The *Marshalsea* Underwater: Natural Disasters and Legal Debt Defaults*†

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October, 2024

Abstract

National estimates suggest that a large fraction of the low-level traffic violation fines and fees are unpaid before their due date. At the same time, natural disasters are increasing in frequency, intensity, and duration with ever-expanding destruction potential. Using exposure to natural disasters, I examine if defendants are more likely to default on their legal financial obligations. Constructing a novel dataset of defendants with traffic citations in Oklahoma, I find that natural disaster exposure increases the likelihood that the defendant defaults on their legal debt. The effect appears immediately after the disaster exposure and persists for more than 100 days following the natural disaster. I do not uncover significant heterogeneity in legal debt default likelihood by defendant characteristics, potentially due to a lack of statistical power. These estimates suggest that interventions designed to provide reprieve for legal debt repayment may alleviate defendants getting entangled in the criminal justice system, a phenomenon that is extremely costly economically and socially.

JEL Classifications: K40, Q54, R49

Keywords: Natural disasters, legal debt, criminal justice system

*I am indebted to Garth Heutel for his support and continued guidance throughout this project. I am grateful for many helpful comments and suggestions by audiences at various conferences, seminars, and workshops. Any remaining errors are my own. Corresponding Author: Singh (email: tpratapsingh1@student.gsu.edu)

†*Marshalsea* was a prison in London operating between 14th and 19th centuries that was notorious for housing poorest of London's debtors. The prison gained widespread popularity through the writings of Charles Dickens, whose father was incarcerated in the prison for failing to service a debt to a baker.

1 Introduction

According to recent estimates, approximately 37% of Americans indicate an inability to cover an emergency $400 expense using liquid savings (Board of Governors of the Federal Reserve System, 2023). The fraction of illiquid respondents may increase if the nominal value of negative unexpected shock is larger. One such shock is fines for traffic violations. For instance, the minimum speeding fine in Oklahoma is $172. If unpaid, the original fine not only increases in nominal value but may result in suspension of driving privileges and even incarceration. Unpaid traffic fines result in instances of failure to pay (FTP) or failure to appear (FTA).

FTP or FTA instances are pervasive for lower-level cases. In New York City, for instance, 47% of defendants fail to appear for their hearings (Fishbane et al., 2020). In my context, the fraction of traffic citations that result in an FTP or FTA instance has steadily increased over the years with a downward trend in more recent years. At the same time, the legal debt's nominal value has also followed a similar temporal pattern (see Figure A1).

Existing work highlights the detrimental consequences of traffic fines on household finances such as decline in credit scores, lower borrowing limits, and increased unemployment (Mello, 2023). We, however, lack knowledge about the determinants of FTP or FTA. In this paper, I aim to fill this gap. I examine how exposures to natural disasters affect the FTP or FTA likelihood. Due to climate change, natural disasters are projected to become more frequent and intense. The existing works on the local economic impacts of natural disasters provide conflicting empirical evidence.[1] While some studies document positive impacts of natural disaster exposure both in the short- and long-run, others find negative effects over the same time horizon. Nonetheless, Hsiang and Jina (2014) document that in the short-run, three out of four potential paths of long-run adjustment lead to negative effects on the local economy. I build on this framework and evaluate if the worsened economic prospects in the short-run also affect the ability of the affected residents to pay fines and penalties owed to the court.

I construct novel data on traffic citations by scraping the Oklahoma State Court Network (OSCN). These data provide extremely detailed information related to traffic citation like the date of offense, the statute violated, the amount of fines owed, the location of the offense, and information on the vehicle of the defendant. From the traffic citation data, I also obtain information on the defendant's residence ZIP Code and birth date. I complement traffic citation data with data on natural disasters that I derive from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. To uncover potential heterogeneities and for mechanism analysis, I also use data from the US Census Bureau's decadal census and the five-year American Community Survey (ACS).

[1] See Tran and Wilson (2023) and the references therein. See Botzen et al. (2019) for a review of economic studies on the impact of natural disasters.

The main empirical strategy used to uncover the causal effect of natural disaster exposure on FTP or FTA instances on a traffic citation is regression discontinuity design (RDD). Leveraging information on the start of a natural disaster and the traffic citation's initial appearance date, I classify the defendant as exposed to natural disaster if their residence ZIP Code experiences a natural disaster before the initial appearance date on the traffic citation. Therefore, I exploit a sharp discontinuity in the natural disaster exposure emanating from the initial appearance date of each traffic citation. The initial appearance date for a traffic citation is determined based on the existing dockets caseload of the courts. Therefore, it is unlikely that the initial appearance date is subject to manipulation by the defendant. Indeed, I establish through multiple empirical checks that there is no evidence of manipulation of the initial appearance date and that the observable characteristics of the defendants are balanced across the discontinuity (Cattaneo et al., 2024).

Natural disaster exposure increases the likelihood of an FTP or FTA instance on a traffic citation by 5.9 percentage points. This effect is not only highly statistically significant but also quantitatively large. As a proportion of the pre-natural disaster mean, the increase in FTP or FTA instance likelihood is 26.34%. This conclusion is robust to a host of empirical checks suggested for the continuity based approach in an RDD framework (Cattaneo et al., 2020b). RDD estimates suggest that the increased likelihood of FTP or FTA instances persists for more than 100 days following the natural disaster onset.

The increase in the likelihood of an FTP or FTA instance is more pronounced for defendants who are residents of ZIP codes with below median urbanization. The likelihood of FTP or FTA instances does not differ across other subpopulations. Given a restricted sample, this could potentially be due to low statistical power.

With this work, I contribute to multiple strands of literature. To the literature examining the determinants of FTA or FTP instances, I contribute by highlighting the role of natural disasters as a potential driver of defaults on LFOs. The existing literature suggests roles of limited transportation options (Brough et al., 2022; Mahoney et al., 2001), cognitive overload (Chohlas-Wood et al., 2024; Emanuel and Ho, 2024; Kofman, 2019), and non-salience of court appearance date information (Fishbane et al., 2020). I also expand the existing literature on the consequences of natural disaster exposure by demonstrating that natural disasters may be leading to involvement in the criminal justice system by increasing the likelihood of the defendant's FTP or FTA instance on traffic citations (Botzen et al., 2019). Finally, by showing a relatively more pronounced effect on vulnerable subpopulations exposed to natural disasters, I contribute to an extensive literature on socioeconomic disparities in the criminal justice system (Agan, 2024; Harris et al., 2010; Harris, 2016).

The rest of the paper proceeds as follows. Section 2 provides a brief background of the context. Section 3 and Section 4 present data and empirical strategy employed to uncover causal effects of natural disaster exposure on FTP or FTA instances on traffic citations. Results are reported in Section

5. Section 6 discusses and concludes.

2 Background

In this section, I briefly provide background on legal debt and natural disasters. I begin by providing an overview of the extent of legal debt in the United States of America (US) and how it is distributed across various socioeconomic groups. I then situate failure-to-pay or failure-to-appear (FTA/FTP) instances within the US legal debt landscape. I conclude the section by discussing the history and predicted trajectory of natural disasters in the US.

Legal debt includes the fees, fines, restitution orders, and other financial obligations that courts and other criminal justice (CJ) agencies impose on individuals accused of crimes (Harris et al., 2010). Historically, unpaid legal debt was used in the convict lease system wherein the inmates repaid their fees and fines through bondage labor (Blackmon, 2009). Although the use of legal debt has been declining, it continues to pervade vast swathes of the US CJ system (Harris et al., 2010). If unpaid, legal debt may be subject to interest, surcharges, collection fees, or other monetary penalties. The interest or fees charged can be up to 40%, foreshadowing a considerable increase in legal debt over time. Nonpayment of legal debt may lead to warrants being issued and the defendant arrested (Bonczar, 1997; Harris et al., 2010; McLean and Thompson, 2007). Issue of a warrant, for instance, can lead to loss of driving privileges constraining the employment opportunities of the defendant (Pawasarat and Quinn, 2013). The negative economic consequences of incarceration or confinement are well documented (Looney and Turner, 2018; Mueller-Smith, 2015; Pager, 2003). Existing work demonstrates that racial and ethnic minorities are subjected to legal financial obligations (LFOs) at a much higher rate (Pacewicz and Robinson, 2020; Slavinski and Pettit, 2021). This disparity also extends to relatively poorer individuals, who are already disadvantaged and unable to pay their assessed fines and fees (Harris, 2016).

In this paper, I focus on FTA/FTP on traffic citations issued in Oklahoma. Additionally, I focus on citations issued by highway patrol, county sheriff, and university police. These citations are processed in state court. FTA/FTP for a traffic citation results in the court judge issuing a bench warrant. This warrant essentially requires the CJ system to produce the defendant before the judge. Law enforcement and CJ authorities do not actively hunt for defendants after a bench warrant is issued. However, a future encounter with these authorities may result in an arrest of the defendant. Furthermore, if the citation is not paid for a considerable period, it may be sent to a collection agency. This not only increases the total amount owed but may also severely harm the credit profile of the defendant. Overall, the FTA/FTP instance has the potential to severely affect the defendant both socially and economically.

The past four decades have seen an increase in the frequency and intensity of weather-related disasters.

Every three weeks there is a billion-dollar disaster and extreme events cause damages worth $150 billion each year (USGCRP, 2023). Existing work provides conflicting evidence on the short-run effects of natural disaster exposure. Some studies find a positive effect on earnings but a decline in employment due to natural disasters (Belasen and Polachek, 2008). Other studies, however, document an increase in wages after the natural disasters (Deryugina et al., 2018; Groen et al., 2020). Extreme weather events are very likely to become more frequent, intense, and severe in the future.

While not restricted to Oklahoma, almost all the defendants in my analytical sample are residents of Oklahoma. All the traffic citations in the analytical sample are issued in Oklahoma but not all defendants are Oklahoma residents. Of all the traffic citations with complete information on the residence ZIP code of the defendant, more than 82% have the defendant being an Oklahoma resident. The most common disaster type in Oklahoma is severe storms. These include tornadoes. In this paper, I restrict the analytical sample to natural disasters that occur during 2018 or 2019. This period covers instances of both flooding and tornadoes as part of severe storms along with wildfires. Furthermore, 59 of the 77 counties are affected by at least one of these natural disasters. The exposed counties are presented in Figure A2. Between 2018 and 2019, six severe storms, two flooding, and one drought billion-dollar disaster events affected Oklahoma.[2] Consistent with the national trend, Oklahoma has seen an increase in the disaster count since the turn of the century (see Figure A3).

Due to the localized impact of severe storms, the judges who are assigned to hear pleas on traffic citations are unlikely to decipher whether the defendant is exposed to these natural disasters. As I highlight in Section 4, this accords well with the identification of assumptions that need to be satisfied for the causal estimation through the empirical framework that I employ in this study. Overall, highly destructive natural disasters that are likely to become more frequent in the future could potentially affect whether the defendant defaults on their legal debt. In what follows, I examine if this is indeed the case.

3 Data

I combine data from multiple sources to examine if natural disasters lead to increased defaults on legal financial obligations. In this section, I describe each data source that I use. The final subsection presents descriptive statistics from the estimation sample.

[2]Billion-dollar disaster events information is drawn from NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2024). These data can be accessed here.

