Housing Voucher Discrimination and Deaths of Despair

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Abstract

Housing policy relating to the opioid epidemic is receiving increased scrutiny. Concerns have arisen that rejecting housing vouchers is harming public health. We estimate the relationship between legalizing housing discrimination of Section 8 housing vouchers (VDA) and deaths of despair using state level mortality data on U.S. adults from the Centers for Disease and Control database. Leveraging 2015 legislation in Texas and Indiana that legalizes Section 8 housing voucher discrimination, results suggest the policy increased the prescription opioid mortality rate by 2.438 deaths per 100,000 people. The findings imply that legalizing Section 8 housing discrimination may worsen public health in the ongoing opioid crisis.

Keywords: Section 8 Housing, Housing Vouchers, Deaths of Despair, Opioid Mortality, Public Policy, Housing Discrimination

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1. Introduction

While housing voucher discrimination occurs throughout the United States, Texas and Indiana explicitly demonstrate this reality. Under Texas and Indiana law enacted in 2015 and effective in 2016, landlords can refuse to accept Section 8 housing vouchers—a vital form of rental assistance, as explained by Walters and Satija (2018). As a result, individuals receiving housing vouchers may be unable to find landlords who will accept them. For instance, Walters and Satija (2018) note that 1 in 4 families receiving a housing voucher in the Houston, Texas area never get to use it. While this source of income discrimination arguably reduces housing accessibility, it could have other effects. Namely, permitting voucher discrimination may produce the unintended consequence of worsening the ongoing opioid epidemic.

According to Venkataramani and Tsai (2020), opioid deaths, suicide, and alcohol related mortality constitute deaths of despair and contribute to rising midlife mortality rates. Ashley C. Bradford and W. David Bradford (2020) note that the CDC measures deaths of despair in the context of the substances used such as heroin, benzodiazepines, psychostimulants, cocaine, antidepressants, and alcohol. Allik et al. (2020) attest that the deaths of despair stem from economic pressures and breakdowns in social support structures. Given the economic and social pressures that people can face as a result of housing instability, there is concern that housing discrimination could lead to more deaths of despair.

To provide new information on housing policy, we conduct our study to provide the first empirical estimate of the effects of introducing legal source of income discrimination on deaths of despair. We use a difference-in-differences empirical approach to evaluate if legal voucher discrimination leads to higher substance-related mortality rates for all opioids, prescription opioids, synthetic opioids, heroin, cocaine, stimulants, benzodiazepines, antidepressants, and alcohol poisoning. Our results directly address a paucity of research that exists on source of income discrimination and deaths of despair. Our contribution expands the existing body of research, including the A. C. Bradford and W. D. Bradford (2020) study on evictions and housing discrimination.

Empirical results from the CDC WONDER database reveal that introducing a legal discrimination policy for Section 8 vouchers in Texas and Indiana in 2016 increases mortality from prescription opioids. Specifically, we report that the source of income discrimination policy increased the prescription opioid mortality rate by 2.438 deaths per 100,000 people. The increase suggests that policymakers should be aware that an unintended consequence of voucher discrimination is higher mortality in the opioid epidemic. As one consideration, stakeholders in Section 8 housing vouchers may wish to make the program and its requirements easier to administer and carry out to help prevent discrimination and its legalization from occurring.

We divide our paper into five sections. Section 2 covers relevant literature and background information. Section 3 delivers details on our data and econometric approach. Section 5 features a discussion of our results while section 6 concludes.

2. Relevant Literature and Background

According to the U.S. Department of Housing and Urban Development (2023), the Section 8 voucher program, also known as the Housing Choice program, is managed by the U.S. Department of Housing and Urban Development (HUD) and executed locally through regional Public Housing Authorities (PHAs). The initiative seeks to subsidize rent for low-income households. Part of the intent of Section 8 is to improve access to decent, safe, and sanitary housing in private markets. The PHA determines eligibility for a voucher. Generally, a family's income may not exceed 50% of the median income for the county or metropolitan area where the family uses its voucher.

Landlords who participate in accepting Section 8 vouchers must deal with PHAs and associated regulations, which can result in long delays for inspections and lease approvals, according to Turner (2003). Landlords also have concerns that voucher holders may cause significant property damage and can be relatively harder to evict than regular tenants. Bolton and Bravve (2012) and Turner (2000) argue that concerns with voucher holders may be racially motivated because most Section 8 recipients are black or Hispanic. Moreover, neighborhood opposition appears more prevalent in areas experiencing racial or ethnic transition. Some states and cities have attempted to address landlord hesitancy by prohibiting source of income discrimination. However, landlord cooperation is not federally required and neither Texas or Indiana banned source of income discrimination during the 2010-2018 period we consider as noted in Treat (2017) and Charlotte (2022). Given weak incentives to participate in the program and no federal restrictions against Section 8 voucher discrimination, discrimination occurs. The bias is especially concerning as the loss of Section 8 vouchers can make it more difficult to acquire housing, which increases housing instability.

Housing and its quality play a pivotal role in shaping individual health and overall well-being. Rauh et al. (2008) note that the location and quality of housing impacts the quality and presence of roads, schools, social networks, safety, and other physical and social infrastructure. People with poorer quality homes, or those who face housing uncertainty, suffer from less stability, safety, affordability, and worse neighborhoods, according to Taylor (2018). The effects of housing are particularly significant for children—Priorities (2023) states that 70% of voucher recipients are families with children. D'Alessandro and Appolloni (2020) also highlight that children with less stability have poorer self-related health, hypertension, and worse mental health outcomes. Moreover, racial disparities in housing stability are substantive. For instance, Acosta (2022) notes that 36% of black Americans with children report that their household is behind on rental payments, which is less than 17% of white Americans with children.

While housing impacts numerous health outcomes, it also affects deaths of despair. Venkataramani and Tsai (2020) define deaths of despair as deaths from opioid overdoses, suicide, and alcohol related mortality that contribute to rising midlife mortality rates. Much of the rise in deaths of despair comes from the ongoing opioid epidemic. Opioids are a class of drugs that treat severe pain. At peak, CDC (2023) and Schiller et al. (2023) estimate dispensing of 255 million opioid prescriptions in 2012. While prescribing opioids has declined since 2012, opioids remain a leading cause of accidental death in the United States, according to Schiller et al. (2023) and CDC (2023).

