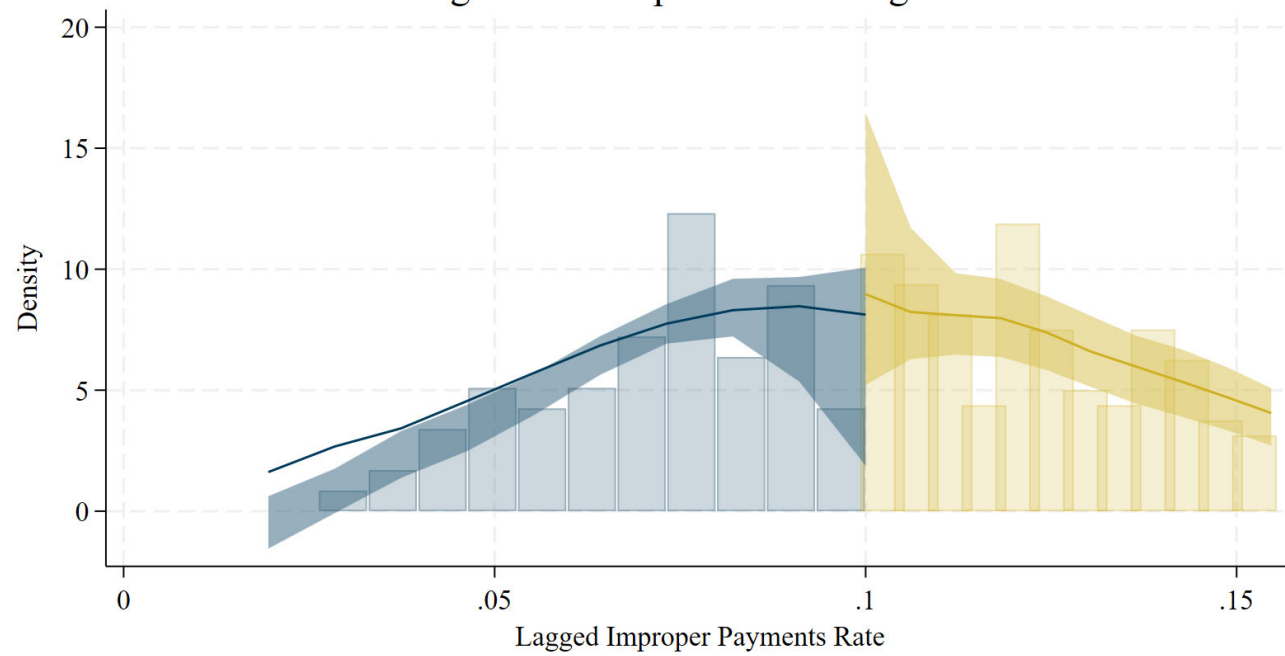
D. 2012 Total Amount Overpaid by Cause



Sources: Department of Labor.