3.1 Oklahoma Traffic Citations Data

My main data source is the Oklahoma State Court Network (OSCN). OSCN provides data on traffic citations for all citations issued by highway patrol, county sheriff, and university police. These data are obtained through a scraping program. Although publicly available, OSCN does not allow for unrestricted queries to the server hosting these data. Through a program that attempts to bypass bot detection checks, I have scraped two years of traffic citation data from OSCN. These two years are 2018 and 2019. It is worth emphasizing that although the data are centrally hosted, each county has a different reporting format. OSCN data are used to examine the effect of local natural disaster exposure on legal financial obligation defaults as I am unaware of any other jurisdiction within the United States that provides publicly available traffic citation data. Even when traffic citations data are available, they are often available for select police departments or municipalities in contrast to entire state as in my context.[3]

From the scraped data, I obtain information on defendants and their attorneys. I observe the date-of-birth and residential address of the defendants. The finest geographical unit that is reported for these citations is the ZIP code. To assign counties to the ZIP codes, I use HUD-USPS ZIP crosswalk.[4] ZIP codes are mapped to counties as that is the finest spatial unit available in the natural disasters data that are discussed in the following subsection. Thus, I use the county of reported address of the defendant to determine the exposure to natural disasters as detailed in the following subsection.

OSCN data provide detailed information on the exact statute of the law that the defendant violated. For each count that the defendant is charged with, I also observe the date of offense. These data also provide me information on the timeline of events from the citation issuance to the case dismissal if dismissed. These data provide me with a wealth of information on the citation. I observe the arresting agency, location of the offense, violation type, and some details on the vehicle like make and model. Importantly, I can ascertain the bond amount from the citation.

Case docket data for each traffic citation provides me information on the dates of appearance, line items for the payment and charges, and other case proceedings such as notification of driver's license suspension to the Department of Public Safety. The docket data allow me to determine if the defendant has a failure to pay (FTP) or Failure to Appear (FTA) instance. The main dependent variable in the subsequent analysis is an indicator variable for whether the defendant has an FTP or FTA instance.

[3] See for instance available data from Sowd and Otto (2024).
[4] More information on this crosswalk is available here.

3.2 Natural Disasters Data

The data on natural disasters is obtained from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. These data include all official FEMA disaster declarations. There are three disaster declaration types: major disaster, emergency, and fire management assistance. In subsequent analysis, I do not use fire management assistance disaster declarations. Disaster declarations are issued at the state government's request and after examination of disaster damages by the FEMA staff. FEMA assistance is provided at the individual-, household-, and local government-level in the form of grants and loans.

For each disaster declaration, the summaries dataset provide information on the county and state of the disaster, the time the disaster began, the type of declaration (disaster, emergency, or fire management assistance), and incident type. The types of incidents covered include floods, hurricanes, severe storms, tornadoes, and fires. I also observe information on the time when the declaration is issued.

For a robustness check, I also use data from the National Weather Service damage assessment toolkit. These data provide information on the exact path of the storms. Additionally, from these data, I also obtain information on the extent of injuries and fatalities. The severity of storms is based on the Enhanced Fujita Scale (EF Scale). For the estimates reported using these data, the ZIP code is the geographical unit used to construct exposure to storms. These data are not used as the main source of natural disasters as the coverage in terms of disaster types is smaller than the disaster declarations summaries dataset. At the same time, these data allow me to construct ZIP code-level exposure measures.

3.3 Additional Data

Additional data for county-level control variables and various heterogeneities is obtained from multiple sources. I use data from the Bureau of Economic Analysis (BEA) Regional Economic Information System (REIS), County Business Patterns (CBP), and the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW). These data provide information on income, poverty, transfers, employment, and wages at the county-level. Additionally, I also use county population data from the Census Bureau. The US Census Bureau also provides data at the ZIP code-level for various demographic characteristics. In particular, I use information on the fraction of the ZIP code that is urbanized, white, and of working age. These data are used to establish the validity of the research design, as delineated in the following section. ZIP Code-level income data are derived from the Internal Revenue Service (IRS) Statistics of Income (SOI). Adjusted gross income is derived from individual income tax returns (Forms 1040).

I use the information on the defendant's name for probabilistic race and ethnicity assignment. These data are derived from Rosenman et al. (2023). These data provide probabilistic measures of race and ethnicity which in turn are derived from voter files of six Southern states with self-reported racial data. For race and ethnicity imputation, I use the defendant's first name.

3.4 Analytical Sample Construction

Exposure to natural disasters is based on the reported county of the defendant. More than 80% of residents in a given county also work in that county in the United States (Monte et al., 2018). Furthermore, if the county of employment is a county adjacent to the residence county, the spatial correlation in natural disaster impact attenuates measurement error in treatment assignment. Regardless, natural disasters based on reported county in the traffic citation are likely to impose significant unexpected costs on the defendant potentially leading to an FTP or FTA instance.

To assign the defendant into treatment and control groups, I use the defendant's reported county information along with their initial court appearance date. As detailed in the next section, my main empirical specification is based on a regression discontinuity design (RDD) framework. For all my RDD specifications, I drop all traffic citations where the defendant is not a resident of a county exposed to a natural disaster. For the remaining traffic citations, I construct the running variable based on the initial court appearance date and date of disaster onset. Specifically, the running variable takes negative values if the court appearance date is before the natural disaster onset and positive values if the court appearance date is after the natural disaster onset. For the estimates reported in Section 5, I use traffic citations from 2018 and 2019.

3.5 Descriptive Statistics

In Figure A3, I report the annual frequency of disaster declarations from the FEMA for Oklahoma. Since 2005, not only there has been at least one disaster almost every year, but the frequency of natural disasters has also increased. Table **??** reports summary statistics for the analytical sample. Almost 24% of the traffic citations have an FTA or FTP instance. More importantly, there is no evidence that observable demographic and socioeconomic characteristics differ systematically across treatment and control groups.

4 Empirical Strategy

To uncover the effect of natural disasters on various outcomes related to debt owed to the court, I will leverage the initial appearance date associated with each traffic citation in a regression discontinuity design (RDD) empirical framework.[5] Each traffic citation has an initial appearance date by which the defendant should either plead guilty and pay the associated fines or costs. Alternatively, the defendant can challenge the citation in court at the reported date of initial appearance. Under certain situations and if the assigned judge agrees, the defendant can enroll in a payment plan to pay off the legal debt over time. Defendants who have an initial appearance date before their reported county experienced a natural disaster are classified as untreated while those whose initial appearance date is after the natural disaster began are designated to be treated. Since the classification of the defendant is based on the initial appearance date, I use a sharp regression discontinuity where the outcomes of the defendants slated to initially appear right before the cutoff are compared to those who are to initially appear right after.

To estimate the causal effect of natural disaster exposure on the outcome variable, I estimate the following specifications:

$$\begin{aligned} y_i = &\alpha_h + \tau_h \cdot \mathbb{1}\{Date_i > NaturalDisaster_d\} + \beta_h^- \cdot (Date_i - NaturalDisaster_d) \\ &+ \beta_h^+ \cdot \mathbb{1}\{Date_i > NaturalDisaster_d\} \cdot (Date_i - NaturalDisaster_d) + \varepsilon_i \end{aligned} \tag{1}$$

In Equation 1, y_i is the outcome of interest for defendant i. The main outcome of interest is an indicator variable for whether the defendant i default on their legal debt. $Date_i$ refers to the day on which the defendant i is to initially appear in the court. $NaturalDisaster_d$ is the day on which the natural disaster d began. As a defendant on a traffic citation may have exposure to different natural disasters, I stack all natural disasters while estimating specification in Equation 1.

The estimate of τ_h captures the effect of being scheduled to initially appear in the court after the reported county is exposed to the natural disaster on the outcome variable. This parameter estimate depends on the bandwidth h used to determine the estimating sample. In all my specifications, I use optimal bandwidth according to the method of Calonico et al. (2017). I allow the slope of the conditional expectation function to be different on either side of the cutoff and use a triangular kernel, which assigns a higher weight to an observation close to the threshold. The slope parameter to the left of the cutoff is given by β_h^- while β_h^+ is the slope parameter to the right of the cutoff. The running variable takes discrete values only but has rich support permitting the use of standard estimation methods for continuous running variable (Cattaneo et al., 2020b; Kolesár and Rothe, 2018). Following the suggested approach in Cattaneo et al. (2024), for each discrete running variable, I take the average of

[5] The adopted empirical approach is similar to Finlay et al. (2023).

all traffic citations for all estimations of specification in Equation 1. This is operationalized by first averaging the traffic citations with a running variable value and natural disaster. The resulting data is then collapsed to the discrete running variable values by averaging over all natural disasters in the analytical sample. Thus, I obtain a single mass point corresponding to each discrete running variable value.

I establish the robustness of the empirical framework through multiple validity checks according to Cattaneo et al. (2020b). The identifying assumption in the empirical framework is the continuity of potential outcomes of defendants who are to initially appear on either side of the day of the natural disaster. One way to assess the validity of this assumption is to establish that observable covariates that are potentially correlated with the outcome of interest do not change discontinuously around the cutoff. In Figure A5 and Figure A6, I show that none of the observable covariates change discontinuously on the day of the start of the natural disaster. The corresponding estimates and inference are reported in Table **??**. Figure A4 shows that the density of caseloads across the treatment threshold has no discontinuity.[6]

I also perform a falsification check where artificial cutoffs are chosen before and after the actual cutoff. The results from this exercise in Figure A7 to Figure A11 show that there is no evidence of discontinuity in the outcome variable away from the cutoff, estimates are not sensitive to observations near the cutoff, alternate bandwidth choices, alternate kernel choices, and alternate polynomial order. The estimates and inference corresponding to these robustness checks are reported in Table **??**. These balance tests and placebo checks suggest that the identification assumptions for the estimates to be interpreted as causal are not violated.

For defendants, it is plausible to defer the initial appearance date. For a deferment request to be successful, the court clerk can be contacted. The court clerk can issue a deferment only once. Any additional request for deferment is to be approved by the judge. My treatment is defined based on the initial appearance date which is extremely unlikely to be manipulated as it is determined at the time of traffic citation issuance. Furthermore, the officer that issues the citation assigns the initial appearance date based on the existing backlog of court dockets, something the defendant cannot control. The potential inability to influence the initial court appearance date notwithstanding, I also show that the bounds on the FTP or FTA likelihood if the residence county of the defendant experiences a natural disaster contain the estimate reported in Section 5. In particular, the estimated bounds for the FTP or FTA are $[0.045, 0.055]$. These bounds are derived from the partial identification approach of Gerard et al. (2020). Using the same specification in Equation 1 with an indicator variable for whether the traffic citation has an instance of extension or deferment as the dependent variable, Figure A12 shows

[6]The corresponding p-value is 0.3592. The asymmetry between point estimate and confidence bounds results from different polynomial degrees for their estimation (Cattaneo et al., 2020a).

that defendants potentially exposed to the natural disasters are not more likely to seek an extension or deferment of their initial court appearance date.

5 Results

I begin by reporting the visual plot of the bin mean and polynomial fit in Figure 1. The outcome variable in this figure is an indicator variable for whether the traffic citation has an instance of failure to pay (FTP) or failure to appear (FTA). The discontinuity at the cutoff, the day of the disaster start, suggests that in the immediate aftermath of the natural disaster, defendants are more likely to have an instance of FTP or FTA.

Table **??** reports the RDD estimates along with the robust inference statistics. The estimates in this table are derived from following the default options in Calonico et al. (2017). The point estimate suggests that immediately after the natural disaster, the likelihood of the traffic citation having an instance of FTP or FTA increases by 5.9 percentage points. As a proportion of the pre-disaster mean, this is a large increase of approximately 26.34%. This increase in FTP or FTA instance likelihood is statistically significant at the conventional levels of significance.