Specific drugs contribute to a significant portion of overdose deaths. Research by Jones et al. (2012) finds that 71-98% of all overdose deaths involve multiple substance use. Combinations of opioids, alcohol, and benzodiazepines play a crucial role in deaths of despair, resulting in potentially lethal interactions and substantial increases in mortality. Amplifying the risks, Jones et al. (2014) report that alcohol combined with opioids or benzodiazepines heightens central nervous depression and elevates the risk of overdose. Notably, alcohol plays a role in 18.5% of opioid related emergency department (ED) visits and 27.2% of benzodiazepine related ED visits in 2010, according to Jones et al. (2014).

Moreover, the combination of opioids and benzodiazepines poses a substantive risk and is the leading cause of multiple substance overdose fatalities. Benzodiazepines may contribute up to 80% of unintentional overdose deaths involving opioids, often leading to respiratory desperation such as hyperventilation, as Gudin et al. (2013) states. Of particular note, the perilous mix colloquially known as the "Houston cocktail," involves benzodiazepines, opioids, and muscle relaxants. The Houston cocktail's prevalence in Texas caught the attention of the National Institutes of Health (NIH), who identify it in their review of substance abuse trends in June 2014 (Maxwell, 2014).

Individuals combining benzodiazepines and opioids often seek to intensify the opioid high, sometimes resorting to 'doctor shopping' to maintain a steady supply of medication, which Gudin et al. (2013) communicate. Opportune behavior challenges healthcare professionals in monitoring and treating overdoses. Housing insecurity further compounds the complexity of treatment. Individuals grappling with housing insecurity may struggle to access consistent healthcare and treatment services. Notably, homelessness creates pressures that drive individuals to engage in drug abuse for the first time. For instance, Johnson and Chamberlain (2008) reveals that heightened stress and a pervasive sense of despair associated with homelessness contribute to drug use as a coping mechanism. The harsh environment of homelessness can foster a desire for more intense highs and drug cocktails. Johnson and Chamberlain (2008) also state that 66% of respondents in their study develop drug abuse problems after becoming homeless. The problem applies especially to young people facing housing insecurity.

Despite housing's relationship with health, scarce research exists on the connection between housing policy and deaths of despair. A. C. Bradford and W. D. Bradford (2020) study the connection between evictions and deaths of despair and report that more evictions cause increases in deaths of despair, particularly opioid deaths. Research such as Dow et al. (2019) focuses on the impact of economic policies on deaths of despair, where the authors report that economic policy can lessen deaths of despair. An additional study by Jou et al. (2020) examines the influence of household wealth on self-reported health scores. The authors reveal that individuals with greater wealth reported better health and highlight the role of housing in a gradual continuum, where higher-valued housing produces stronger health scores.

Fischer (2015) and Fischer et al. (2019) demonstrate the significant impact of Section 8 vouchers on reducing homelessness and housing instability. The findings reveal that vouchers result in an 80% reduction in homelessness and improvements in various aspects of well-being, including child health, development, and education (Fischer, 2015). Additionally, vouchers correspond with decreased poverty and healthcare costs (Fischer et al., 2019). Meanwhile, A. C. Bradford and W. D. Bradford (2020) highlight that interventions aimed at reducing housing instability correlate with overall health improvements. They emphasize the negative correlation between housing instability and access to health services, mental health, and quality of life.

3. Data and Econometric Approach

Data for our analysis comes from a collection of sources for the years 2010-2018 at the state level. Our dependent variables are the rates of poisoning from nine substance categories that represent "deaths of despair". The CDC National Center for Health Statistics National Vital Statistic System originally collects data on the nine causes of substance-related deaths and provides access through the CDC WONDER database. The CDC classifies the nine causes with the standard International Classification of Diseases, Tenth Revision (ICD-10) underlying cause of death codes using 20-underlying cause of death fields including overall opioid use (T40.0-T40.4, T40.6), prescription opioids (T40.2-T40.3), synthetic opioids (T40.4), heroin (T40.1), cocaine (T40.5), stimulants (T43.6), benzodiazepines (T42.4), antidepressants (T43,0-T43.2), and alcohol poisoning (X45, Y15). Due to confidentiality and privacy concerns, the CDC

WONDER database only provides public data in cases where a state has at least 10 deaths with a substance-related cause.[2]

Our dependent variables contain the number of deaths where a substance is one of multiple possible underlying causes of death. Some deaths include more than one substance (e.g. heroin and prescription opioids together) as possible causes. Therefore, we cannot add the number of deaths in our data to compute a total number of substance deaths because of double-counting. We calculate our nine mortality rate dependent variables by weighting state-level deaths by state population per 100,000 residents.

Because our empirical strategy closely follows the approach of Ashley C. Bradford and W. David Bradford (2020), we use independent variables that closely align with them. Our first independent variable is the state-level eviction rate per 100 households. We compute the eviction rate by dividing the number of eviction judgements by the number of renter-occupied houses and multiplying by 100. Data for evictions and renter-occupied houses comes from the Eviction Lab at Princeton University. The Eviction Lab extracts data for 46 states and the District of Columbia from partnerships with record-collecting companies, text parsing, web scraping, and court records. The most recent year of available data on evictions is 2018, which is why our sample ends in 2018.

The next set of independent variables that we employ serve as demographic controls. The controls include the state population, percent population that is male, percent population aged 18-64 years, percent population that is white, state income per capita, poverty rate, percent

[2] Unlike Bradford and Bradford (2020), we conduct our study at the state level instead of the county level. A county-level analysis using public data would result in a substantial amount of missing observations because mortality data is only publicly available in cases where a county has at least 10 deaths with a substance-related cause.

population with no health insurance, unemployment rate, and the active physician rate. We collect data for these measures from the U.S. Department of Health & Human Services' 2011-2021 Area Health Resources Files. The earliest year that our demographic controls have data available is 2010, which is why our sample begins in 2010. As Ashley C. Bradford and W. David Bradford (2020) note and Buchmueller and Carey (2018) attest, the existence of a must-access prescription drug monitoring program (PDMP) system in a state can have a statistically significant effect on opioid use. Therefore, our last independent variable is PDMP, where a 1 indicates the presence of a must-access PDMP system in a state and a 0 indicates a lack thereof. Data for PDMP comes from the Prescription Drug Abuse Policy System at Temple University.

Table 1 displays descriptive statistics for our sample. Average overall opioid mortality in the sample is 11.811 deaths per 100,000 people in the state. Each individual substance-related mortality rate average ranges from 1.817 to 5.909 deaths per 100,000 people in the state. The eviction rate average presents at 0.808 eviction judgments per 100 renting households in the state. Demographic controls show the average state population is 8.204 million, 49.329 percent male, 60.384 percent aged 18-64 years, and 67.518 percent white. The average state income per capita is $48,881, poverty rate is 14.377 percent, uninsured rate is 10.999 percent, unemployment rate, is 6.214, and active physicians rate is 2.913 per 1,000 people in the state. Approximately 32.1 percent of the sample consists of observation from states with a must-access PDMP.