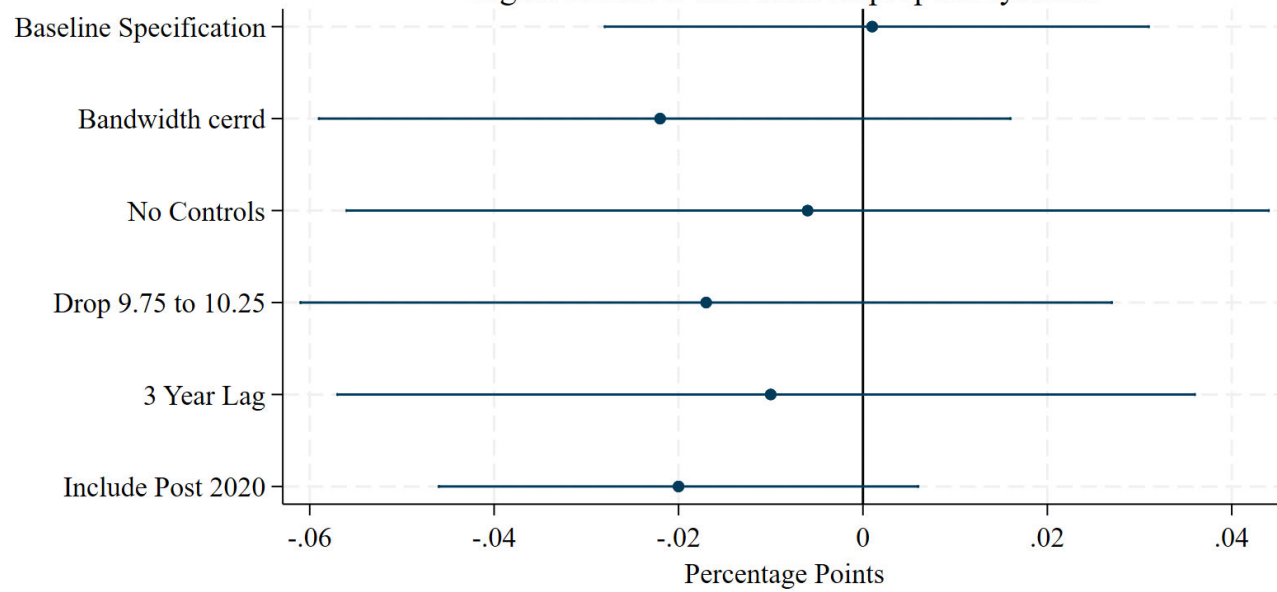
Notes: High overpayment states have overpayment rates $\geq 10\%$. ES stands for employment services.

Figure 2. Manipulation Testing Plot



Sources: Department of Labor.
Notes: Data post 2020 are dropped.

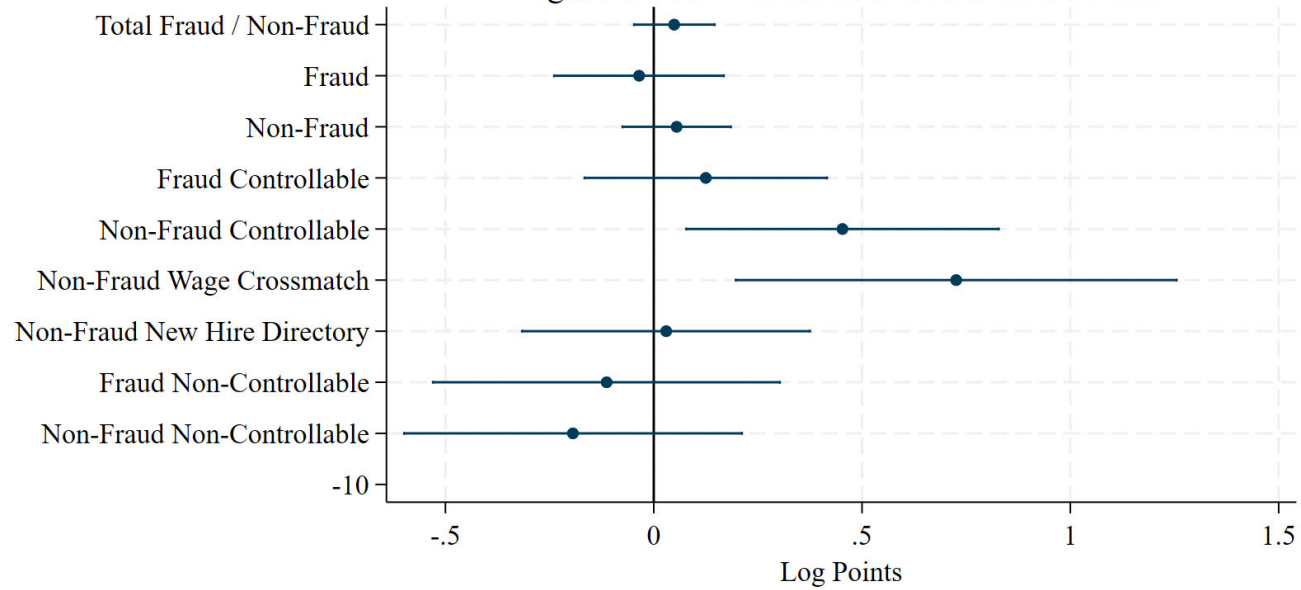
Figure 3. Effect on Future Improper Payments



Sources: Department of Labor.