Following recommendations in Cattaneo et al. (2024), I also provide estimates from a local randomization approach in Table **??**. When there are enough mass points between the minimum value of the running variable on the treated side and the maximum value of the running variable on the control side, then in a context with discrete running variable, Cattaneo et al. (2024) suggest using this window for local randomization analysis. The local randomization approach assumes that the treatment is as if randomly assigned in an appropriate window around the cutoff. Local randomization approach estimates that I report in Table **??** are considerably smaller than the continuity based approach estimates and lose statistical significance.[7] This could be because of not enough mass in the narrow bandwidth of one day. When the optimal window is selected such that the observable characteristics of the defendants are balanced across the cutoff, then the local randomization approach estimates using this optimal window are very similar to the baseline estimates.[8]

As is extensively discussed, the main estimates are robust to a series of empirical checks recommended for continuity based approaches in Cattaneo et al. (2020b). These sensitivity checks are reported in Figure A7 to Figure A11. The corresponding estimates along with inference are reported in Table **??**. The baseline estimates are not sensitive to using artificial cutoffs, dropping observations around the

[7]Note that the data for local randomization approach has not been averaged across discrete running variable values and different natural disasters. This is the reason why the number of observations is different across the two approaches.

[8]The RD estimate is 0.0701 with an asymptotic p-value 0.035. I have used a minimum window of seven days on either side of the cutoff with each step adding seven more days while searching for the optimal window.

actual cutoff, alternate bandwidths, alternate kernels, or alternate polynomial order used to construct the conditional expectation function on either side of the cutoff.

I now turn to examining if the increase in the likelihood of FTP or FTA instances differs across various subpopulations. These estimates are reported in Figure A13 and Figure A14. Table **??** reports these estimates along with inference. On examining whether the likelihood of FTP or FTA instances differs across the age of the defendant, I do not find statistically significant differences between younger and older defendants. The only ZIP code-level characteristics that influence the FTP or FTA likelihood are the extent of urbanization and income in the ZIP code. Defendants from ZIP codes with below median urbanization have a higher likelihood of an FTP or FTA instance if their ZIP code experiences a natural disaster. This effect is absent for defendants from ZIP codes with above median urbanization. When examining the difference in FTP or FTA likelihood change due to natural disaster exposure, there is evidence of an inverted U-shaped relationship. None of these estimates, however, are significant at conventional levels of statistical significance.

6 Discussion and Conclusion

In this paper, I examine if natural disaster exposure affects the likelihood of defendants defaulting on their legal financial obligations. Using novel data on traffic citations from Oklahoma, I find a quantitatively large increase in the likelihood of failure to pay (FTP) or failure to appear (FTA). Relative to the pre-disaster mean, the 5.9 percentage point increase in the FTP or FTA likelihood is approximately 26% increase. I establish that my estimates are robust to a host of empirical checks. In particular, I establish that there is no manipulation of the running variable which is based on the initial appearance date associated with each traffic citation. Heterogeneity analysis suggests that the increase in FTP or FTA likelihood is concentrated in the ZIP codes with below median urbanization.

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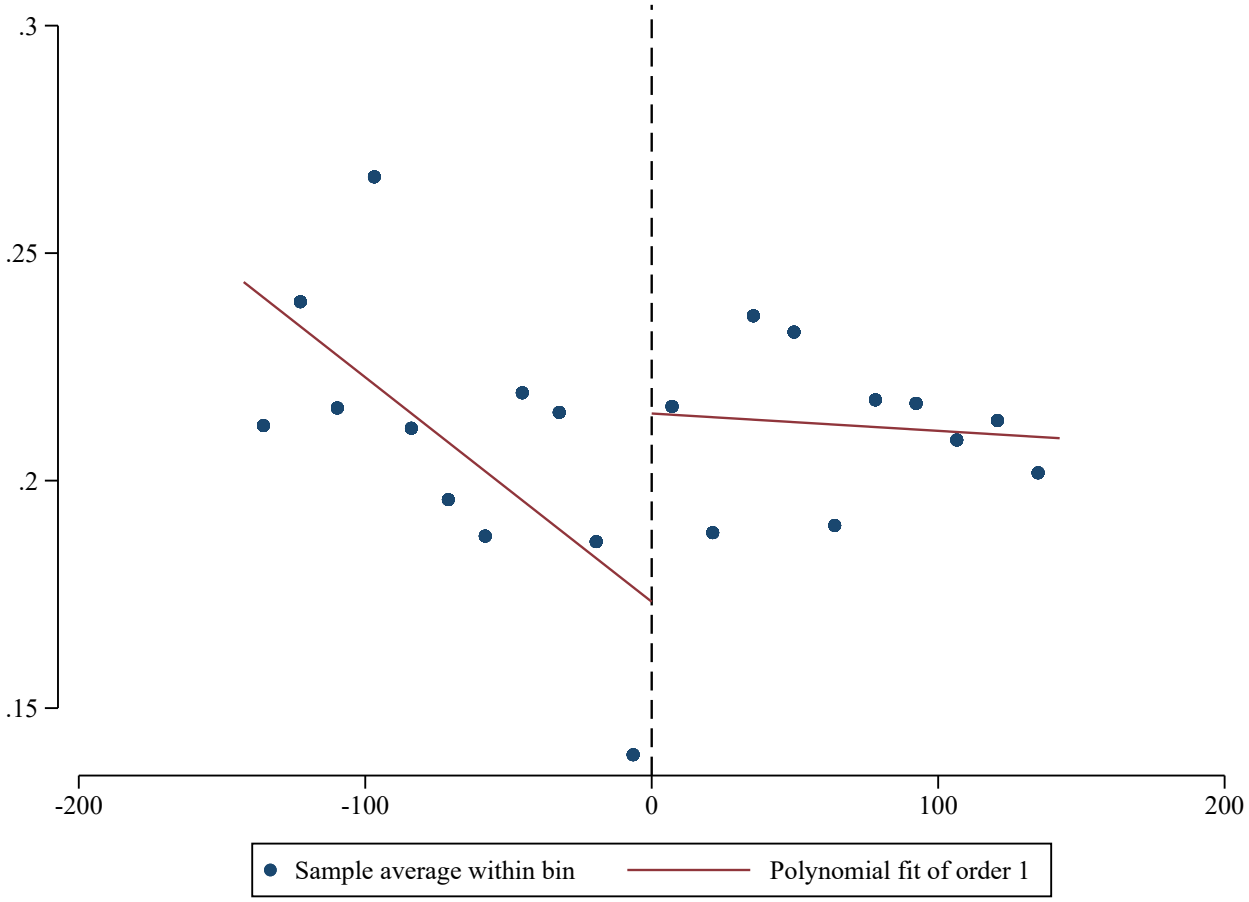
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Figure 1: Effect of Natural Disaster on Legal Debt Default



Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. The optimal bandwidth is 80.043 on either side of the cutoff. Default options, as documented in Calonico et al. (2017) are used. Solid lines are polynomial fit of order one. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Table 1: Effect of Natural Disaster on Legal Debt Default – Main Effect

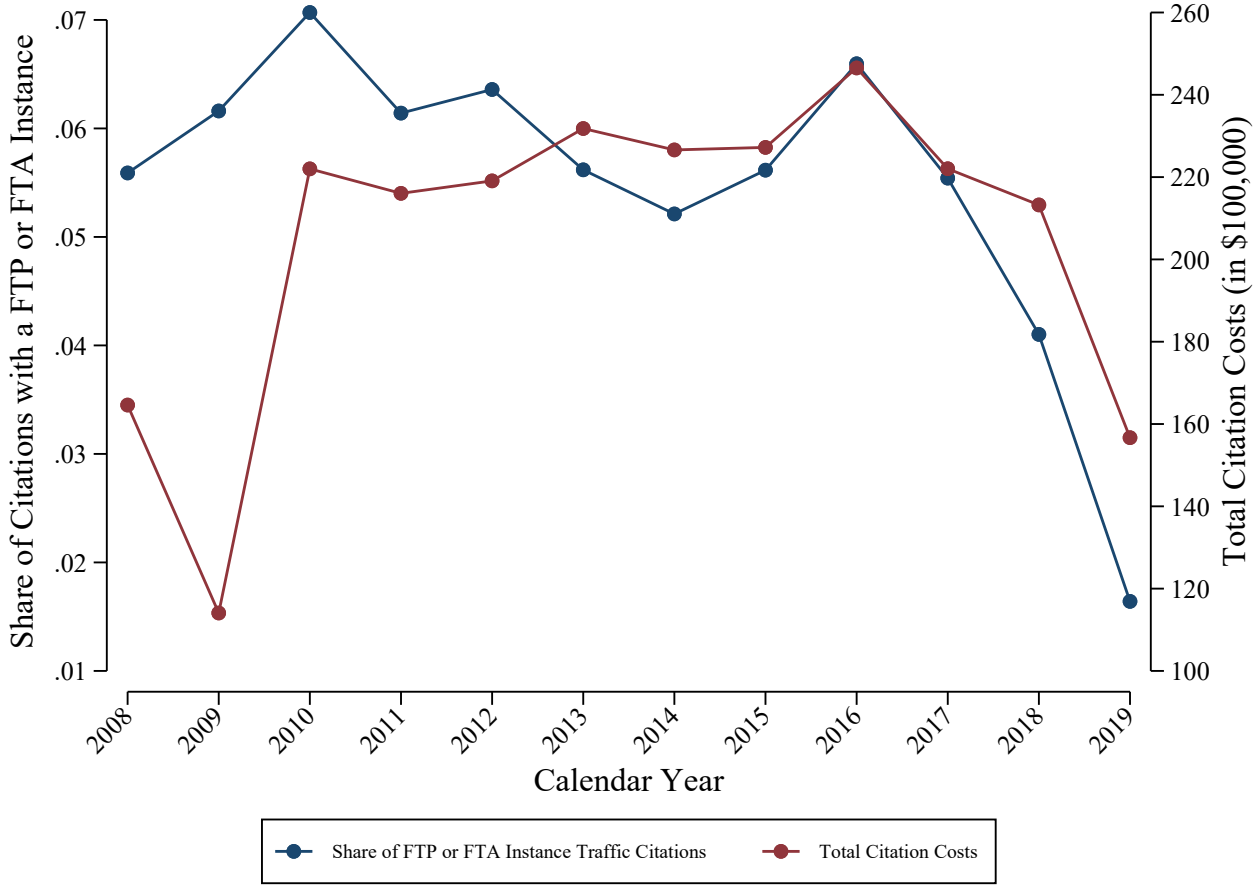
	Optimal	RD	Robust Inference		Number of	Dep. Var.	Dep. Var.
	Bandwidth	Estimator	p-value	95% CI	Observations	Mean	SD
Local Polynomial	142.41	0.059	0.01	[0.02, 0.10]	285	0.23	0.15
Local Randomization	1.00	0.007	0.74		2,061	0.22	0.42

Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Estimates labeled "Local Polynomial" are derived using the default options in Calonico et al. (2017). Estimates labeled "Local Randomization" are derived using the default options in Cattaneo et al. (2016). Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Appendices