To evaluate the relationship between housing voucher policy and deaths of despair, we apply a two-way fixed effects differences-in-differences model. We also adopt specific determinants to follow the approach of Ashley C. Bradford and W. David Bradford (2020). The following specification shows our estimating equation:

$$Y_{st} = \alpha + \beta\, VDA_{st} + \delta X_{st} + s_s + d_t + \varepsilon_{st} \qquad (1)$$

We let the vector $\boldsymbol{Y_{st}}$ denote the dependent variables of substance-related mortality rates for each state *s* in year *t*. Our greatest measure of interest, $\boldsymbol{VDA_{st}}$, is a binary measure equal to 1 for years that a state has a voucher discrimination allowed policy in place, which is years 2016-2018 in the states of Texas and Indiana in our study. The vector $\boldsymbol{X_{st}}$includes our controls such as the eviction rate, state population, percent population that is male, percent population aged 18-64 years, percent population that is white, state income per capita, poverty rate, percent population with no health insurance, unemployment rate, active physicians rate, and state has must-access PDMP. We employ $\boldsymbol{s_s}$ and $\boldsymbol{d_t}$ as state and year dummies, respectively. The idiosyncratic error term is $\boldsymbol{\varepsilon_{st}}$. We cluster standard errors by state because errors are likely to be dependent within states over time.

4. Results

Our difference-in-differences results appear in Table 2. The table contains robust standard errors that we cluster by state. Each column of the table includes a separate regression for a separate dependent variable. The first through ninth columns display results for substance-related mortality for all opioids, prescription opioids, synthetic opioids, heroin, cocaine, stimulants, benzodiazepines, antidepressants, and alcohol poisoning, respectively.

Table 2 shows our core specification results. A VDA policy in Texas and Indiana results in no significant change in substance-related mortality for all opioids, synthetic opioids, heroin, cocaine, and stimulants. According to the second column of the table, applying a VDA policy change leads to an increase of 2.438 deaths from prescription opioids per 100,000 people. In the seventh column, a VDA policy change correlates with 1.872 additional deaths from benzodiazepines per 100,000 people. The eighth column indicates that a VDA policy change associates with 1.063 additional deaths from antidepressants per 100,000 people. The ninth column shows that a VDA policy change correlates with 0.976 additional deaths from alcohol poisoning per 100,000 people. As a robustness check, we exclude our control variables and obtain results with positive coefficients for prescription opioids, benzodiazepines, antidepressants, and alcohol poisoning that are statistically insignificant in Table 3. For another robustness check, in Table 4, we exclude the years 2015 and 2016 from our analysis that straddle our treatment date. The table shows results that are consistent with our findings in Table 2. For our final robustness check, we exclude the eviction rate to increase our sample size in Table 5. We find results that are consistent with Table 2.

We display a regression-based event study analysis in Figure 2 for all of our dependent variables. The panels in the figure each show a different dependent variable. Panel a displays all opioids, panel b reveals prescription opioids, panel c illustrates synthetic opioids, panel d shows heroin, panel e contains cocaine, panel f reveals stimulants, panel g displays benzodiazepines, panel h shows antidepressants, and panel i contains alcohol poisoning. Each model has a set of policy leads, or event times that align with six, five, four, three, or two years before treatment to aid our evaluation of the common trends assumption. The models also contain a treatment measure that aligns with the first year Texas and Indiana applied VDA and a set of policy lags, or event times that go with two or one years after treatment. The policy lags help us consider the impact of a VDA policy over its first few years. We let event time -1, which is the year prior to the VDA policy becoming effective, be the omitted category.

Panels a, c, d, e, f, g, h, and i show no impact of VDA on substance-related mortality for all opioids, synthetic opioids, heroin, cocaine, stimulants, benzodiazepines, antidepressants, and alcohol poisoning. Panel b shows some evidence that a VDA policy leads to an increase in prescription opioids a year after the policy begins and that the effect continues in a similar size in the second year after implementation. Overall, the regression-based event study results appear to support a causal interpretation for the prescription opioids estimates in Table 2.

Using an approach similar to Hair et al. (2021), we evaluate concerns about inference in difference-in-differences with few treated groups, which Wooldridge (2006) and Donald and Lang (2007) describe, by contrasting our results in Table 2 with additional difference-in-differences estimates that assign placebo status to each pair of states in our sample that do not have a voucher discrimination policy. In essence, we repeat our difference-in-differences estimates for each potential pair of control states to consider the 703 placebo estimates we acquire as the sampling distribution for our parameter. We display our placebo results in Figure 4. We employ a solid line treatment effect in each panel in the figure and use dashed lines for the 5^{th} and 95^{th} percentiles of the placebo distribution. The treatment effect falls within the placebo distribution for all opioids, synthetic opioids, heroin, cocaine, stimulants, benzodiazepines, and alcohol poisoning. Simultaneously, the treatment effect falls just outside the 95^{th} percentile boundary for prescription opioids and outside the distribution boundaries for antidepressants. The results indicate that we can reject the null hypothesis that the effect of a VDA policy on prescription opioid and antidepressant related mortality is zero.

Our overall results provide evidence of an increase in prescription opioid deaths in response to a VDA policy. In light of our finding, we argue that it is essential to reconsider and revaluate housing policy. Voucher discrimination weakens an existing program designed to reduce housing instability and enhance housing accessibility. Without a viable alternative program, our evidence shows that source of income discrimination worsens the opioid crisis by increasing prescription opioid-related deaths. As a policy alternative, we argue that policymakers could modify the current Section 8 program to address concerns from landlords relating to administration and implementation. For example, Turner (2003) notes that long delays for inspections and lease approvals can occur with Section 8. Reasonable streamlining of the inspection and lease approval process could enhance revenues for landlords and improve their participation in the Section 8 program. Policymakers should exercise caution when adjusting the program to ensure it still upholds principles of fairness and non-discrimination. Preventing fatal unintended consequences when addressing the interconnected challenges of housing insecurity and substance-related mortality requires considerable care and discretion.

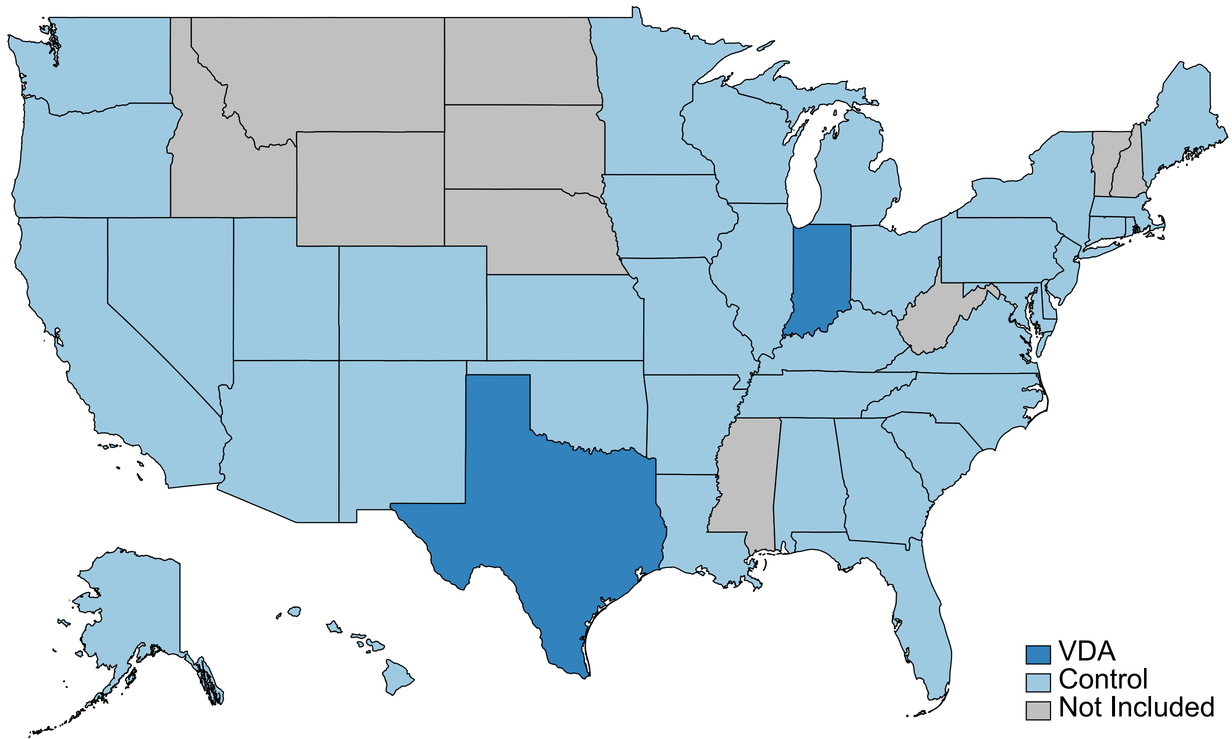
5. Conclusions

The United States faces ongoing challenges with housing. The Section 8 voucher program is the largest federal initiative to address housing insecurity and promote economic mobility for the disadvantaged. However, recent laws in Texas and Indiana legalize source of income discrimination against Section 8 vouchers. Using a difference-in-differences approach, our empirical results show that this discrimination results in an unintended consequence of higher mortality from prescription opioids.

Our study has limitations. We conduct our study at the state level using publicly available data due to restrictions that make a county analysis difficult. Therefore, our analysis relies on a relatively few number of treated observations. A state-level analysis also precludes exploration of whether empirical results vary by urban, suburban, or rural setting Finally, our study only considers the U.S. and may not generalize to other countries.

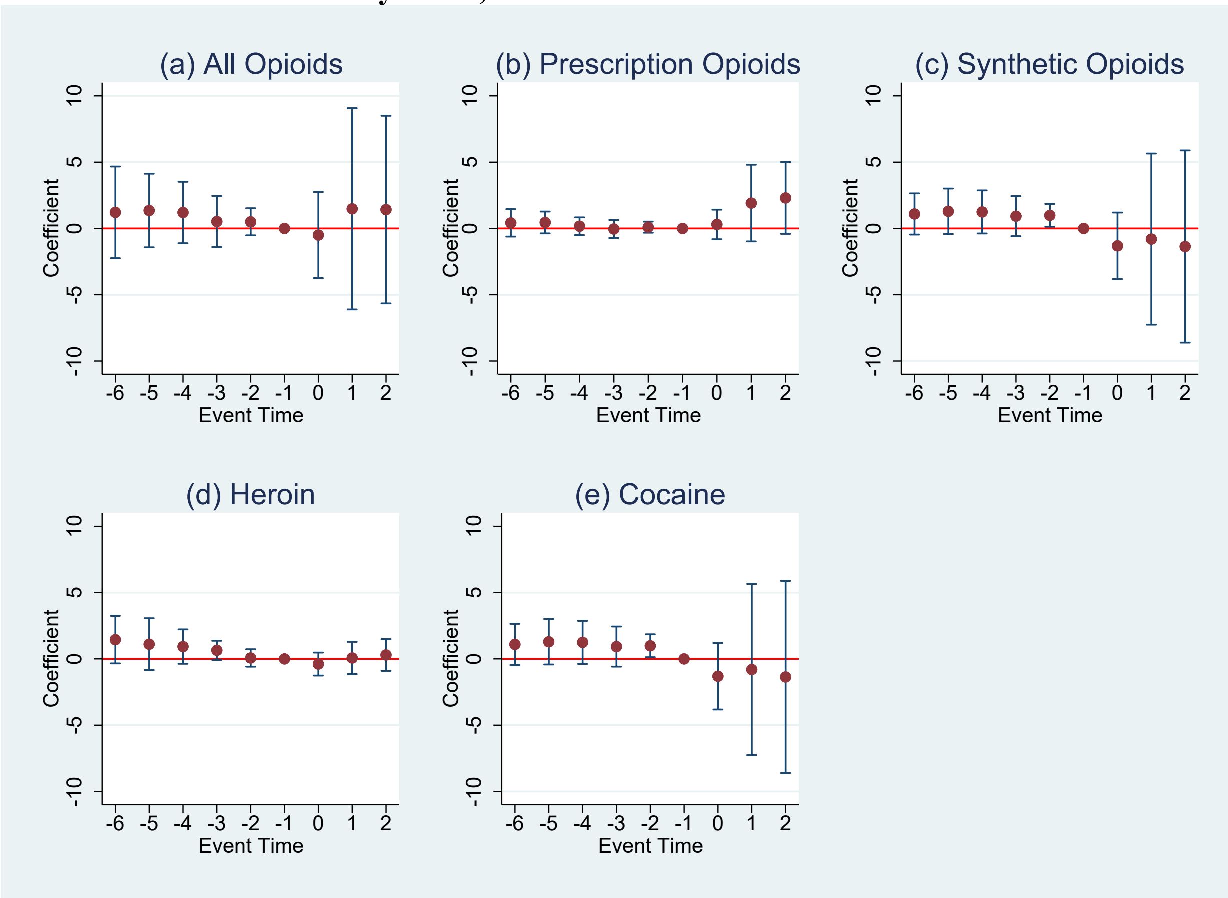
Future research should undertake the lengthy and expensive process of obtaining access to restricted data at the county level that allows examination at a more granular level. A local approach could further elucidate causality and refine policy recommendations tailored to the specific needs of distinct communities. If additional data on evictions becomes available beyond 2018, future work should include additional years to evaluate a longer post-treatment period.

