CARES and Crime

Alexander Henke and Linchi Hsu

Department of Economics, Howard University, Washington,
District of Columbia, USA

May 18, 2022

Purpose: The U.S. signed the Coronavirus Aid, Relief, and Economic Security (CARES) Act in March 2020 to alleviate the harsh economic effects of the pandemic and related shutdowns. A substantial part of the bill expanded and increased unemployment insurance payments, where a growing area of research estimates strong anti-poverty effects. We examine the effect of these policies on crime.

Design/methodology/approach: We use new event study and difference-in-differences techniques to estimate the effect of increasing unemployment insurance payments on property crime and violent crime. Then, we estimate the effect of expanded unemployment qualification programs on crime. We use a rich set of controls including unemployment, contemporaneous policies, and mobile device tracking data to estimate the degree to which people stayed at home.

Findings: We find that increasing unemployment insurance payments decreased crime by 20%, driven by a 24% decrease in property crime. We also find suggestive evidence that expanding unemployment qualifications decreases crime.

Practical implications: We find a new and substantial benefit of expanded unemployment insurance beyond their antipoverty effects.

Originality: To our knowledge, this is the first study that directly examines the impact of the CARES Act on crime.

Keywords Crime, COVID-19, Unemployment Insurance, Pandemics, CARES Act, PUA, PEUC, FPUC

JEL Codes K42 · I18 · J65

Acknowledgement: We thank Gerald Daniels, Sarah Reber, Bill Spriggs, Omari Swinton, Alessandra Voena, as well as seminar participants at Howard University, Dickenson College, and the 2021 CeMENT Workshop for helpful comments. We also thank Albina Khatiwoda for excellent research assistance. All errors are our own.

I. Introduction

To slow the initial spread of COVID-19, local governments in the U.S. shut down non-essential businesses and ordered individuals to shelter in place, which led to a significant loss of jobs (Chetty *et al.*, 2020). On March 27, 2020, the U.S. government passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act, providing direct relief and expanded unemployment insurance (UI) benefits.

The unemployment insurance portion of the CARES Act, arguably the most significant part of the bill for poverty reduction, has three primary arms: the Federal Pandemic Unemployment Compensation (FPUC) program increased all UI benefits by $600 per week; the Pandemic Unemployment Assistance (PUA) program extended benefits to more workers, such as self-employed, freelancers, and independent contractors; and the Pandemic Emergency Unemployment Compensation (PEUC) program extended UI benefits by an extra 13 weeks.[1]

Unemployment and low incomes can significantly increase the chance of crime. We hypothesize that the UI policies in the CARES Act reduced crime. We find evidence that FPUC reduced crime by 20%, driven by a decrease in property crime, and we find suggestive evidence that PUA and PEUC also reduced crime. With some additional assumptions, we estimate that roughly half of the FPUC program in 2020 was effectively paid for by reducing crimes, especially homicides.

To our knowledge, we are the first to examine this question in the context of the CARES Act. Beach and Lopresti (2019) find that UI attenuates the effect of import-

---

[1] Some provisions of the CARES Act were extended through the Continued Assistance Act from Dec. 27, 2020 until March 13, 2021.

competition-induced labor shocks on crime. Other researchers have estimated the overall effect of the pandemic on crime across the U.S., especially early on (Abrams, 2021; Ashby, 2020), but not the direct effect of this policy channel.

One reason our question is unstudied is that, while the initial overall effect of the pandemic can be relatively easily identified, identifying component pieces of the pandemic presents more challenges. First, other factors, such as the degree to which people stayed at home, and unemployment itself, may influence crime during the pandemic. Crime dropped at the beginning of the pandemic, especially drug crimes, theft, residential burglaries, and most violent crimes (Abrams 2021).[2] Second, although the CARES Act was signed into law on March 27, 2020, states have different "enactment" dates for the various UI provisions of the CARES Act due to differences in manpower or the number of claimants. This staggered policy adoption complicates common estimation approaches to a difference-in-differences (DID) research design (Goodman-Bacon, 2021). Third, other relief measures may also influence crime. For instance, the economic impact payments (i.e., the stimulus payments) were issued around the same time, starting April 10, 2020 (Parker *et al.*, 2022). Fourth, anticipation of the policy could attenuate our estimated effects. Finally, the number of PUA and PEUC claimants varies both across location and over time substantially, which means studying the timing of PUA/PEUC implementation may not present the full picture.

[2] Crime also dropped in Sweden, (Gerell *et al.*, 2020), Mexico (Hoehn-Velasco *et al.*, 2020), Australia (Payne *et al.*, 2020), and the UK (Halford *et al.*, 2020) after lockdowns, among other countries. The exception to the overall crime trend is domestic violence, which sharply increased as people stayed at home (Hsu and Henke, 2021; Leslie and Wilson, 2020).

We attempt to overcome these challenges first by identifying granular variation in the timing of the implementation of FPUC, as well as weekly changes in the take-up rate for PUA and PEUC. Second, we use new event study and DID methods to estimate the impact of the FPUC program on crime, both over time and overall. Third, we control for a variety of likely confounders such as unemployment. In addition, the pandemic changed mobility and thus the availability of potential victims of or witnesses to crimes. In response, we use a novel control by estimating the local daily fraction of people staying at home using anonymous mobile device tracking data at the county level. Finally, when we account for anticipation effects in our analysis, our estimated effect strengthens. Our estimates assuming no anticipation are, therefore, conservative.

Our main contribution is to estimate how expanded UI programs in the CARES Act affected crime. We add to a small but growing literature on unemployment insurance and crime that contains strong policy implications for social insurance and antipoverty programs.

II. Overview of the CARES Act

The CARES Act had several major components, including a $1,200 stimulus payment to individuals, over $800 billion in loans to businesses, and extended and expanded unemployment, dwarfing normal income transfer programs such as the Supplemental Nutritional Assistance Program (Parolin *et al.*, 2020).[3] The assistance was substantial enough that overall real disposable income increased (U.S. Bureau

[3] Autor *et al.* (2022) review the effects of the paycheck protection program which provided loans to businesses. Along with modest pro-employment effects, they find that most of the money went to business owners rather than employees. Here, we focus on programs primarily aimed at individual workers.

of Economic Analysis, 2022) and many unemployed individuals received higher pay during the first months of the pandemic compared to when they were working (Ganong *et al.*, 2020).

Increasing household income has clear antipoverty effects. Between April to May 2020, the CARES Act lifted 17.8 million individuals from poverty and prevented almost 80 million "person-months" of poverty from March through December 2020 (Curran and Wimer, 2021). It also helped households maintain a basic level of spending for fifteen more weeks on average, primarily caused by its unemployment insurance programs (Aylward *et al.*, 2021).

Policies that alleviate poverty and economic hardship affect crime because poverty and economic hardship themselves affect crime (Beach and Lopresti, 2019; Chalfin and McCrary, 2017; Chalfin and Raphael, 2011; Gould et al., 2002; Raphael and Winter-Ember, 2001). When unemployment increases (and similarly, when wages and income decrease), the marginal gain from committing property crime increases, and the opportunity cost of prison time decreases. Therefore, property crime increases. Besides the economic incentives of crime, violent crime such as aggravated assault or homicide may also be affected by increasing stress levels (Artello and Williams, 2014). Thus, we hypothesize that the antipoverty effects of the CARES Act also reduced property crime and violent crime.

III. Data and Methods

All data were collected online and cover dates from January 1, 2019 to December 31, 2020. Since the CARES Act was enacted in 2020, the inclusion of earlier data primarily improves efficiency. We specify when a method analyzes a shorter time period.

Crime reports

We collect data sets on our outcomes of interest, crimes and incidents reported to police, from 17 U.S. cities. These cities provide daily crime or incident data through searchable, open data portals. Property crime includes larceny, motor vehicle theft, and burglary.[4] Violent crime includes homicide, rape, robbery, and aggravated assault.[5] Overall crime includes both categories. See Table I for the cities in the sample and the crimes covered by city. To capture location-specific seasonal trends in crime, we also create a seven-day moving average of the local crime rate one year prior to the day, by city-day. [6]

[Table I]

Unemployment and UI

Weekly state-level data on PUA, PEUC, and regular UI claims are from the U.S. Department of Labor (DOL). We measure state-level FPUC implementation through public announcements of official state entities. All payment increases were retroactive, but some states started before others based on the ability to comply with DOL guidance and process the increases in a timely fashion. The FPUC program expired on July 31, 2020, but our primary methodologies focus on differences in

---

[4] Larceny includes all kinds of theft except motor vehicle theft, which we include as a separate category; burglary is the unlawful entry of a structure to commit a felony or a theft.

[5] Homicide includes murder and manslaughter; rape is defined as sexual penetration but not including statutory rape where it is possible to separate; robbery is defined as the taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear; aggravated assault is defined as an attack with severe physical injury that is usually inflicted using a lethal weapon. Some cities do not report rapes; their violent crime count sums all reported offenses.

[6] This means we drop the first three days of 2019 in our analyses. Fort Worth, TX crime data begin in 2019, so with the moving average the analysis of Fort Worth begins in 2020.

implementation dates, which range from March 30 to April 27, 2020. Table I shows the FPUC enactment dates by city.

City-month-level unemployment data are from the Local Area Unemployment Statistics program, part of the U.S. Bureau of Labor Statistics. An ideal data set would contain more granular unemployment estimates to fully control for aspects of unemployment which could confound our estimates. Therefore, we use both unemployment data by city-month and UI take-up data by state-week.

Other data sources

We estimate the proportion of people who stay at home all day using data from the SafeGraph Data Consortium.[7] SafeGraph pings 45 million anonymized mobile devices in the U.S. and tracks where they are at different times of day. We count the number of pinged devices that never left their designated home area in a day and divide by the total number of sampled devices in that county.

To create a per-capita crime rate, we use city population estimates from the U.S. Census Bureau in 2019. Daily city-level maximum temperature data are compiled from the Global Historical Climatological Network (GHCN). The GHCN daily weather records are retrieved from the National Oceanic and Atmospheric Administration. Temperature is a useful control because it is clearly not caused by other factors, and it affects crime (Ranson, 2014), meaning its inclusion improves efficiency and does not introduce any bias.

[7] SafeGraph is a data company that aggregates anonymized location data from numerous applications to provide insights about physical places. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month from a given census block group. SafeGraph collected and provided this data for free to scholars until April 2021.

Summary statistics

Table II shows that, on average, cities in the sample report 9.93 property crimes and 2.02 violent crimes per 100,000 people per day, combining to 11.9. The average rate of workers receiving UI benefits due to the PUA and PEUC programs is 3.34 per 100 people in the labor force (the average in 2020 is 6.67). More common crimes such as larceny and motor vehicle theft will play an outsized role when we estimate effects on overall crime counts, and less common crimes such as rapes and homicides will not substantially affect our estimates of overall effects, though they are important to consider on their own.

[Table II]

Figure 1 plots the 7-day moving average of crime rates for 2019 and 2020. The sharp spike in reported violent and property crime starting in late May 2020 is likely to be related to concurrent Black Lives Matter (BLM) protests, possibly due to changes in actual criminal behavior and possibly due to changes in police reporting behavior.

[Figure 1]

Methods

Once local governments processed the federal FPUC subsidy and abided by guidance from the DOL, UI benefit recipients automatically received $600 more per week essentially as a single event. This effectively creates a natural experiment of increased transfer sizes, allowing us to employ event study and DID designs.

Classic DID compares the trends of treated and never-treated units. However, there are no never-treated units in our sample, as every UI recipient eventually received the additional $600 per week. The reason we can use a DID strategy at all is the staggered roll-out of FPUC, which allows us to compare treated with not-yet-treated groups. Thus, the key period of comparison is from the first FPUC implementation in our sample on March 30, 2020, to the last implementation on April 27, 2020. The set of data occurring prior to March 30 does not directly identify the effect of interest, but it helps improve efficiency. The ability for a state government to implement FPUC quickly may relate to efficient governance within that state and thus may relate to crime. We argue that (in)efficient governance associated with a (slow) quick roll-out did not arise in the Spring of 2020, but rather was a static property of that state. City dummies capture static differences across states.

We assume parallel trends conditional on controlling for the pandemic's most likely confounders, including the degree to which people stay at home and unemployment. Several policies were enacted around the same time, and we attempt to identify the effect of the FPUC program. Importantly, these policies were not implemented at precisely the same time in all places in the same manner. Our research design assumes that the effect of policies that occurred at roughly the same time across the U.S., such as the economic impact payments, are relatively uniform and therefore can be absorbed by appropriate time dummies. Controlling for unemployment covers policies that influenced unemployment, such as loans to businesses. Finally, we also control for PUA and PEUC.[8]

Event Study and Difference-in-differences

In our event study and DID specifications, we use the estimator developed by Borusyak *et al.* (2021) (BJS hereafter).[9] BJS note that DID designs effectively use

[8] Estimates without PUA+PEUC controls are very similar and are available on request.

[9] We use the Stata code *did_imputation* for Table III and *event_plot* for Figure 2.

untreated groups to impute unobserved counterfactual values—i.e., what would have happened to treated units if they weren't treated. BJS then use "imputation"-style methods to generate a DID estimator that is both efficient and robust to treatment effect heterogeneity. This contrasts with the ordinary least squares two-way fixed effects estimator, which can suffer from severe bias unless treatment effects are homogenous (Goodman-Bacon 2021), and other recent estimators that are robust but lack the same efficiency properties (BJS).

Modern DID estimators avoid leveraging comparisons between already-treated groups. For example, we can only leverage comparisons that are point identified given the presence of time fixed effects, meaning we must drop all observations after all units are treated. Therefore, any event occurring after April 27, 2020 does not affect the analysis.

We control for the PUA and PEUC take-up rate, the regular UI rate, the fraction of people at home all day in that area on that day, the unemployment rate, the seven-day moving average of the local crime rate one year prior, and maximum temperature, as well as day and city fixed effects. The unit of measurement for the DID specification is city-day, with some controls varying by city-day, some by city-week, and unemployment by city-month. For ease of reading the figure, we aggregate data for the event study to the city-week level.

PUA and PEUC

Next, we estimate the effect of PUA and PEUC implementation on crime. One benefit of analyzing PUA and PEUC is that we can exploit more variation and obtain more precise estimates as a result. A key limitation is that PUA and PEUC do not have as "clean" of an implementation. It took time for people to learn about the expanded unemployment system, apply for it, be approved, and then finally start receiving payments. Different states had different capabilities in processing claims. Therefore, the take-up rate changes dramatically both across locations and time. We estimate the effect of the take-up rate of PUA and PEUC on crime using a simple fixed effects specification:

$$Crime_{c,t} = \alpha_c + \beta(PUA_{s,t} + PEUC_{s,t}) + \boldsymbol{X}'\boldsymbol{\gamma} + \epsilon$$

Crime is the count of violent and property crimes in the sample by city-day per 100,000 people. *PUA* is the take-up rate for both continuous and initial UI claims due to expanded qualification by state-week; *PEUC* is the take-up rate for UI due to its extension by state-week. α_c is a city dummy. The controls in $\boldsymbol{X}$ are dummies indicating FPUC is active, regular UI rate, fraction of people at home all day in that area on that day, unemployment rate, the seven-day moving average of the local crime rate one year prior, and maximum temperature, as well as dummies for year, month, day of the week, holidays, the two weeks of BLM protests following George Floyd's murder, and the estimated timing of stimulus payments from April 10 to April 15, 2020, by which time 45% of all eligible recipients had received payments (Parker et al., 2022). We implement a wild bootstrap approach to clustering standard errors (Cameron et al., 2008).