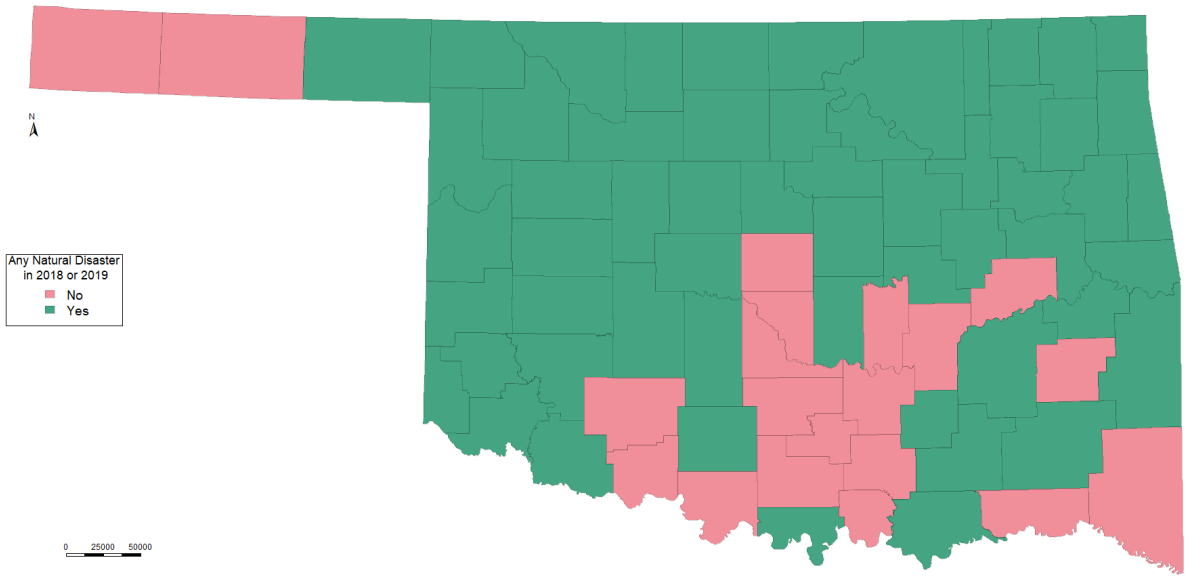
Appendix A Figures and Tables

Figure A1: Temporal Variation in Share of FTP or FTA Citations and Total Costs in Oklahoma



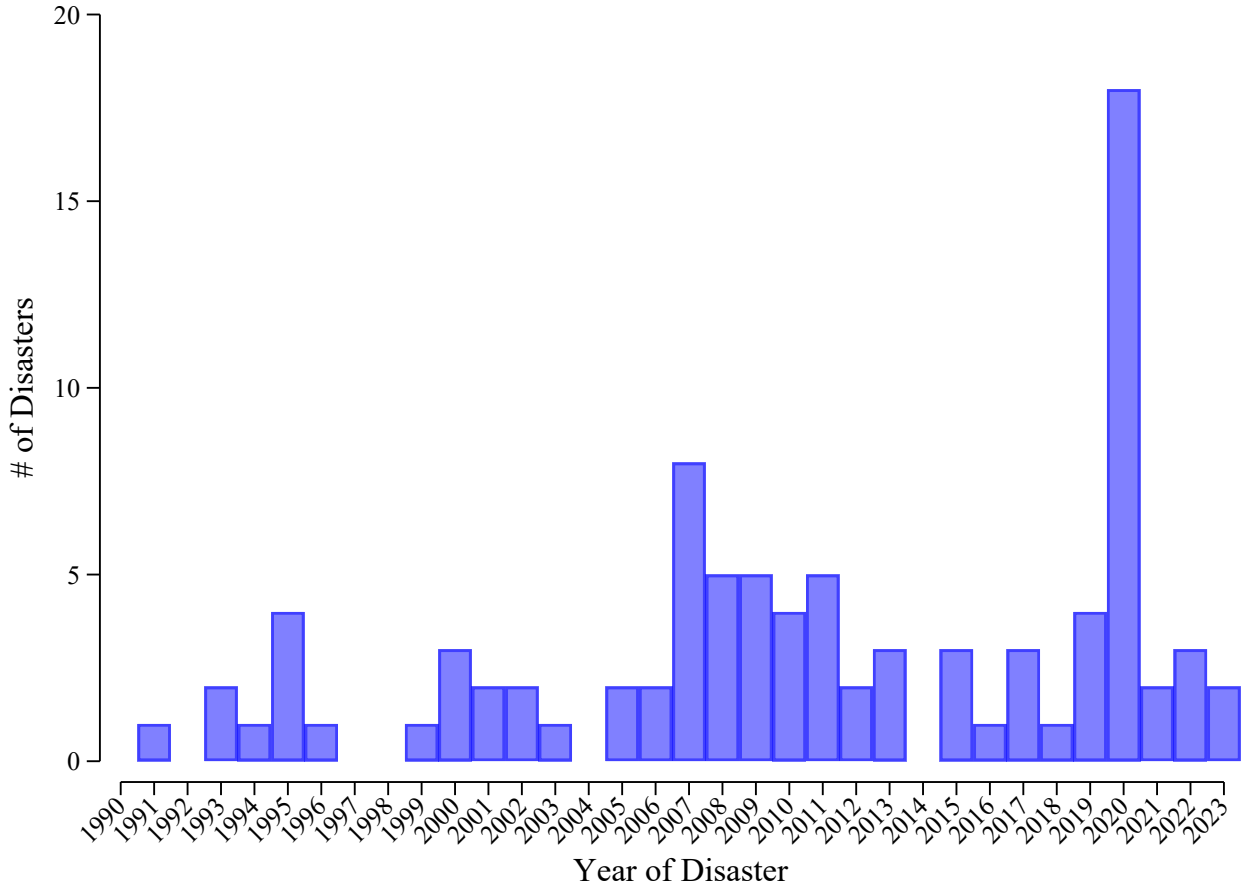
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). The classification of traffic citation having an instance of failure to pay (FTP) or failure to appear (FTA) is derived from Gaebler et al. (2023). Total costs include administrative costs.

Figure A2: Oklahoma Counties with at least One Natural Disaster During the Sample Years



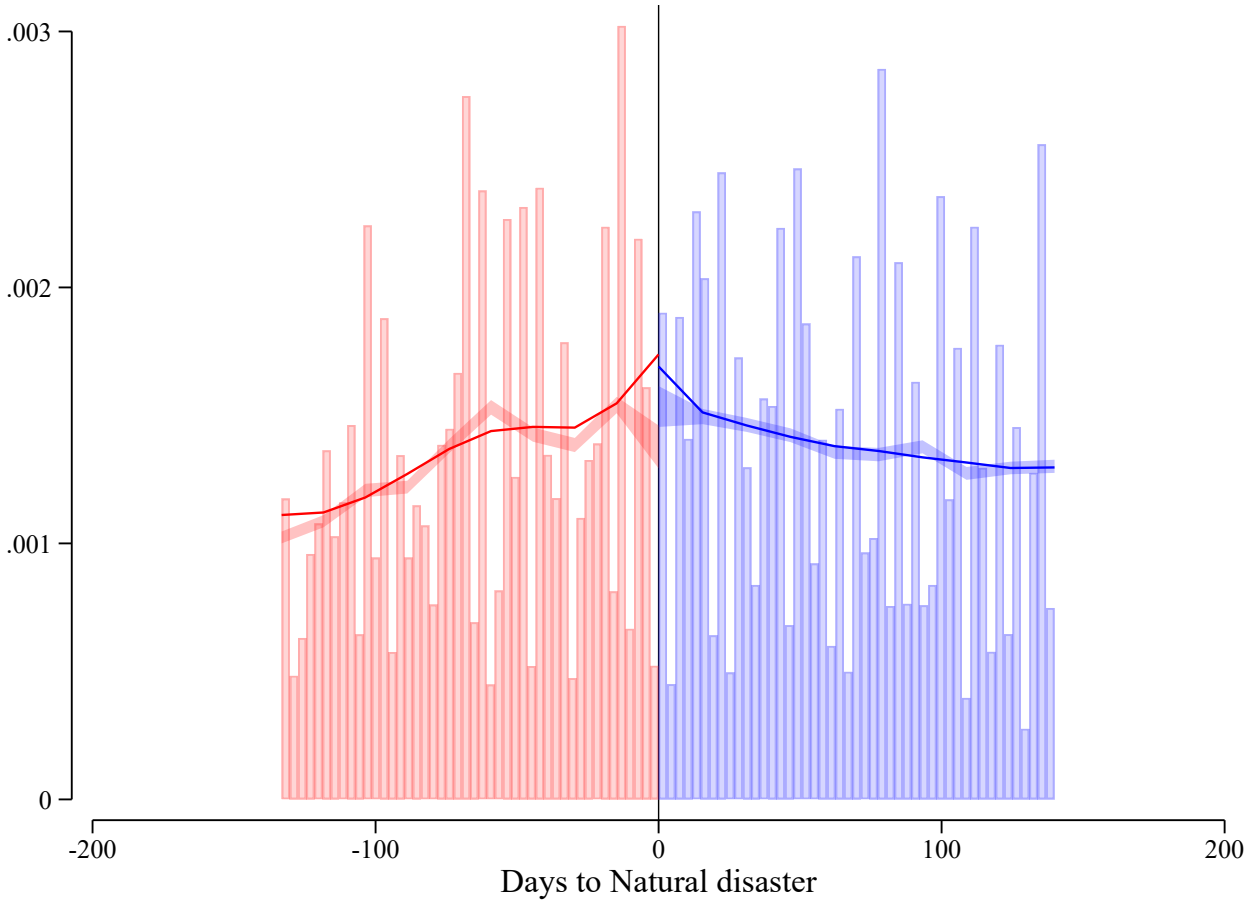
Note: Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Natural disasters only for years 2018 and 2019 are kept in the analytical sample. County shapefiles data are derived from United States Census Bureau.

Figure A3: Temporal Variation in Natural Disasters in Oklahoma



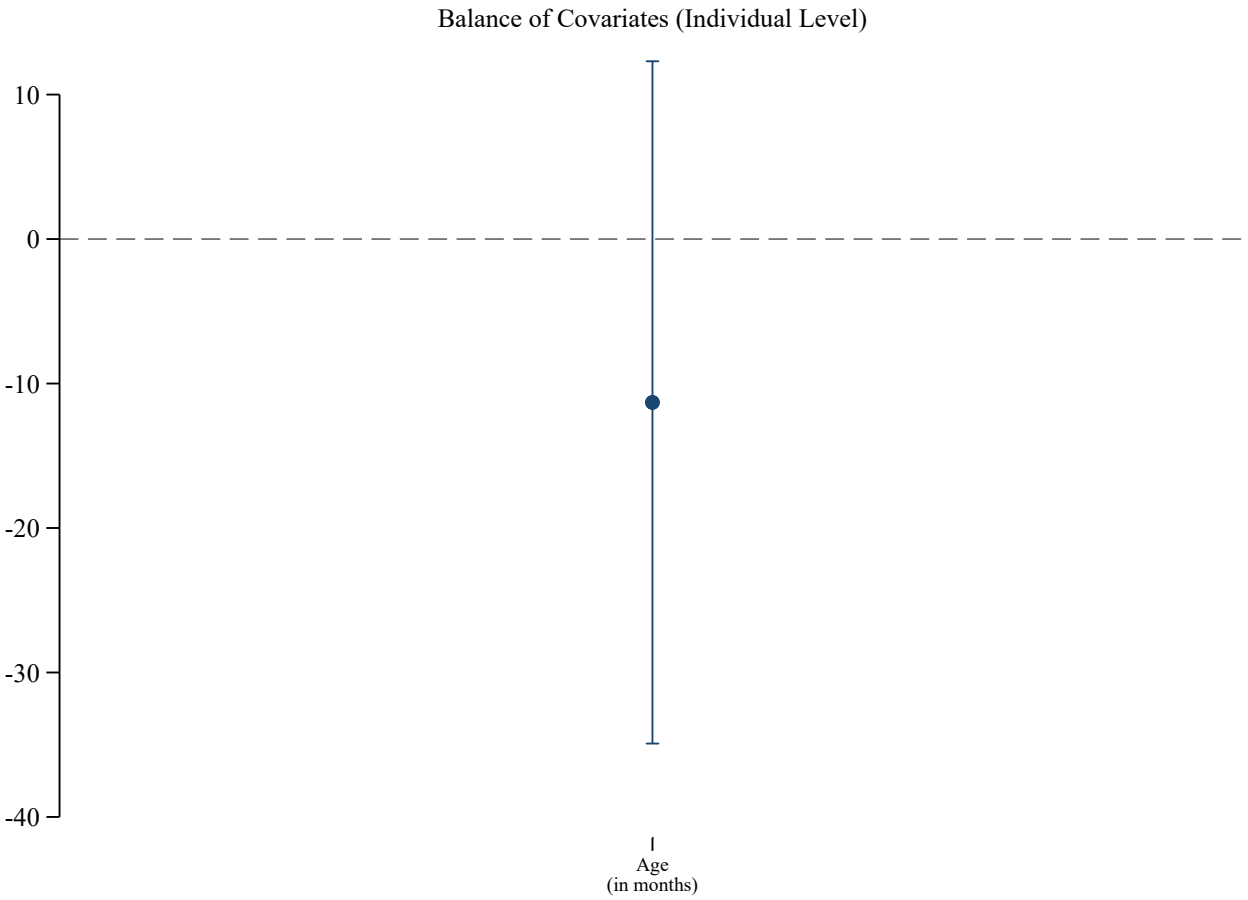
Note: Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. The year on the horizontal axis corresponds to the year in which the underlying incident of the disaster declaration began.