Figure 1: States with Voucher Discrimination Allowed (VDA), 2010-2018



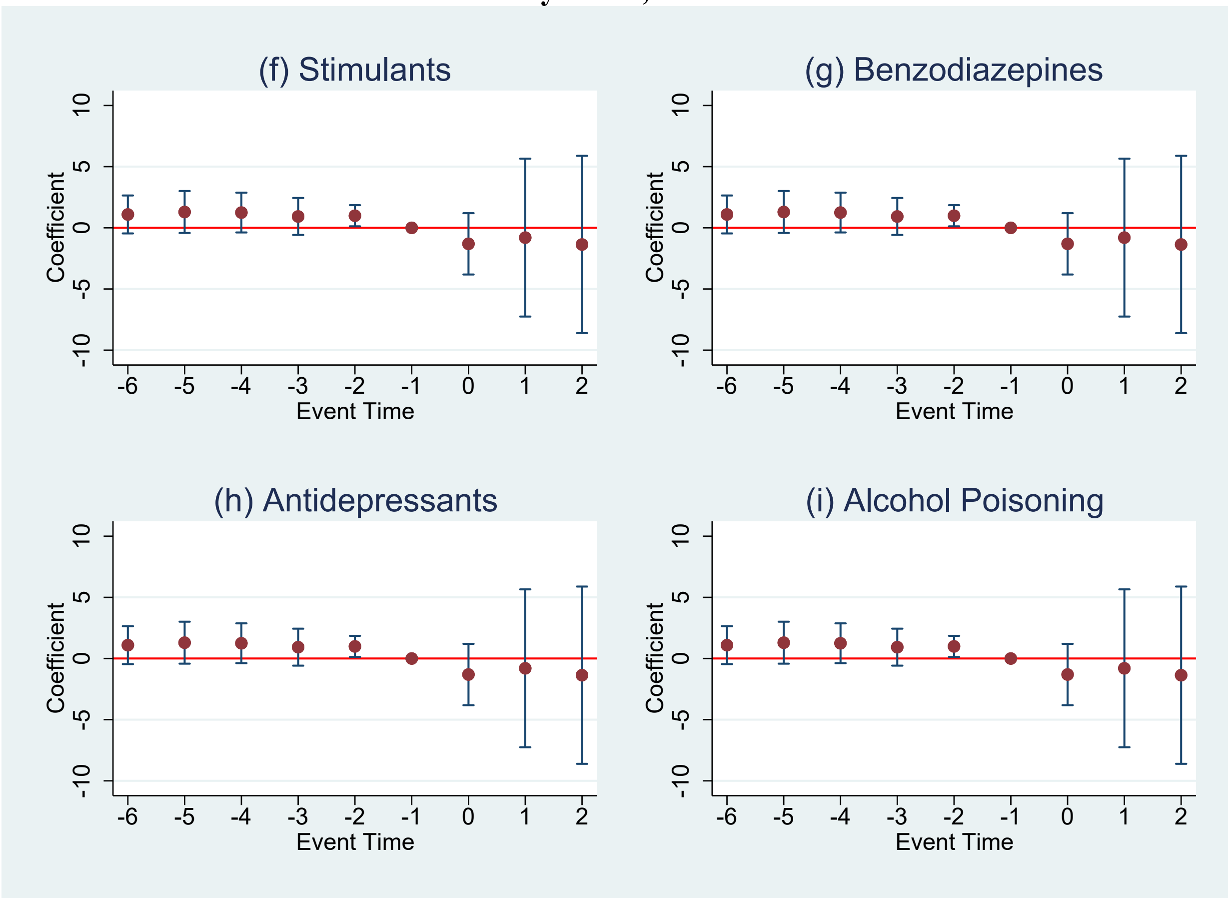
Notes: The map displays states that we include in the control and treatment groups for our analysis. We exclude states that do not have eviction data or publicly available mortality data during our study period (Idaho, Montana, Wyoming, North Dakota, South Dakota, Nebraska, Mississippi, West Virginia, Vermont, New Hampshire, and the District of Columbia).

Figure 2: Event Study Estimates of the Effects of Voucher Discrimination Allowed on Substance-Related Mortality Rates, 2010-2018



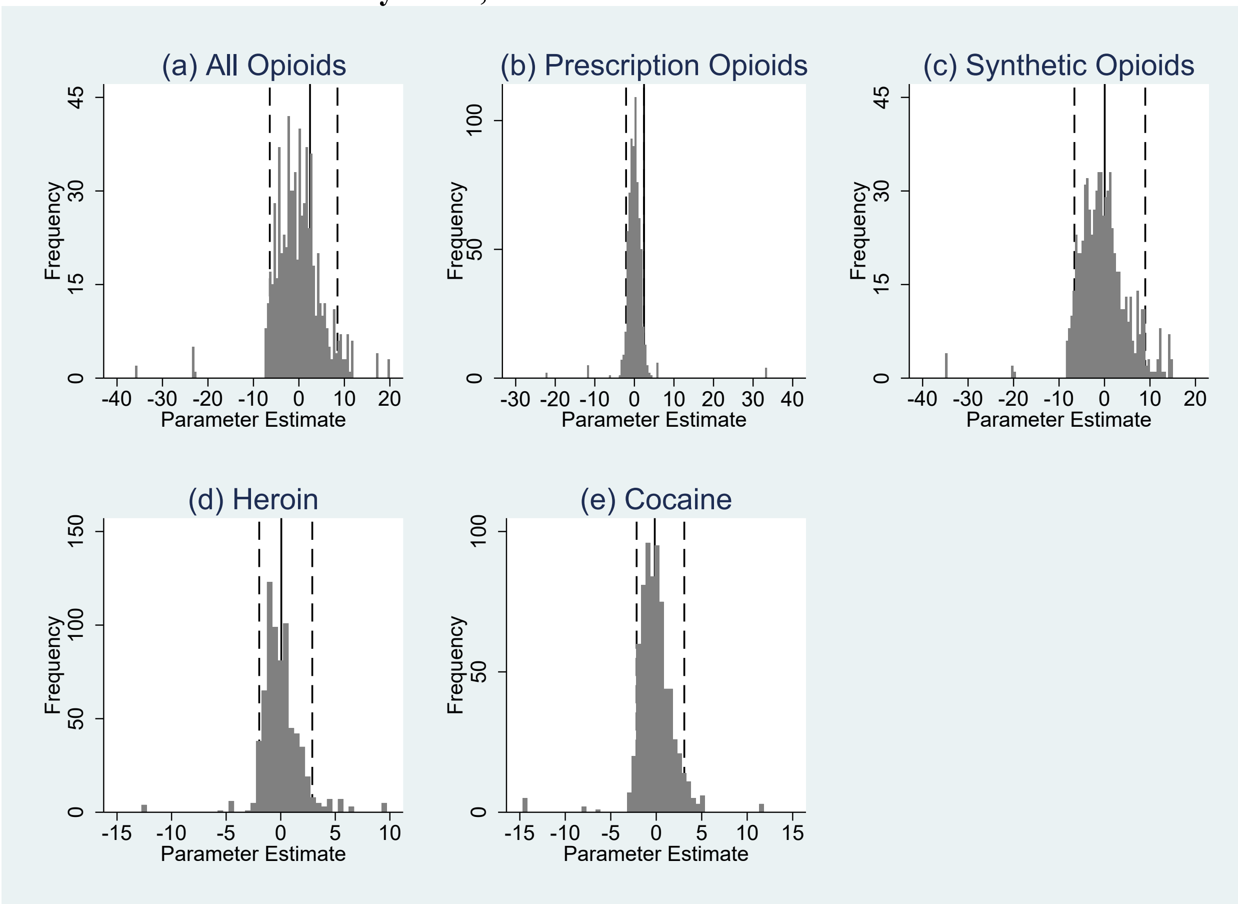
Notes: The figure displays results from a regression-based study analysis. We use vertical bars to show the 95% confidence range around each estimate. We set the year before the policy goes into effect (i.e. event time -1) as the omitted category. The outcomes of interest are the substance-related mortality rates for all opioids, prescription opioids, synthetic opioids, heroin, cocaine, stimulants, benzodiazepines, antidepressants, and alcohol poisoning. We separately control for state-specific linear cohort trends and present our results in Figure 3.

Figure 2 (continued): Event Study Estimates of the Effects of Voucher Discrimination Allowed on Substance-Related Mortality Rates, 2010-2018



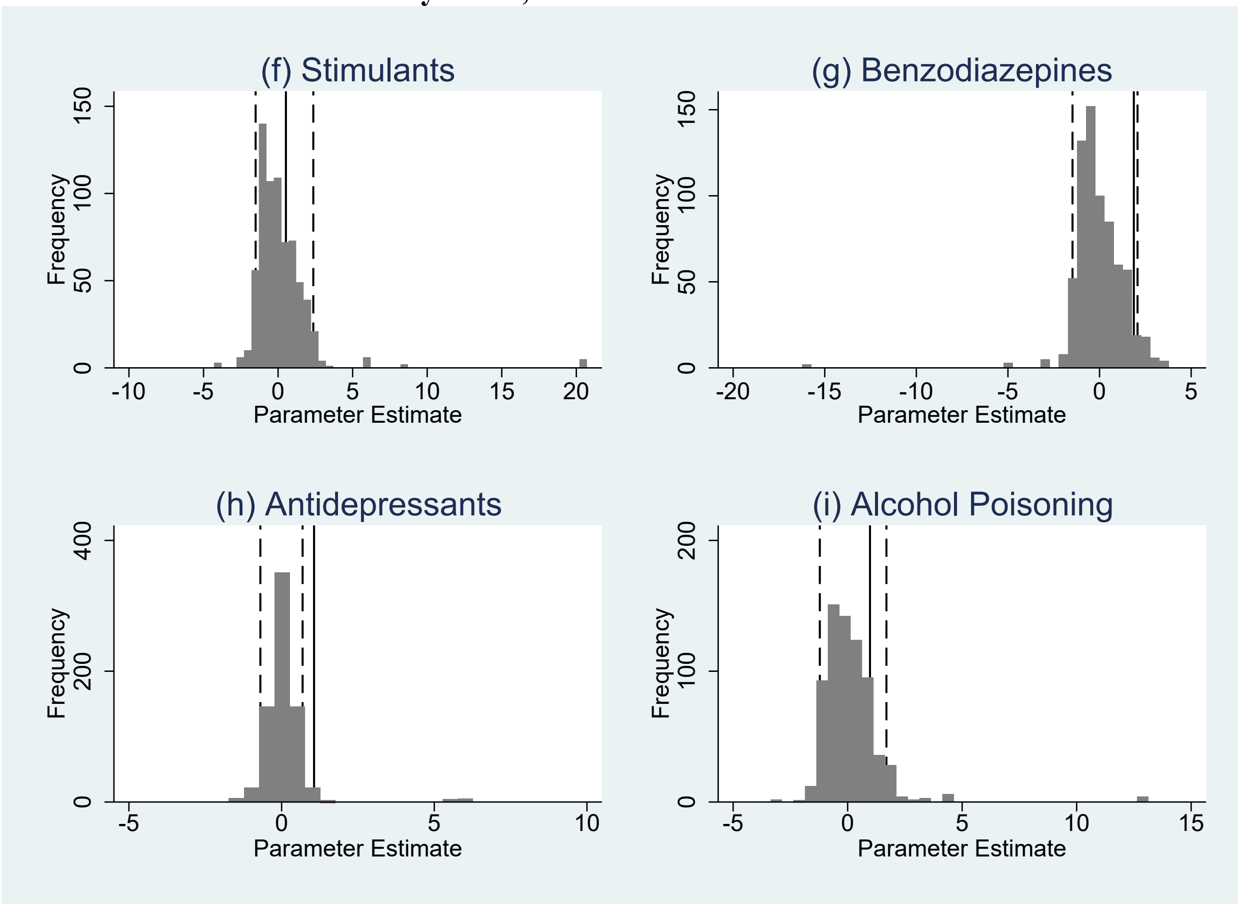
Notes: The figure displays results from a regression-based study analysis. We use vertical bars to show the 95% confidence range around each estimate. We set the year before the policy goes into effect (i.e. event time -1) as the omitted category. The outcomes of interest are the substance-related mortality rates for all opioids, prescription opioids, synthetic opioids, heroin, cocaine, stimulants, benzodiazepines, antidepressants, and alcohol poisoning. We separately control for state-specific linear cohort trends and present our results in Figure 3.

Figure 3: Placebo Estimates of the Effects of Voucher Discrimination Allowed on Substance-Related Mortality Rates, 2010-2018



Notes: The histograms show the results of our falsification tests. We compare our voucher discrimination allowed treatment effect coefficients for Texas and Indiana to 703 additional coefficient estimates where we designate placebo treatment status to 2 of the 38 states in our control group that do not explicitly allow voucher discrimination. We mark the 95th and 5th percentile critical values for the placebo coefficients using dashed lines. The solid lines denote our coefficient estimates for Texas and Indiana. The outcomes of interest are the substance-related mortality rates for all opioids, prescription opioids, synthetic opioids, heroin, cocaine, stimulants, benzodiazepines, antidepressants, and alcohol poisoning.

Figure 3 (continued): Placebo Estimates of the Effects of Voucher Discrimination Allowed on Substance-Related Mortality Rates, 2010-2018



Notes: The histograms show the results of our falsification tests. We compare our voucher discrimination allowed treatment effect coefficients for Texas and Indiana to 703 additional coefficient estimates where we designate placebo treatment status to 2 of the 38 states in our control group that do not explicitly allow voucher discrimination. We mark the 95th and 5th percentile critical values for the placebo coefficients using dashed lines. The solid lines denote our coefficient estimates for Texas and Indiana. The outcomes of interest are the substance-related mortality rates for all opioids, prescription opioids, synthetic opioids, heroin, cocaine, stimulants, benzodiazepines, antidepressants, and alcohol poisoning.

Table 1: Descriptive Statistics, 2010-2018

	Mean	Standard Deviation
Mortality Rates		
Opioid Mortality Rate	11.811	6.370
Prescription Opioid Mortality Rate	5.909	2.930
Synthetic Opioid Mortality Rate	4.054	5.667
Heroin Mortality Rate	3.519	2.756
Cocaine Mortaliity Rate	2.546	2.306
Stimulant Mortality Rate	2.578	2.540
Benzodiazepine Mortality Rate	3.227	2.129
Antidepressant Mortality Rate	1.817	1.150
Alcohol Poisoning Mortality Rate	4.051	1.866
Independent Variables		
Eviction Rate	0.808	1.127
Total State Population (in 1,000,000's)	8.204	7.461
Percent Population that is Male	49.329	0.616
Percent Population Aged 18-64	60.384	1.269
Percent Population White Only	67.518	13.741
State Income Per Capita (in $1,000's)	48.881	7.482
Poverty Rate	14.377	2.861
Percent of Population with No Health Insurance	10.999	4.526
Unemployment Rate	6.214	2.237
Active Physicians per 1,000 Persons in State	2.913	0.599
State has Must-Access PDMP	0.321	0.468

Notes: Data on all states with measured eviction rates and mortality rates from 2010 to 2018. Each substance-related mortality rate is deaths involving each substance per 100,000 people in the state. Eviction rate is number of judgements per 100 renting households. PDMP is an electronic prescription drug monitoring program.

Table 2: Difference-in-Differences Results for Substance-Related Mortality Rates, 2010-2018

Variable	All Opioids	Prescription Opioids	Synthetic Opioids	Heroin	Cocaine	Stimulants	Benzodia-zepines	Antidepre-ssants	Alcohol Poisoning
VDA	2.444	2.438***	0.051	0.052	-0.161	0.526	1.872***	1.063***	0.976**
	(2.071)	(0.813)	(1.489)	(0.523)	(0.596)	(0.723)	(0.650)	(0.346)	(0.371)
Observations	277	277	277	277	277	277	277	277	277
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered by state robust standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%
Control Variables include: Eviction Rate, State Population, Percent Population that is Male, Percent Population Aged 18-64 Years, Percent Population that is White, State Income Per Capita, Poverty Rate, Percent Population with no Health Insurance, Unemployment Rate, Active Physicians Rate, State has must-access Prescription Drug Monitoring Program.
Each substance-related mortality rate is deaths involving each substance per 100,000 people.

Table 3: Difference-in-Differences Results for Substance-Related Mortality Rates with Control Variables Dropped, 2010-2018

Variable	All Opioids	Prescription Opioids	Synthetic Opioids	Heroin	Cocaine	Stimulants	Benzodia-zepines	Antidepre-ssants	Alcohol Poisoning
VDA	0.003	1.322	-2.080	-0.705	-0.349	-0.070	0.740	0.734	0.180
	(3.659)	(1.153)	(2.997)	(0.846)	(0.737)	(0.992)	(0.986)	(0.588)	(0.757)
Observations	277	277	277	277	277	277	277	277	277
Control Variables	No	No	No	No	No	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered by state robust standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%
Control Variables include: Eviction Rate, State Population, Percent Population that is Male, Percent Population Aged 18-64 Years, Percent Population that is White, State Income Per Capita, Poverty Rate, Percent Population with no Health Insurance, Unemployment Rate, Active Physicians Rate, State has must-access Prescription Drug Monitoring Program.
Each substance-related mortality rate is deaths involving each substance per 100,000 people.

Table 4: Difference-in-Differences Results for Substance-Related Mortality Rates with Treatment-Straddling Years Dropped, 2010-2018

Variable	All Opioids	Prescription Opioids	Synthetic Opioids	Heroin	Cocaine	Stimulants	Benzodia-zepines	Antidepre-ssants	Alcohol Poisoning
VDA	3.124	3.273**	0.161	-0.071	-0.193	0.836	2.475**	1.337**	1.009**
	(3.118)	(1.231)	(2.364)	(0.662)	(0.922)	(0.899)	(1.015)	(0.553)	(0.475)
Observations	208	208	208	208	208	208	208	208	208
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Years 2015 and 2016 dropped.

Clustered by state robust standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%
Control Variables include: Eviction Rate, State Population, Percent Population that is Male, Percent Population Aged 18-64 Years, Percent Population that is White, State Income Per Capita, Poverty Rate, Percent Population with no Health Insurance, Unemployment Rate, Active Physicians Rate, State has must-access Prescription Drug Monitoring Program.
Each substance-related mortality rate is deaths involving each substance per 100,000 people.

Table 5: Difference-in-Differences Results for Substance-Related Mortality Rates with Eviction Rate Dropped, 2010-2018

Variable	All Opioids	Prescription Opioids	Synthetic Opioids	Heroin	Cocaine	Stimulants	Benzodiazepines	Antidepressants	Alcohol Poisoning
VDA	2.428	2.718**	-0.060	0.175	-0.028	0.315	1.715**	1.328***	0.817**
	(2.165)	(1.035)	(1.428)	(0.494)	(0.493)	(0.831)	(0.669)	(0.420)	(0.392)
Observations	369	369	369	369	369	369	369	369	369
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Eviction Rate Omitted

Clustered by state robust standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%
Control Variables include: State Population, Percent Population that is Male, Percent Population Aged 18-64 Years, Percent Population that is White, State Income Per Capita, Poverty Rate, Percent Population with no Health Insurance, Unemployment Rate, Active Physicians Rate.
Each substance-related mortality rate is deaths involving each substance per 100,000 people.