Notes: Outcomes post 2020 are dropped. Estimates are from local linear regressions ($p=1$) with a local quadratic regression for bias correction ($q=2$). The bandwidth selection procedure uses the mserrd one common MSE-optimal bandwidth selector. Covariates include the number of initial and continuing claims as well as state and year indicators. The running variable is the lagged improper payments rate.

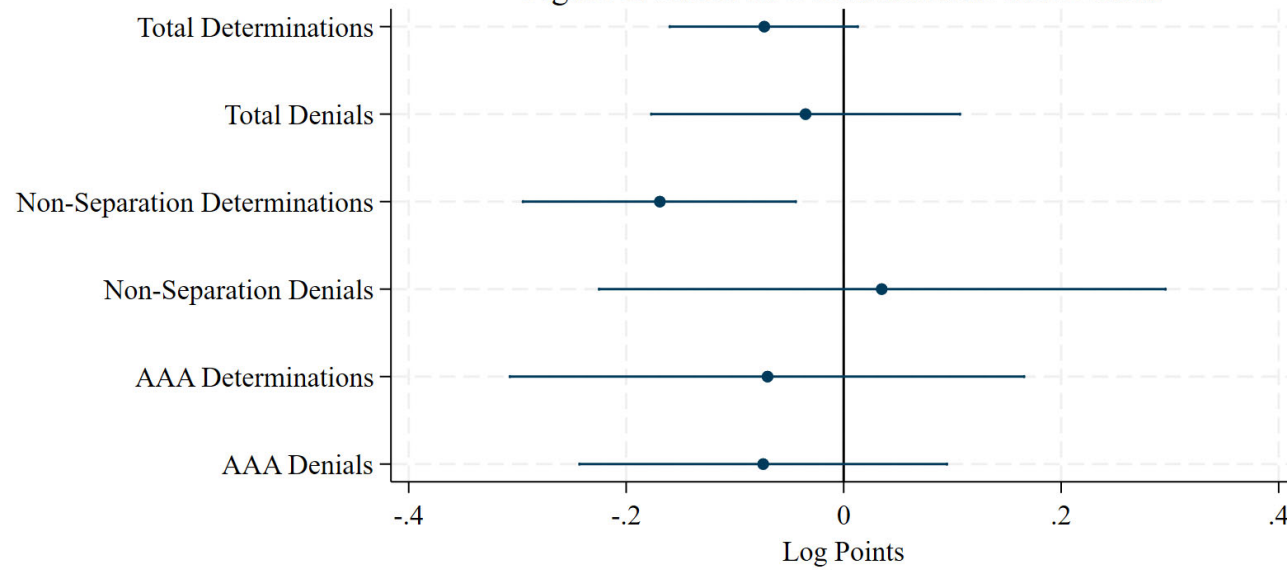
Figure 4. Effect on Fraud and Non-Fraud Cases



Sources: Department of Labor.

Notes: Outcomes post 2020 are dropped. Estimates are from local linear regressions ($p=1$) with a local quadratic regression for bias correction ($q=2$). The bandwidth selection procedure uses the `mserd` one common MSE-optimal bandwidth selector. Covariates include the number of initial and continuing claim as well as state and year indicators. The running variable is the lagged improper payments rate.