Figure A4: Traffic Citation Density Relative to the Natural Disaster Date



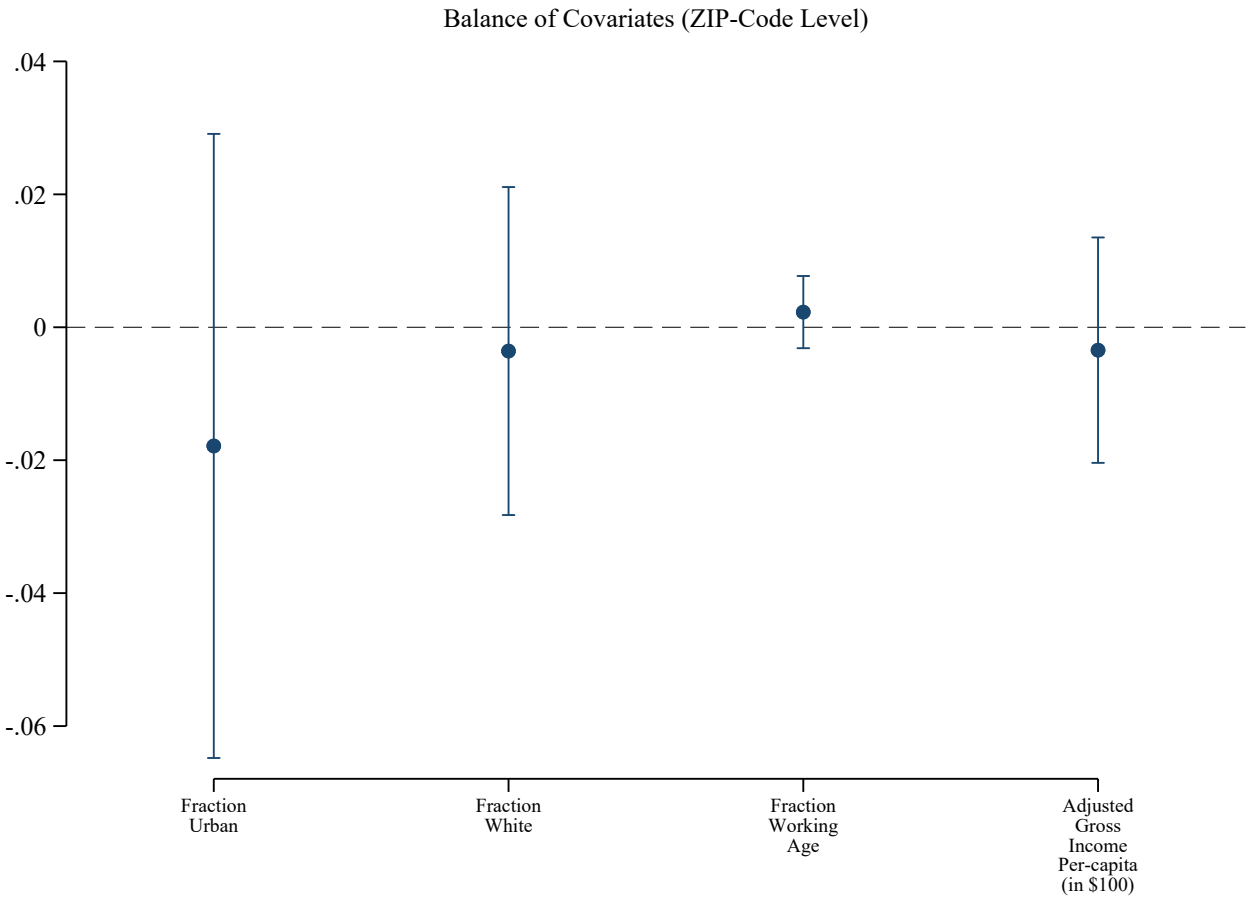
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. The optimal bandwidth used for density estimators is 44.396 to the left of the cutoff and 46.637 to the right of the cutoff. The p-value from the statistical test of no difference in the density of the running variable on either side of the cutoff is 0.9715. Default options, as documented in Cattaneo et al. (2018) and Cattaneo et al. (2022) are used. Daily bins; the first bin after the value 0 refers to the day of the natural disaster beginning. Solid lines are density estimates, and 95% confidence intervals are bands. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Figure A5: Effect of Natural Disaster on Pre-determined Defendant Characteristics



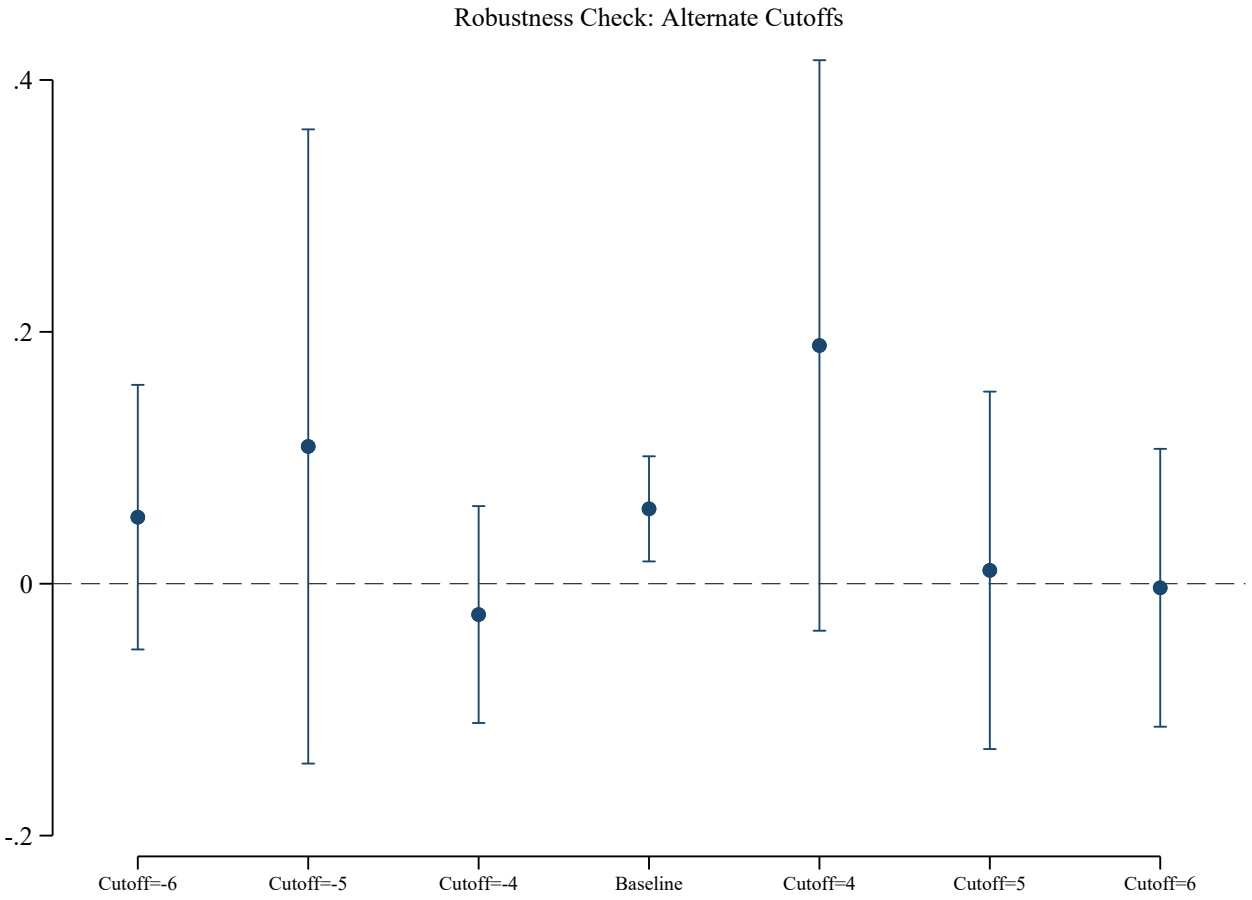
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Default options, as documented in Calonico et al. (2017) are used except for the bandwidth that optimizes the coverage-error (CER) of the confidence intervals. 95% confidence intervals are reported. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Figure A6: Effect of Natural Disaster on Pre-determined ZIP Code Characteristics