References

Uncategorized References

Acosta, S. (2022). *Stable Housing Is Foundational to Children's Well-Being*. Center on Budget and Policy Priorities. Retrieved 11/04/2023 from https://www.cbpp.org/blog/stable-housing-is-foundational-to-childrens-well-being

Allik, M., Brown, D., Dundas, R., & Leyland, A. H. (2020). Deaths of despair: cause-specific mortality and socioeconomic inequalities in cause-specific mortality among young men in Scotland. *International Journal for Equity in Health*, *19*(1). https://doi.org/10.1186/s12939-020-01329-7

Bolton, M., & Bravve, E. (2012). Who Lives in Federally Assisted Housing? *Housing Spotlight*, *2*(2), 1-6. https://nlihc.org/sites/default/files/HousingSpotlight2-2.pdf

Bradford, A. C., & Bradford, W. D. (2020). The effect of evictions on accidental drug and alcohol mortality. *Health services research*, *55*(1), 9-17.

Bradford, A. C., & Bradford, W. D. (2020). The effect of evictions on accidental drug and alcohol mortality. *Health Serv Res*, *55*(1), 9-17. https://doi.org/10.1111/1475-6773.13256

Buchmueller, T. C., & Carey, C. (2018). The effect of prescription drug monitoring programs on opioid utilization in Medicare. *American Economic Journal: Economic Policy*, *10*(1), 77-112.

CDC. (2023). *U.S. Opioid Dispensing Rate Maps*. CDC. Retrieved 11/7/2023 from https://www.cdc.gov/drugoverdose/rxrate-maps/index.html

Charlotte, W. (2022). *Charlotte City Council bans 'source of income discrimination' for renters*. WCNC Charlotte. Retrieved 08/12/2023 from https://www.wcnc.com/article/money/markets/real-estate/affordable-housing-crisis/charlotte-affordable-housing-rental-vouchers-section-8-source-of-income-discrimination/275-35a5dc27-9025-46b7-8327-93cc15196320

D'Alessandro, D., & Appolloni, L. (2020). Housing and health: An overview. *Annali di Igiene*, *32*(5), 17-26.

Donald, S. G., & Lang, K. (2007). Inference with difference-in-differences and other panel data. *The review of Economics and Statistics*, *89*(2), 221-233.

Dow, W. H., Godøy, A., Lowenstein, C. A., & Reich, M. (2019). Can Economic Policies Reduce Deaths of Despair?

Fischer, W. (2015). Research shows housing vouchers reduce hardship and provide platform for long-term gains among children. *Center on Budget and Policy Priorities*.

Fischer, W., Rice, D., & Mazzara, A. (2019). *Research Shows Rental Assistance Reduces Hardship and Provides Platform to Expand Opportunity for Low-Income Families*. Center on Budget and Policy Priorities. Retrieved 09/08/2023 from https://www.cbpp.org/research/housing/research-shows-rental-assistance-reduces-hardship-and-provides-platform-to-expand

Gudin, J. A., Mogali, S., Jones, J. D., & Comer, S. D. (2013). Risks, management, and monitoring of combination opioid, benzodiazepines, and/or alcohol use. *Postgraduate medicine*, *125*(4), 115-130.

Hair, N. L., Gruber, A., & Urban, C. (2021). Personal belief exemptions for school-entry vaccinations, vaccination rates, and academic achievement. *Journal of health economics*, *78*, 102464.

Johnson, G., & Chamberlain, C. (2008). Homelessness and substance abuse: Which comes first? *Australian Social Work*, *61*(4), 342-356.

Jones, C. M., Paulozzi, L. J., & Mack, K. A. (2014). Alcohol involvement in opioid pain reliever and benzodiazepine drug abuse–related emergency department visits and drug-related deaths—United States, 2010. *Morbidity and Mortality Weekly Report*, *63*(40), 881.

Jones, J. D., Mogali, S., & Comer, S. D. (2012). Polydrug abuse: a review of opioid and benzodiazepine combination use. *Drug and Alcohol Dependence*, *125*(1-2), 8-18.

Jou, A., Mas, N., & Vergara-Alert, C. (2020). Housing wealth, health and deaths of despair. *The Journal of Real Estate Finance and Economics*, 1-34.

Maxwell, J. C. (2014). *Substance Abuse Trends in Texas: June 2014*. NIH. Retrieved 11/24/2023 from

Priorities, C. o. B. a. P. (2023). *United States Housing Choice Vouchers Fact Sheet*. Retrieved 11/7/2023 from https://www.cbpp.org/sites/default/files/atoms/files/3-10-14hous-factsheets_us.pdf

Rauh, V. A., Landrigan, P. J., & Claudio, L. (2008). Housing and health: intersection of poverty and environmental exposures. *Annals of the New York Academy of Sciences*, *1136*(1), 276-288.

Schiller, E. Y., Goyal, A., & Mechanic, O. J. (2023). Opioid Overdose. In *StatPearls*. StatPearls Publishing

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Taylor, L. A. (2018). Housing And Health: An Overview Of The Literature. *HealthAffairs*(Health Policy Breif). https://doi.org/10.1377/hpb20180313.396577

Treat, J. (2017). Establishing a More Effective SAFMR System: The Costs and Benefits of HUD's 2016 Small Area Fair Market Rent Rule. *U. Mich. JL Reform*, *51*, 643.

Turner, M. A. (2000). Section 8 mobility and neighborhood health.

Turner, M. A. (2003). Strengths and weaknesses of the Housing Voucher Program.

U.S. Department of Housing and Urban Development. (2023). *Housing Choice Vouchers Fact Sheet*. U.S. Department of Housing and Urban Development. Retrieved 08/12/2023 from https://www.hud.gov/topics/housing_choice_voucher_program_section_8

Venkataramani, A. S., & Tsai, A. C. (2020). Housing, housing policy, and deaths of despair. *Health services research*, *55*(1), 5.

Walters, E., & Satija, N. (2018). *Section 8 vouchers are supposed to help the poor reach better neighborhoods. Texas law gets in the way.* The Texas Tribune. Retrieved 09/07/2023 from https://www.texastribune.org/2018/11/19/texas-affordable-housing-vouchers-assistance-blocked/

Wooldridge, J. M. (2006). Cluster-sample methods in applied econometrics: an extended analysis. *Michigan State University mimeo*.