IV. Results

FPUC and crime

The event study in Figure 2 shows persistent negative effects after the implementation of FPUC. However, it also shows anticipation effects shortly before the policy was enacted. A priori, it was unclear whether there would be anticipation effects, as prospective criminals often face financial constraints which do not permit them to leverage the fact that money is coming soon. Foley (2011) finds that welfare recipients commit more property crimes at the end of the month as they exhaust their predictable, regularly scheduled payments. We identify the effect of FPUC by measuring differences between treated and not-yet-treated groups. Anticipation attenuates our estimated effect, since not-yet-treated groups who anticipate increased UI payments will behave more like treated groups who already received increased UI payments. Insofar as anticipation is an issue, our preferred specification produces a conservative estimate of the effect of FPUC implementation on crime. We also present alternative results that attempt to account for anticipation.

[Figure 2]

Panel A of Table III presents results for the combined crime rate, property crime, violent crime, and combined crime restricted to cities that report all crime types. Panel B presents results for property crimes, Panel C presents results for violent crimes, and Panel D presents estimates assuming one week of anticipation—i.e., where the FPUC start date is one week earlier. We estimate that the local implementation of FPUC on average reduces violent and property crime by 2.3 incidents per 100,000 people per day, a 20% decrease over the sample average. Our estimate strengthens when we limit the sample to agencies that report all types of crime that we cover.

[Table III]

The effect is driven by a 24% decrease in property crime relative to the sample average, which itself is driven by strong reductions in all reported types of property crime. We find no statistically significant effect of the policy on violent crime, including estimates of robbery and aggravated assault. We do find a substantial increase in reported rapes, and a substantial decrease in homicides.

When we assume the "event" occurs one week earlier due to anticipation, our results strengthen, especially for violent crime. Anticipated-FPUC decreased the combined crime rate by 32%, violent crime by 37%, and property crime by 31%, all relative to the sample average.

One limitation of this analysis is that we only identify the short-term effect on crime within the one-month staggered adoption period. It is plausible that giving significant amounts of money to unemployed workers also has long term effects which our estimate does not capture. Nonetheless, an immediate 20% reduction in property and violent crime, including a 24% reduction in property crime, is substantial on its own.

By comparison, Beach and Lopresti (2019) consider more modest changes over a longer term; they find that a change in UI generosity by roughly an extra $60 per week decreases trade-competition-induced property crime by 2%. They provide evidence of a positive externality of UI generosity. We complement their research and show this effect holds even for a substantial increase in UI generosity. The increase in UI generosity under FPUC is roughly ten times larger than their baseline change in UI generosity, as is the corresponding effect on crime.

PUA, PEUC, and Crime

Table IV presents the estimated effects of the take-up rate of PUA and PEUC on crime. Panel A presents results for overall crime, property crime, violent crime, and overall crime with a limited sample. Panel B presents results for property crimes, and Panel C presents results for violent crimes.

We find that expanded unemployment is significantly negatively associated with crime. As the PUA and PEUC take-up rate increases by one standard error (6.82 additional workers per 100 receiving expanded unemployment insurance), we see an associated decline of 0.31 crimes per 100,000 people (3% relative to the sample average). As a percentage decline relative to the sample average, for the same standard-deviation increase in expanded unemployment take-up, we see the largest declines for larcenies (3%) and robberies (5%).

[Table IV]

Discussion

The FPUC program within the CARES Act acted as a large-scale policy experiment in the generosity of unemployment insurance. By our most conservative estimate, its implementation decreased crime by 20%. This represents a significant positive externality of unemployment insurance generosity.

With some caveats, we conduct a cost-benefit analysis to roughly approximate how much of the FPUC program was "paid for" by a reduction in crime alone. The nationwide cost of the FPUC program in 2020 was approximately $189 billion.[10] To estimate the benefit, we extrapolate our results to the entire U.S. population over the initial 2020 period FPUC was in effect and use Cohen and Piquero's (2009) "willingness to pay" estimates of the cost of crimes to calculate the value of crime reduction.[11] Using this method, we find that the crime reduction aspect of the FPUC

---

[10] We take the total number of people receiving UI benefits in weeks ranging from March 28 to July 31, 2020 and sum them to calculate the total person-weeks of UI beneficiaries, then multiply by $600.
[11] We use our point estimates by crime type, which present effects per one hundred thousand people per day. We first multiply these estimates by the U.S. population (approximately 329500 hundred thousand people), then the number of days FPUC was in effect (126). We then multiply by Cohen and Piquero's (2009) willingness to pay estimates for each crime type; for instance, the willingness to

program paid for roughly \$89 billion of the total program, or roughly half of the program's cost.

Homicides are incredibly costly (Cohen and Piquero 2009) and drive overall estimated benefits of crime reduction despite their relative rarity. Specifically, the reduction in homicide explains \$83 billion of the estimated benefits, with a 95% confidence interval of \$5 billion to \$157 billion. All property crime reductions, by comparison, accounts for \$14 billion of benefits. If we use the Environmental Protection Agency's statistical value of human life (\$7.4 million) to value homicide reduction, its benefit becomes \$52 billion, with a 95% confidence interval of \$3 billion to \$98 billion.

We interpret these results with some caution. We rely on our rich set of controls to capture how treated and not-yet-treated groups diverged shortly after the implementation of the CARES Act, so that our assumption of conditional parallel trends may hold. We can at least rule out our results being confounded by changes in unemployment, isolation due to the pandemic, different local seasonal trends, or other policies which were uniformly implemented across states.

Our results on PUA and PEUC require more caution. We rely on stronger assumptions to identify the true treatment effect because the treatment varies in intensity over states and over time. We consider our evidence on these programs to be suggestive.

---

prevent one murder is estimated at \$11.8 million. This is similar to the approach taken by Beach and Lopresti (2019), except we include more crimes.

Reported rape offenses may be subject to changes in reporting incentives over this time period, so we take those results with more caution. By contrast, changing police department policies are less likely to affect the reporting of crimes such as robbery or homicide. Abrams (2021) finds that changes in reporting are unlikely to cause the decline in overall crime reports.

Another potential issue is that some places do not report rapes. In Panel A, Column (4) of Tables III and IV, we drop cities that do not report rapes. The results are slightly stronger, but not statistically distinguishable from before.

V. Conclusion

We add to the small but growing literature on the effects of antipoverty policies on crime. Using police data from 17 cities in the U.S., we find that unemployment policies from the CARES Act substantially reduced crime. The increased UI payments from the FPUC program decreased overall crime reports by 20%, and the expansion of UI qualification through PUA and PEUC has a robust negative association with crime reports. These effects are driven primarily by property crimes, which are more common, but increased FPUC payments also significantly decrease homicides. We employ new quasi-experimental techniques developed in the blossoming econometric literature on event studies and DID, and we use a rich set of controls including mobile device tracking data to overcome the challenges of evaluating policy during a pandemic.

Previous research on this topic analyzed more modest differences in the generosity of UI programs. One concern when scholars identify modest benefits for modest policy changes is that the effect will not scale due to diminishing returns, but we offer evidence contrary to this theory: We analyze a policy change that is an order of magnitude larger than pre-pandemic policy differences and we find the effect scales. In addition, we identify a positive externality of increased UI generosity which we estimate pays for roughly half of the FPUC program's costs. The pandemic presents serious complications for any empirical work in this area, and we invite more research to complement and broaden these findings.

References

Abrams, D.S., 2021. COVID and crime: An early empirical look. Journal of Public Economics 194, 104344.

Artello, K., Williams, S., 2014. Stress and Crime, in: The Wiley Blackwell Encyclopedia of Health, Illness, Behavior, and Society. American Cancer Society, pp. 2283–2285. https://doi.org/10.1002/9781118410868.wbehibs357

Ashby, M.P., 2020. Initial evidence on the relationship between the coronavirus pandemic and crime in the United States. Crime Science 9, 1–16.

Autor, D., Cho, D., Crane, L.D., Goldar, M., Lutz, B., Montes, J.K., Peterman, W.B., Ratner, D.D., Villar Vallenas, D., Yildirmaz, A., 2022. The $800 Billion Paycheck Protection Program: Where Did the Money Go and Why Did it Go There? (Working Paper No. 29669), Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w29669

Aylward, J., Laderman, E., Oliveira, L.E., Teng, T., 2021. How Much Did the CARES Act Help Households Stay Afloat? FRBSF Economic Letter 1–6.

Beach, B., Lopresti, J., 2019. Losing by Less? Import Competition, Unemployment Insurance Generosity, and Crime. Economic Inquiry 57, 1163–1181. https://doi.org/10.1111/ecin.12758

Borusyak, K., Jaravel, X., Spiess, J., 2021. Revisiting event study designs: Robust and efficient estimation. arXiv preprint arXiv:2108.12419.

Cameron, A.C., Gelbach, J.B., Miller, D.L., 2008. Bootstrap-Based Improvements for Inference with Clustered Errors. The Review of Economics and Statistics 90, 414–427. https://doi.org/10.1162/rest.90.3.414

Chalfin, A., McCrary, J., 2017. Criminal Deterrence: A Review of the Literature. Journal of Economic Literature 55, 5–48. https://doi.org/10.1257/jel.20141147

Chalfin, A., Raphael, S., 2011. "Work and Crime." In The Oxford handbook of crime and criminal justice, edited by Michael Tonry. Oxford University Press.

Chetty, R., Friedman, J., Hendren, N., Stepner, M., 2020. The economic impacts of COVID-19: Evidence from a new public database built from private sector data. Opportunity Insights.

Cohen, M., Piquero, A., 2009. New evidence on the monetary value of saving a high risk youth. Journal of Quantitative Criminology 25.1, 25-49.

Curran, M., Wimer, C., 2021. Executive Actions to Reduce Poverty: A Menu of Options and Estimated Impacts on Poverty. The Brookings Institution.

Foley, C.F., 2011. Welfare payments and crime. The review of Economics and Statistics 93, 97–112.

Ganong, P., Noel, P., Vavra, J., 2020. US unemployment insurance replacement rates during the pandemic. Journal of public economics 191, 104273.

Gerell, M., Kardell, J., Kindgren, J., 2020. Minor covid-19 association with crime in Sweden. Crime Science 9, 19. https://doi.org/10.1186/s40163-020-00128-3

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. Journal of Econometrics.

Gould, E.D., Weinberg, B.A., Mustard, D.B., 2002. Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997. Review of Economics and Statistics 84, 45–61. https://doi.org/10.1162/003465302317331919

Halford, E., Dixon, A., Farrell, G., Malleson, N., Tilley, N., 2020. Crime and coronavirus: social distancing, lockdown, and the mobility elasticity of crime. Crime science 9, 1–12.

Hoehn-Velasco, L., Silverio-Murillo, A., Balmori de la Miyar, J.R., 2020. The U-shaped Crime Recovery during COVID-19: Evidence from National Crime Rates in Mexico (SSRN Scholarly Paper No. ID 3741795). Social Science Research Network, Rochester, NY. https://doi.org/10.2139/ssrn.3741795

Hsu, L., Henke, A., 2021. COVID-19, staying at home, and domestic violence. Review of Economics of the Household 19, 145–155.

Leslie, E., Wilson, R., 2020. Sheltering in place and domestic violence: Evidence from calls for service during COVID-19. Journal of Public Economics 189, 104241.

Parker, J., Schild, J., Erhard, L., Johnson, D., 2022. Household Spending Responses to the Economic Impact Payments of 2020: Evidence from the Consumer Expenditure Survey (No. w29648). National Bureau of Economic Research, Cambridge, MA. https://doi.org/10.3386/w29648

Parolin, Z., Curran, M., Matsudaira, J., Waldfogel, J., Wimer, C., 2020. Monthly poverty rates in the united states during the COVID-19 pandemic. Poverty and social policy working paper, center on poverty & social policy.

Payne, J.L., Morgan, A., Piquero, A.R., 2020. COVID-19 and social distancing measures in Queensland, Australia, are associated with short-term decreases in recorded violent crime. Journal of Experimental Criminology 1–25.

Ranson, M., 2014. Crime, weather, and climate change. Journal of environmental economics and management 67, 274–302.

Raphael, S., Winter-Ember, R., 2001. Identifying the effect of unemployment on crime. The Journal of Law and Economics 44, 259–283.

U.S. Bureau of Economic Analysis, 2022. Real Disposable Personal Income [WWW Document]. FRED, Federal Reserve Bank of St. Louis. URL https://fred.stlouisfed.org/series/DSPIC96 (accessed 1.23.22).

I. Introduction

To slow the initial spread of COVID-19, local governments in the U.S. shut down non-essential businesses and ordered individuals to shelter in place, which led to a significant loss of jobs (Chetty *et al.*, 2020). On March 27, 2020, the U.S. government passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act, providing direct relief and expanded unemployment insurance (UI) benefits.

The unemployment insurance portion of the CARES Act, arguably the most significant part of the bill for poverty reduction, has three primary arms: the Federal Pandemic Unemployment Compensation (FPUC) program increased all UI benefits by $600 per week; the Pandemic Unemployment Assistance (PUA) program extended benefits to more workers, such as self-employed, freelancers, and independent contractors; and the Pandemic Emergency Unemployment Compensation (PEUC) program extended UI benefits by an extra 13 weeks.[1]

Unemployment and low incomes can significantly increase the chance of crime. We hypothesize that the UI policies in the CARES Act reduced crime. We find evidence that FPUC reduced crime by 20%, driven by a decrease in property crime, and we find suggestive evidence that PUA and PEUC also reduced crime. With some additional assumptions, we estimate that roughly half of the FPUC program in 2020 was effectively paid for by reducing crimes, especially homicides.

To our knowledge, we are the first to examine this question in the context of the CARES Act. Beach and Lopresti (2019) find that UI attenuates the effect of import-

[1] Some provisions of the CARES Act were extended through the Continued Assistance Act from Dec. 27, 2020 until March 13, 2021.

competition-induced labor shocks on crime. Other researchers have estimated the overall effect of the pandemic on crime across the U.S., especially early on (Abrams, 2021; Ashby, 2020), but not the direct effect of this policy channel.

One reason our question is unstudied is that, while the initial overall effect of the pandemic can be relatively easily identified, identifying component pieces of the pandemic presents more challenges. First, other factors, such as the degree to which people stayed at home, and unemployment itself, may influence crime during the pandemic. Crime dropped at the beginning of the pandemic, especially drug crimes, theft, residential burglaries, and most violent crimes (Abrams 2021).[2] Second, although the CARES Act was signed into law on March 27, 2020, states have different "enactment" dates for the various UI provisions of the CARES Act due to differences in manpower or the number of claimants. This staggered policy adoption complicates common estimation approaches to a difference-in-differences (DID) research design (Goodman-Bacon, 2021). Third, other relief measures may also influence crime. For instance, the economic impact payments (i.e., the stimulus payments) were issued around the same time, starting April 10, 2020 (Parker *et al.*, 2022). Fourth, anticipation of the policy could attenuate our estimated effects. Finally, the number of PUA and PEUC claimants varies both across location and over time substantially, which means studying the timing of PUA/PEUC implementation may not present the full picture.

[2] Crime also dropped in Sweden, (Gerell *et al.*, 2020), Mexico (Hoehn-Velasco *et al.*, 2020), Australia (Payne *et al.*, 2020), and the UK (Halford *et al.*, 2020) after lockdowns, among other countries. The exception to the overall crime trend is domestic violence, which sharply increased as people stayed at home (Hsu and Henke, 2021; Leslie and Wilson, 2020).

We attempt to overcome these challenges first by identifying granular variation in the timing of the implementation of FPUC, as well as weekly changes in the take-up rate for PUA and PEUC. Second, we use new event study and DID methods to estimate the impact of the FPUC program on crime, both over time and overall. Third, we control for a variety of likely confounders such as unemployment. In addition, the pandemic changed mobility and thus the availability of potential victims of or witnesses to crimes. In response, we use a novel control by estimating the local daily fraction of people staying at home using anonymous mobile device tracking data at the county level. Finally, when we account for anticipation effects in our analysis, our estimated effect strengthens. Our estimates assuming no anticipation are, therefore, conservative.

Our main contribution is to estimate how expanded UI programs in the CARES Act affected crime. We add to a small but growing literature on unemployment insurance and crime that contains strong policy implications for social insurance and antipoverty programs.

II. Overview of the CARES Act

The CARES Act had several major components, including a $1,200 stimulus payment to individuals, over $800 billion in loans to businesses, and extended and expanded unemployment, dwarfing normal income transfer programs such as the Supplemental Nutritional Assistance Program (Parolin *et al.*, 2020).[3] The assistance was substantial enough that overall real disposable income increased (U.S. Bureau

[3] Autor *et al.* (2022) review the effects of the paycheck protection program which provided loans to businesses. Along with modest pro-employment effects, they find that most of the money went to business owners rather than employees. Here, we focus on programs primarily aimed at individual workers.

of Economic Analysis, 2022) and many unemployed individuals received higher pay during the first months of the pandemic compared to when they were working (Ganong *et al.*, 2020).

Increasing household income has clear antipoverty effects. Between April to May 2020, the CARES Act lifted 17.8 million individuals from poverty and prevented almost 80 million “person-months” of poverty from March through December 2020 (Curran and Wimer, 2021). It also helped households maintain a basic level of spending for fifteen more weeks on average, primarily caused by its unemployment insurance programs (Aylward *et al.*, 2021).

Policies that alleviate poverty and economic hardship affect crime because poverty and economic hardship themselves affect crime (Beach and Lopresti, 2019; Chalfin and McCrary, 2017; Chalfin and Raphael, 2011; Gould et al., 2002; Raphael and Winter-Ember, 2001). When unemployment increases (and similarly, when wages and income decrease), the marginal gain from committing property crime increases, and the opportunity cost of prison time decreases. Therefore, property crime increases. Besides the economic incentives of crime, violent crime such as aggravated assault or homicide may also be affected by increasing stress levels (Artello and Williams, 2014). Thus, we hypothesize that the antipoverty effects of the CARES Act also reduced property crime and violent crime.

III. Data and Methods

All data were collected online and cover dates from January 1, 2019 to December 31, 2020. Since the CARES Act was enacted in 2020, the inclusion of earlier data primarily improves efficiency. We specify when a method analyzes a shorter time period.

Crime reports

We collect data sets on our outcomes of interest, crimes and incidents reported to police, from 17 U.S. cities. These cities provide daily crime or incident data through searchable, open data portals. Property crime includes larceny, motor vehicle theft, and burglary.[4] Violent crime includes homicide, rape, robbery, and aggravated assault.[5] Overall crime includes both categories. See Table I for the cities in the sample and the crimes covered by city. To capture location-specific seasonal trends in crime, we also create a seven-day moving average of the local crime rate one year prior to the day, by city-day. [6]

[Table I]

Unemployment and UI

Weekly state-level data on PUA, PEUC, and regular UI claims are from the U.S. Department of Labor (DOL). We measure state-level FPUC implementation through public announcements of official state entities. All payment increases were retroactive, but some states started before others based on the ability to comply with DOL guidance and process the increases in a timely fashion. The FPUC program expired on July 31, 2020, but our primary methodologies focus on differences in

---

[4] Larceny includes all kinds of theft except motor vehicle theft, which we include as a separate category; burglary is the unlawful entry of a structure to commit a felony or a theft.

[5] Homicide includes murder and manslaughter; rape is defined as sexual penetration but not including statutory rape where it is possible to separate; robbery is defined as the taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear; aggravated assault is defined as an attack with severe physical injury that is usually inflicted using a lethal weapon. Some cities do not report rapes; their violent crime count sums all reported offenses.

[6] This means we drop the first three days of 2019 in our analyses. Fort Worth, TX crime data begin in 2019, so with the moving average the analysis of Fort Worth begins in 2020.

implementation dates, which range from March 30 to April 27, 2020. Table I shows the FPUC enactment dates by city.

City-month-level unemployment data are from the Local Area Unemployment Statistics program, part of the U.S. Bureau of Labor Statistics. An ideal data set would contain more granular unemployment estimates to fully control for aspects of unemployment which could confound our estimates. Therefore, we use both unemployment data by city-month and UI take-up data by state-week.

Other data sources

We estimate the proportion of people who stay at home all day using data from the SafeGraph Data Consortium.[7] SafeGraph pings 45 million anonymized mobile devices in the U.S. and tracks where they are at different times of day. We count the number of pinged devices that never left their designated home area in a day and divide by the total number of sampled devices in that county.

To create a per-capita crime rate, we use city population estimates from the U.S. Census Bureau in 2019. Daily city-level maximum temperature data are compiled from the Global Historical Climatological Network (GHCN). The GHCN daily weather records are retrieved from the National Oceanic and Atmospheric Administration. Temperature is a useful control because it is clearly not caused by other factors, and it affects crime (Ranson, 2014), meaning its inclusion improves efficiency and does not introduce any bias.

[7] SafeGraph is a data company that aggregates anonymized location data from numerous applications to provide insights about physical places. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month from a given census block group. SafeGraph collected and provided this data for free to scholars until April 2021.

Summary statistics

Table II shows that, on average, cities in the sample report 9.93 property crimes and 2.02 violent crimes per 100,000 people per day, combining to 11.9. The average rate of workers receiving UI benefits due to the PUA and PEUC programs is 3.34 per 100 people in the labor force (the average in 2020 is 6.67). More common crimes such as larceny and motor vehicle theft will play an outsized role when we estimate effects on overall crime counts, and less common crimes such as rapes and homicides will not substantially affect our estimates of overall effects, though they are important to consider on their own.

[Table II]

Figure 1 plots the 7-day moving average of crime rates for 2019 and 2020. The sharp spike in reported violent and property crime starting in late May 2020 is likely to be related to concurrent Black Lives Matter (BLM) protests, possibly due to changes in actual criminal behavior and possibly due to changes in police reporting behavior.

[Figure 1]

Methods

Once local governments processed the federal FPUC subsidy and abided by guidance from the DOL, UI benefit recipients automatically received $600 more per week essentially as a single event. This effectively creates a natural experiment of increased transfer sizes, allowing us to employ event study and DID designs.

Classic DID compares the trends of treated and never-treated units. However, there are no never-treated units in our sample, as every UI recipient eventually received the additional $600 per week. The reason we can use a DID strategy at all is the staggered roll-out of FPUC, which allows us to compare treated with not-yet-treated groups. Thus, the key period of comparison is from the first FPUC implementation in our sample on March 30, 2020, to the last implementation on April 27, 2020. The set of data occurring prior to March 30 does not directly identify the effect of interest, but it helps improve efficiency. The ability for a state government to implement FPUC quickly may relate to efficient governance within that state and thus may relate to crime. We argue that (in)efficient governance associated with a (slow) quick roll-out did not arise in the Spring of 2020, but rather was a static property of that state. City dummies capture static differences across states.

We assume parallel trends conditional on controlling for the pandemic's most likely confounders, including the degree to which people stay at home and unemployment. Several policies were enacted around the same time, and we attempt to identify the effect of the FPUC program. Importantly, these policies were not implemented at precisely the same time in all places in the same manner. Our research design assumes that the effect of policies that occurred at roughly the same time across the U.S., such as the economic impact payments, are relatively uniform and therefore can be absorbed by appropriate time dummies. Controlling for unemployment covers policies that influenced unemployment, such as loans to businesses. Finally, we also control for PUA and PEUC.[8]

Event Study and Difference-in-differences

In our event study and DID specifications, we use the estimator developed by Borusyak *et al.* (2021) (BJS hereafter).[9] BJS note that DID designs effectively use

[8] Estimates without PUA+PEUC controls are very similar and are available on request.

[9] We use the Stata code *did_imputation* for Table III and *event_plot* for Figure 2.

untreated groups to impute unobserved counterfactual values—i.e., what would have happened to treated units if they weren't treated. BJS then use "imputation"-style methods to generate a DID estimator that is both efficient and robust to treatment effect heterogeneity. This contrasts with the ordinary least squares two-way fixed effects estimator, which can suffer from severe bias unless treatment effects are homogenous (Goodman-Bacon 2021), and other recent estimators that are robust but lack the same efficiency properties (BJS).

Modern DID estimators avoid leveraging comparisons between already-treated groups. For example, we can only leverage comparisons that are point identified given the presence of time fixed effects, meaning we must drop all observations after all units are treated. Therefore, any event occurring after April 27, 2020 does not affect the analysis.

We control for the PUA and PEUC take-up rate, the regular UI rate, the fraction of people at home all day in that area on that day, the unemployment rate, the seven-day moving average of the local crime rate one year prior, and maximum temperature, as well as day and city fixed effects. The unit of measurement for the DID specification is city-day, with some controls varying by city-day, some by city-week, and unemployment by city-month. For ease of reading the figure, we aggregate data for the event study to the city-week level.

PUA and PEUC

Next, we estimate the effect of PUA and PEUC implementation on crime. One benefit of analyzing PUA and PEUC is that we can exploit more variation and obtain more precise estimates as a result. A key limitation is that PUA and PEUC do not have as "clean" of an implementation. It took time for people to learn about the expanded unemployment system, apply for it, be approved, and then finally start receiving payments. Different states had different capabilities in processing claims. Therefore, the take-up rate changes dramatically both across locations and time. We estimate the effect of the take-up rate of PUA and PEUC on crime using a simple fixed effects specification:

$$Crime_{c,t} = \alpha_c + \beta(PUA_{s,t} + PEUC_{s,t}) + \boldsymbol{X}'\boldsymbol{\gamma} + \epsilon$$

Crime is the count of violent and property crimes in the sample by city-day per 100,000 people. *PUA* is the take-up rate for both continuous and initial UI claims due to expanded qualification by state-week; *PEUC* is the take-up rate for UI due to its extension by state-week. α_c is a city dummy. The controls in $\boldsymbol{X}$ are dummies indicating FPUC is active, regular UI rate, fraction of people at home all day in that area on that day, unemployment rate, the seven-day moving average of the local crime rate one year prior, and maximum temperature, as well as dummies for year, month, day of the week, holidays, the two weeks of BLM protests following George Floyd's murder, and the estimated timing of stimulus payments from April 10 to April 15, 2020, by which time 45% of all eligible recipients had received payments (Parker et al., 2022). We implement a wild bootstrap approach to clustering standard errors (Cameron et al., 2008).

IV. Results

FPUC and crime

The event study in Figure 2 shows persistent negative effects after the implementation of FPUC. However, it also shows anticipation effects shortly before the policy was enacted. A priori, it was unclear whether there would be anticipation effects, as prospective criminals often face financial constraints which do not permit them to leverage the fact that money is coming soon. Foley (2011) finds that welfare recipients commit more property crimes at the end of the month as they exhaust their predictable, regularly scheduled payments. We identify the effect of FPUC by measuring differences between treated and not-yet-treated groups. Anticipation attenuates our estimated effect, since not-yet-treated groups who anticipate increased UI payments will behave more like treated groups who already received increased UI payments. Insofar as anticipation is an issue, our preferred specification produces a conservative estimate of the effect of FPUC implementation on crime. We also present alternative results that attempt to account for anticipation.

[Figure 2]

Panel A of Table III presents results for the combined crime rate, property crime, violent crime, and combined crime restricted to cities that report all crime types. Panel B presents results for property crimes, Panel C presents results for violent crimes, and Panel D presents estimates assuming one week of anticipation—i.e., where the FPUC start date is one week earlier. We estimate that the local implementation of FPUC on average reduces violent and property crime by 2.3 incidents per 100,000 people per day, a 20% decrease over the sample average. Our estimate strengthens when we limit the sample to agencies that report all types of crime that we cover.

[Table III]

The effect is driven by a 24% decrease in property crime relative to the sample average, which itself is driven by strong reductions in all reported types of property crime. We find no statistically significant effect of the policy on violent crime, including estimates of robbery and aggravated assault. We do find a substantial increase in reported rapes, and a substantial decrease in homicides.

When we assume the "event" occurs one week earlier due to anticipation, our results strengthen, especially for violent crime. Anticipated-FPUC decreased the combined crime rate by 32%, violent crime by 37%, and property crime by 31%, all relative to the sample average.

One limitation of this analysis is that we only identify the short-term effect on crime within the one-month staggered adoption period. It is plausible that giving significant amounts of money to unemployed workers also has long term effects which our estimate does not capture. Nonetheless, an immediate 20% reduction in property and violent crime, including a 24% reduction in property crime, is substantial on its own.

By comparison, Beach and Lopresti (2019) consider more modest changes over a longer term; they find that a change in UI generosity by roughly an extra \$60 per week decreases trade-competition-induced property crime by 2%. They provide evidence of a positive externality of UI generosity. We complement their research and show this effect holds even for a substantial increase in UI generosity. The increase in UI generosity under FPUC is roughly ten times larger than their baseline change in UI generosity, as is the corresponding effect on crime.

PUA, PEUC, and Crime

Table IV presents the estimated effects of the take-up rate of PUA and PEUC on crime. Panel A presents results for overall crime, property crime, violent crime, and overall crime with a limited sample. Panel B presents results for property crimes, and Panel C presents results for violent crimes.

We find that expanded unemployment is significantly negatively associated with crime. As the PUA and PEUC take-up rate increases by one standard error (6.82 additional workers per 100 receiving expanded unemployment insurance), we see an associated decline of 0.31 crimes per 100,000 people (3% relative to the sample average). As a percentage decline relative to the sample average, for the same standard-deviation increase in expanded unemployment take-up, we see the largest declines for larcenies (3%) and robberies (5%).

[Table IV]

Discussion

The FPUC program within the CARES Act acted as a large-scale policy experiment in the generosity of unemployment insurance. By our most conservative estimate, its implementation decreased crime by 20%. This represents a significant positive externality of unemployment insurance generosity.

With some caveats, we conduct a cost-benefit analysis to roughly approximate how much of the FPUC program was "paid for" by a reduction in crime alone. The nationwide cost of the FPUC program in 2020 was approximately $189 billion.[10] To estimate the benefit, we extrapolate our results to the entire U.S. population over the initial 2020 period FPUC was in effect and use Cohen and Piquero's (2009) "willingness to pay" estimates of the cost of crimes to calculate the value of crime reduction.[11] Using this method, we find that the crime reduction aspect of the FPUC

---

[10] We take the total number of people receiving UI benefits in weeks ranging from March 28 to July 31, 2020 and sum them to calculate the total person-weeks of UI beneficiaries, then multiply by $600.

[11] We use our point estimates by crime type, which present effects per one hundred thousand people per day. We first multiply these estimates by the U.S. population (approximately 329500 hundred thousand people), then the number of days FPUC was in effect (126). We then multiply by Cohen and Piquero's (2009) willingness to pay estimates for each crime type; for instance, the willingness to

program paid for roughly $89 billion of the total program, or roughly half of the program's cost.

Homicides are incredibly costly (Cohen and Piquero 2009) and drive overall estimated benefits of crime reduction despite their relative rarity. Specifically, the reduction in homicide explains $83 billion of the estimated benefits, with a 95% confidence interval of $5 billion to $157 billion. All property crime reductions, by comparison, accounts for $14 billion of benefits. If we use the Environmental Protection Agency's statistical value of human life ($7.4 million) to value homicide reduction, its benefit becomes $52 billion, with a 95% confidence interval of $3 billion to $98 billion.

We interpret these results with some caution. We rely on our rich set of controls to capture how treated and not-yet-treated groups diverged shortly after the implementation of the CARES Act, so that our assumption of conditional parallel trends may hold. We can at least rule out our results being confounded by changes in unemployment, isolation due to the pandemic, different local seasonal trends, or other policies which were uniformly implemented across states.

Our results on PUA and PEUC require more caution. We rely on stronger assumptions to identify the true treatment effect because the treatment varies in intensity over states and over time. We consider our evidence on these programs to be suggestive.

---

prevent one murder is estimated at $11.8 million. This is similar to the approach taken by Beach and Lopresti (2019), except we include more crimes.

Reported rape offenses may be subject to changes in reporting incentives over this time period, so we take those results with more caution. By contrast, changing police department policies are less likely to affect the reporting of crimes such as robbery or homicide. Abrams (2021) finds that changes in reporting are unlikely to cause the decline in overall crime reports.

Another potential issue is that some places do not report rapes. In Panel A, Column (4) of Tables III and IV, we drop cities that do not report rapes. The results are slightly stronger, but not statistically distinguishable from before.

V. Conclusion

We add to the small but growing literature on the effects of antipoverty policies on crime. Using police data from 17 cities in the U.S., we find that unemployment policies from the CARES Act substantially reduced crime. The increased UI payments from the FPUC program decreased overall crime reports by 20%, and the expansion of UI qualification through PUA and PEUC has a robust negative association with crime reports. These effects are driven primarily by property crimes, which are more common, but increased FPUC payments also significantly decrease homicides. We employ new quasi-experimental techniques developed in the blossoming econometric literature on event studies and DID, and we use a rich set of controls including mobile device tracking data to overcome the challenges of evaluating policy during a pandemic.

Previous research on this topic analyzed more modest differences in the generosity of UI programs. One concern when scholars identify modest benefits for modest policy changes is that the effect will not scale due to diminishing returns, but we offer evidence contrary to this theory: We analyze a policy change that is an order of magnitude larger than pre-pandemic policy differences and we find the effect scales. In addition, we identify a positive externality of increased UI generosity which we estimate pays for roughly half of the FPUC program's costs. The pandemic presents serious complications for any empirical work in this area, and we invite more research to complement and broaden these findings.

References

Abrams, D.S., 2021. COVID and crime: An early empirical look. Journal of Public Economics 194, 104344.

Artello, K., Williams, S., 2014. Stress and Crime, in: The Wiley Blackwell Encyclopedia of Health, Illness, Behavior, and Society. American Cancer Society, pp. 2283–2285. https://doi.org/10.1002/9781118410868.wbehibs357

Ashby, M.P., 2020. Initial evidence on the relationship between the coronavirus pandemic and crime in the United States. Crime Science 9, 1–16.

Autor, D., Cho, D., Crane, L.D., Goldar, M., Lutz, B., Montes, J.K., Peterman, W.B., Ratner, D.D., Villar Vallenas, D., Yildirmaz, A., 2022. The $800 Billion Paycheck Protection Program: Where Did the Money Go and Why Did it Go There? (Working Paper No. 29669), Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w29669

Aylward, J., Laderman, E., Oliveira, L.E., Teng, T., 2021. How Much Did the CARES Act Help Households Stay Afloat? FRBSF Economic Letter 1–6.

Beach, B., Lopresti, J., 2019. Losing by Less? Import Competition, Unemployment Insurance Generosity, and Crime. Economic Inquiry 57, 1163–1181. https://doi.org/10.1111/ecin.12758

Borusyak, K., Jaravel, X., Spiess, J., 2021. Revisiting event study designs: Robust and efficient estimation. arXiv preprint arXiv:2108.12419.

Cameron, A.C., Gelbach, J.B., Miller, D.L., 2008. Bootstrap-Based Improvements for Inference with Clustered Errors. The Review of Economics and Statistics 90, 414–427. https://doi.org/10.1162/rest.90.3.414

Chalfin, A., McCrary, J., 2017. Criminal Deterrence: A Review of the Literature. Journal of Economic Literature 55, 5–48. https://doi.org/10.1257/jel.20141147

Chalfin, A., Raphael, S., 2011. "Work and Crime." In The Oxford handbook of crime and criminal justice, edited by Michael Tonry. Oxford University Press.

Chetty, R., Friedman, J., Hendren, N., Stepner, M., 2020. The economic impacts of COVID-19: Evidence from a new public database built from private sector data. Opportunity Insights.

Cohen, M., Piquero, A., 2009. New evidence on the monetary value of saving a high risk youth. Journal of Quantitative Criminology 25.1, 25-49.

Curran, M., Wimer, C., 2021. Executive Actions to Reduce Poverty: A Menu of Options and Estimated Impacts on Poverty. The Brookings Institution.

Foley, C.F., 2011. Welfare payments and crime. The review of Economics and Statistics 93, 97–112.

Ganong, P., Noel, P., Vavra, J., 2020. US unemployment insurance replacement rates during the pandemic. Journal of public economics 191, 104273.

Gerell, M., Kardell, J., Kindgren, J., 2020. Minor covid-19 association with crime in Sweden. Crime Science 9, 19. https://doi.org/10.1186/s40163-020-00128-3

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. Journal of Econometrics.

Gould, E.D., Weinberg, B.A., Mustard, D.B., 2002. Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997. Review of Economics and Statistics 84, 45–61. https://doi.org/10.1162/003465302317331919

Halford, E., Dixon, A., Farrell, G., Malleson, N., Tilley, N., 2020. Crime and coronavirus: social distancing, lockdown, and the mobility elasticity of crime. Crime science 9, 1–12.

Hoehn-Velasco, L., Silverio-Murillo, A., Balmori de la Miyar, J.R., 2020. The U-shaped Crime Recovery during COVID-19: Evidence from National Crime Rates in Mexico (SSRN Scholarly Paper No. ID 3741795). Social Science Research Network, Rochester, NY. https://doi.org/10.2139/ssrn.3741795

Hsu, L., Henke, A., 2021. COVID-19, staying at home, and domestic violence. Review of Economics of the Household 19, 145–155.

Leslie, E., Wilson, R., 2020. Sheltering in place and domestic violence: Evidence from calls for service during COVID-19. Journal of Public Economics 189, 104241.

Parker, J., Schild, J., Erhard, L., Johnson, D., 2022. Household Spending Responses to the Economic Impact Payments of 2020: Evidence from the Consumer Expenditure Survey (No. w29648). National Bureau of Economic Research, Cambridge, MA. https://doi.org/10.3386/w29648

Parolin, Z., Curran, M., Matsudaira, J., Waldfogel, J., Wimer, C., 2020. Monthly poverty rates in the united states during the COVID-19 pandemic. Poverty and social policy working paper, center on poverty & social policy.

Payne, J.L., Morgan, A., Piquero, A.R., 2020. COVID-19 and social distancing measures in Queensland, Australia, are associated with short-term decreases in recorded violent crime. Journal of Experimental Criminology 1–25.

Ranson, M., 2014. Crime, weather, and climate change. Journal of environmental economics and management 67, 274–302.

Raphael, S., Winter-Ember, R., 2001. Identifying the effect of unemployment on crime. The Journal of Law and Economics 44, 259–283.

U.S. Bureau of Economic Analysis, 2022. Real Disposable Personal Income [WWW Document]. FRED, Federal Reserve Bank of St. Louis. URL https://fred.stlouisfed.org/series/DSPIC96 (accessed 1.23.22).

Table I: FPUC start date and unreported crime category by city

City	FPUC start date	Types of crimes covered
Austin	April 12, 2020	All
Boston	April 9, 2020	All
Chicago	April 6, 2020	All
Dallas	April 12, 2020	All except rape
Denver	April 27, 2020	All
Detroit	April 9, 2020	All
Fort Worth	April 12, 2020	All except rape
Los Angeles	April 6, 2020	All
Louisville	April 9, 2020	All
Memphis	April 14, 2020	All except rape
Nashville	April 14, 2020	All
New York	April 10, 2020	All
Philadelphia	April 4, 2020	All
Phoenix	April 13, 2020	All
San Francisco	April 6, 2020	All
Seattle	April 12, 2020	All
Washington D.C.	March 30, 2020	All

Note: For cities that do not report separate burglary crimes, they report total burglaries.

Table II: Summary Statistics

	(1) N	(2) Mean	(3) Std. Dev.
Overall crime rate	12,427	11.9	4.47
Property crime rate	12,427	9.93	4.04
Larceny	12,427	6.88	3.05
Motor vehicle theft	12,427	1.52	1.09
Burglary	12,427	1.53	1.11
Violent crime rate	12,427	2.02	1.19
Homicide	12,427	0.042	0.081
Rape	10,234	0.11	0.15
Robbery	12,427	0.63	0.40
Aggravated Assault	12,427	1.25	0.94
PUA + PEUC rate	12,427	3.34	6.82
Regular UI rate	12,427	4.24	4.80
Unemployment rate	12,427	6.93	5.29
Fraction of people stay at home	12,427	0.33	0.064
Maximum temperature (°C)	12,427	20.8	10.2

Note: The crime rate is reported incidents per 100,000 people. The rates of regular UI, PUA, and PEUC are number of claims per 100 people in the labor force. The unemployment rate is the number of unemployed per 100 people in the labor force.

Table III: FPUC implementation and Crime

Panel A: The effect of FPUC implementation on overall crime, property crime, and violent crime

	(1)	(2)	(3)	(4)
	Overall	Property	Violent	Overall
FPUC treatment effect	-2.329***	-2.406***	0.090	-2.445***
	[-2.977,-1.681]	[-3.093,-1.718]	[-0.055,0.236]	[-3.310,-1.581]
Observations	7778	7778	7778	6706

Panel B: The effect of FPUC implementation on property crime

	(1)	(2)	(3)
	Larceny	Motor Vehicle Theft	Burglary
FPUC treatment effect	-1.335***	-0.387***	-0.622**
	[-1.538,-1.132]	[-0.482,-0.292]	[-1.163,-0.080]
Observations	7778	7778	7778

Panel C: The effect of FPUC implementation on violent crimes

	(1)	(2)	(3)	(4)
	Homicide	Rape	Robbery	Aggravated Assault
FPUC treatment effect	-0.017**	0.060***	-0.041	0.057
	[-0.032,-0.001]	[0.019,0.101]	[-0.163,0.082]	[-0.117,0.231]
Observations	7778	6341	7778	7778

Panel D: The effect of FPUC implementation on crimes with one-week anticipation

	(1)	(2)	(3)
	Overall	Violent	Property
FPUC treatment effect	-3.791***	-0.750***	-3.099***
	[-4.595,-2.987]	[-1.137,-0.363]	[-3.598,-2.600]
Observations	7659	7659	7659

Note: All regressions include the 7-day moving average crime rate of the previous year, unemployment rate, rate of regular unemployment insurance claim, rate of PUA and PEUC claim, fraction of people staying at home, maximum temperature, day dummies, and city dummies. In Panel A, column (4) drops the cities with incomplete crime coverage. This table provides the average treatment coefficient and the associated 95% confidence intervals for the imputation estimator in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IV: Expanded UI and Crime

Panel A: The effects of expanded UI on overall crime, property crime and violent crime

	(1)	(2)	(3)	(4)
	Overall	Property	Violent	Overall
PUA + PEUC	-0.046***	-0.038***	-0.007***	-0.053***
	-0.004	-0.003	-0.001	-0.004
Observations	12011	12011	12011	10192
R^2	0.80	0.79	0.75	0.76

Panel B: The effects of expanded UI on different property crime

	(1)	(2)	(3)
	Larceny	Motor Vehicle Theft	Burglary
PUA + PEUC	-0.033***	-0.003***	-0.003*
	-0.003	-0.001	-0.002
Observations	12011	12011	12011
R^2	0.77	0.76	0.56

Panel C: The effects of expanded UI on different violent crime

	(1)	(2)	(3)	(4)
	Homicide	Rape	Robbery	Aggravated Assault
PUA + PEUC	-0.0003**	0.000	-0.005***	-0.002**
	-0.0001	(0.000)	-0.001	-0.001
Observations	12011	9827	12011	12011
R^2	0.21	0.31	0.40	0.75

Note: All regressions include the 7-day moving average crime rate of the previous year, unemployment rate, rate of regular unemployment insurance claim, dummy of FPUC enactment, dummy for stimulus payment distribution period, fraction of people stay at home, maximum temperature, BLM, year, month, day of week, city, and holiday dummies. In Panel A, column (4) drops the cities with incomplete crime coverage. Standard errors are obtained by bootstrapping and are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: 7-day moving average crime rate in 2020

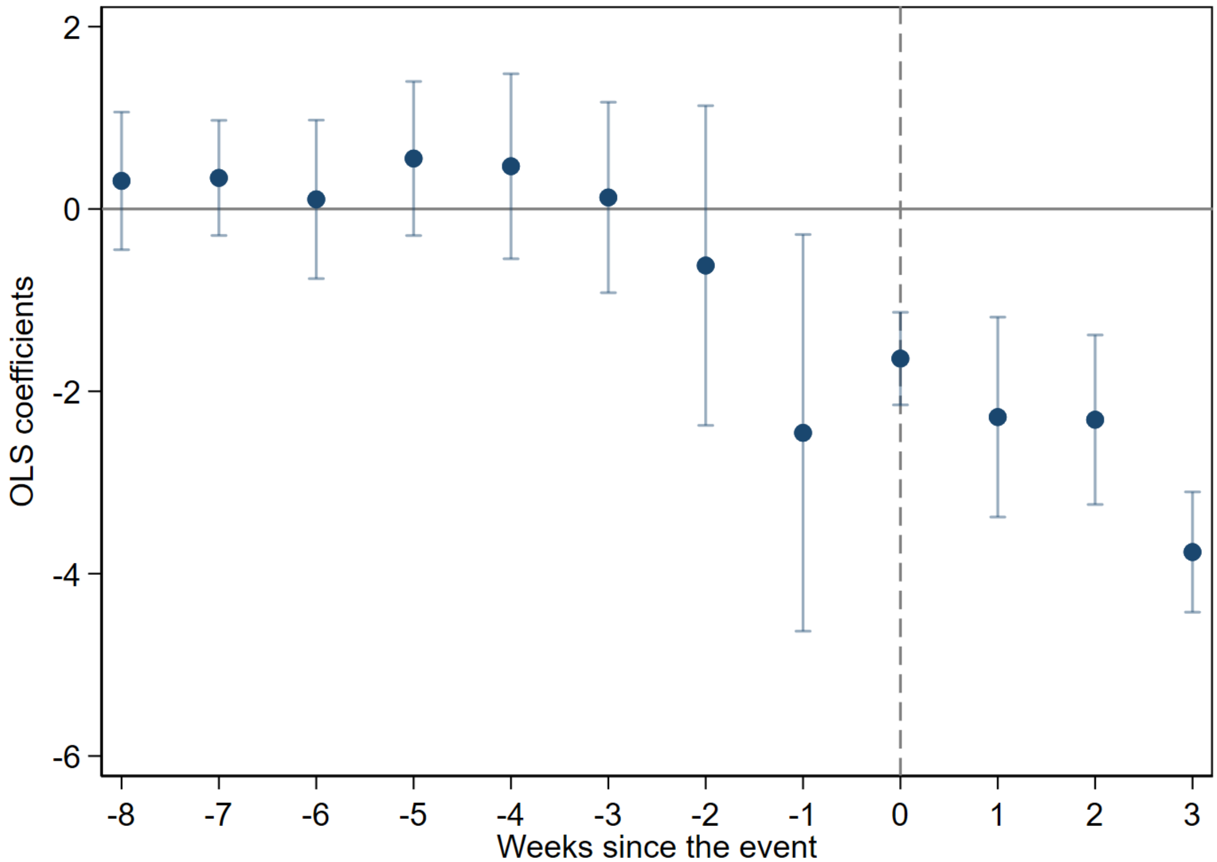

Figure 2: Event Study of FPUC and Crime

Note: Figure 2 displays the treatment effect estimates using the BLS event study estimator including rates of regular UI claims, PUA + PEUC claims, unemployment rate, fraction of people stay at home, maximum temperature, day, and city FE.