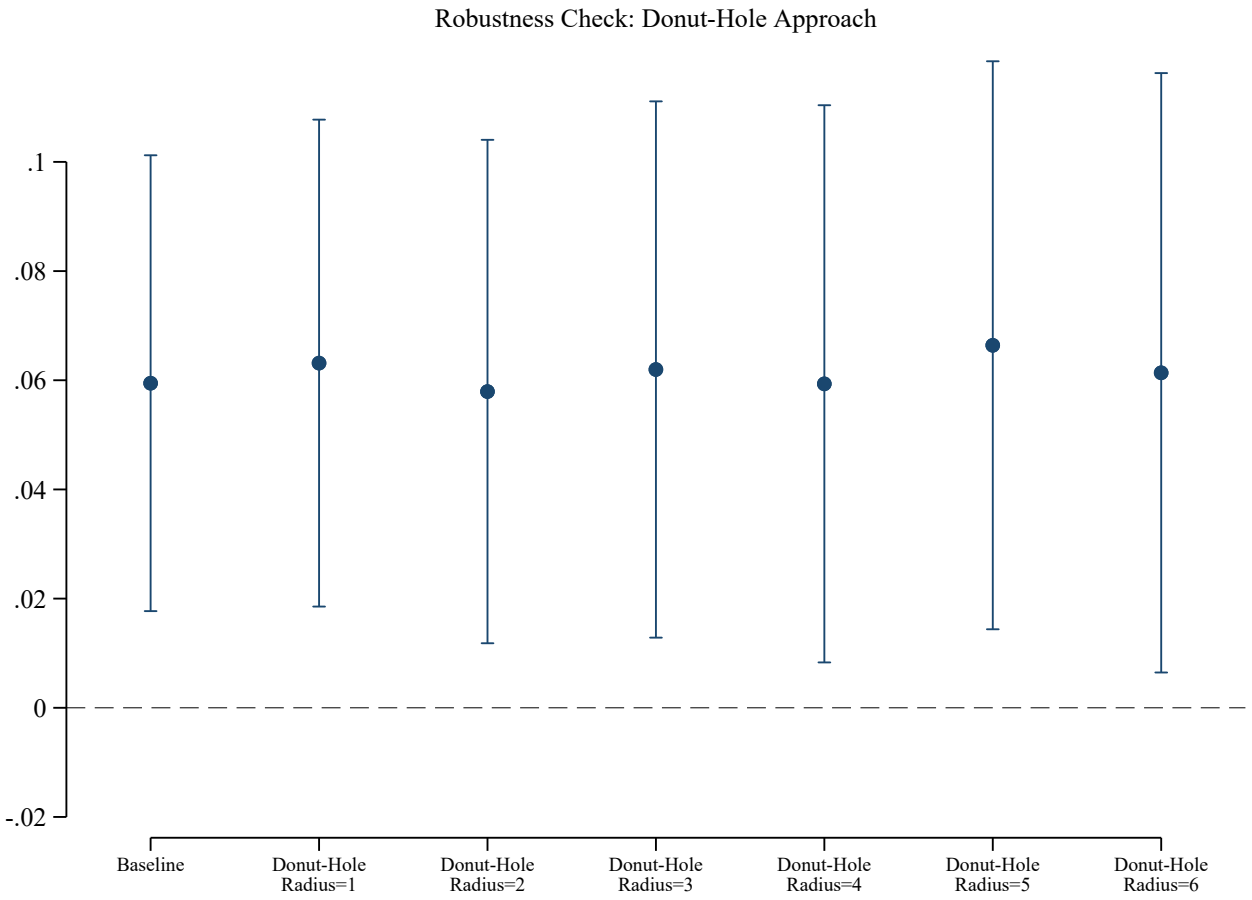
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Data on ZIP code demographics are derived from the United States Census Bureau 2010 Census Summary File 1. Data on ZIP Code income are derived from the Internal Revenue Service (IRS) Statistics of Income (SOI). Adjusted gross income is derived from individual income tax returns (Forms 1040). Default options, as documented in Calonico et al. (2017) are used except for the bandwidth that optimizes the coverage-error (CER) of the confidence intervals. 95% confidence intervals are reported. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Figure A7: Robustness Check: Artificial Cutoff Values



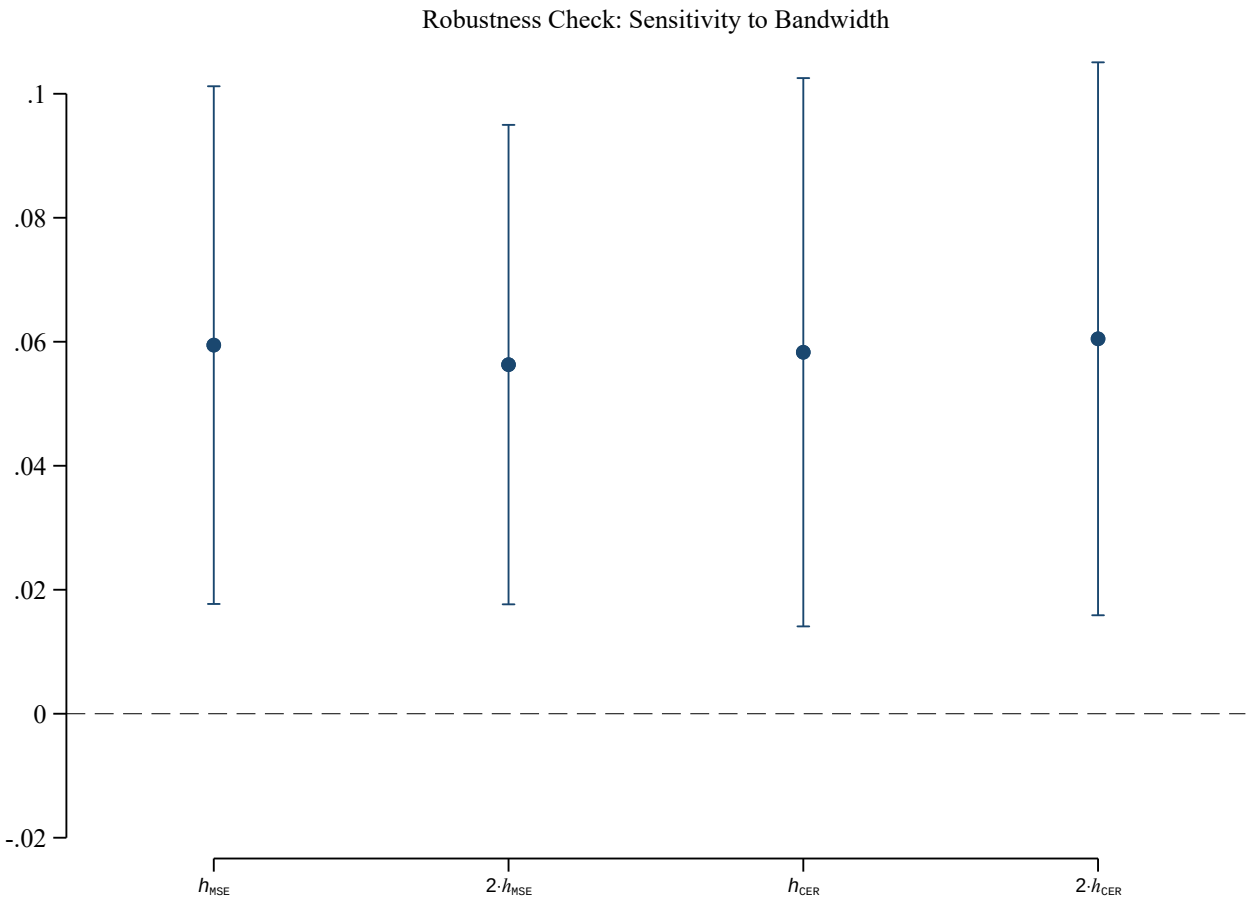
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Default options, except for the cutoff, as documented in Calonico et al. (2017) are used. 95% confidence intervals are reported. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Figure A8: Robustness Check: Donut-Hole Approach



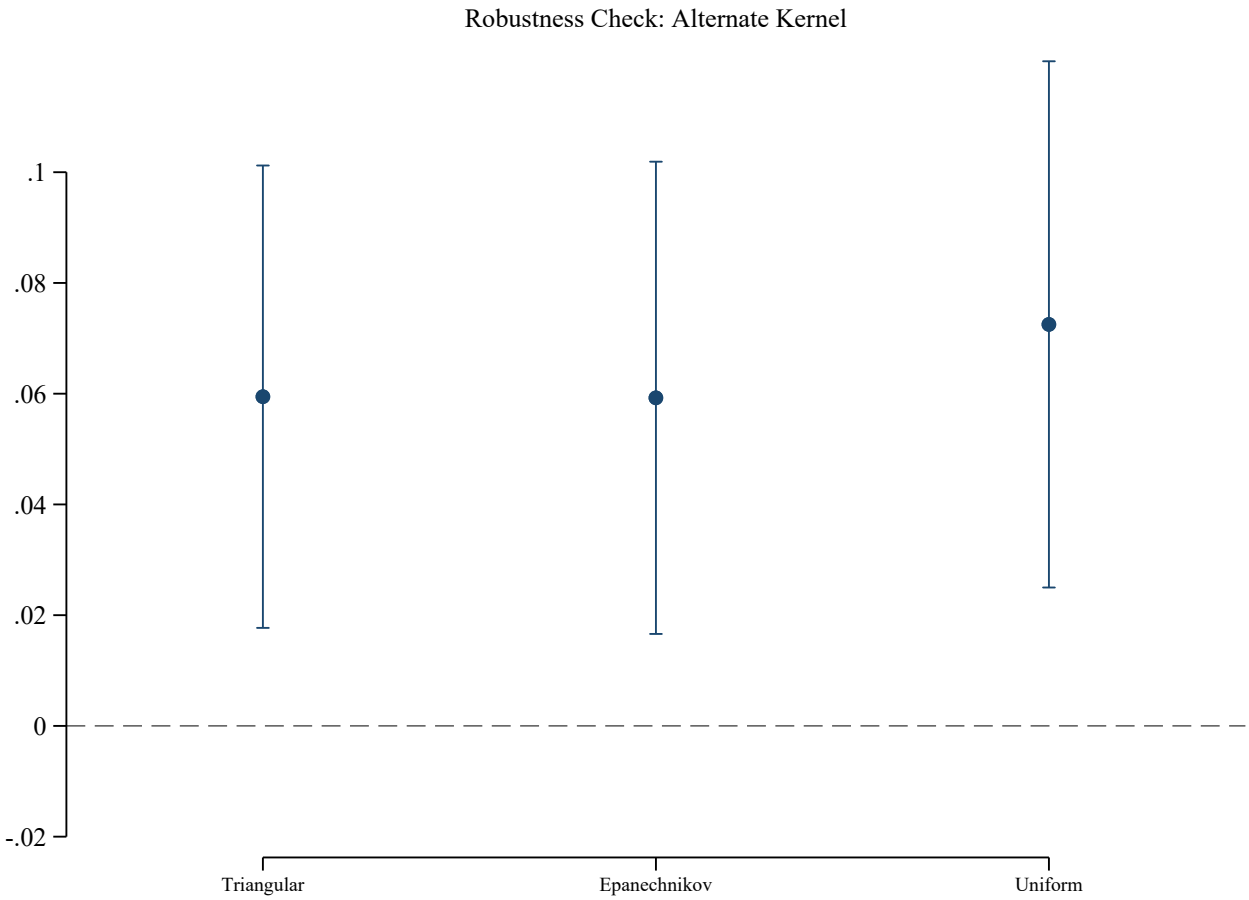
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Default options, as documented in Calonico et al. (2017) are used. 95% confidence intervals are reported. Donut-hole radius is the value of the running variable for which all observations with absolute values less than the radius are dropped from the analytical sample. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Figure A9: Robustness Check: Alternate Bandwidth