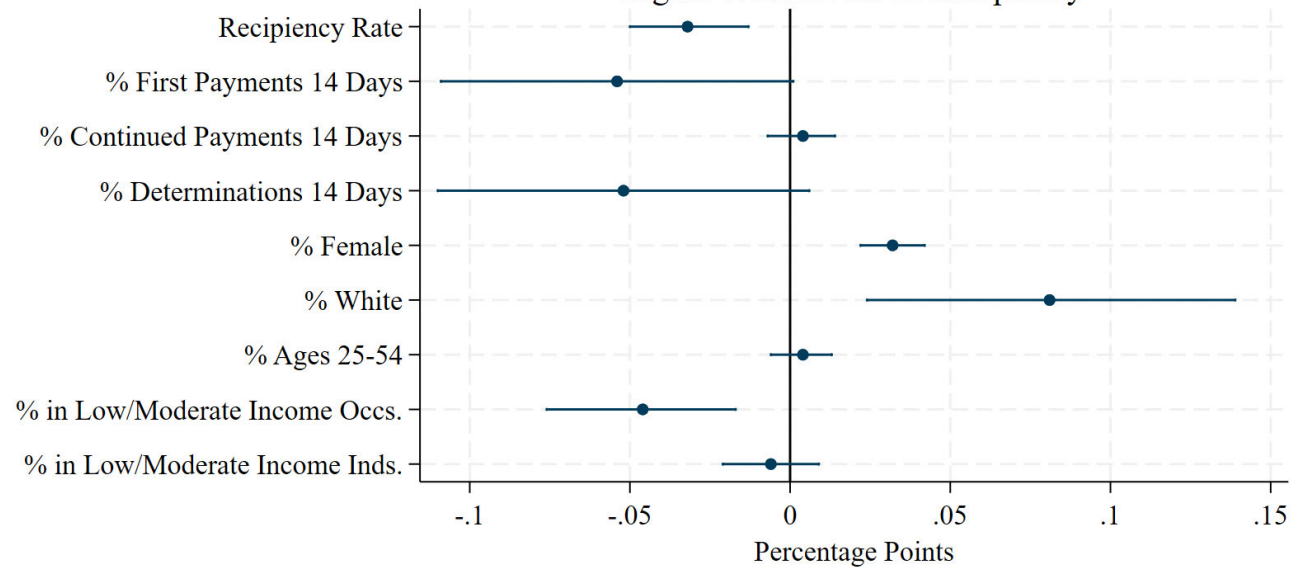
Figure 5. Effect on Determinations and Denials



Sources: Department of Labor.

Notes: Outcomes post 2020 are dropped. Estimates are from local linear regressions ($p=1$) with a local quadratic regression for bias correction ($q=2$). The bandwidth selection procedure uses the mserrd one common MSE-optimal bandwidth selector. Covariates include the number of initial and continuing claims as well as state and year indicators. The running variable is the lagged improper payments rate. AAA stands for able, available, and actively seeking.

Figure 6. Effect on UI Reciprocity



Sources: Department of Labor.

Notes: Outcomes post 2020 are dropped. Estimates are from local linear regressions ($p=1$) with a local quadratic regression for bias correction ($q=2$). The bandwidth selection procedure uses the mserd one common MSE-optimal bandwidth selector. Covariates include the number of initial and continuing claims as well as state and year indicators. The running variable is the lagged improper payments rate.

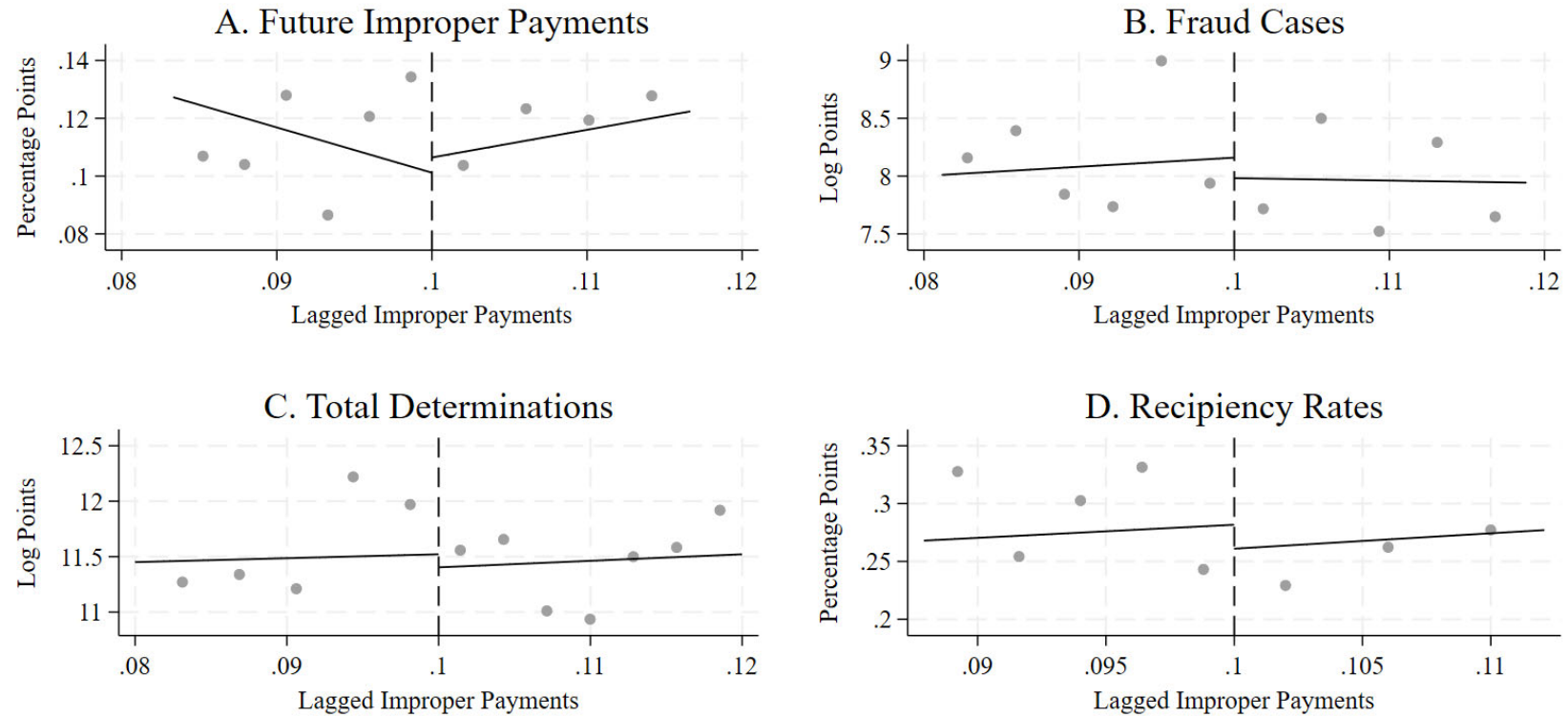
**Table 1 -
Summary Statistics for Selected Variables**

	<u>Lagged Improper Payment Rates $\geq .1$</u>		<u>Lagged Improper Payment Rates $< .1$</u>	
	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)
Improper Payments Rate	14%	7%	9%	5%
Total Fraud and Non-Fraud Cases	27959	29881	26439	34477
Fraud Cases	5369	6110	10495	24189
Controllable Fraud Cases	4620	5312	7920	17426
Total Determinations	125256	118431	150994	201337
Total Denials	85514	79133	96156	120095
Non-Separation Determinations	62667	65166	74898	100882
Able Available Actively Seeking Determinations	22752	24078	25563	39166
Reciprocity Rate	26%	10%	28%	9%
Percent of First Payments in 14 Days	84%	10%	84%	9%
Percent of Continuing Payments in 14 Days	95%	3%	94%	5%
Percent of Determinations in 14 Days	23%	14%	24%	14%
Percent Female	42%	7%	41%	7%
Percent White	59%	19%	60%	21%
Percent Ages 25-54	68%	5%	68%	3%
Percent in Low/Moderate Income Occupations	49%	12%	45%	16%
Percent in Low/Moderate Income Industries	30%	9%	33%	7%
Initial Claims	250217	253079	359749	592900
Continuing Claims	2083878	2277979	2882516	4758580
Year	2016	2	2016	3

Sources: Department of Labor.

Notes: Data post 2020 are excluded.

Figure A1. RD Plots for Selected Outcomes



Sources: Department of Labor.

