Name: Krishna Regmi

Email: krishna.regmi.econ@gmail.com, kregmi@fgcu.edu

Current University Affiliation: Florida Gulf Coast University

Date of Ph.D.: 2015

Website link: www.krishnaregmi.com

Summer Institute session that would be of most interest: SI 2023 Labor Studies

A short summary of current research activity

My primary research interests are in the areas of labor economics and the economics of education. Important policy issues motivate my specific research questions. My research projects focus on investigating the effects of labor market policies on various outcomes. Some of my work is also related to studying policies or labor market conditions that affect the process of human capital accumulation. I provide some examples of my ongoing recent research activity to illustrate the type of work that I am doing.

Unemployment insurance: I have been working on a few projects that examine the impact of unemployment insurance (UI) on family well-being. In a recent working paper, I analyze the potential of UI to mitigate ``deaths of despair." In another paper, I examine the impact of mass layoffs on domestic violence and the potential of UI to mitigate it. In a follow-up paper of mine that was published in the Review of Economics and Statistics, I analyze whether UI helps to promote marriage.

Minimum wage: In a working paper, I provide one of the first investigations of the connection between the minimum wage and the uptake of Supplemental Security Income (SSI). Likewise, I have initiated a paper that examines the effect of the real minimum wage on employment by creating a county-level cost of living.

Economics of Education: I am working on a paper that examines the long-term effect of the paid maternity leave program on children's educational attainment and employment in the U.S. Similarly, I recently started a project that examines the effect of the Child Nutrition Programs on high school graduation rates and college attendance. In yet another paper, I examine how district size affects the bargaining power of teachers and student achievement.

Krishna Regmi

Department of Economics and Finance
Lutgert College of Business
Florida Gulf Coast University
Lutgert Hall 3352, 10501 FGCU Blvd. South
Fort Myers, FL 33965

Email: krishna.regmi.econ@gmail.com
Website: www.krishnaregmi.com
Phone: (603) 203-4132

Citizenship: Nepal. Permanent resident of the U.S.

CURRENT EMPLOYMENT AND AFFILIATION

2022-	Assistant Professor of Economics, Department of Economics and Finance, Florida Gulf Coast University, FL
2020-	Research Fellow, IZA - Institute of Labor Economics, Bonn, Germany

PAST EMPLOYMENT

2021-2022	Assistant Professor of Economics, Limited Term, Department of Economics, Finance and Quantitative Analysis, Kennesaw State University, GA
2020-2021	Lecturer, Department of Economics, University of Oklahoma, OK
2019-2020	Visiting Assistant Professor, Department of Economics, Miami University, OH
2018-2019	IRAEA Visiting Scholar, Department of Ag. Economics and Economics, Montana State University, MT
2016-2018	Instructor, Department of Economics, Finance and Legal Studies, University of Alabama, AL
2015-2016	Lecturer, Department of Economics and Finance, Georgia College & State University, GA

EDUCATION

2010-2015	Ph.D. in Economics	Lehigh University, PA
2008-2009	M.A. in Economics	University of New Hampshire, NH

RESEARCH INTERESTS

Labor Economics, Economics of Education

PUBLICATIONS

1. "Stable Income, Stable Family"(with Jason Lindo and Isaac Swensen)
   Accepted at ***Review of Economics and Statistics***
   Media Coverage: EconoFact , October 21, 2020
2. "Maternity Leave"(with Le Wang)
   Forthcoming at the ***Handbook of Labor, Human Resources and Population***

Economics

3. "New Evidence on Teacher Pay," (Single-authored),
   ILR Review, October 2022, Volume 75(5), pp. 1240–1268
4. "The Effect of the Minimum Wage on Children's Cognitive Achievement," (Single-authored),
   Labour Economics*, Volume 65, August 2020*
5. "Labor Demand Shocks at Birth and Cognitive Achievement during Childhood" (with Daniel Henderson), ***Economics of Education Review***, Volume 73, December 2019
   IZA Discussion Paper No. 1252
6. "Examining the Externality of Unemployment Insurance on Children's Educational Achievement," (Single-authored), ***Economic Inquiry***, January 2019, Volume 57, Issue 1, pp. 172-187
7. "Impact of the Minimum Wage on Youth Labor Markets" (with Shanshan Liu and Thomas Hyclak), ***LABOUR: Review of Labour Economics and Industrial Relations***, March 2016, Volume 30, Issue 1,
   Media Coverage: The Wall Street Journal, December 15, 2015
8. "To Be or Not to Be: An Optimum Currency Area for South Asia?" (with Alex Nikolsko-Rzhevskyy and Robert Thornton), ***Journal of Policy Modeling***, November-December 2015, Volume 37, Issue 6, pp. 930-944
9. "Extended Unemployment Insurance and Job Search: Evidence from Time Use Data" (Single-authored), ***The B.E. Journal of Economic Analysis and Policy (Contributions)***, April 2015, Volume 15, Issue 2, pp. 653-683

WORKING PAPERS

10. "Minimum Wages and the Uptake of Supplemental Security Income"
    R&R at ***Labour Economics***
11. "Collective Bargaining Laws and Returns to STEM Majors in the Labor Market for Teachers" (with Andrew Ju, Jacksonville State University)
    R&R
12. "Paid Maternity Leave and Children's Educational Outcomes: Evidence from the Pregnancy Discrimination Act " (with Le Wang, University of Oklahoma)
13. "Unemployment Insurance and Deaths of Despair" (with Isaac Swensen and Andrew Hill, Montana State University)
14. "School District Size, the Bargaining Power of Unions, and Student Achievement" (with Ben Scafidi, Kennesaw State University)

SELECT WORK IN PROGRESS

15. "Social Insurance and Marriage Market" (with Jason Lindo, Texas A&M University and Isaac Swensen, Montanta State University)
16. "Social Safety Net and Domestic Violence " (with Andrew Hill, Montana State University and Isaac Swensen, Montanta State University)

17. "The Effects of Changes in Resources on Outcomes for Students in Texas"(with Rodney Andrews, University of Texas at Dallas, Gregory Phelan, BenjaminScafidi, John Thompson, Kennesaw State University)
18. "Gender Specific Labor Demand Shocks and Children's Educational Outcomes"
19. "When Unemployment Insurance Meets the Minimum Wage"
20. "Trade Shocks and Social Safety Nets"

PRESENTATIONS

2023	Florida Gulf Coast University
2022	2022 Fall Research Conference of the Association for Public Policy Analysis and Management, Kennesaw State University, Northern Kentucky University, Florida Gulf Coast University
2021	University of Oklahoma
2019	Lafayette College, Miami University, University of Arkansas at Little Rock, Montana State University
2018	Montana State University, University of Alabama
2017	University of Alabama
2016	86th Annual Meeting of the Southern Economic Association
2015	Mercer University
2014	2014 Fall Research Conference of the Association for Public Policy Analysis and Management (Poster), Lehigh University
2013	39th Annual Conference of the Eastern Economic Association, 2013 Academic Symposium, Lehigh University

REFEREE FOR

Labour Economics, Economic Inquiry, Economics of Education Review, China Economic Review, Economics & Human Biology, Journal of Development Studies, Journal of Labor Research, Bulletin of Economic Research, Social Science Research, Journal of Business Cycle Research

TEACHING EXPERIENCE

Instructor

Florida Gulf Coast University

Principles of Microeconomics

Kennesaw State University

Business Statistics (2 Sections), Fall 2021

University of Oklahoma

Principles of Macroeconomics (2 Sections), Fall 2020, Spring 2021(1 Section)

Principles of Microeconomics (2 Sections), Fall 2020, Spring 2021(1 Section)

Miami University

Principles of Macroeconomics (3 sections), Spring 2020

Principles of Macroeconomics (3 sections), Fall 2019

University of Alabama

Principles of Microeconomics (3 sections), Spring 2018

Intermediate Microeconomics (2 sections), Fall 2016, Spring 2017, Fall 2017

Intermediate Macroeconomics (2 sections), Fall 2016, Spring 2017, Fall 2017, Spring 2018 (1 section)

Georgia College & State University

Principles of Microeconomics, Spring 2016

Principles of Macroeconomics (2 sections), Spring 2016

Money, Banking, and Financial Markets, Fall 2015

Principles of Macroeconomics (3 sections), Fall 2015

Lehigh University

Money, Banking, and Financial Markets, Summer 2014

Teaching Assistant

Money, Banking, and Financial Markets, Department of Economics, Lehigh University, Spring 2013, Fall 2013, Spring 2014, Spring 2015

Principles of Economics, Department of Economics, Lehigh University, Fall 2010, Spring 2011, Fall 2011, Spring 2012, Fall 2012, Fall 2014

AWARDS

Summer Research Grant ($4,000), University of Alabama, 2018

SOFTWARE SKILLS

STATA, MATA, R, Python, SQL

Unemployment Insurance and the Deaths of Despair

Andrew Hill* Krishna Regmi† Isaac Swensen‡

Abstract

Unprecedented increases in unemployment insurance (UI) claims and dramatic changes in UI delivery across the U.S during the recent pandemic stress the importance of understanding the wide-ranging effects of UI receipt. In this paper, we document the effect of UI on suicide and drug overdose death following mass layoff events. Using quarterly county-level data from 1999-2010 and leveraging interactions between state-specific UI generosity and mass layoff events, regression models and event studies show that more generous UI reduces suicide and drug overdose deaths, and these mitigation effects coincide with otherwise large spikes in mortality following mass layoff events.

JEL classification: J65, H53, I38
Keywords: unemployment insurance, job loss, mortality, suicide, drug abuse

*Montana State University (email: andrew.hill6@montana.edu)
†Florida Gulf Coast University and IZA (email: krishna.regmi.econ@gmail.com)
‡Montana State University (email: isaac.swensen@montana.edu)

1 Introduction

Over 20 million U.S. jobs were lost over the span of a few months in 2020 due to pandemic-induced labor market disruptions.[1] With jobless rates at historic highs, many displaced workers relied on unemployment insurance (UI) to help meet short-term needs and obligations. In the ensuing months, the US experienced record increases in UI benefit claims, quickly followed by intensified UI policy responses from state and federal governments.[2] These sudden and dramatic changes highlight the key role UI plays in assisting displaced workers, particularly in times of economic turmoil. Indeed, the documented follow-on effects of UI receipt extend beyond those captured by standard economic indicators. For instance, recent evidence has shown that UI affects health (Kuka (2020)), housing (Hsu, Matsa, and Melzer (2018)), college enrollment (Barr and Turner (2015)), fertility, and family stability (Lindo, Regmi, and Swensen (2020)).

In this study, we investigate the degree to which UI benefits offset the documented spike in mortality following job loss. Specifically, we estimate the effect of state-specific UI generosity on death by suicide and drug overdose following mass layoff events over the period 1999 to 2010. These causes of death have been shown to increase with job displacement, and have been the primary drivers of increased death rates among White working class individuals over recent years—labeled deaths of despair in work by Case and Deaton (2015, 2017). We measure these deaths using restricted-use individual mortality records. Our empirical approach utilizes two primary sources of variation: mass layoff events at the county level and state-level UI generosity. We leverage the timing of mass layoff events interacted with state-specific UI generosity to explore the extent to which UI mitigates the adverse effect of mass layoffs on suicides and overdose deaths. We show results from both difference-in-difference-type models and event studies, the latter confirming timing that points strongly to a causal relationship.

Consistent with the existing literature, our estimates show large spikes in mortality in the

[1] The Department of Labor reported 20.5 million jobs were lost in April, 2020, leading to an unemployment rate of 14.7%.

[2] https://www.bostonfed.org/publications/community-development-issue-briefs/2020/unemployment-insurance-claims-during-covid-19.aspx

quarter following a mass layoff event. Of primary interest, our estimates show that UI mitigates these increases in suicides and overdose deaths. Our estimates suggests that the mitigating effect of a one standard deviation increase in maximum weekly UI benefits offsets a quarter of the mean increase in suicide rates caused by a mass layoff event. The mitigation effects are more pronounced for suicide than for drug overdose deaths, and are particularly stark in counties with more intense mass layoff events. Our dynamic analysis demonstrates that these effects are apparent following, but not prior to, the mass layoff events. We also find that these effects are most evident for males, White, and middle-aged individuals, which is consistent with the demographic group identified by Case and Deaton as being most at risk of "deaths of despair".[3]

Our findings are consistent with the existing evidence that UI can reduce the often-devastating effects of job loss. In particular, our results add evidence that policies intending to help households maintain stable incomes during economic hardships can also help avoid the costliest adverse consequences that follow job loss.

Most related to our study, Cylus, Glymour, and Avendano (2014) show that the interaction between state-level UI benefits and the annual unemployment rate is negatively related to annual suicide rates. We expand on this initial evidence by investigating the effects of plausibly exogenous shocks to local labor markets—mass layoff events measured at the county level and observed quarterly. This approach avoids the concern that the annual unemployment rate is a function of labor supply decisions that may directly relate to suicides and drug overdoses, and therefore may be affected by the same contemporaneous shocks affecting the studied mortality outcomes. In contrast to what is likely for the pool of the unemployed, monthly mass layoffs are arguably exogenous to individual health problems, behaviors, and death risk. We also broaden our focus to include drug overdose deaths in addition to suicides to better capture short-run deaths that are responsive to these types of local economic shocks. We outline the background and existing literature in more detail in Section 2.