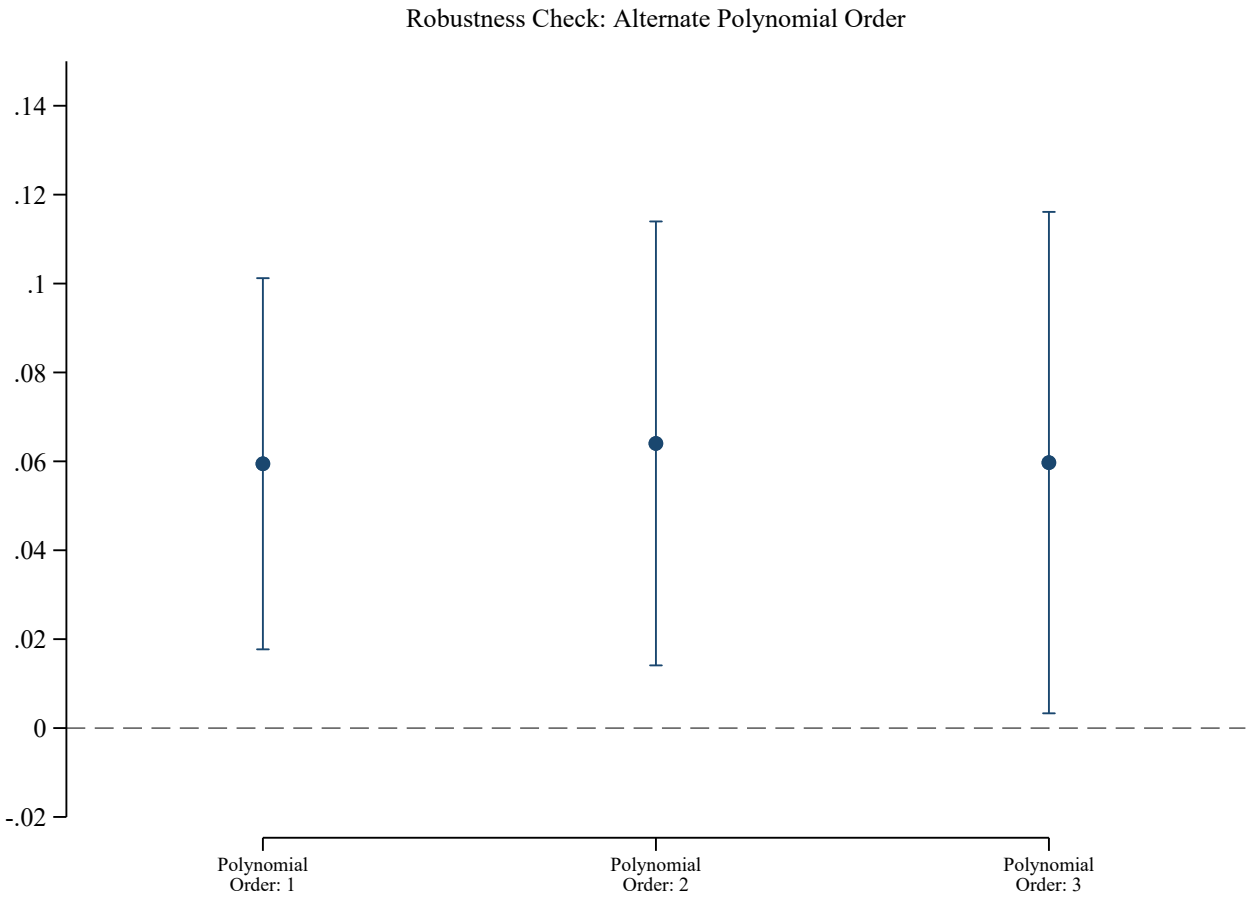
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Default options, except for the bandwidth selection, as documented in Calonico et al. (2017) are used. 95% confidence intervals are reported. h_{MSE} refers to the bandwidth that optimizes the mean squared error (MSE). h_{CER} refers to the bandwidth that minimizes an approximation to the coverage error (CER) of the confidence interval. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Figure A10: Robustness Check: Alternate Kernel



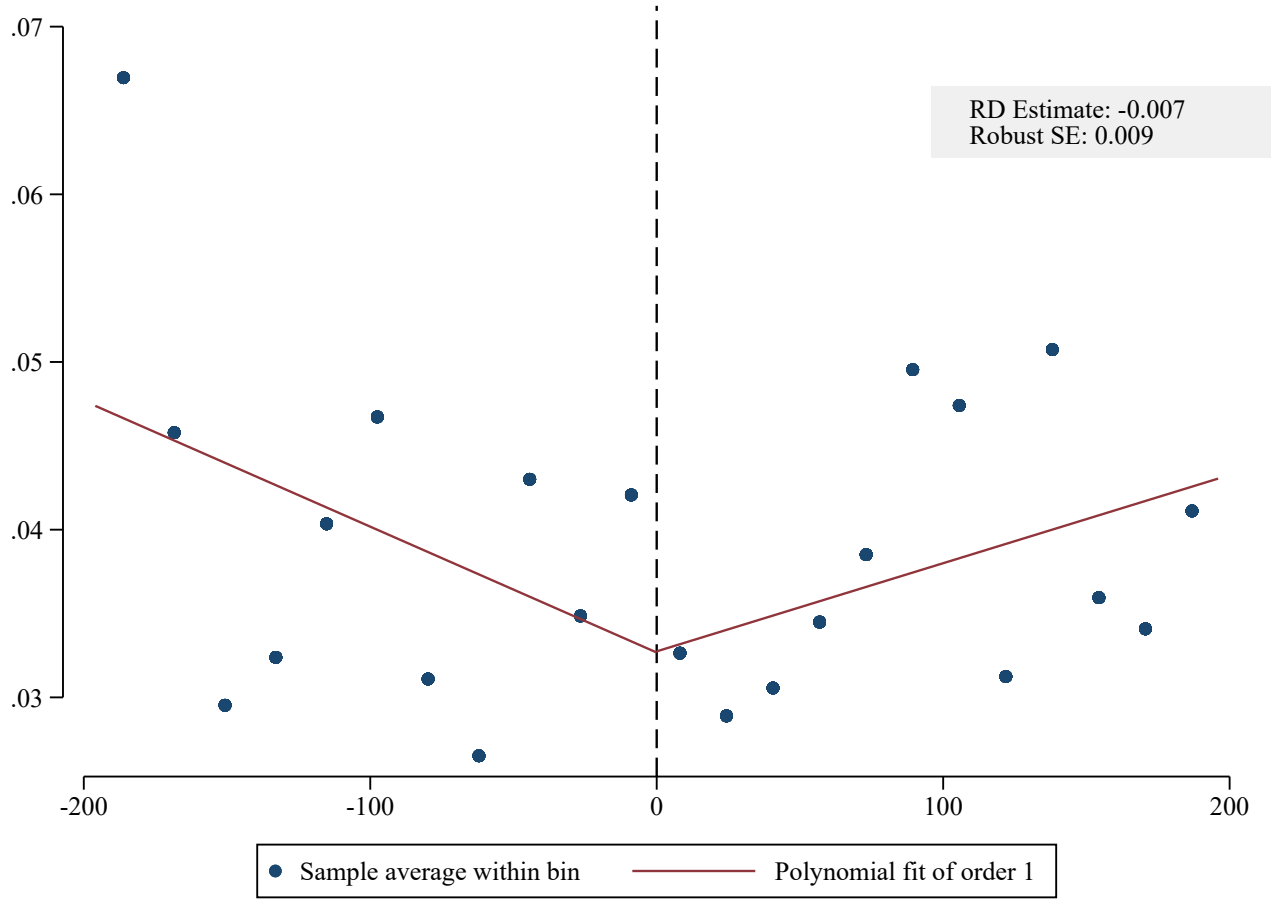
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Default options, except for kernel, as documented in Calonico et al. (2017) are used. 95% confidence intervals are reported. Kernel on the horizontal axis refers to the kernel function used to construct the local-polynomial estimator. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Figure A11: Robustness Check: Alternate Polynomial Order



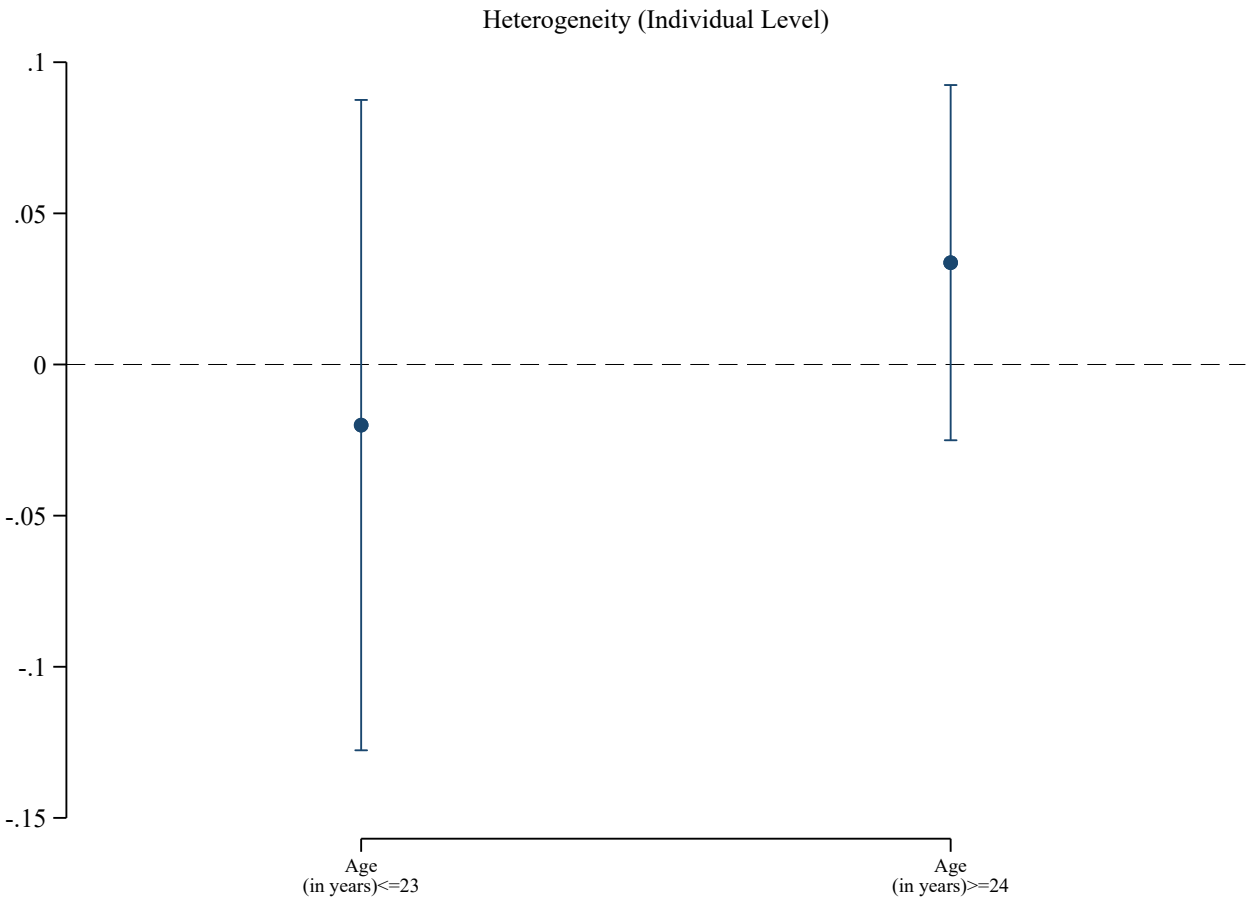
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Default options, except for polynomial order, as documented in Calonico et al. (2017) are used. 95% confidence intervals are reported. Polynomial order on the horizontal axis is the order of the local polynomial used to construct the point estimator. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Figure A12: Effect of Natural Disaster on Initial Appearance Date Extension or Deferment