Notes: Outcomes post 2020 are dropped. Estimates are from local linear regressions ($p=1$) with a local quadratic regression for bias correction ($q=2$). The bandwidth selection procedure uses the msrd one common MSE-optimal bandwidth selector. Covariates include the number of initial and continuing claims as well as state and year indicators. The running variable is the lagged improper payments rate.

**Table A1 -
Effect of Discontinuity on Future Improper Payments Rates**

	Baseline	Bandwidth crrd	No Controls	Drop 9.75 to 10.25	3 Year Lag	Include Post 2020
	(1)	(2)	(3)	(4)	(5)	(6)
Bias-Corrected Estimate	0.001	-0.022	-0.006	-0.017	-0.010	-0.020
Robust Standard Error	0.015	0.019	0.025	0.022	0.024	0.013
Robust 95% Conf. Interval	[-.028 ; .031]	[-.059 ; .016]	[-.056 ; .044]	[-.061 ; .027]	[-.057 ; .036]	[-.046 ; .006]
Conventional Estimate	-0.001	-0.019	-0.008	-0.016	-0.013	-0.019
Conventional Standard Error	0.011	0.010	0.021	0.013	0.012	0.011
Effective Observations Left	39.000	31.000	54.000	38.000	28.000	91.000
Effective Observations Right	51.000	44.000	70.000	42.000	36.000	91.000
BW Loc. Poly. (h)	0.017	0.013	0.022	0.017	0.015	0.020
BW Bias (b)	0.033	0.033	0.032	0.035	0.028	0.033

Sources: Department of Labor.

Notes: Outcomes post 2020 are dropped. Estimates are from local linear regressions (p=1) with a local quadratic regression for bias correction (q=2). The bandwidth selection procedure uses the msrd one common MSE-optimal bandwidth selector.

Covariates include the number of initial and continuing claims as well as state and year indicators. The running variable is the lagged improper payments rate.

**Table A2 -
Effect of Discontinuity on Future Fraud and Non-Fraud Cases**

	Total Fraud / Non-Fraud	Fraud	Non-Fraud	Fraud Controllable	Non-Fraud Controllable
	(1)	(2)	(3)	(4)	(5)
Bias-Corrected Estimate	0.049	-0.035	0.055	0.125	0.453
Robust Standard Error	0.049	0.104	0.066	0.149	0.191
Robust 95% Conf. Interval	[-.047 ; .146]	[-.239 ; .168]	[-.075 ; .185]	[-.166 ; .416]	[.078 ; .828]
Conventional Estimate	0.050	-0.054	0.046	0.097	0.374
Conventional Standard Error	0.042	0.070	0.052	0.109	0.141
Effective Observations Left	36.000	47.000	40.000	40.000	42.000
Effective Observations Right	48.000	53.000	51.000	52.000	52.000
BW Loc. Poly. (h)	0.015	0.019	0.017	0.017	0.018
BW Bias (b)	0.025	0.027	0.027	0.029	0.025
	Non-Fraud Wage Crossmatch	Non-Fraud New Hire Directory	Fraud Non- Controllable	Non-Fraud Non- Controllable	
	(6)	(7)	(8)	(9)	
Bias-Corrected Estimate	0.726	0.030	-0.113	-0.194	
Robust Standard Error	0.270	0.176	0.213	0.207	
Robust 95% Conf. Interval	[.197 ; 1.255]	[-.316 ; .375]	[-.53 ; .303]	[-.599 ; .212]	
Conventional Estimate	0.547	0.003	-0.029	0.015	
Conventional Standard Error	0.191	0.134	0.140	0.085	
Effective Observations Left	47.000	39.000	41.000	39.000	
Effective Observations Right	53.000	51.000	51.000	48.000	
BW Loc. Poly. (h)	0.020	0.017	0.018	0.016	
BW Bias (b)	0.028	0.033	0.029	0.025	

Sources: Department of Labor.

Notes: Outcomes post 2020 are dropped. Outcomes are logged. Estimates are from local linear regressions (p=1) with a local quadratic regression for bias correction (q=2). The bandwidth selection procedure uses the msrd one common MSE-optimal bandwidth selector. Covariates include the number of initial and continuing claims as well as state and year indicators. The running variable is the lagged improper payments rate.

**Table A3 -
Effect of Discontinuity on Future Determinations and Denials**

	Total Determinations	Total Denials	Non-Separation Determinations	Non-Separation Denials	AAA Determinations	AAA Denials
	(1)	(2)	(3)	(4)	(5)	(6)
Bias-Corrected Estimate	-0.073	-0.035	-0.169	0.035	-0.070	-0.074
Robust Standard Error	0.044	0.072	0.064	0.133	0.121	0.086
Robust 95% Conf. Interval	[-.16 ; .013]	[-.177 ; .107]	[-.295 ; -.044]	[-.225 ; .296]	[-.307 ; .166]	[-.243 ; .095]
Conventional Estimate	-0.079	-0.079	-0.155	-0.097	-0.032	-0.047
Conventional Standard Error	0.031	0.034	0.048	0.046	0.077	0.072
Effective Observations Left	47.000	42.000	54.000	36.000	34.000	47.000
Effective Observations Right	56.000	52.000	69.000	48.000	45.000	53.000
BW Loc. Poly. (h)	0.020	0.018	0.022	0.015	0.014	0.019
BW Bias (b)	0.028	0.026	0.038	0.025	0.029	0.039

Sources: Department of Labor.

Notes: Outcomes post 2020 are dropped. Outcomes are logged. AAA stands for able, available, and actively seeking. Estimates are from local linear regressions (p=1) with a local quadratic regression for bias correction (q=2). The bandwidth selection procedure uses the mserd one common MSE-optimal bandwidth selector. Covariates include the number of initial and continuing claims as well as state and year indicators. The running variable is the lagged improper payments rate.

**Table A4 -
Effect of Discontinuity on Future UI Reciprocity**

	<u>A. Reciprocity and Timeliness</u>				
		% First	% Continued	%	
	Reciprocity	Payments 14	Payments 14	Determinations	
	Rate	Days	Days	14 Days	
	(1)	(2)	(3)	(4)	
Bias-Corrected Estimate	-0.032	-0.054	0.004	-0.052	
Robust Standard Error	0.009	0.028	0.005	0.030	
Robust 95% Conf. Interval	[-.05 ; -.013]	[-.109 ; .001]	[-.007 ; .014]	[-.11 ; .006]	
Conventional Estimate	-0.034	-0.020	0.004	-0.045	
Conventional Standard Error	0.005	0.014	0.004	0.023	
Effective Observations Left	29.000	40.000	48.000	48.000	
Effective Observations Right	43.000	51.000	63.000	63.000	
BW Loc. Poly. (h)	0.012	0.016	0.021	0.021	
BW Bias (b)	0.024	0.025	0.040	0.032	
	<u>B. Recipient Characteristics</u>				
				% in	% in
	% Female	% White	% Ages 25-54	Low/Moderate	Low/Moderate
				Income Occs	Income Inds.
	(5)	(6)	(7)	(8)	(9)
Bias-Corrected Estimate	0.032	0.081	0.004	-0.046	-0.006
Robust Standard Error	0.005	0.029	0.005	0.015	0.008
Robust 95% Conf. Interval	[.022 ; .042]	[.024 ; .139]	[-.006 ; .013]	[-.076 ; -.017]	[-.021 ; .009]
Conventional Estimate	0.023	0.042	0.003	-0.031	-0.010
Conventional Standard Error	0.003	0.014	0.004	0.005	0.006
Effective Observations Left	31.000	40.000	50.000	28.000	58.000
Effective Observations Right	44.000	50.000	67.000	39.000	72.000
BW Loc. Poly. (h)	0.013	0.016	0.022	0.012	0.023
BW Bias (b)	0.023	0.026	0.045	0.021	0.047

Sources: Department of Labor.

Notes: Outcomes post 2020 are dropped. Estimates are from local linear regressions (p=1) with a local quadratic regression for bias correction (q=2). The bandwidth selection procedure uses the msrd one common MSE-optimal bandwidth selector. Covariates include the number of initial and continuing claims as well as state and year indicators. The running variable is the lagged improper payments rate.