[3]This pattern of heterogeneity is particularly evident for effects on suicide, and is less clear for drug overdose deaths.

2 Background

Our work contributes to a large literature documenting the detrimental effects of economic turmoil on health and well-being. Research in this area explore the links between health and macroeconomic cycles (e.g. Ruhm 2000; Stevens et al. 2015; Ruhm 2015; Lindo 2015 and Miller et al. 2009), economic crises (e.g. Ruhm 2016), initial labor market conditions (e.g. Von Wachter 2020), import competition (e.g. Adda and Fawaz 2020), and other broad and localized economic shocks.

Within this literature, our study is closely related to a large number of studies analyzing the effects of job loss on individuals and households. Existing evidence highlights that job loss is an extremely stressful life event that has both short- and long-term consequences for health and well-being. Most well-identified studies in this area leverage involuntary job loss typically due to mass layoffs or plant closures—demand-side factors that are arguably exogenous to physical and mental health outcomes that may also affect labor supply-side decisions.[4] Such studies document adverse effects of job loss on mortality (Sullivan and Von Wachter 2009; Eliason and Storrie 2009; Classen and Dunn 2012; Browning and Heinesen 2012; Bloemen, Hochguertel, and Zweerink 2018), mental health (Tefft 2011; Kuhn, Lalive, and Zweimüller 2009) and self-reported health (Burgard, Brand, and House 2007; Kuka 2020).[5]

Focusing specifically on the effects of job loss on mortality, several studies use detailed administrative data from European countries to offer insight into these effects. Notably, direct extrapolation to the U.S. context may be limited by stark institutional differences, especially with regard to existing social safety nets. Bloemen, Hochguertel, and Zweerink (2018) find that job loss due to firm closure increases the probability of death in the subsequent two years by 34 percent in the Netherlands. They also find evidence that this effect is driven, in part, by stress

[4]There is some evidence that workforce dynamics may lead to those with poorer health selecting into firms that are more likely to experience plant closure (Bloemen, Hochguertel, and Zweerink (2018)). This concern is partly mitigated in panel studies such as ours that use a dynamic framework to exploit the timing of the disruption.

[5]See also McKee-Ryan et al. (2005) for a review of the mental health effects of unemployment within the psychology literature.

and changes in lifestyle as suggested by increases in alcohol and smoking related deaths. Using Austrian data, Kuhn, Lalive, and Zweimüller (2009) find that job loss increases expenditures for antidepressant and hospitalizations for mental health. Similarly, Browning and Heinesen (2012) analyze data from Denmark and find that plant closures lead to increases in suicide, mental illness and alcohol-related disease. Finally, Eliason and Storrie (2009) find large increases in suicide and alcohol-related mortality following plant closures in Sweden.[6]

In the U.S. context, Sullivan and Von Wachter (2009) find large effects of mass layoffs on mortality in the 1970s and 1980s over an extended time frame, and show that these effects are more pronounced for those in their middle ages. Classen and Dunn (2012) find that unemployment duration is a primary factor when considering the relationship between job loss and suicide, although mass layoffs also increase suicide in the short run. While not using variation in job loss, Pierce and Schott (2020) find increases in suicide and overdoses in counties with labor markets that are negatively affected by international trade policy. The effects are particularly stark among White individuals.

Turning to the evidence on drug use following job loss, the most rigorous studies in the US exploit variation in general economic downturns. For instance, Carpenter, McClellan, and Rees (2017) find evidence that downturns increase the intensity of prescription pain medication use and substance use disorders involving opioids. These effects are concentrated among working age White males with low educational attainment. Also related, Schwandt and Von Wachter (2019) and Cutler, Huang, and Lleras-Muney (2015) show that poor initial labor market conditions are correlated with drug use and overdose, among other detrimental health consequences.[7]

Taken together, these studies suggest that involuntary job loss can lead to adverse health and mortality consequences. Moreover, despite the varied and complex risk factors associated

[6]While our focus is on suicide and drug overdose deaths, note that our definition of drug overdose includes alcohol poisoning. The short-term nature of the effects we study precludes an analysis of deaths related to chronic alcohol consumption, such as deaths related to liver disease.

[7]Notably, however, there is evidence that prices and availability of drugs rather than macroeconomic conditions are the primary drivers of the drug epidemic (Ruhm (2019); Currie, Jin, and Schnell (2019)), although this does not preclude the possibility that household economic shocks lead to adverse drug-related consequences.

with suicide and drug overdose death, job displacement is a clear cause of drug use, drug overdose, correlates of suicidal ideation, and realized suicide. Existing evidence also points to more pronounced effects among working class White males, which is consistent with the longer-run increases in these deaths of despair identified by Case and Deaton (2015, 2017), and motivates the investigation of heterogeneous effects across demographic subgroups in our paper.[8]

The adverse consequences of job loss highlight the potential for unemployment insurance that offsets the financial consequences of job loss to serve a crucial mitigating role. The related literature provides clear evidence that UI is effective in reducing various types of layoff-induced negative shocks: Hsu, Matsa, and Melzer (2018) find that more generous UI reduces mortgage delinquency; Lindo, Regmi, and Swensen (2020) provide evidence that laid-off workers with access to more generous UI benefits see reductions in the divorce and fertility effects of job loss; Tefft (2011) documents overall decreases in depression and anxiety as the number of individuals claiming UI increases in a state; Kuka (2020) reports that a higher UI benefit level can improve health insurance coverage and self-reported health; and, as discussed above, Cylus, Glymour, and Avendano (2014) find a negative correlation between more generous UI policies and suicides during periods of higher unemployment.

3 Data

We assemble data from several sources to measure county-specific layoff events, county-specific mortality outcomes, and state-specific UI details. First, we use county-level layoff data from the Bureau of Labor Statistics' (BLS) Mass Layoff Statistics Program, which began in 1995 and was discontinued in 2012. The program collected detailed information on mass layoffs, which include incidents where at least 50 laid-off workers from the same place of employment claim UI benefits in a five-week window. As these layoffs are the direct result of an establishment being downsized or closed, they are plausibly unrelated to the individual characteristics of the

[8] Existing evidence also shows that job displacement affects spousal health (Marcus 2013; Jolly 2020).

workers or supply-side labor market factors. The publicly available data report mass layoffs at an annual frequency. In this paper, we use a richer version of the data from Lindo, Schaller, and Hansen (2018) obtained from the BLS that provide quarterly layoff information at the county level from 1995 to 2010. We restrict the sample to prime working-age individuals (ages 25 to 54), a group that has a strong attachment to the labor force and is more likely to be eligible for and collect UI benefits (Cullen and Gruber 2000). This restriction also aims to guard our results against concerns pertaining to early career choices between schooling and market work by younger individuals and early retirement decisions of older individuals.

Figure 1 displays the mean mass layoff rate across counties during our study period, where the layoff rate is defined relative to the county labor force.[9] Mean layoff rates tend to be higher in what has been refereed to as the Rust Belt region, particularly Michigan, Indiana, Ohio and Pennsylvania, which have experienced declines in their manufacturing base since the 1950s. South-western coastal areas and western coastal states (California, Oregon, and Washington) also have relatively high layoff rates. We provide summary statistics in Table 1, which show a mean county layoff rate of 0.002. In other words, on average, there are two layoffs associated with a mass layoff event for every 1,000 individuals in the labor force per quarter.

Second, we obtain the restricted-use national vital statistics micro-data from the Centers for Disease Control and Prevention (CDC), which contains monthly mortality incidents with county identifiers broken down by various demographic groups and underlying causes. Mortality causes are classified using the International Classification of Disease (ICD) codes.[10] We construct mortality rates using the estimates of the county-level population demographics from the Surveillance, Epidemiology, and End Results (SEER) Program. We follow the general practice in the literature of expressing deaths per 100,000 county population. The mean suicide rate per quarter in our sample is 3.8 and the mean overdose death rate per quarter is 3.5, shown in Table 1. This table also shows mortality outcomes by gender and race. Suicide rates and overdose

[9] Using the county population as the denominator yields findings similar to our main results.
[10] In these data, mortality causes are identified with ICD-9 (1995-1998) and ICD-10 (1999+) codes.

death rates are highest for males and White individuals.[11]

We present mean county-level suicide rates during the study period in Figure 2, and mean county-level overdose death rates in Figure 3. A comparison of Figures 1 and 2 shows that, in the cross-section, counties with high mean suicide rates are not typically counties with high layoff rates. Suicide rates are higher in the mountain states of Colorado, Nevada, Wyoming, and Montana, but are not as high in the Rust Belt region, on average. Drug overdose death rates are generally correlated with suicide rates, although there are some stark differences, such as southern New York and Connecticut, where we observe high rates of drug overdose death but low rates of suicide death.

Third, we collect maximum weekly unemployment insurance (UI) benefit levels, our measure of UI generosity, from the "Significant Provisions of State UI Laws: Benefit and Tax" reports published biannually by the BLS. The benefit schedules—providing a cap on amount an eligible laid-off worker can collect in a state—are published twice a year, in January and July. States decide both the levels and changes in maximum UI, leading to substantial differences across states and over time. For example, in 2010, Alabama had the least generous UI benefits program in nominal terms with maximum weekly benefits of $200 and Massachusetts had the most generous UI benefits program in nominal terms with maximum weekly benefits of $721. Figure 4 displays the cross-sectional variation in mean maximum weekly UI benefits during the study period. Table 1 reports a mean maximum amount of weekly unemployment benefits of $356 across all counties during our study period, and a standard deviation of $105.

Finally, we collect labor force statistics from the Local Area Unemployment Statistics (LAUS) program,[12] and obtain various other county-level characteristics from census data.

In addition to the means of the key variables already discussed above, Table 1 reports descriptive statistics of these variables separately for counties experiencing zero mass layoff events, below median mass layoffs conditional on experiencing a mass layoff event, and above

[11] Appendix Table A1 provides the ICD codes used to classify mortality outcomes.
[12] The links are: https://oui.doleta.gov/unemploy/DataDashboard.asp; and https://www.bls.gov/lau/

median mass layoffs conditional on experiencing a mass layoff event–these breakdowns will be used in our empirical analyses. Other than the layoff rate and the overall population count, which vary mechanically across these three categories, there are no striking differences in UI benefits, suicide rates, or overdose death rates, providing support for interpreting the timing and location of mass layoff events as exogenous.

4 Empirical Strategy

We consider a variety of empirical approaches to identify whether UI mitigates the effect of job loss on suicides and overdose deaths. In all approaches, mass layoff events in a county are used to measure exogenous negative shocks to the local economy.[13]

In our first model, suicides or overdoses per 100,000 in county j and quarter t are modeled as a function of the statewide maximum amount of weekly UI benefits that quarter, $MaxUI_{jt}$; whether the county experienced a mass layoff in the previous quarter, $I[LayoffRate_{j,t-1} > 0]$; and the interaction between these two variables. This interaction is the key variable as it allows for the possibility that the direct effect of job loss on suicides or overdose deaths is dampened by more generous UI benefits.

$$\begin{aligned} Outcome_{jt} &= \delta_1 MaxUI_{jt} + \delta_2 I[LayoffRate_{j,t-1} > 0] + \delta_3 MaxUI_{jt} \times I[LayoffRate_{j,t-1} > 0] \\ &\quad + \theta_j + \theta_t \times T + \epsilon_{jt} \end{aligned} \tag{1}$$

The model includes county fixed effects θ_j and quarter-by-year fixed effects $\theta_t \times T$ to control for fixed county characteristics and time-varying national shocks. We also use population weights, cluster standard errors at the state level, and include time-varying county demographic

[13]Recent developments have highlighted potential problems with fixed effects estimators in the context of research designs comparing individuals and/or groups across time (Callaway, Goodman-Bacon, and Sant'Anna, 2021). While researchers have identified alternative estimators to address these problems when treatment is discrete, work is still ongoing to solve these problems in the presence of continuous treatment, such as the state-level UI benefit generosity and the county-level mass-layoff rate studied in our paper. We look forward to continued developments in this space to further test the robustness of our results.

controls in additional specifications.[14]

The first two terms in the above model deal with baseline factors that may affect suicides and overdoses. The association between state UI generosity and county suicide or overdose rates, described by the parameter δ_1, may be positive or negative, and does not have a causal interpretation. For example, increasing the generosity of UI within a state may improve the general quality of life for individuals prone to suicide and drug overdoses in that state, reducing the likelihood of suicides and overdoses, but it may also be a policy response to poor economic conditions in the state that reduced the general quality of life for these individuals and increased the probability of suicides or overdoses.

Mass layoff events are known to increase suicides and overdoses (Sullivan and Von Wachter, 2009). We therefore expect a positive estimate of δ_2, the coefficient on the county layoff indicator. This would indicate that county-quarters with positive layoff rates the previous quarter experience more suicides or overdose deaths than county-quarters with zero layoff rates the previous quarter, holding other factors constant. Exploiting the exogenous variation in the timing of involuntary job losses after a mass layoff event, we interpret δ_2 as a causal effect that closely parallels those identified in related literature (e.g. Bloemen, Hochguertel, and Zweerink 2018).

We now turn to how this estimating equation deals with the focus of this paper, the extent to which the generosity of statewide UI mitigates the effect of job loss on suicides and overdose deaths. This effect is measured by δ_3, the coefficient on the interaction between maximum UI benefits in the state and an indicator for a mass layoff event. Negative estimates would indicate that for county-quarters that experienced a mass layoff event, more generous statewide UI benefits reduce the corresponding rate of suicides or overdose deaths in the county. The magnitude of δ_3 relative to δ_2 would provide an indication of how much the maximum amount of weekly UI benefits would need to increase to compensate for a mass layoff event.

The above specification only captures mean differences between counties that experience

[14]Specifically, we weight all estimates by the county population ages 25-54.

mass layoff events and counties that experience no mass layoff events. To allow the intensity of local negative economic shocks to vary, we enrich the model by splitting county-quarters into those with zero layoff rates, below-median layoff rates $I[BelowMedianLayoffRate_{j,t-1}]$, and above-median layoff-rates $I[AboveMedianLayoffRate_{j,t-1}]$. The median is defined based on county-quarters with non-zero layoff rates, so the below-median and above-median indicators will be switched on for a similar number of county-quarter observations, but there will be many more county-quarters with zero layoff rates.[15] The omitted category is county-quarters with zero layoff rates.

$$\begin{aligned} Outcome_{jt} &= \mu_1 MaxUI_{jt} + \mu_2 I\left[BelowMedianLayoffRate_{j,t-1}\right] + \\ &\quad \mu_3 I\left[AboveMedianLayoffRate_{j,t-1}\right] + \mu_4 MaxUI_{jt} \times I[BelowMedianLayoffRate_{j,t-1}] \\ &\quad + \mu_5 MaxUI_{jt} \times I[AboveMedianLayoffRate_{j,t-1}] + \theta_j + \theta_t \times T + \epsilon_{jt} \end{aligned} \tag{2}$$

We anticipate that counties with below-median (but positive) layoff rates will experience more suicides or overdose deaths than counties that do not experience mass layoff events. We also expect counties with above-median layoff rates to have higher suicide or overdose death rates than counties with below-median layoff rates. Our expectation for the estimates is therefore $0 < \mu_2 < \mu_3$. If UI generosity mitigates these effects, we expect the coefficients on the interactions, μ_4 and μ_5, to be negative.

The above models assume that previous quarter economic shocks only affect current quarter suicides or overdose deaths. Since we anticipate effects on mortality to follow economic shocks that could occur at any time during the quarter, our focus on previous-quarter layoffs avoids the possibility of loading the effects of a mass layoff event occurring near the end of a quarter on suicides or overdose deaths that occur earlier in the quarter. We also anticipate that there may a lag between negative economic shocks and mortality consequences. Ultimately, though,

[15] As the median is an arbitrary cutoff, we also show results from alternative delineations to measure the intensity of the layoff events.

we need not rely on speculating about the timing of effects, and explore the dynamics of the relationship directly with an event study approach. Specifically, we estimate models that take the following form:

$$\begin{aligned} Outcome_{jt} &= \gamma_1 MaxUI_{jt} + \sum_{k=-3}^{3} \gamma_k I[LayoffRate_{j,t+k} > 0] \\ &\quad \sum_{m=-3}^{3} \gamma_m MaxUI_{jt} \times I[LayoffRate_{j,t+m} > 0] + \theta_j + \theta_t \times T + \epsilon_{jt} \end{aligned} \tag{3}$$

This specification allows the suicide or overdose death rate in quarter t to be affected by lags and leads of indicators for mass layoff events in the county, $I[LayofRate_{j,t+k} > 0]$, and interactions between the statewide maximum UI benefits and lags and leads of the county layoff rate indicators.

Our hypothesis is that suicide or overdose rates in quarter t should only be affected by job losses in contemporaneous or prior quarters, and not future job losses. Estimates of γ_k should therefore only be non-zero for $k \leq 0$. Similarly, we expect the coefficients on the interactions of the layoff indicators with the state maximum UI benefits should only be non-zero for $m \leq 0$. These event study estimates speak to the timing, persistence, and robustness of the relationship between local economic shocks and suicide or overdose death rates. We also estimate variations of this model in which each lag or lead of the county layoff rate enters individually into the specification as a sensitivity check.

Finally, our work is related to recent literature focusing on suicides and overdoses more pronounced among certain demographic groups of the US population. In particular, there have been documented increases in these outcomes for White males, most often in their middle ages (e.g. Case and Deaton (2015, 2017) Pierce and Schott (2020)). To explore gender and race heterogeneity, we estimate Equation 2 but restrict the outcomes to gender-specific or race-specific suicide and overdose death rates within the county. We continue to rely on population-wide county layoff rates to measure local negative economic shocks in these specifications.

5 Results

5.1 Regression Models

In Table 2, we report the results from estimating Equation 1, the model with a binary indicator for a mass layoff event the previous quarter. The effects on suicide rates are reported in Panel A and the effects on drug overdose death rates are reported in Panel B. Column 1 reports estimates from a baseline model with only county, year, and quarter fixed effects; Column 2 includes time-varying county demographic controls; and Column 3 replaces the year and quarter fixed effects with year-by-quarter fixed effects, a more flexible control for national time-varying shocks affecting health outcomes.[16]

The estimates in Panel A confirm that counties with mass layoff events experience an increase in suicides the subsequent quarter. This is consistent with existing evidence on the relationship between negative economic shocks and suicide. Given the mean county suicide rate is 3.8 suicides per 100,000 (Table 1), the increase of 0.20** (0.09) reported in Column 3 reveals that when a county-quarter experiences a mass layoff event, there is a sizable 5 percent increase in suicide rates.[17]

We now turn to our primary question of interest: to what extent is this spike in suicides following job loss mitigated by UI generosity? The coefficient in Column 3 on the interaction between maximum UI benefits and the indicator for a mass layoff event in the county-quarter is -0.52** (0.22), which is clear evidence of a mitigating role played by UI. More specifically, a one standard deviation increase (approximately a $100 increase) in weekly maximum UI benefits would mitigate a quarter of the spike in suicide rates following a mass layoff event.[18]

[16] Table A2 reports similar results with even richer fixed effects: state-by-quarter, state-by-year and state-by-year-by-quarter.

[17] On average, a mass layoff event is associated with 2 out of every 1,000 workers in the county being laid off. The increase in suicides is 0.2 per 100,000 individuals. Under the strong assumption that the increase in suicides is coming solely from individuals who are laid off, it is worth noting that this 5 percent increase in the suicide rate corresponds to a very small share of laid off workers committing suicide for the typical mass layoff event.

[18] Note that since MaxUI is measured in thousands, a $100 increase corresponds to 0.1. The calculation is therefore $(0.52 \times 0.1)/0.20 = 0.26$.

While we see the same pattern of effects in Panel B for drug overdose death rates, the estimates for the layoff event and the interaction in Columns 2 and 3 of Panel B are not statistically different from zero at conventional levels of significance.

In both panels, we observe no clear relationship between statewide UI benefits and suicides or drug overdose deaths, which is not surprising given the ambiguity of this relationship discussed in the empirical strategy section.[19]

Table 3 reports results from Equation 3, which introduces additional parameters to capture the intensity of local mass layoff events, but in a way that retains the tractability of the binary treatment model. Recall that in this model counties with positive layoff rates (counties that experienced a mass layoff event) are classified as above-median or below-median rather than being identified by a single indicator. The omitted category remains county-quarters with no layoff events.

The estimates in Panel A show that counties with below-median layoff rates experience larger increases in suicide rates following a mass layoff event relative to counties with zero layoff rates, and counties with above-median layoff rates experience an even larger spike in suicide rates following a mass layoff event. This is consistent with the notion that larger mass layoff events are associated with larger spikes in suicide rates. More importantly for this paper, we observe clear mitigating effects of UI on this relationship; the estimates on the interactions between statewide maximum UI benefits and the county layoff rate bins are negative. Our estimates show that the effect of a given dollar increase in UI benefits has a greater mitigating effect in counties with the highest (above-median) county layoff rates. The above-median layoff estimate in Column 3 is -0.76** (0.27), which suggests that a $100 increase in UI benefits would mitigate 26 percent of the observed increase in suicide rates following a mass layoff event.

Turning to Panel B, the effects on drug overdose deaths, we find more evidence for a

[19]In Table A3 we also show that state-wide max UI levels are not systematically related to other state-level economic conditions including GDP, employment rates, and unionization rates, which alleviates some concerns that changes in UI are correlated with or driven by alternative state policies.

mitigating role played by UI than in Panel B of Table 2 where we used a simple indicator for mass layoff events. Across Columns 1 to 3, there is a precisely estimated negative effect of UI generosity on overdose deaths for counties with above-median layoff rates. Slightly larger than the mitigation effect on suicides following above-median layoff events, the estimated interaction in Column 3 suggests an approximate 30 percent mitigation effect associated with a $100 increase in weekly UI benefits.

5.2 Event Studies

We unpack the timing of our estimated effects by considering event studies taking the form of Equation 3, and report results graphically in Figures 5 and 6. Specifically, we allow for effects three quarters before and after the mass layoff event, and use the more flexible model with below-median and above-median county layoff rate indicators to capture the intensity of the mass layoff events.

In Figure 5 Panel A we first plot the direct effects of job loss on mortality for the quarters leading up to and following mass layoff events. We show effects related to both below-median and above-median layoff rate county-quarters. The figure shows a stark spike in suicide rates corresponding to the quarter immediately following the layoff event, particularly for above-median layoff events. There is no evidence of effects prior to the event nor in the quarter of the event (recalling that the mass layoff event could occur near the end of the quarter), and the effect does not persist beyond the quarter immediately following the event. This panel provides further strong support for the causal relationship between negative economic shocks and mortality that has been documented in other contexts, but with an emphasis on short-run effects on suicides.

Panel B speaks to the focus of our paper, the mitigating effect of UI on these layoff-induced deaths. In this panel, we plot the estimated interactions between the maximum UI benefit and lags and leads of the below-median or above-median county layoff rate. They follow a similarly striking pattern to Panel A. We observe no non-zero effects in the quarters leading up to the

layoff; no evidence of an effect in the quarter of the layoff; a clear negative effect in the quarter after the layoff (the mitigating effect of UI), and no further effects for subsequent quarters.

Overall, Figure 5 Panels A and B provide compelling evidence of both the mortality spike following job loss and the mitigating role played by UI, and the timing of effects is strongly indicative of a causal relationship.

In Figure 6 Panels A and B, we plot the corresponding estimates for drug overdose deaths. The patterns in both panels closely parallel those seen in Figure 5, albeit not quite as stark. There is also evidence of a slightly more persistent effect after above-median layoff events; increased overdose deaths are observed in the two quarters following job loss rather than just the subsequent quarter.[20]

Taken together, these event studies provide clear evidence of a short-run mitigating effect of UI generosity on suicide and overdose death rates following mass layoff events, and show no evidence of extraneous effects before the mass layoff event that would question the validity of the model. Furthermore, the mitigating effect of UI is larger in counties with above-median county layoff rates compared to counties with below-median county layoff rates, consistent with the results in Table 2 and Table 3.

5.3 Heterogeneity

Table 5 explores heterogeneity by gender and race. Specifically, we report results in which gender- or race-specific county suicide or overdose death rates are regressed on the same set of explanatory variables as in Table 3. We observe that the direct effect of job losses on suicide and overdose rates and the corresponding mitigating role played by UI are most evident for males and White individuals. The findings indicate a weaker, but discernible, effect for females, while there appears to be no effect on Black and Hispanic individuals.

[20] We note that there is a significant below-median indicator two quarters prior to the event, which we interpret as a statistical anomaly.

Using a similar approach to Table 5, Table 6 considers heterogeneity by age. As shown in Panel A, albeit with varying levels of statistical significance, the effects on job loss on suicides are largest among middle-aged individuals between the ages of 35 and 54 years old, while there is some evidence of an effect in the 25 to 34 age group when exposed to the most intense mass layoff events. The heterogeneity by age is less clear in Panel B for drug overdose deaths; the pattern of increased mortality following job loss and a mitigating effect of UI is observed for all groups, although the magnitudes are larger for middle-aged individuals.

Tables A6 and A7 consider heterogeneous effects by age for males and females, respectively. These estimates reinforce our findings that middle-aged males have particularly pronounced spikes in suicide and mitigation effects following mass layoff events. Similar to the previous results, the pattern is less clear for drug overdose deaths.[21]

The concentration of mortality effects from job losses on White individuals, males, and individuals between the ages of 36 and 55, is broadly consistent with existing evidence. Case and Deaton (2015, 2017) find that suicides and drug overdoses have been primary drivers of mortality for White Americans in recent years, and Carpenter, McClellan, and Rees (2017) finds substance use disorders increase after economic downturns particularly among White individuals.[22] Our evidence that the mitigating effects of UI are concentrated among this subpopulation experiencing elevated risks of suicide more generally suggests increasing UI benefits may be an appropriately targeted policy response.

5.4 Additional Robustness and Sensitivity

We provide a series of robustness and sensitivity checks. We consider whether job loss affects other causes of death (and whether these effects are mitigated by UI), we explore alternative approaches to measuring the intensity of mass layoff events, and we investigate the role played

[21] In other results, we have explored estimates for subpopulations defined by gender, age, and race, which are noisy, but generally also point to effects being most pronounced among middle-age White men.

[22] The gender differences we observe are also in line those reported in Lindo, Regmi, and Swensen (2020), in which UI generosity reduces the probability of divorce after a job layoff for men more than women.

by UI duration.

In a falsification exercise, we report effects on other common causes of mortality in Table 4. We explore deaths related to cardiovascular disease, cancer, respiratory disease, long-term alcohol diseases, and motor vehicle crashes.[23] Columns 1 to 3 consider deaths that are related to chronic, underlying conditions. Consistent with our priors, the coefficients in these columns show no clear evidence of any effects on these common causes of death. In Column 4, there is some evidence of an effect of job loss on deaths caused by long-term alcohol disease, although it is only evident for less intense mass layoff events. We continue to find that UI mitigates this effect. We interpret this finding as more suggestive than conclusive given the direct effect of job loss is not monotonic in layoff intensity. Finally, Column 5 shows some evidence that motor vehicle deaths decline after job loss. We speculate that this may be because workers reduce commute times after losing their jobs. Given this behavioral response to job loss is unlikely to be affected by UI benefits, it is not surprising that there is no mitigating effect of UI generosity on these deaths. Together, the absence of effects in Table 4 reinforces the validity of our empirical approach and suggests a unique short-run relationship between job loss, suicides, and overdose deaths.

Our previous models use indicator variables to categorize our mass layoff treatment into either two or three bins depending on the specification. This makes estimated parameters easier to interpret and highlights that effects are more apparent following larger mass layoff events. To ensure that our parameterization is not driving the findings, we test whether results are sensitive to binning positive county layoff rates into groups defined by other cutoffs. Specifically, we consider cutoffs from below and above the 5th percentile to below and above the 95th percentile. Figures A1 andA2 report results using the corresponding 19 different cutoffs, showing that findings are not generally sensitive to how county-quarters with positive county layoff rates are categorized into bins.

We also explore estimates similar to our event study models in which the county-quarter

[23]ICD codes for these categories are provided in Appendix Table A1

layoff rate enters continuously as opposed to indicator variables. Table A4 considers effects on suicide rates. In the first seven columns, each lag and lead of the county layoff rate enters the equation separately, while Column 8 combines them. Similar to our event study results discussed above, we observe short-run effects of job losses leading to higher suicide rates that do not persist and that these increases are mitigated by more generous UI benefits. The results in Columns 1 to 7 provide a sensitivity check that supports the patterns seen in Column 8, though the estimates are less precise. Table A5 reveals a noisier pattern of effects for drug overdose deaths. While the pattern of the estimates still suggest more deaths and more mitigation post-layoff event, the imprecise estimates are consistent with the effect on drug overdoses being more apparent following relatively large mass layoff events as shown in Figure 5 and Table 3. As such, while some of the findings using the continuous measure of layoffs are harder to interpret, it is reassuring that these results on suicides and drug overdoses reinforce our main estimates.

As a final robustness test, we use potential UI duration rather than maximum UI benefits as our measure of UI generosity. We leverage state-specific expansions in UI duration that occurred during and after the Great Recession of 2008. States generally provide up to 26 weeks of regular benefits; however, the duration of benefits was extended up to a maximum of 99 weeks after the beginning of the recession.[24] We collect information on the potential duration of UI benefits using the weekly Trigger Notice reports of Emergency Unemployment Compensation and Extended Benefits from the Bureau of Labor Statistics (BLS).[25] We aggregate these data to the quarterly level, and restrict our analysis to 2008-2010, the period of UI duration expansion that overlaps with our study period. We estimate a model similar to Equation 2, but replace the variable measuring maximum UI benefits with a variable measuring potential UI duration in weeks. As reported in Table A8, we find that increasing the number of weeks of potential UI benefits reduces layoff-induced suicides, while the effects on drug overdose deaths are imprecisely estimated.

[24]See Lindo, Regmi, and Swensen (2020) for more details of the UI duration policies.
[25]The link is https://oui.doleta.gov/unemploy/claims_arch.asp.

6 Conclusion

In this paper we document the effect of UI on suicide and drug overdose death following mass layoff events across the United States. Using quarterly county-level mass layoff and mortality data, our estimates show that more generous UI mitigates the spikes in suicide and drug overdose deaths that follow these mass layoff events. The estimates are robust to various model specification and effects are evident following, but not leading up to, mass layoff events. Our dynamic estimates also show that both the increase in mortality and the mitigation effects are only apparent in the quarter immediately following the mass layoff event. Broadly consistent with the longer-term trends in suicides and drug overdose deaths identified in the deaths of despair literature, our estimated effects are larger for White individuals, males, and those in their middle ages.

We can perform a back-of-the-envelope calculation to speak to the costs and benefits of increasing UI generosity. Our main estimates (Table 3, Column 3) suggest that counties with above-median layoff rates driven by mass layoff events experience an average increase of about 7 suicides and 18 drug overdose deaths annually compared to counties with zero mass layoff events, and that a $100 increase in the weekly maximum UI benefit would save about 2 lives from suicide and 5 lives from overdose death.[26] To estimate how much it would cost to increase weekly maximum UI benefits by $100, we assume a 50% UI take-up rate[27], an average layoff rate in counties with above-median layoff rates of 0.005 (Table 1), and an average county labor force of 750,000. This translates to 7,500 laid off workers receiving a $100 dollar increase in UI. Given an average duration for UI receipt of 13 weeks, this suggests a total cost of 9.75 million dollars to save 7 lives.[28] This is a low cost in the context of typical cost-benefit values used by

[26] An increase of 0.29 in the suicide rate per 100,000 individuals per quarter corresponds to an increase of 1.7 suicides per quarter in the average county with a population (ages 25-54) of about 600,000, which is multiplied by 4 to scale from quarters to years, and recall that a $100 increase (about one standard deviation) in maximum UI mitigates about a quarter of this spike.

[27] This take-up rate is based on Wandner and Stettner (2000), although some more recent data suggests UI take-up rates may have declined.

[28] The total cost is calculated as 7,500 UI recipients × $100 increase × 13 weeks. Note that this is conservative in the sense that it assumes all recipients actually receive the $100 increase in the maximum weekly UI benefit.

the federal government when making risk assessments to justify policies.[29] These calculations suggest that in the context of mass layoff events increasing UI benefits would pass a cost-benefit assessment based solely on mortality reductions.

The labor market disruptions induced by the COVID pandemic focused attention on UI, and there have been calls for the federal and state governments to revise UI policies. In concert with other recent evidence of spillover benefits generated by UI, our finding that UI reduces the mortality effects of negative economic shocks emphasizes the importance of considering the full range of social benefits when considering the optimal design of UI policies.

[29]For instance, the EPA's recommended central estimate of the value of a statistical life is 7.4 million dollars (see https://www.epa.gov/environmental-economics/mortality-risk-valuation).

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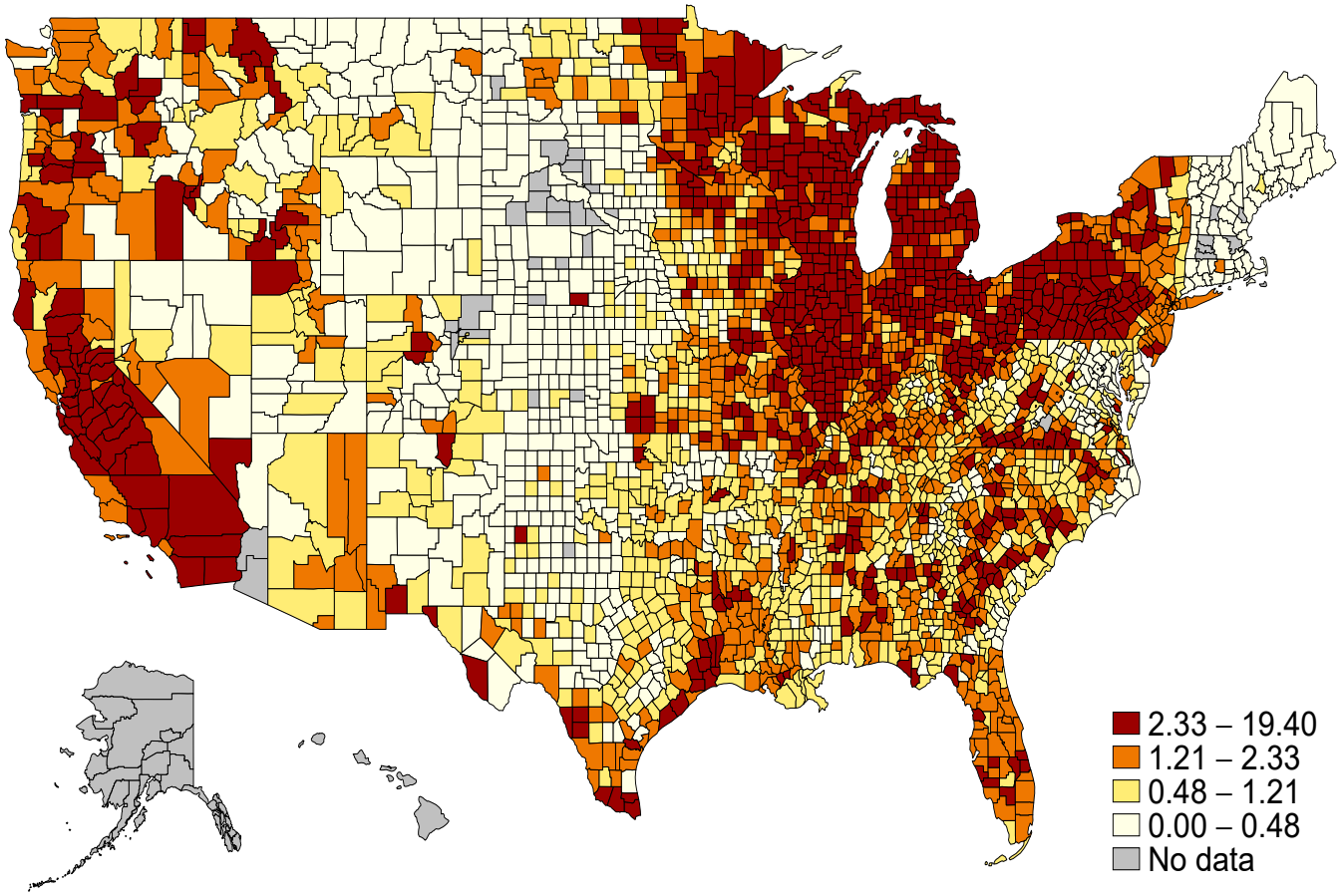
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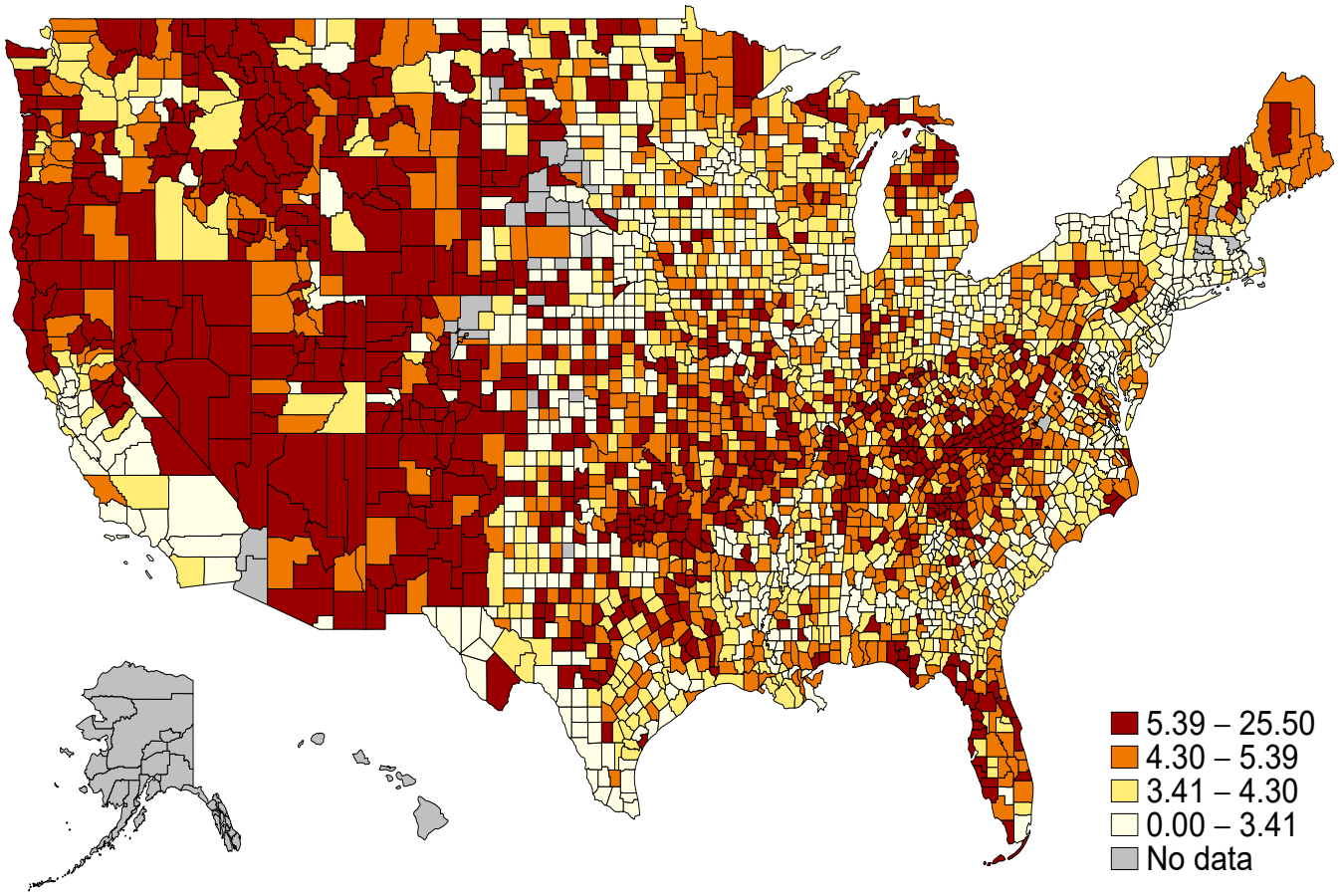
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Figure 1: Mean layoff rates across US counties



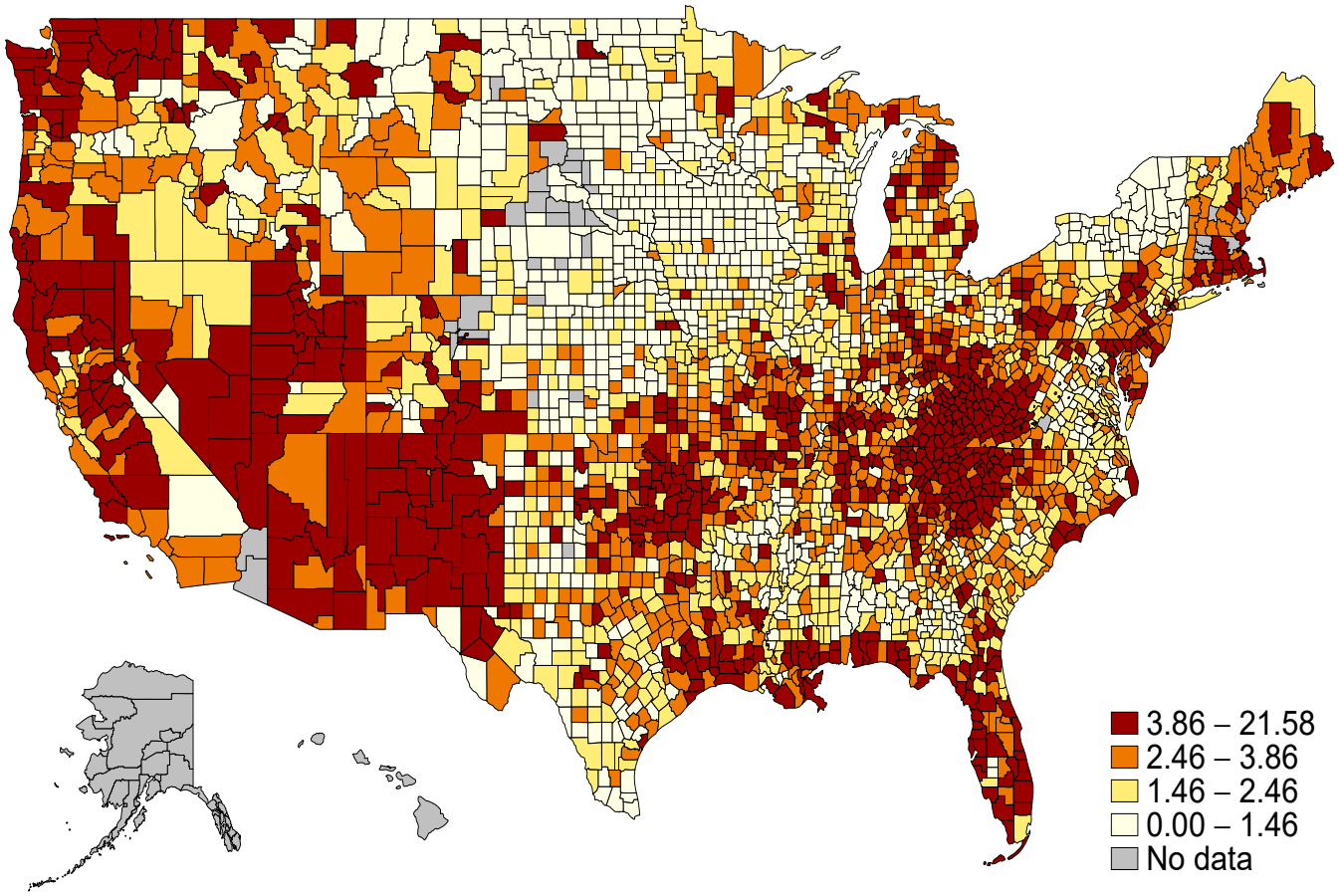
Notes: This figure displays the mean mass layoff rate per quarter across counties from 1995-2010, where the layoff rate is the number of layoffs divided by the labor force (measured per 1,000 laborers) in each county. The color breakdowns correspond to quartiles.

Figure 2: Mean suicide rates across US counties



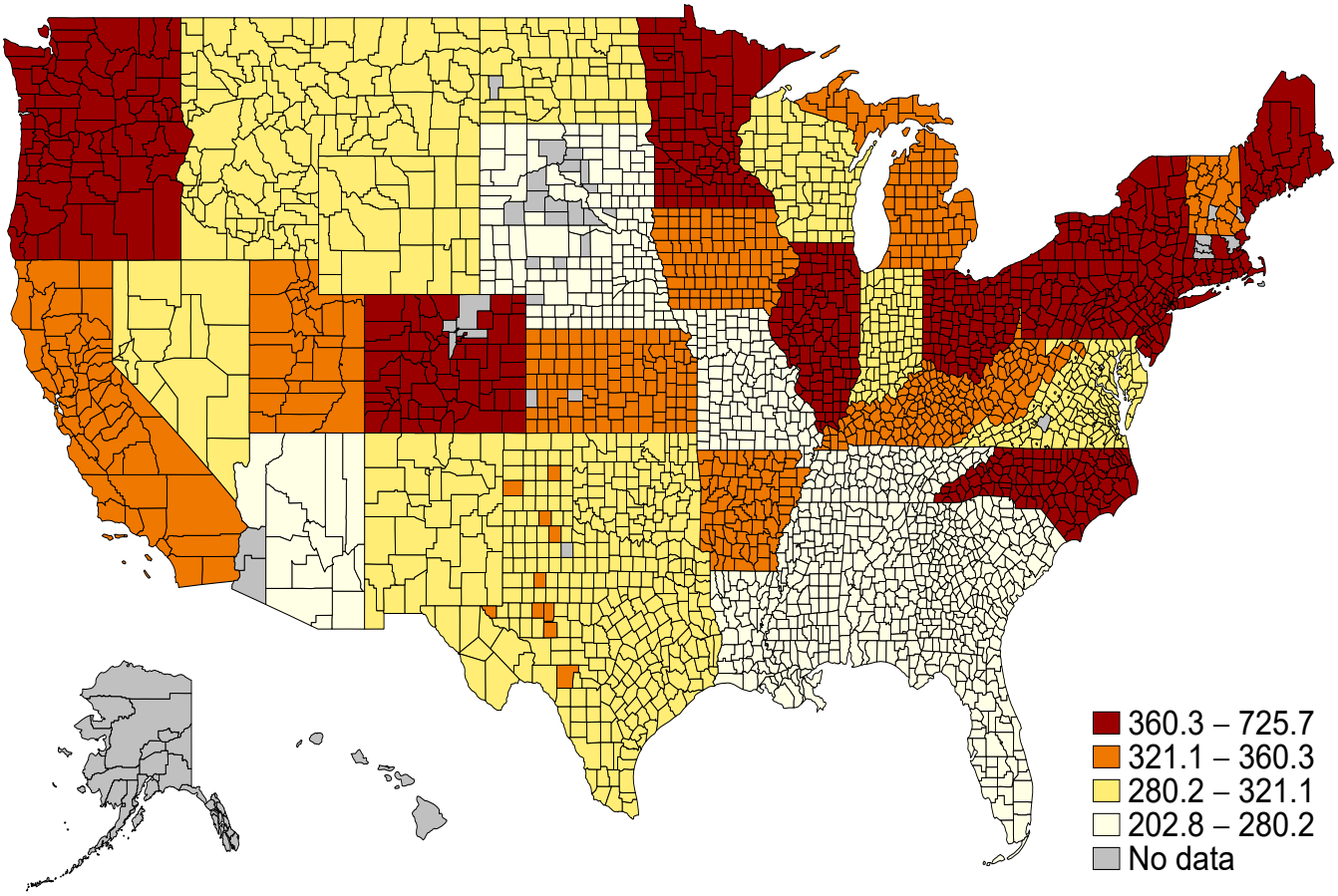
Notes: This figure displays the mean suicide rate per quarter for individuals ages 25-54 across counties from 1995-2010, where the suicide rate is the number of suicides divided by the number of county residents ages 25-54 (measured per 100,000 residents). The color breakdowns correspond to quartiles.

Figure 3: Mean drug overdose death rates across US counties



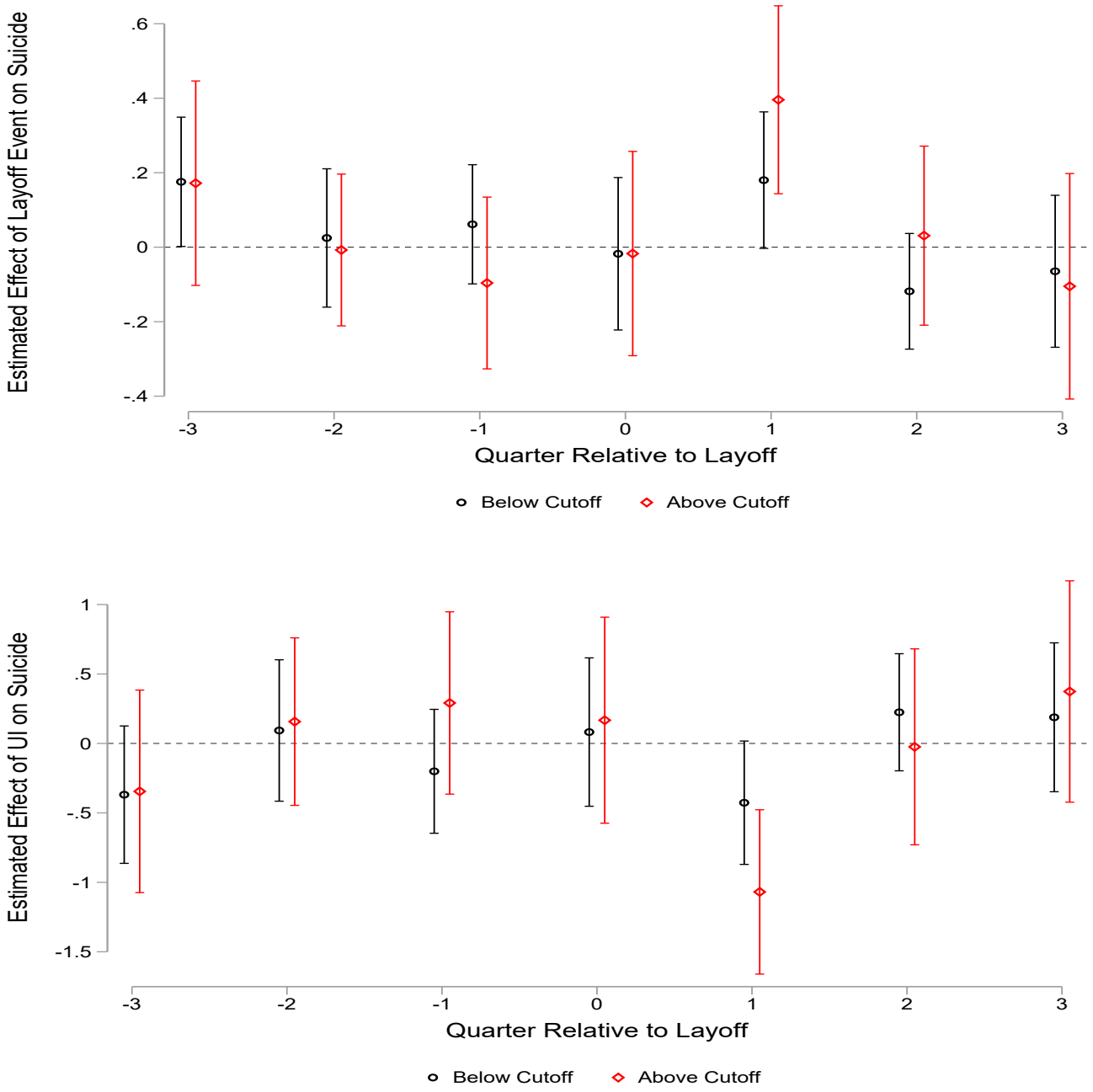
Notes: This figure displays the mean drug overdose rate per quarter for individuals ages 25-54 across counties from 1995-2010, where the drug overdose rate is the number of suicides divided by the number of county residents ages 25-54 (measured per 100,000 residents). The color breakdowns correspond to quartiles.

Figure 4: Mean maximum weekly UI benefits across US counties (hundreds); 1995 to 2010)



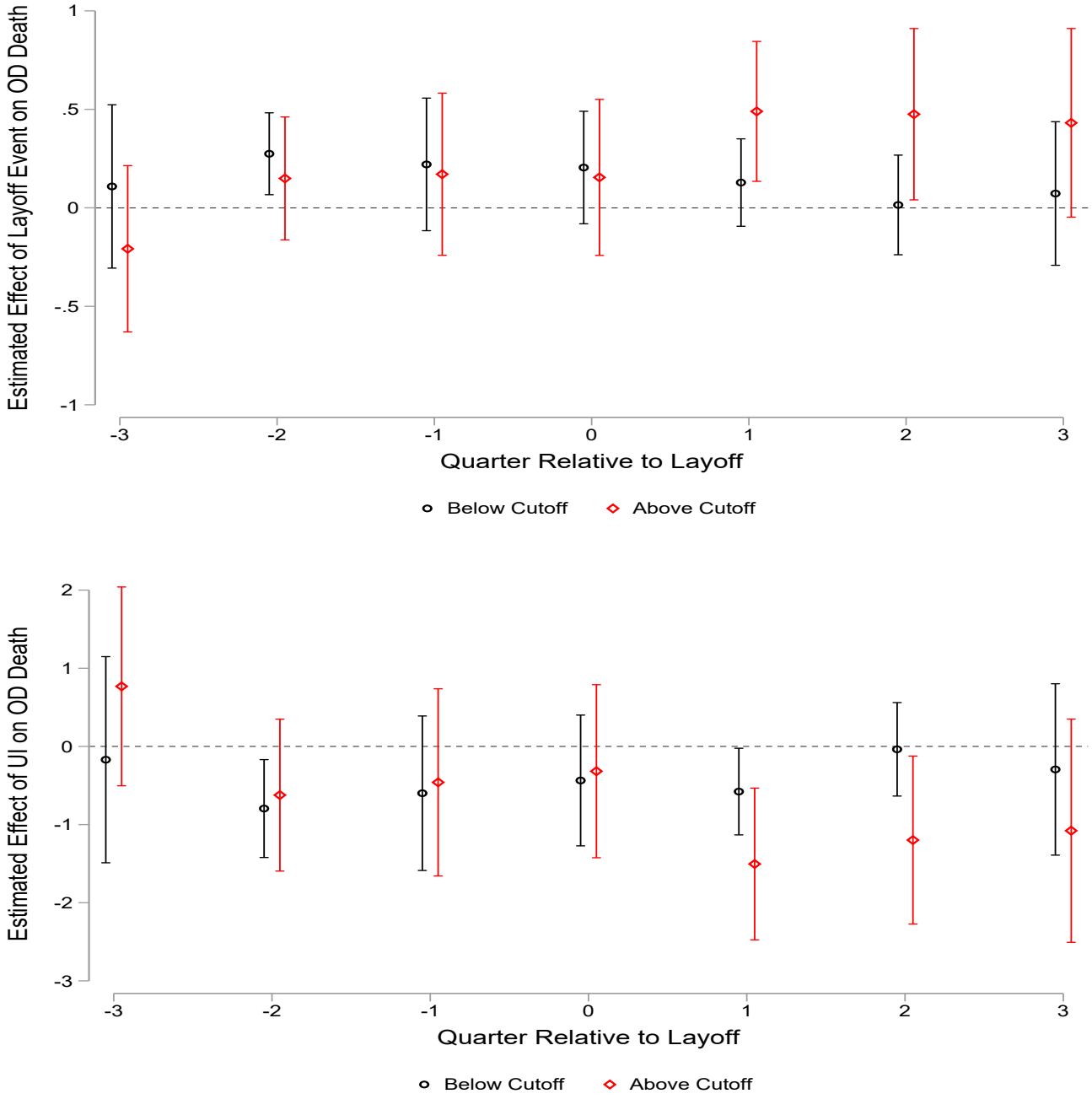
Notes: This figure displays the mean maximum weekly unemployment insurance benefits (measured in dollars) across counties from 1995-2010. The color breakdowns correspond to quartiles.

Figure 5: Effect of UI generosity on suicide rates: event study



Notes: Estimates are based on 189,743 monthly observations spanning 1995–2010 for 3,071 U.S. counties. Both panels plot coefficients and 95 percent confidence intervals from the same regression model which includes indicators for being above or below the median layoff rate. Panel A plots the estimated effect on suicide rates (per 100k ages 25-54) using lags and leads of these indicators. Panel B plots the estimated effect on suicide rates using lags and leads of these indicators interacted with the maximum weekly unemployment insurance benefit. The models also include year-by-quarter fixed effects, agency fixed effects, and county demographic controls for the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the county level.

Figure 6: Effect of UI generosity on overdose death rates: event study



Notes: Estimates are based on 189,743 monthly observations spanning 1995–2010 for 3,071 U.S. counties. Both panels plot coefficients and 95 percent confidence intervals from the same regression model which includes indicators for being above or below the median layoff rate. Panel A plots the estimated effect on drug OD rates (per 100k ages 25-54) using lags and leads of these indicators. Panel B plots the estimated effect on drug OD rates using lags and leads of these indicators interacted with the maximum weekly unemployment insurance benefit. The models also include year-by-quarter fixed effects, agency fixed effects, and county demographic controls for the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the county level.

Table 1: **Summary Statistics**

	(1)	(2)	(3)	(4)	(5)
			Means by County Layoff Rates		
	Mean	Std. Dev.	Zero Layoffs	Below Median Layoff Rate	Above Median Layoff Rate
Maximum Weekly UI	0.354	0.105	0.337	0.349	0.375
Layoff Rate	0.002	0.003	0.000	0.001	0.005
Suicide Rate	3.764	3.633	4.310	3.628	3.691
Male Suicide Rate	5.903	6.385	6.808	5.664	5.809
Female Suicide Rate	1.650	3.128	1.816	1.629	1.588
White Suicide Rate	3.159	3.500	3.854	2.999	3.042
Black Suicide Rate	0.249	0.713	0.198	0.277	0.227
Hispanic Suicide Rate	0.244	0.743	0.156	0.247	0.292
Overdose Death (OD) Rate	3.480	3.778	3.146	3.473	3.692
Male OD Rate	4.729	5.608	4.087	4.792	4.996
Female OD Rate	2.265	3.869	2.228	2.196	2.415
White OD Rate	2.672	3.383	2.712	2.611	2.764
Black OD Rate	0.449	1.072	0.198	0.509	0.488
Hispanic OD Rate	0.305	0.813	0.173	0.306	0.381
Pop ages 25-54 (10k)	4.258	6.608	0.708	4.456	6.015
Frac College	0.276	0.103	0.233	0.298	0.258
Frac High School	0.604	0.087	0.641	0.588	0.610
Frac Less than High School	0.121	0.058	0.127	0.113	0.132
Frac White	0.707	0.201	0.814	0.689	0.677
Frac Black	0.121	0.124	0.100	0.134	0.109
Frac Hisp	0.118	0.136	0.057	0.122	0.149
Frac Other	0.053	0.061	0.028	0.055	0.066
Frac Married	0.634	0.076	0.669	0.628	0.626
Frac ages 25-54	0.431	0.034	0.418	0.437	0.428
Number of Counties	3,071		2,872	2,280	2,704
N	189,743		104,032	42,856	42,855

Notes: Summary statistics are calculated using county-by-month level data spanning 1995-2010. Suicide and drug-overdose include causes of death identified by International Classification of Diseases (ICD-9 and ICD-10) codes. Mortality rates are calculated per 100,000 county residents ages 25-54. Maximum weekly UI measures the maximum UI benefit level an eligible worker can collect each week (measured in thousands of dollars). Layoff rates are the number of layoffs divided by the labor force in each county.

Table 2: **Effect of UI on mortality following job loss: counties with and without mass layoff events**

	(1)	(2)	(3)
Panel A: Suicide Death Rates			
MaxUI*I[LayoffEvent]	-1.10***	-0.50**	-0.52**
	(0.30)	(0.22)	(0.22)
I[LayoffEvent]	0.41***	0.20**	0.20**
	(0.11)	(0.09)	(0.09)
MaxUI	0.35	0.36	0.37
	(0.49)	(0.47)	(0.48)
N	189711	189711	189711
Panel B: Drug-Overdose Death Rates			
MaxUI*I[LayoffEvent]	-3.51**	-1.39	-1.39
	(1.42)	(0.86)	(0.86)
I[LayoffEvent]	1.17**	0.42	0.42
	(0.47)	(0.29)	(0.29)
MaxUI	-3.09	-1.32	-1.32
	(2.61)	(2.79)	(2.80)
N	189711	189711	189711
County FEs	Y	Y	Y
Year FE	Y	Y	-
Quarter FE	Y	Y	-
Demographic Controls	N	Y	Y
YearXQuarter FE	N	N	Y

Notes: Estimates are based on county-by-month observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are mortality rates per 100k county residents ages 25-54 corresponding to each panel title. The model includes an indicator for having a positive layoff rate, the same variable interacted with maximum weekly unemployment insurance benefit, and other fixed effects and controls as indicated. County demographic controls include the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the county level.

Table 3: **Effect of UI on mortality following job loss: counties with above and below median layoff rates**

	(1)	(2)	(3)
Panel A: Suicide Death Rates			
MaxUI*I[AboveMedianLayoff]	-1.40***	-0.74***	-0.76***
	(0.39)	(0.27)	(0.27)
MaxUI*I[BelowMedianLayoff]	-0.99***	-0.42*	-0.44*
	(0.27)	(0.23)	(0.23)
I[AboveMedianLayoff]	0.51***	0.28**	0.29**
	(0.15)	(0.11)	(0.11)
I[BelowMedianLayoff]	0.37***	0.17*	0.17*
	(0.10)	(0.09)	(0.09)
N	189711	189711	189711
Panel B: Drug-Overdose Death Rates			
MaxUI*I[AboveMedianLayoff]	-4.57***	-2.18**	-2.24**
	(1.45)	(1.02)	(1.02)
MaxUI*I[BelowMedianLayoff]	-3.15**	-1.13	-1.12
	(1.39)	(0.86)	(0.86)
I[AboveMedianLayoff]	1.48***	0.71*	0.73**
	(0.49)	(0.36)	(0.36)
I[BelowMedianLayoff]	1.04**	0.31	0.31
	(0.47)	(0.30)	(0.30)
N	189711	189711	189711
County FEs	Y	Y	Y
Year FE	Y	Y	-
Quarter FE	Y	Y	-
Demographic Controls	N	Y	Y
YearXQuarter FE	N	N	Y

Notes: Estimates are based on county-by-month observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are mortality rates per 100k county residents ages 25-54 corresponding to each panel title. The model indicators for above and below the median layoff rate, the same variables interacted with the maximum weekly unemployment insurance benefit and other fixed effects and controls as indicated. County demographic controls include the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the county level.

Table 4: **Effect of UI generosity on other mortality outcomes following job loss**

	(1)	(2)	(3)	(4)	(5)
	Cardiovascular disease	Cancer	Respiratory disease	Long-term alcohol-related disease	Motor vehicle crashes
MaxUI*I[AboveMedianLayoff]	0.53	0.02	-0.42	-0.38	0.37
	(0.93)	(0.76)	(0.58)	(0.29)	(0.48)
MaxUI*I[BelowMedianLayoff]	-0.16	-1.11*	-0.26	-0.29*	0.24
	(0.79)	(0.63)	(0.54)	(0.16)	(0.32)
I[AboveMedianLayoff]	-0.20	-0.05	0.08	0.13	-0.34**
	(0.33)	(0.27)	(0.18)	(0.10)	(0.17)
I[BelowMedianLayoff]	0.03	0.35	0.07	0.14**	-0.25**
	(0.28)	(0.23)	(0.17)	(0.06)	(0.11)
N	189711	189711	189711	189711	189711

Notes: Estimates are based on county-by-month observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are mortality rates per 100k county residents ages 25-54 corresponding to each panel title. The model indicators for above and below the median layoff rate, the same variables interacted with the maximum weekly unemployment insurance benefit and other fixed effects and controls as indicated. County demographic controls include the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the county level.

Table 5: **Effect of UI generosity on deaths following job loss: gender and race**

	Gender		Race		
	Male	Female	White	Black	Hispanic
Panel A: Suicide Death Rates					
MaxUI*I[AboveMedianLayoff]	-1.27***	-0.24	-0.57**	-0.06	-0.02
	(0.45)	(0.28)	(0.26)	(0.07)	(0.10)
MaxUI*I[BelowMedianLayoff]	-0.78**	-0.09	-0.31	-0.02	-0.01
	(0.39)	(0.15)	(0.20)	(0.04)	(0.07)
I[AboveMedianLayoff]	0.50***	0.08	0.20*	0.03	0.01
	(0.18)	(0.11)	(0.10)	(0.03)	(0.03)
I[BelowMedianLayoff]	0.31**	0.03	0.11	0.02	0.01
	(0.14)	(0.07)	(0.08)	(0.02)	(0.03)
N	189711	189711	189711	189711	189711
Panel B: Drug-Overdose Death Rates					
MaxUI*I[AboveMedianLayoff]	-2.89**	-1.59*	-1.82**	-0.08	-0.07
	(1.23)	(0.91)	(0.86)	(0.14)	(0.20)
MaxUI*I[BelowMedianLayoff]	-1.23	-1.02	-0.95	-0.05	0.05
	(1.06)	(0.72)	(0.69)	(0.13)	(0.13)
I[AboveMedianLayoff]	0.97**	0.48	0.60*	0.01	0.01
	(0.44)	(0.31)	(0.31)	(0.05)	(0.07)
I[BelowMedianLayoff]	0.34	0.28	0.27	0.01	-0.03
	(0.38)	(0.24)	(0.24)	(0.05)	(0.04)
N	189711	189711	189711	189711	189711
County FEs	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
YearXQuarter FE	Y	Y	Y	Y	Y

Notes: Estimates are based on county-by-month observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are gender- and race-specific mortality rates per 100k county residents of the same age corresponding to each column title. The model indicators for above and below the median layoff rate, the same variables interacted with the maximum weekly unemployment insurance benefit and other fixed effects and controls as indicated. County demographic controls include the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the county level.

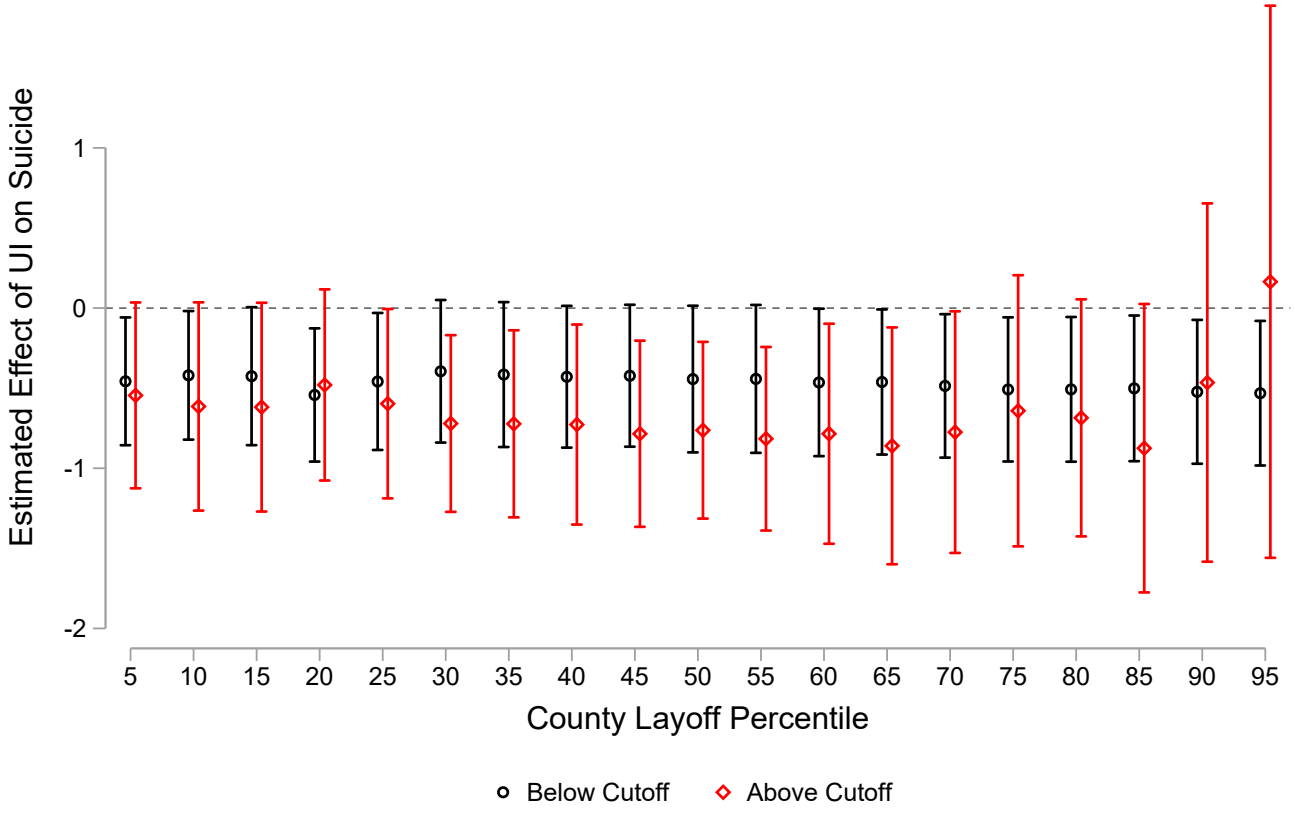
Table 6: **Effect of UI generosity on deaths following job loss: age**

			Age		
	25-54	18-24	25-34	35-44	45-54
Panel A: Suicide Death Rates					
MaxUI*I[AboveMedianLayoff]	-0.76***	0.09	-0.18	-0.68	-1.54***
	(0.27)	(0.58)	(0.39)	(0.44)	(0.52)
MaxUI*I[BelowMedianLayoff]	-0.44*	0.33	-0.04	-0.39	-0.82**
	(0.23)	(0.54)	(0.38)	(0.35)	(0.39)
I[AboveMedianLayoff]	0.29**	-0.03	0.10	0.22	0.62***
	(0.11)	(0.21)	(0.15)	(0.17)	(0.19)
I[BelowMedianLayoff]	0.17*	-0.08	0.06	0.15	0.30**
	(0.09)	(0.20)	(0.14)	(0.14)	(0.13)
N	189711	189710	189711	189711	189711
Panel B: Drug-Overdose Death Rates					
MaxUI*I[AboveMedianLayoff]	-2.24**	-0.33	-2.32**	-2.71**	-1.84
	(1.02)	(0.49)	(1.07)	(1.35)	(1.14)
MaxUI*I[BelowMedianLayoff]	-1.12	-0.10	-0.93	-2.27*	0.07
	(0.86)	(0.45)	(1.01)	(1.28)	(0.71)
I[AboveMedianLayoff]	0.73**	0.20	0.72*	0.87*	0.65
	(0.36)	(0.20)	(0.37)	(0.46)	(0.40)
I[BelowMedianLayoff]	0.31	0.05	0.26	0.73*	-0.10
	(0.30)	(0.16)	(0.34)	(0.42)	(0.26)
N	189711	189710	189711	189711	189711
County FEs	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
YearXQuarter FE	Y	Y	Y	Y	Y

Notes: Estimates are based on county-by-month observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are age-specific mortality rates per 100k county residents ages 25-54 corresponding to each column title. The model indicators for above and below the median layoff rate, the same variables interacted with the maximum weekly unemployment insurance benefit and other fixed effects and controls as indicated. County demographic controls include the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the county level.

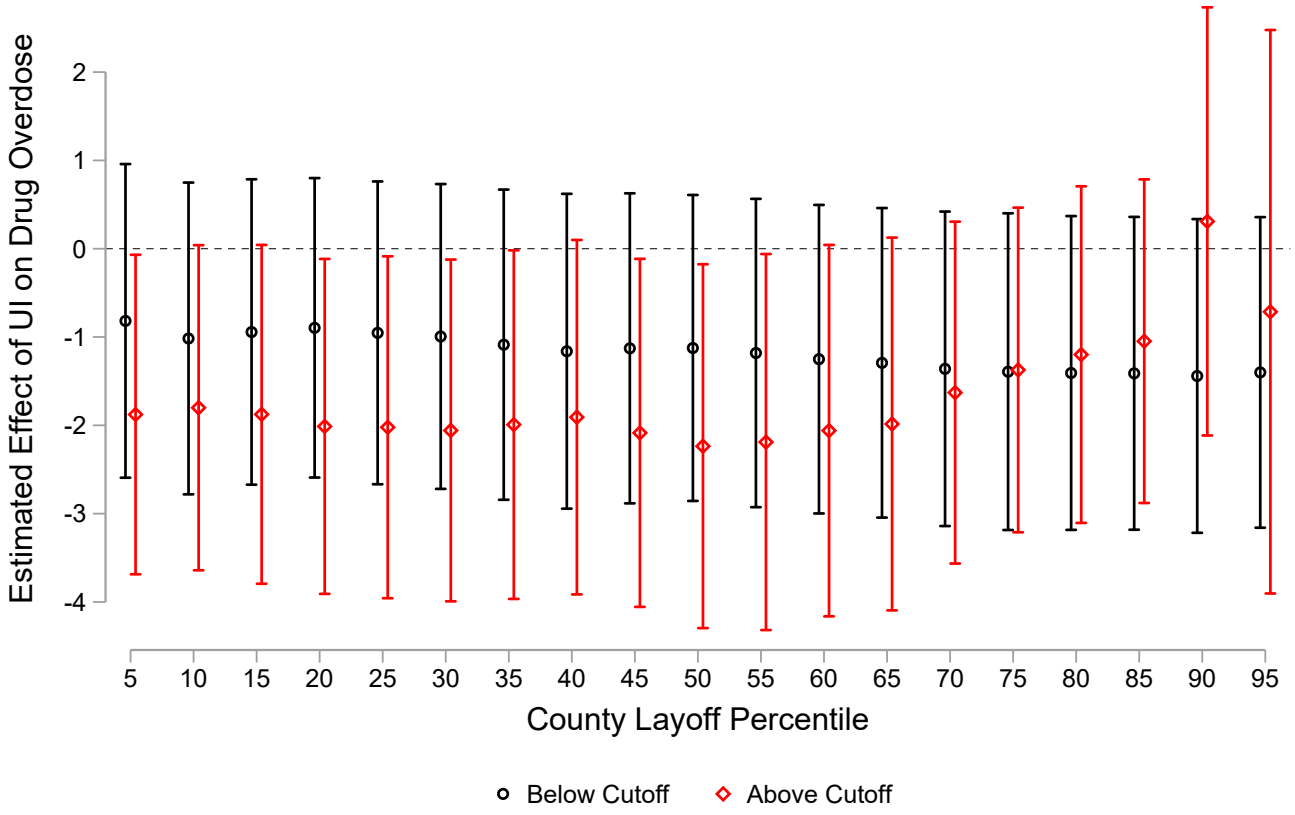
Appendix A

Figure A1: Effect of UI generosity on suicides following job loss: counties above and below various layoff rate thresholds



Notes: Estimates are based on 189,743 monthly observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are suicide rate per 100k county residents ages 25-54. We bin positive county layoff rates above or below 19 different cutoff points, ranging from the 5th percentile to the 95th percentile. For each cutoff point, we run a separate model. The figure plots estimates and 95 percent confidence intervals of interaction terms between unemployment insurance benefits and indicators for county layoff rates being above or below the cutoff point. The models also include below and above the cutoff indicators, year-by-quarter fixed effects, county fixed effects, and county demographic controls for the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the state level.

Figure A2: Effect of UI generosity on overdose deaths following job loss: counties above and below various layoff rate thresholds



Notes: Estimates are based on 189,743 monthly observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are drug overdose death rate per 100k county residents ages 25-54. We bin positive county layoff rates above or below 19 different cutoff points, ranging from the 5th percentile to the 95th percentile. For each cutoff point, we run a separate model. The figure plots estimates and 95 percent confidence intervals of interaction terms between unemployment insurance benefits and indicators for county layoff rates being above or below the cutoff point. The models also include below and above the cutoff indicators, year-by-quarter fixed effects, county fixed effects, and county demographic controls for the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the state level.

Table A1: Classification of Cause of Death

Death Category	**ICD-10 (1999-2010)**	**ICD-9 (1995-1998)**
Suicide	*113 Category Recode:* 124-126	*72 Category Recode:* 820
Drug-Overdose	X40-X45, X60-X65, X85, Y10-Y15	*282 Category Recode:* 31700, 33800, 35300
Cardiovascular	*113 Category Recode:* 53-75	*72 Category Recode:* 320-490
Cancer	*113 Category Recode:* 19-44	*72 Category Recode:* 160-250
Respiratory	R092 *113 Category Recode:* 76-89	500, 501, 512, 514, 515, 5070, 5109, 5119, 5130, 5168, 5184, 5185, 5188, 5191, 5198, 7991 *72 Category Recode:* 500-580
Alcohol	E244, G312, G621, G721, I426, K292, K700-K704, K709, K852, K860	3050, 3030, 3575, 4255, 5710-5713, 7903
Motor-Vehicle Accidents	*113 Category Recode:* 115-123	*72 Category Recode:* 800

Notes: The ninth revision of the International Classification of Diseases (ICD) corresponds with 1995-1998 data and the tenth revision with 1999-2010 data. To group deaths into the above categories, we use either the actual ICD code or a recode of ICD codes grouped into categories as indicated.

Table A2: **Effect of UI generosity on deaths following job loss: additional fixed effects**

	(1)	(2)	(3)
Panel A: Suicide Death Rates			
MaxUI*I[AboveMedianLayoff]	-0.58**	-0.91***	-0.73**
	(0.27)	(0.34)	(0.35)
MaxUI*I[BelowMedianLayoff]	-0.36	-0.78***	-0.62***
	(0.23)	(0.19)	(0.21)
N	189711	189711	189711
Panel B: Drug-Overdose Death Rates			
MaxUI*I[AboveMedianLayoff]	-2.20**	-0.90	-0.52
	(1.08)	(0.78)	(0.64)
MaxUI*I[BelowMedianLayoff]	-1.18	-1.23*	-0.54
	(0.89)	(0.68)	(0.53)
N	189711	189711	189711
StateXQuarter FE	Y	N	-
StateXYear FE	N	Y	N
StateXYearXQuarter FE	N	N	Y

Notes: Estimates are based on county-by-month observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are mortality rates per 100k county residents ages 25-54 corresponding to each panel title. The model includes indicators for above and below the median layoff rate, the same variables interacted with the maximum weekly unemployment insurance benefit and other fixed effects and controls as indicated. County demographic controls include the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the state level.

Table A3: **Correlation between Max UI and Economic Conditions**

	(1) MaxUI	(2) MaxUI	(3) MaxUI	(4) MaxUI
GDP	-0.495			-0.611
	(0.545)			(0.557)
UnempRate		-1.021		-1.212
		(3.077)		(3.136)
UnionDensity			1.666	1.596
			(1.999)	(2.035)
N	1,530	1,530	1,530	1,530
State and Year FEs	Y	Y	Y	Y

Notes: We regress maximum unemployment insurance (UI) benefits on major state-level economic conditions, including state and year fixed effects for the period 1995-2015. Each column presents estimates based on a separate regression and standard errors clustered at the state level.

Table A4: **Effect of UI generosity on suicides following job loss: event studies using continuous measure of layoff rates**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MaxUI*LR[t=3]	43.99							75.17*
	(33.39)							(43.15)
MaxUI*LR[t=2]		8.41						7.99
		(30.26)						(35.17)
MaxUI*LR[t=1]			-47.85					-125.74***
			(32.80)					(30.91)
MaxUI*LR[t=0]				24.21				18.20
				(39.01)				(40.99)
MaxUI*LR[t=-1]					55.14*			67.12*
					(32.33)			(37.13)
MaxUI*LR[t=-2]						50.96		8.56
						(41.93)		(42.54)
MaxUI*LR[t=-3]							25.27	28.03
							(35.36)	(34.63)
LR[t=3]	-15.80							-25.83
	(13.11)							(15.42)
LR[t=2]		0.50						1.91
		(11.09)						(12.59)
LR[t=1]			11.48					37.48***
			(12.90)					(12.02)
LR[t=0]				-6.09				-4.57
				(14.80)				(15.93)
LR[t=-1]					-16.80			-21.80
					(12.14)			(13.64)
LR[t=-2]						-16.26		-3.58
						(14.74)		(15.19)
LR[t=-3]							-6.02	-6.91
							(14.26)	(14.33)
MaxUI	-0.10	-0.08	0.04	-0.12	-0.15	-0.14	-0.09	-0.15
	(0.41)	(0.36)	(0.39)	(0.40)	(0.36)	(0.35)	(0.39)	(0.39)
N	183569	186640	189711	189711	186642	183573	180504	174361
County FEs	Y	Y	Y	Y	Y	Y	Y	Y
Quarter×Year FEs	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Estimates are based on 189,711 monthly observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are suicide rates per 100k county residents ages 25-54. Each column presents estimates from a different regression. We derive estimates using varying lead and lags of the county layoff rate and their interactions with maximum unemployment insurance (UI) benefits. The model also includes year-by-quarter fixed effects, agency fixed effects, and county demographic controls for the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the state level.

Table A5: **Effect of UI generosity on overdose deaths following job loss: event studies using continuous measure of layoff rates**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MaxUI*LR[t=3]	-137.39							-124.31*
	(86.45)							(64.97)
MaxUI*LR[t=2]		-123.62						-105.17*
		(89.65)						(57.43)
MaxUI*LR[t=1]			-67.37					-56.13
			(89.49)					(53.52)
MaxUI*LR[t=0]				-55.06				-10.59
				(93.43)				(61.31)
MaxUI*LR[t=-1]					-22.72			42.10
					(93.32)			(66.33)
MaxUI*LR[t=-2]						-62.92		-54.89
						(95.07)		(54.48)
MaxUI*LR[t=-3]							-25.51	24.46
							(96.89)	(71.98)
LR[t=3]	64.41*							55.95**
	(33.82)							(26.72)
LR[t=2]		54.24						45.98**
		(32.75)						(21.00)
LR[t=1]			33.26					25.72
			(33.67)					(21.25)
LR[t=0]				35.26				18.16
				(34.03)				(22.86)
LR[t=-1]					22.87			-2.32
					(33.41)			(24.27)
LR[t=-2]						28.37		17.86
						(33.13)		(20.04)
LR[t=-3]							22.21	2.23
							(33.99)	(26.02)
MaxUI	-2.01	-2.13	-2.30	-2.33	-2.32	-2.15	-2.24	-1.43
	(2.56)	(2.56)	(2.56)	(2.56)	(2.58)	(2.59)	(2.61)	(2.33)
N	183569	186640	189711	189711	186642	183573	180504	174361
County FEs	Y	Y	Y	Y	Y	Y	Y	Y
Quarter×Year FEs	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Estimates are based on 189,711 monthly observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are drug overdose death rates per 100k county residents ages 25-54. Each column presents estimates from a different regression. We derive estimates using varying lead and lags of the county layoff rate and their interactions with maximum unemployment insurance (UI) benefits. The model also includes year-by-quarter fixed effects, agency fixed effects, and county demographic controls for the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the state level.

Table A6: **Effect of UI generosity on male deaths following job loss: age**

	Age				
	25-54	18-25	26-35	36-45	46-55
Panel A: Suicide Death Rates					
MaxUI*I[AboveMedianLayoff]	-1.27***	0.02	0.14	-1.17	-3.00***
	(0.45)	(1.16)	(0.77)	(0.89)	(0.72)
MaxUI*I[BelowMedianLayoff]	-0.78**	0.53	-0.02	-0.71	-1.52**
	(0.39)	(0.87)	(0.61)	(0.69)	(0.58)
I[AboveMedianLayoff]	0.50***	0.03	0.05	0.39	1.19***
	(0.18)	(0.44)	(0.29)	(0.34)	(0.28)
I[BelowMedianLayoff]	0.31**	-0.10	0.13	0.24	0.57**
	(0.14)	(0.32)	(0.22)	(0.28)	(0.22)
N	189711	189710	189711	189711	189711
Panel B: Drug-Overdose Death Rates					
MaxUI*I[AboveMedianLayoff]	-2.89**	-0.27	-2.74*	-3.47**	-2.80*
	(1.23)	(0.91)	(1.47)	(1.68)	(1.51)
MaxUI*I[BelowMedianLayoff]	-1.23	-0.12	-0.73	-2.95*	0.04
	(1.06)	(0.80)	(1.30)	(1.66)	(1.01)
I[AboveMedianLayoff]	0.97**	0.16	0.88*	1.16*	0.99*
	(0.44)	(0.35)	(0.53)	(0.58)	(0.51)
I[BelowMedianLayoff]	0.34	0.03	0.16	0.99*	-0.12
	(0.38)	(0.27)	(0.45)	(0.55)	(0.37)
N	189711	189710	189711	189711	189711
County FEs	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
YearXQuarter FE	Y	Y	Y	Y	Y

Notes: Estimates are based on county-by-month observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are mortality rates per 100k county residents in various age groups corresponding to each column and panel title. The model includes indicators for above and below the median layoff rate, the same variables interacted with the maximum weekly unemployment insurance benefit and other fixed effects and controls as indicated. County demographic controls include the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the state level.

Table A7: **Effect of UI generosity on female deaths following job loss: age**

	Age				
	25-54	18-24	25-34	35-44	45-54
Panel A: Suicide Death Rates					
MaxUI*I[AboveMedianLayoff]	-0.24	-0.05	-0.38	-0.17	-0.17
	(0.28)	(0.45)	(0.37)	(0.43)	(0.55)
MaxUI*I[BelowMedianLayoff]	-0.09	0.16	0.07	-0.12	-0.15
	(0.15)	(0.37)	(0.42)	(0.26)	(0.40)
I[AboveMedianLayoff]	0.08	-0.01	0.13	0.04	0.09
	(0.11)	(0.16)	(0.15)	(0.16)	(0.19)
I[BelowMedianLayoff]	0.03	-0.08	-0.04	0.07	0.05
	(0.07)	(0.14)	(0.14)	(0.10)	(0.14)
N	189711	189710	189710	189711	189711
Panel B: Drug-Overdose Death Rates					
MaxUI*I[AboveMedianLayoff]	-1.59*	-0.42	-1.92**	-1.94	-0.96
	(0.91)	(0.33)	(0.83)	(1.24)	(1.00)
MaxUI*I[BelowMedianLayoff]	-1.02	0.00	-1.11	-1.64	0.07
	(0.72)	(0.34)	(0.77)	(1.00)	(0.65)
I[AboveMedianLayoff]	0.48	0.26**	0.55*	0.58	0.33
	(0.31)	(0.11)	(0.28)	(0.40)	(0.36)
I[BelowMedianLayoff]	0.28	0.06	0.34	0.48	-0.09
	(0.24)	(0.11)	(0.25)	(0.32)	(0.24)
N	189711	189710	189710	189711	189711
County FEs	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
YearXQuarter FE	Y	Y	Y	Y	Y

Notes: Estimates are based on county-by-month observations spanning 1995–2010 for 3,071 U.S. counties. The outcome variables are mortality rates per 100k county residents in various age groups corresponding to each column and panel title. The model includes indicators for above and below the median layoff rate, the same variables interacted with the maximum weekly unemployment insurance benefit and other fixed effects and controls as indicated. County demographic controls include the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the state level.

Table A8: **Effect of UI generosity measured by UI duration on deaths following job loss: 2008-2010**

	(1)	(2)	(3)
Panel A: Suicide Death Rates			
Potential UI Duration*I[AboveMedianLayoff]	-0.36**	-0.34**	-0.34**
	(0.14)	(0.13)	(0.13)
Potential UI Duration*I[BelowMedianLayoff]	-0.31**	-0.28**	-0.28**
	(0.12)	(0.12)	(0.12)
I[AboveMedianLayoff]	0.35*	0.32*	0.33*
	(0.18)	(0.18)	(0.18)
I[BelowMedianLayoff]	0.41**	0.38**	0.38**
	(0.16)	(0.16)	(0.16)
N	33657	33657	33657
Panel B: Drug-Overdose Death Rates			
Potential UI Duration*I[AboveMedianLayoff]	-0.21	-0.15	-0.16
	(0.25)	(0.25)	(0.25)
Potential UI Duration*I[BelowMedianLayoff]	-0.23	-0.19	-0.18
	(0.23)	(0.22)	(0.22)
I[AboveMedianLayoff]	0.06	-0.00	0.03
	(0.32)	(0.32)	(0.34)
I[BelowMedianLayoff]	0.19	0.14	0.15
	(0.30)	(0.28)	(0.28)
N	33657	33657	33657
County FEs	Y	Y	Y
Year FE	Y	Y	-
Quarter FE	Y	Y	-
Demographic Controls	N	Y	Y
YearXQuarter FE	N	N	Y

Notes: Estimates are based on county-by-month observations spanning 2008–2010 for 3,071 U.S. counties. The outcome variables are mortality rates per 100k county residents ages 25-54 corresponding to each panel title. The model also includes indicators for above and below the median layoff rate, the same variables interacted with the potential duration of unemployment insurance benefit and other fixed effects and controls as indicated. County demographic controls include the fraction of the population that are college educated, high school educated, less than high school educated, White, Black, Hispanic, other race, married, and ages 25-54. The regressions are weighted by the county population ages 25-54 and standard-error estimates allow for clusters at the state level.