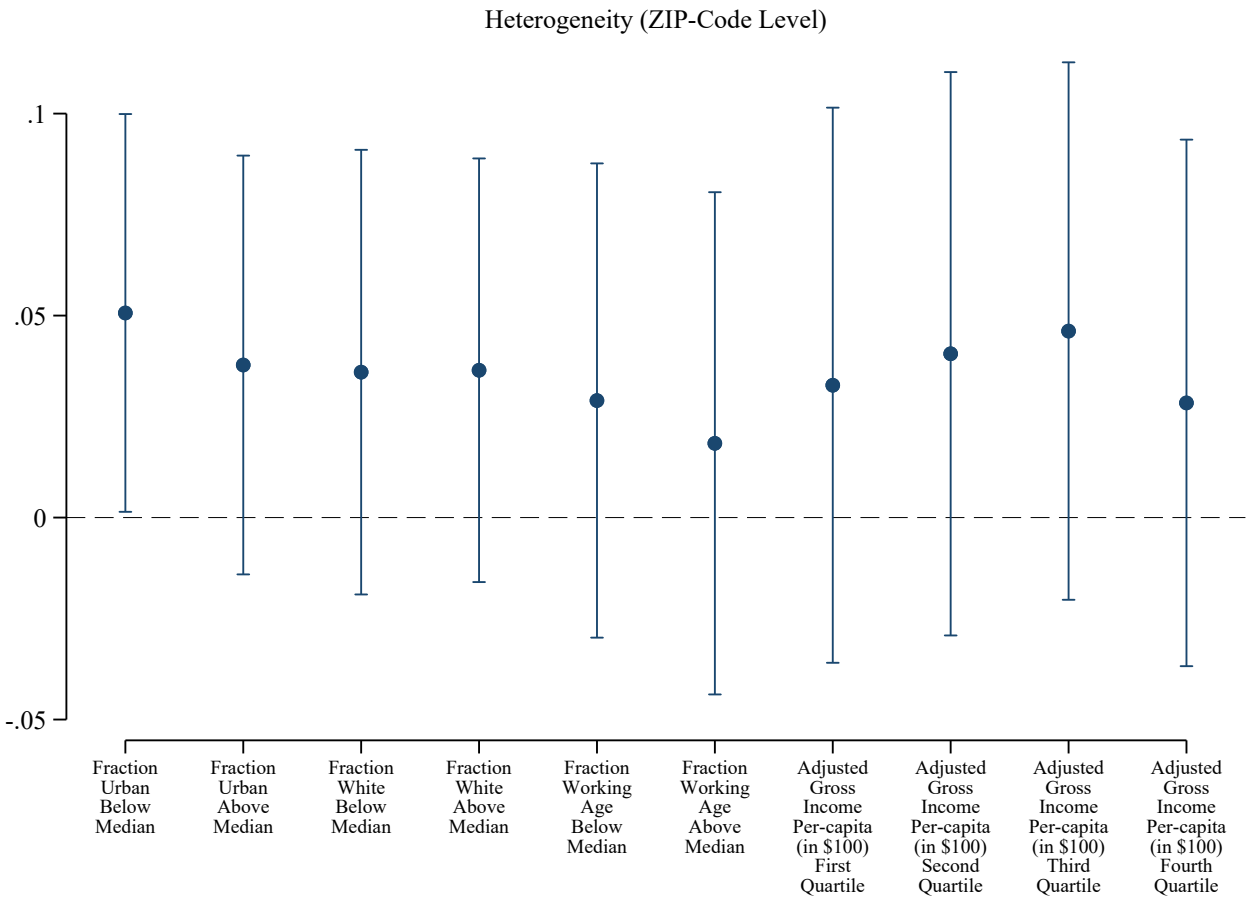
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Default options, as documented in Calonico et al. (2017) are used. Solid lines are polynomial fit of order one. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Figure A13: Heterogeneity: Pre-determined Defendant Characteristics



Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Default options, as documented in Calonico et al. (2017) are used. 95% confidence intervals are reported. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Figure A14: Heterogeneity: Pre-determined ZIP Code Characteristics



Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Data on ZIP code demographics are derived from the United States Census Bureau 2010 Census Summary File 1. Data on ZIP Code income are derived from the Internal Revenue Service (IRS) Statistics of Income (SOI). Adjusted gross income is derived from individual income tax returns (Forms 1040). Default options, as documented in Calonico et al. (2017) are used. 95% confidence intervals are reported. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Table A1: Summary Statistics

	All	Control	Treatment
Outcomes			
$\mathbb{1}$ (FTP Citation)	0.240	0.246	0.234
	(0.427)	(0.431)	(0.423)
Individual Variables			
Age (in months)	426.597	424.138	429.218
	(323.490)	(413.537)	(184.072)
ZIP Code-level Variables			
Fraction Urban	0.618	0.582	0.652
	(0.379)	(0.379)	(0.376)
Fraction White	0.710	0.713	0.707
	(0.163)	(0.158)	(0.168)
Fraction Working Age	0.651	0.649	0.653
	(0.038)	(0.038)	(0.039)
Adjust Gross Income (AGI) Per-capita ($100)	0.236	0.233	0.240
	(0.113)	(0.108)	(0.117)
Natural Disaster Variables			
$\mathbb{1}$ (Major Disaster)	0.759	0.753	0.768
	(0.428)	(0.431)	(0.422)
$\mathbb{1}$ (Emergency)	0.241	0.247	0.232
	(0.428)	(0.431)	(0.422)

Notes: The number of observations in the column labeled "All" is 432,064. The number of observations in the column labeled "Control" is 204,122. The number of observations in the column labeled "Treatment" is 227,942. Sample labeled "All" comprises of all the traffic citations irrespective of their initial appearance date. The sample labeled "Control" comprises of all the traffic citations where the initial appearance date is before the onset of the natural disaster. The sample labeled "Treatment" comprises of all the traffic citations where the initial appearance date is after the onset of the natural disaster. Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on ZIP code demographics are derived from the United States Census Bureau 2010 Census Summary File 1. Data on ZIP Code income are derived from the Internal Revenue Service (IRS) Statistics of Income (SOI). Adjusted gross income is derived from individual income tax returns (Forms 1040). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Each cell reports the mean of the variable in the left column with the standard deviations reported in the parenthesis.

Table A2: Effect of Natural Disaster on Pre-determined Characteristics

	Optimal	RD	Robust Inference		Number of	Dep. Var.	Dep. Var.
	Bandwidth	Estimator	p-value	95% CI	Observations	Mean	SD
Defendant Characteristics							
Age (in months)	148.89	-11.555	0.34	[-35.17, 12.06]	297	437.54	69.50
Zip Code Characteristics							
Fraction Urban	91.27	-0.020	0.41	[-0.07, 0.03]	183	0.66	0.15
Fraction White	135.92	-0.004	0.73	[-0.03, 0.02]	271	0.73	0.08
Fraction Working Age	119.98	0.002	0.39	[-0.00, 0.01]	239	0.66	0.01
Adjusted Gross Income Per-capita (in $100)	115.58	-0.003	0.75	[-0.02, 0.01]	231	0.24	0.05

Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Data on ZIP code demographics are derived from the United States Census Bureau 2010 Census Summary File 1. Data on ZIP Code income are derived from the Internal Revenue Service (IRS) Statistics of Income (SOI). Adjusted gross income is derived from individual income tax returns (Forms 1040). Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Table A3: Robustness Checks

	Optimal	RD	Robust Inference		Number of	Dep. Var.	Dep. Var.
	Bandwidth	Estimator	p-value	95% CI	Observations	Mean	SD
Baseline							
Baseline	142.41	0.059	0.01	[0.02, 0.10]	285	0.23	0.15
Artificial Cutoff Values							
Cutoff= -6	52.05	0.053	0.32	[-0.05, 0.16]	58	0.23	0.15
Cutoff= -5	69.20	0.109	0.40	[-0.14, 0.36]	74	0.23	0.15
Cutoff= -4	49.28	-0.024	0.58	[-0.11, 0.06]	53	0.23	0.15
Cutoff= 4	55.54	0.189	0.10	[-0.04, 0.42]	59	0.23	0.15
Cutoff= 5	58.27	0.011	0.88	[-0.13, 0.15]	63	0.23	0.15
Cutoff= 6	60.14	-0.003	0.95	[-0.11, 0.11]	66	0.23	0.15
Donut-Hole Approach							
Donut-Hole Radius= 1	138.37	0.063	0.01	[0.02, 0.11]	274	0.23	0.15
Donut-Hole Radius= 2	136.30	0.058	0.01	[0.01, 0.10]	268	0.23	0.15
Donut-Hole Radius= 3	128.97	0.062	0.01	[0.01, 0.11]	250	0.23	0.15
Donut-Hole Radius= 4	128.80	0.059	0.02	[0.01, 0.11]	248	0.23	0.15
Donut-Hole Radius= 5	123.87	0.066	0.01	[0.01, 0.12]	236	0.23	0.15
Donut-Hole Radius= 6	126.32	0.061	0.03	[0.01, 0.12]	240	0.23	0.15
Alternate Bandwidth							
$2 \cdot h_{MSE}$	284.83	0.056	0.00	[0.02, 0.09]	569	0.23	0.15
$1 \cdot h_{CER}$	99.51	0.058	0.01	[0.01, 0.10]	199	0.23	0.15
$2 \cdot h_{CER}$	199.02	0.060	0.01	[0.02, 0.11]	399	0.23	0.15
Alternate Kernel							
Epanechnikov	133.20	0.059	0.01	[0.02, 0.10]	267	0.23	0.15
Uniform	94.89	0.073	0.00	[0.02, 0.12]	189	0.23	0.15
Alternate Polynomial Order							
Polynomial Order: 2	201.21	0.064	0.01	[0.01, 0.11]	403	0.23	0.15
Polynomial Order: 3	238.55	0.060	0.04	[0.00, 0.12]	477	0.23	0.15

Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Donut-hole radius is the value of the running variable for which all observations with absolute values less than the radius are dropped from the analytical sample. h_{MSE} refers to the bandwidth that optimizes the mean squared error (MSE). h_{CER} refers to the bandwidth that minimizes an approximation to the coverage error (CER) of the confidence interval. Kernel refers to the kernel function used to construct the local-polynomial estimator. Polynomial order is the order of the local polynomial used to construct the point estimator. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.

Table A4: Heterogeneity

	Optimal	RD	Robust Inference		Number of	Dep. Var.	Dep. Var.
	Bandwidth	Estimator	p-value	95% CI	Observations	Mean	SD
Baseline							
Baseline	142.41	0.059	0.01	[0.02, 0.10]	285	0.23	0.15
Defendant-level Characteristics Heterogeneity							
Age (in years) ≤ 23	168.38	-0.024	0.66	[-0.13, 0.08]	335	0.22	0.22
Age (in years) ≥ 24	170.11	0.031	0.29	[-0.03, 0.09]	341	0.23	0.17
ZIP Code-level Characteristics Heterogeneity							
Below Median Fraction Urban	183.96	0.054	0.03	[0.00, 0.10]	367	0.21	0.18
Above Median Fraction Urban	143.08	0.048	0.07	[-0.00, 0.10]	287	0.23	0.15
Below Median Fraction White	152.27	0.045	0.11	[-0.01, 0.10]	305	0.24	0.17
Above Median Fraction White	202.20	0.037	0.16	[-0.02, 0.09]	405	0.18	0.17
Below Median Fraction Working Age	153.68	0.034	0.26	[-0.02, 0.09]	307	0.22	0.17
Above Median Fraction Working Age	169.84	0.024	0.45	[-0.04, 0.09]	339	0.24	0.18
First Quartile Adjusted Gross Income Per-capita (in $100)	158.43	0.040	0.25	[-0.03, 0.11]	317	0.27	0.20
Second Quartile Adjusted Gross Income Per-capita (in $100)	168.99	0.048	0.18	[-0.02, 0.12]	337	0.23	0.20
Third Quartile Adjusted Gross Income Per-capita (in $100)	208.84	0.050	0.14	[-0.02, 0.12]	417	0.19	0.17
Fourth Quartile Adjusted Gross Income Per-capita (in $100)	163.21	0.034	0.30	[-0.03, 0.10]	327	0.19	0.19

Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Data on ZIP code demographics are derived from the United States Census Bureau 2010 Census Summary File 1. Data on ZIP Code income are derived from the Internal Revenue Service (IRS) Statistics of Income (SOI). Adjusted gross income is derived from individual income tax returns (Forms 1040). Estimates are derived using the default options in Calonico et al. (2017). Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster.