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

Tejendra P. Singh[1]

[1]Georgia State University

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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 (LFOs). 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. Increased default likelihood is more pronounced for poorer and non-White defendants. My estimate reveals a statistically significant increase in arrests resulting from warrants issued due to defaults on legal debt for low-level traffic violations, suggesting these defaults are a contributing factor to the pipeline-to-prison. Finally, my mechanism analysis rules out cognitive demands in the aftermath of natural disasters and suggests liquidity constraints as the likely mechanism leading to LFO defaults. 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
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†*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 or there are no alternate funding sources. One such emergency expense is fines for traffic violations. For instance, the minimum speeding fine in Oklahoma, the context of this research, is \$172. These fines are part of legal financial obligations (LFOs) which are costs imposed by the courts. Unpaid traffic fines, used interchangeably with legal debt default, result in failure to pay (FTP) or failure to appear (FTA). FTP or FTA instances on traffic violations are highly consequential as they lead to loss of driving privileges, an increase in the outstanding amount owed to the courts, and issuance of a warrant for arresting the defendants.

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, Ouss and Shah, 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, suggesting that legal debt defaults increase the amount owed to the courts by the defendant.

Existing work highlights the detrimental consequences of traffic fines on household finances such as the decline in credit scores, lower borrowing limits, and increased unemployment with these effects being more pronounced for racial and ethnic minorities (Mello, 2023). We, however, lack knowledge about the determinants of economically and socially costly FTP or FTA. In this paper, I examine how exposures to natural disasters affect the likelihood of FTP or FTA and how these effects vary across various subpopulations. Hsiang and Jina (2014) document that in the short-run, three out of four potential paths of long-run adjustment to natural disasters lead to negative effects on the local economy.[1] 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)

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

website. These data provide extremely detailed information related to traffic citations like the date of offense, the statutes that are 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 month-year. 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).

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, Idrobo and Titiunik, 2024).

Results show that natural disaster exposure increases the likelihood of an FTP or FTA instance on a traffic citation by 4 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 16.13%. This conclusion is robust to a host of empirical checks suggested for the continuity based approach, made plausible in my setting through a large mass of traffic citations close to the threshold, in an RDD framework (Cattaneo, Idrobo and Titiunik, 2020b). RDD estimates suggest that the increased likelihood of FTP or FTA instances persists for more than 100 days following the natural disaster onset.

Heterogeneity analysis reveals that the increase in the likelihood of an FTP or FTA instance is more pronounced for defendants who are less wealthy and non-White. Relative to their wealthier counterparts, poor defendants are 48 times more likely to default on their legal financial obligations (LFOs). Natural disasters, thus, have the potential to worsen the existing socioeconomic disparities in the CJ system. Leveraging multiple natural disaster types, I also document that the main effect of the increased likelihood of legal debt default is driven by floods, hurricanes, and severe storms. No effect of tornadoes on legal debt default likelihood suggests adaptation to natural disasters that occur more frequently. Examining heterogeneous effects of natural disaster exposure on legal debt defaults by the severity of the offense for which the defendant is cited shows FTP or FTA likelihood increases monotonically with the offense severity.

I also establish that defaults on low-level traffic violations contribute to defendants getting involved with the wider criminal justice (CJ) system as I show that arrest warrants issued in the aftermath of FTP or FTA by the defendant when their residence ZIP Code is affected by the natural disasters are more likely to be exercised. Thus, defaults on low-level traffic LFOs are a contributing factor towards pipeline-to-prison (Pager, Goldstein, Ho and Western, 2022).

Using the detailed information on fines and fees owed to the courts from the docket data, I am able to examine the increase in total fines and fees after the defendant's residence ZIP Code is affected by a natural disaster. In the immediate aftermath of natural disasters, traffic citations that have an initial appearance date for the defendant after the natural disaster experience an increase of approximately $65 in total fines and fees. Back-of-the-envelope calculation suggests that this increase in total fines and fees is approximately $29.33 million for all traffic citations where the initial appearance date is after the natural disaster.

I examine likely mechanisms through which natural disaster exposure increases LFO default likelihood. I find evidence inconsistent with increased cognitive burdens in the aftermath of natural disasters as the likely pathway leading to the increase in FTP or FTA likelihood. I show that when a defendant's residence ZIP Code is struck by a natural disaster, they are more likely to request an extension or deferment of their court appearance date. I also establish that there is an increase in requests for enrollment in payment plans post-natural disasters. As both extensions and payment plan enrollment requests require defendants to contact county clerks, it is unlikely that defendants are unaware of their LFOs when their residence ZIP Code is affected by a natural disaster.

I do, however, find evidence for liquidity constraints as a likely mechanism for increases in FTP or FTA likelihood after the defendants' residence ZIP Code is affected by a natural disaster. Focusing on the defendants who were already enrolled in a payment plan before their residence ZIP Code was hit by a natural disaster, I find that these defendants are more likely to fall behind on their payment plan obligations post-natural disaster in their residence ZIP Code. Payment plan enrollment suggests that these defendants were already liquidity constrained even before they were exposed to the natural disaster in their residence ZIP Code and natural disaster induced economic losses may have tightened these constraints. Using data on the housing assistance program of FEMA, I also show that short-term financial assistance reduces the likelihood of defendants defaulting on their LFOs highlighting the beneficial role of such relief programs post-natural disasters.

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, Freedman, Ho and Phillips, 2022; Mahoney, Beaudin, Carver III, Ryan and Hoffman, 2001), cognitive overload (Chohlas-Wood, Coots, Nudell, Nyarko, Brunskill, Rogers and Goel, 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 lead 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, Evans and Beckett, 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 (FTP or FTA) 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[2] includes the fees, fines, restitution orders, and other financial obligations that courts and other criminal justice (CJ) agencies impose on individuals accused of crimes or violations like traffic citations (Harris et al., 2010). Since these legal financial obligations (LFOS) are owed to the courts from the time they are assessed and failure to service them leads to consequences similar to those on traditional debt. These consequences include the impact on credit scores and the potential for garnishment of wages or assets. 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 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 FTP or FTA for traffic citations issued in Oklahoma. Additionally, I focus on citations issued by highway patrol, county sheriff, and university police. These citations are processed

[2] I use legal debt and legal financial obligations (LFOS) interchangeably.

in state court. FTP or FTA 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 FTP or FTA 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, Kawano and Levitt, 2018; Groen, Kutzbach and Polivka, 2020). Extreme weather events are very likely to become more frequent, intense, and severe in the future (Jay, Crimmins, Avery, Dahl, Dodder, Hamlington, Lustig, Marvel, Méndez-Lazaro, Osler, Terando, Weeks and Zycherman, 2023). 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 (LFOs). In this section, I describe each data source that I use. The final subsection presents descriptive statistics from the estimation sample.

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 on its website.

These data are obtained through a scraping program. I have scraped four years of traffic citation data from OSCN. These four years are from 2016 to 2019. It is worth emphasizing that although the data are centrally hosted, each county has a different reporting format. Therefore, the construction of the analytical sample is a time- and labor-intensive exercise. OSCN data are used to examine the effect of local natural disaster exposure on LFO defaults as I am unaware of any other jurisdiction within the United States that provides publicly available traffic citation data. Even when traffic citation data are available, they are often available for select police departments or municipalities in contrast to the 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 defendant's residence ZIP Code and for a subset of citations the exact location where the citation is issued. 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.

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, the location of the offense, the violation type, and some details on the vehicle like make and model. Importantly, I can ascertain the bond amount along with information on fines and fees from the citation.

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. Events and case docket data allow me to determine if the court appearance is scheduled for before

[3] See for instance available data from Sowd and Otto (2024). Traffic citation data available from Sowd and Otto (2024) are for individual jurisdictions. Furthermore, these data do not provide information on defendant demographics making them unsuitable to construct natural disaster exposure.

[4] More information on this crosswalk is available here.

or after the defendant's county is exposed to the natural disaster. Appendix Section B presents an example of how traffic citation data are reported on the OSCN website.

3.2 Natural Disasters Data

The data on natural disasters are 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.[5] 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 (NWS) damage assessment toolkit. These data provide information on the exact path of the storms, mainly tornadoes. 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 spatially finer exposure measures.

As part of robustness check, I also use data from the NWS's Storm Prediction Center's data on tornado paths. These data are comparable to damage assessment toolkit data but additionally provide a broader coverage as not all tornadoes have been assessed for their damages.

[5] In subsequent analysis, I do not use fire management assistance disaster declarations.

3.3 Additional Data

The US Census Bureau 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, Olivella and Imai (2023). These data provide probabilistic measures of race and ethnicity which in turn are derived from voter files of six Southern states in the United States with self-reported racial data. For race and ethnicity imputation, I use the defendant's first name.

For heterogeneity based on homeowners insurance availability, I use data from the Department of Treasury. In particular, I use the 2018 nonrenewal rate data. The nonrenewal rate is the ratio of policies that are not renewed at the end of the policy period and the policies in force at the end of the reporting year. Nonrenewal when the policy period ends is due to the risk profiles of properties (e.g., the age of the roof) or areas (e.g., areas with more severe climate-related risks). In areas with high nonrenewal rates, households may have more limited options for insurers or may face increased difficulty purchasing private insurance. These data provide nonrenewal rate data at the ZIP Code-level.

3.4 Analytical Sample Construction

Exposure to natural disasters is based on the reported residence ZIP Code of the defendant. To assign the defendant into treatment and control groups, I use the defendant's reported residence ZIP Code 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 ZIP Code exposed to a natural disaster.

While I do not restrict the estimation sample to citations issued before the natural disaster in the county, in a robustness check I show that my estimates are not sensitive to not including post-disaster citations in the analytical sample. This helps alleviate concerns related to endogenous traffic law enforcement in the aftermath of 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 2016 to 2019.

For the empirical specifications based on the difference-in-differences (D-I-D) framework, the treated group comprises all the defendants who are residents of the ZIP Codes that are exposed to natural disasters. The control group comprises defendants from ZIP Codes that are unaffected by natural disasters over the entire sample period of 2016 to 2019.

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 80% have the defendant being an Oklahoma resident. The most common disaster type in Oklahoma is severe storms. In this paper, I restrict the analytical sample to natural disasters that occur from 2016 to 2019. This period covers instances of both flooding and tornadoes separate from severe storms along with wildfires.

Furthermore, 66 of the 77 counties in Oklahoma are affected by at least one of these natural disasters. The exposed counties are presented in Figure A1. Between 2016 and 2019, 15 severe storms, three flooding, and one drought billion-dollar disaster events affected Oklahoma.[6] Consistent with the national trend, Oklahoma has seen an increase in the disaster count since the turn of the century (see Figure A2). 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.

[6] 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.

The traffic citations are flagged for FTP or FTA instances using the text data scraped from the OSCN website. As each county has a different reporting format, I manually checked the citation data for each county and flagged the traffic citation as having an FTP or FTA instance if there was no ambiguity associated with these instances. In practice, FTA instances always have an FTP instance also if the defendant has an outstanding amount that they owe to the courts. However, since this is not always reported in the traffic citations data that I scraped from the OSCN website, it is likely that I am undercounting the FTP instances. This is due to the fact that a traffic citation in my analytical sample will be flagged as having an FTP instance only if I can ascertain this unambiguously which is not the case when the traffic citations data report FTA even though the defendant had outstanding legal debt.

3.5 Descriptive Statistics

In Figure A2, 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 1 reports summary statistics for the analytical sample. Almost 26% of the traffic citations have an FTP or FTA instance. More importantly, there is no evidence that observable demographic and socioeconomic characteristics differ systematically across treatment and control groups.

The treatment group in Table 1 are those traffic citations for which the initial appearance date is after the natural disaster struck the defendant's residence ZIP Code. The control group, on the other hand, consists of all the traffic citations where the initial court appearance date is before the natural disaster struck the defendant's residence ZIP Code. Urban population fraction is the ratio of the population residing in the urban areas as classified by the U.S. Census Bureau to the total population in the ZIP Code. The working age population comprises those who are between the ages of 15 and 64.

4 Empirical Strategy

To uncover the effect of natural disasters on various outcomes related to debt owed to the courts, I will leverage the initial appearance date associated with each traffic citation in a regression discontinuity design (RDD) empirical framework.[7] 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:

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

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 defaults on their legal debt, i.e., they have either failure to pay (FTP) or failure to appear (FTA) instance. $Date_i$ 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. Thus if a traffic citation is exposed to multiple natural disasters, each natural disaster uniquely contributes to the analytical sample.

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, Cattaneo, Farrell and Titiunik (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

[7]The adopted empirical approach is similar to Finlay, Gross, Lieberman, Luh and Mueller-Smith (2024b).

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 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. It is also worthwhile to note that by comparing traffic citations within the same residence ZIP Code of the defendant on either side of the cutoff, I purge all time invariant unobservable characteristics that may influence FTP or FTA likelihood.

5 Results

5.1 Main 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.

The downward slope in the pre-natural disaster period could be explained by the seasonality in the traffic citations. I examine if this is indeed the case in Figure A3. Neither the monthly total citations nor those citations that have either FTP or FTA instances show any trend by calendar month. The estimates in this figure, therefore, suggest that the downward sloping trend in the pre-disaster period in Figure 1 cannot be explained by the seasonality in the traffic citations.

The downward slope in Figure 1 could be explained by the downward trend in the traffic citations and those with an FTP or FTA instance over the sample period. In Figure A4 the share of traffic citations that have either an FTP or FTA instance is trending downwards over the sample period 2016 to 2019. Figure A5 adds credence to the downward slope in Figure 1 being driven by the downward trend in the FTP or FTA instance traffic citations over the sample period. In Figure A5 I report binscatter using default options in Cattaneo, Crump, Farrell and Feng (2025) to construct bins and global polynomial regression. Furthermore, the analytical sample in Figure A5 is restricted to those ZIP Codes that are not affected by natural disasters over the entire sample period 2016 to 2019. The estimates in this figure show that absent the natural disaster, traffic citations with an FTP or FTA instance are trending downwards.

Figure A6 shows that there is no evidence of a discontinuity in FTP or FTA likelihood for defendants who are residents of ZIP Codes that are never affected by a natural disaster during the sample period of 2016 to 2019. Like Figure A5, the analytical sample in Figure A6 is restricted to those ZIP Codes that are not affected by the natural disasters over the entire sample period 2016 to 2019. The running variable for regression discontinuity design (RDD) estimation in Figure A6 is based on all the natural disasters during the sample period, i.e., those that are used for the RDD estimation in Figure 1.

Taken together, the estimates in Figure 1 along with those in Figures A4, A5, and A6 show that the natural disaster exposure not only breaks the downward trend in the likelihood of traffic citation having an FTP or FTA instance it also puts it on an upward trend in the post-disaster period.

Table 2 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 4 percentage points. In other words, traffic citations whose initial court date was scheduled just after a natural disaster disaster are 4 percentage points more likely to result in FTP or FTA instances. As a proportion of the pre-disaster mean, this is a large increase of approximately 16.13%. This increase in FTP or FTA instance likelihood is statistically significant at the conventional levels of significance.

Table 2 also reports RDD estimates for FTP and FTA individually. The estimates in Table 2 show that immediately post-disaster the likelihood of both FTP and FTA instances increases. The estimates for FTP are slightly less statistically precise. As was discussed in Section 3.4, this could be driven by the approach I take in flagging the traffic citations to have an FTP instance. My approach of flagging traffic citations to have an FTP instance might be undercounting the traffic citations with an FTP instance leading to the statistical imprecision for FTP likelihood increase in Table 2.

5.2 Robustness Checks

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 A7 and Figure A8, 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 A1. For both individual and ZIP Code-level observable covariates, the estimates are from the specification in Equation 1.

In addition to the continuity of the conditional expectation function across the threshold, the validity of the RDD framework in my context requires no manipulation of running variable. The treatment is defined based on the initial appearance date for the traffic citations which is extremely unlikely to be manipulated by the defendant 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.

In order to provide evidence supporting no manipulation of the running variable, I report the density estimates for each discrete running variable value in Figure A9. Figure A9 shows that the density of caseloads across the treatment threshold has no discontinuity. The corresponding p-value is 0.2305. The asymmetry between point estimate and confidence bounds results from different polynomial degrees for their estimation (Cattaneo, Jansson and Ma, 2020a).

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 ZIP Code 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 $[0.0245, 0.0365]$. These bounds are derived from the partial identification approach of Gerard, Rokkanen and Rothe (2020). The magnitude similarity of the partial identification approach bounds with the main estimates in the following section confirms that estimates are not contaminated by the manipulation of the initial court appearance date that underlies the construction of the running variable.

This is further borne out by the estimates reported in Figure A10. The estimates from this figure derive bounds on the average treatment effect using the approach of Gerard et al. (2020) assuming the hypothetical extent of manipulation. Even when assuming twenty percent of the running variable values to be manipulated, natural disasters in the residence ZIP Code of the defendant increase the likelihood of an FTP or FTA instance on the traffic citation. Taken together, estimates using the approach in Gerard et al. (2020) suggest that unobservable characteristics on either side of the threshold are unlikely to be different or that the biasedness of estimates reported in Section 5.1 due to the manipulation of the running variable is minimal.

I also perform a falsification check where artificial cutoffs are chosen before and after the actual cutoff. The results from this exercise are reported in Figure A11. The lack of statistically significant effect on the FTP or FTA likelihood at placebo cutoffs provides evidence for the continuity of the conditional expectation function at points other than the cutoff. Estimates in Figure A11 find no evidence for discontinuity in FTP or FTA likelihood at artificial cutoffs. Note that for cutoffs at either side of the actual threshold, I drop observations on the other side of the actual cutoff so that the estimates at the artificial cutoffs are unaffected by the discontinuity at the actual cutoff. Furthermore, for artificial cutoffs very close to the actual threshold the inference is unreliable. Thus, I report estimates for artificial cutoffs that are at least five days away from the actual threshold in Figure A11.

In Figure A12, I drop observations close to the actual cutoff. By dropping these observations I assess the sensitivity of the estimates reported in Section 5.1 to the few observations close to the cutoff that may exert an outsize influence on local polynomial estimation. Furthermore, this falsification exercise also secures the empirical framework against the manipulation of running variable as it is most likely to occur for observations close to the actual cutoff. Estimates reported in Figure A12 show that the main estimates are not sensitive to the observations close to the cutoff.

The sensitivity of estimates in Section 5.1 to bandwidth choice is examined in Figure A13. By increasing the bandwidth, the bias of the local polynomial estimator increases while its variance decreases. Thus an increase in the bandwidth used for local polynomial estimation is likely to lead to tighter confidence intervals which are displaced due to increased bias. It is also worthwhile to emphasize that bandwidths that are further away from the mean squared error (MSE)-optimal bandwidth will be prone to either too much bias or too much variance making estimation and inference unreliable. The estimates reported in Figure A13 from three alternate bandwidths show that the main estimates are not sensitive to the bandwidth choice. Note that the CER-optimal bandwidth h_{CER}, used for estimation in Figure A13, minimizes the asymptotic coverage error rate of the robust bias-corrected confidence interval for RDD estimate.

The estimates reported in Section 5.1 use the triangular kernel for assigning non-negative weights to the observations on either side of the cutoff. When used in conjunction with MSE-optimal bandwidth, triangular kernel leads to a point estimator with optimal properties (Cattaneo et al., 2020b). When the triangular kernel is used for local polynomial estimation, the weights decline linearly and symmetrically as running variables take values away from the threshold and are maximized at the cutoff. In Figure A14, I show that my main estimates are not sensitive to the kernel used for local polynomial estimation. In this figure, the uniform kernel assigns equal weights to each observation that is within the MSE-optimal bandwidth which is equivalent to estimating a simple linear regression on either side of the cutoff. On the other hand, the Epanechnikov kernel assigns weights to the observations within the MSE-optimal bandwidth that decay quadratically as the running variable takes values away from the cutoff.

Finally, in Figure A15 I also show that my estimates are not sensitive to different polynomial orders used for local polynomial estimation. By using higher polynomial order accuracy of the treatment effect estimator improves at the cost of increased variability. At the same time, higher order polynomials might lead to overfitting which affects the reliability of estimates near the cutoff. I cannot reject the null hypothesis that the estimates from using higher order polynomials are the same as that from the local linear estimator.

The estimates and inference corresponding to these robustness checks are reported in Table A2. These balance tests and placebo checks suggest that the identification assumptions for the estimates to be interpreted as causal are not violated in my empirical context.

Following recommendations in Cattaneo et al. (2024), I also provide estimates from a local randomization approach. 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. The discontinuity estimate from the local randomization approach is -0.015 with asymptotic p-value 0.391. Local randomization approach estimates that I report are considerably smaller than the continuity based approach estimates and lose statistical significance.

Note that the data for the 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. The reduction in discontinuity estimate and loss of statistical significance 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. The RD estimate is 0.024 with an asymptotic p-value 0.032. I have used a minimum window of 10 days on either side of the cutoff with each step adding seven more days while searching for the optimal window.

As I include all traffic citations irrespective of whether they are issued pre- or post-natural disaster, my estimates may be conflated by endogenous policing in the post-natural disaster period. Apriori the direction of the bias is unclear. If post-natural disaster traffic citations are issued to defendants who are more likely to pay the amount owed to the courts, then the estimates reported in Section 5.1 are potentially biased downwards. On the other hand, it may be more likely that traffic citations are issued to relatively poorer defendants who are likely to pay off their court debts at a lower rate (Makowsky and Stratmann, 2009). In Figure A16 I show that my main estimates are not sensitive to restricting the analytical sample by dropping all the traffic citations that are issued post-natural disaster in the defendant's residence ZIP Code. The corresponding point estimates are reported in Table A3.

Next, I discuss estimates from alternate natural disaster data sources that arguably provide a more proximate measure of natural disaster exposure. Information on the exact spatial reach of storms and tornadoes is derived from the National Weather Service's damage assessment toolkit and storm prediction center data. These data provide exact spatial coordinates that are affected by severe storms, mainly tornadoes. The damage assessment toolkit provides information only for those severe weather events for which damage assessment has been conducted. As such, storm prediction center data arguably has wider coverage than damage assessment toolkit data. Nonetheless, the estimates in Figure A17 and Table A4 establish that the main estimates that I document in Section 5.1 are not driven by the natural disaster exposure measure that I use.

I also study whether the main effects discussed in Section 5.1 are robust to dropping deceased defendants from the analytical sample. The estimates from this restricted sample are reported in Figure A18. Deceased defendants can mechanically lead to overcounting FTP or FTA instances in my empirical context. The estimates in Figure A18 suggest that the inclusion of these defendants in the analytical sample is unlikely to be consequential. The estimates from the restricted sample without the deceased defendants are extremely similar to the baseline estimates. The corresponding point estimates are reported in Table A5.

I conclude this section by examining whether the main effects discussed in Section 5.1 are robust to using a different identification strategy. The estimates from difference-in-differences (D-I-D) analysis are reported in Appendix Section C. The estimates in that section show no evidence of non-parallel trends across ZIP Codes affected by at least one natural disaster during the sample period when compared to ZIP Codes that have at least one natural disaster during that same period. The post-natural disaster dynamics resemble those that are reported using the estimates in Figure 1.

5.3 Heterogeneity Analysis

I now turn to examining whether the increase in FTP or FTA likelihood in the aftermath of the defendant's residence ZIP Code being affected by a natural disaster differs across various subpopulations. Using the information on the vehicle make and year from the traffic citations, I can construct a proxy measure of the defendant's wealth level. I borrow from the existing work of Feigenberg and Miller (2025) and flag all the defendants whose vehicle at the time they were cited is older than six years as being relatively less wealthy compared to defendants with a newer vehicle. The estimates reported in Figure 2 show that the relatively poorer defendants are more likely to default on their legal financial obligations (LFOs) in the aftermath of their residence ZIP Code being struck by a natural disaster. Relative to their wealthier counterparts, poor defendants are approximately 14 times more likely to default on their legal financial obligations (LFOs). The corresponding estimates are reported in Table A6.

In order to assuage concerns related to vehicle model year categories, I also report estimates from alternate vehicle model year categorization in Figure A19. None of the reported estimates are statistically significant for this alternate categorization. However, defendants with vehicles older than 13 years at the time they are cited for traffic violation likely drive the increase in FTP or FTA likelihood after their residence ZIP Code is affected by a natural disaster. The corresponding estimates are reported in Table A7. The lack of statistical significance for the estimates reported in Figure A19 could be due to the low number of observations close to the threshold.

Using data from the US Census Bureau, I can examine how the FTP or FTA likelihood change differs across ZIP Code demographics post-natural disaster in the ZIP Code. The estimates from using these data are reported in Figure A20. The corresponding point estimates and inference are reported in Table A8. The most direct comparison of the estimates reported in Figure 2 and Table A6 uses the adjusted gross income data derived from the Internal Revenue Service (IRS) Statistics of Income (SOI). Adjusted gross income is derived from individual income tax returns (Forms 1040). It is worth emphasizing that the two measures are potentially very different from each other. Therefore, apriori the estimates are expected to differ. Indeed, of the four adjusted gross income per-capita quartiles, I find that only the defendants of the ZIP Codes that are at the third quartile of the adjusted gross income per-capita distribution are more likely to default on their LFOs post-natural disaster in their residence ZIP codes.

Contrasting estimates using the ZIP Code-level gross income per-capita data and individual-level information on the market value of the vehicle the defendant has access to at the time of traffic violation highlights the unequal impact of natural disasters across defendants with varying socioeconomic characteristics within the same ZIP Code. Estimates in Figure A20 also show that the defendants of above median urbanized fraction ZIP Codes are the drivers of post-natural disaster increase in FTP or FTA likelihood on their traffic citations.

Estimates in Figure 3 show that non-White defendants drive the increase in FTP or FTA likelihood in the aftermath of a natural disaster in their residence ZIP Code. The race of the defendant is derived using the probabilistic measures of race and ethnicity from Rosenman et al. (2023) which in turn are derived from voter files of six Southern states in the United States with self-reported racial data. To impute the defendant's race I use first name as reported in the traffic citations data scraped from the OSCN website. Non-White defendants are approximately 19 times more likely to default on their LFOs relative to their White counterparts in the immediate aftermath of their residence ZIP Code being impacted by a natural disaster.

Increased FTP or FTA likelihood post-natural disaster only for non-White defendants augurs well with the existing literature that documents racial disparities in the criminal justice (CJ) system (Agan, 2024; Finlay, Luh and Mueller-Smith, 2024a; Harris et al., 2010; Harris, 2016). Estimates in Figure A20 further lend credence to this conclusion. In Figure A20, defendants residing in ZIP Codes with below median White population share are the ones that default on their LFOs emanating from traffic citations. Estimates corresponding to Figure 3 are reported in Table A9.

Figure A21 and Table A10, shows no evidence that there are gender differences in the FTP or FTA likelihood when the defendant's ZIP Codes are affected by a natural disaster. I also do not find any evidence of the heterogeneous impact of natural disaster exposure on FTP or FTA likelihood by the availability of homeowners insurance in the residence ZIP Code of the defendant. These estimates are reported in Figure A22 and Table A11. Homeowners insurance availability data are derived from the Department of Treasury. More details on these data are provided in Section 3.3. In areas with high nonrenewal rates, households may have more limited options for insurers or may face increased difficulty purchasing private insurance. These data provide nonrenewal rate data at the ZIP Code-level.

Next, I examine if different natural disaster types affect the FTP or FTA likelihood after they hit the defendant's residence ZIP Code. FEMA disaster declaration data provides information on the disaster type. Using this information, I report RDD estimates for five disaster types: fires, floods, hurricanes, tornadoes, and severe storms. The estimates from this exercise are reported in Figure 4 and Table A12. The increase in FTP or FTA likelihood after the defendant's residence ZIP Code is affected by a natural disaster is driven by floods, hurricanes, and severe storms. Given the high frequency of tornadoes in Oklahoma, a statistically insignificant effect of natural disaster exposure on the defendant's legal debt default likelihood at conventional levels of statistical significance suggests a role for adaptation (Heutel, Miller and Molitor, 2021).

Using counts for which the defendants are charged, I can examine how offense severity affects the defendant's FTP or FTA likelihood post-natural disaster in their residence ZIP Code. I manually worked through more than 26,000 count descriptions to create three mutually exclusive and exhaustive offense severity categories: low, medium, and high. The amount owed to the courts increases along the offense severity distribution. Thus, it is likely that traffic violations with high offense severity would have a higher rate of FTP or FTA instances post-natural disaster. Estimates in Figure 5 and Table A13 provide evidence supporting this hypothesis. Traffic violations with high offense severity are approximately 5.3 percentage points more likely to have an FTP or FTA instance in the immediate aftermath of a natural disaster in the defendant's residence ZIP Code.

Overall, the estimates in this subsection show robust evidence for the worsening of existing socioeconomic disparities in the CJ system due to LFO defaults by the defendants who reside in ZIP Codes affected by the natural disaster and have an outstanding debt that they owe to the courts (Agan, 2024). Furthermore, I find evidence for adaptation to the most common disaster in my context, tornadoes along with a higher likelihood of legal debt default for traffic citations where the defendant was charged with a more severe offense.

5.4 Mechanisms

In this subsection, I examine two potential mechanisms that might explain the increased FTP or FTA likelihood when the defendant's residence ZIP Code is affected by a natural disaster. The first of these examines if cognitive burdens that are potentially heightened in the aftermath of a natural disaster are a likely channel through which defendants default on their LFOs originating from traffic citations. The second mechanism examines if liquidity constraint is the pathway leading to eventual FTP or FTA instances on the traffic citation.

As natural disasters are widely disruptive, it is plausible that defendants are unable to keep up with their outstanding debt to the courts as well as the date by which they are supposed to either contest or plead guilty on the charges that were brought against them for traffic violations. Defendants, however, can defer their initial court 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 presiding judge.

Furthermore, if the defendant is unable to pay the entirety of the outstanding amount owed to the court, they can request the court clerk or the presiding judge to enroll them in a payment plan. If defendants are unable to keep track of their court appearance in the aftermath of a natural disaster affecting their residence ZIP Code, then there must be a decline in the likelihood of extension or deferment of the initial court appearance date or the defendant's requesting enrollment in the payment plans. Estimates in columns (1) to (3) of Table 3 provide evidence against this hypothesis.

In the first column of Table 3, I show that in the immediate aftermath of a natural disaster striking the defendant's residence ZIP Code they are more likely to request enrolling in a payment plan or an extension or deferment of their initial court appearance date. Columns (2) and (3) break down these two request likelihoods and suggest dynamics extremely similar to those documented in the first column of Table 3. Taken together the estimates in the first column of Table 3 show that it is unlikely that increased cognitive demands after the natural disaster lead to an increase in FTP or FTA likelihood by the defendants in my analytical sample.

Point estimates in Table 3 that there is at least a 3.9 percentage points increase in the likelihood of the defendant requesting an extension or deferment of their initial court appearance date or enrollment in the payment plans. Relative to the pre-natural disaster mean, this likelihood increase is at least approximately 22%.

The final column of Table 3 shows that the total fines and fees assessed for traffic citations increase where the initial court appearance date is after the defendant's ZIP Code is affected by a natural disaster. Back-of-the-envelope calculation suggests that this increase in total fines and fees is approximately $29.33 million for all traffic citations where the initial appearance date is after the natural disaster. More details on this calculation are provided in Appendix Section F.

In Table 4, I investigate whether liquidity constraints due to natural disasters explain the heightened propensity of defendants defaulting on their LFOs originating from traffic citations. The estimates in this table use traffic citations where the defendant is already enrolled in a payment plan before their residence ZIP code is struck by a natural disaster. For these defendants, I examine if there is a change in the likelihood of them keeping up with the payment plan. Since the defendants who are already enrolled in a payment plan are potentially financially constrained, therefore an increase in the likelihood of them being unable to service their payment plan shows that natural disaster in their residence ZIP Code tightens their financial constraints.

It is worth emphasizing that due to restricting the analytical sample to those citations where the initial appearance in the court is scheduled before the defendant's residence ZIP Code is affected by a natural disaster, I am unable to estimate the specification in Equation 1. Thus, I estimate the following specification

$$\mathbb{1}\left(\text{FTP}_i\right) = \alpha_{c(i)} + \alpha_{w(i)\times y(i)} + \beta \cdot \mathbb{1}\left[NaturalDisaster_{z(i)}\right] + \epsilon_i \tag{2}$$

In Equation 2, $\mathbb{1}\left(\text{FTP}_i\right)$ is an indicator variable for whether the traffic citation i has an instance of FTP post-natural disaster in the residence ZIP Code of the defendant $\mathbb{1}\left[NaturalDisaster_{z(i)}\right]$. Equation 2 also controls for time invariant county of residence characteristics through county fixed-effects $\alpha_{c(i)}$ and secular changes common across all ZIP Codes at the calendar week-level corresponding to the initial date of court appearance through calendar week-year fixed effects $\alpha_{w(i)\times y(i)}$. The specification in Equation 2 is estimated after stacking all the natural disasters and collapsing the resulting data at the residence county and calendar week-year-level. Thus, the coefficient of interest in Equation 2, β is the marginal effect of the defendant's residence ZIP Code being struck by a natural disaster on the likelihood of them failing to service their payment plan which they are already enrolled in before the natural disaster event.

Estimates in Table 4 show that there is an increase in the likelihood of defendants failing to service their payment plans. In the immediate aftermath of the residence ZIP Code of the defendant being struck by a natural disaster, the likelihood of them failing to service their payment plan goes up by approximately 2 percentage points. This effect is statistically significant at conventional levels of statistical significance and also quantitatively meaningful at approximately 10 percent of the pre-disaster mean. Thus, there is evidence that liquidity constraints influence the likelihood of defendants' FTP or FTA on their LFOs that originate from them being cited for a traffic violation after their residence ZIP Code is impacted by a natural disaster.

Overall, the estimates in this subsection suggest that cognitive burdens emanating from widely disruptive natural disasters are not a likely channel through which the likelihood of defendants defaulting on their LFOs emerge after their residence ZIP Code is struck by a natural disaster. Rather it is the liquidity constraint that drives the increased likelihood of legal debt default after the natural disasters.

5.5 Pipeline-to-Prison Analysis

Can defaults on LFOs arising from traffic citations explain defendants getting entangled in the CJ system? FTP or FTA instances on outstanding amounts owed to the courts not only lead to an increase in fines and fees that are already owed to the courts, but the presiding judge may also issue a warrant for the arrest of the defendant from the bench. 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.

In Table 5, I examine if the bench warrants issued on traffic citations are more likely to be exercised in the aftermath of the defendant's residence ZIP Code being struck by a natural disaster. In column (1) of Table 5, I show that the likelihood of the defendant getting arrested after their residence ZIP Code is affected by a natural disaster increases. This change in the arrest likelihood of approximately 1 percentage point is not only statistically significant but also economically large at approximately 58 percent increase over the traffic citations where the defendant is scheduled to appear for their initial court appearance before the ZIP Code is struck by the natural disaster.

Furthermore in the second column of Table 5, I show that those traffic citations that had an FTP or FTA instance also have a higher likelihood of the bench warrant being exercised post-natural disaster exposure in the defendant's residence ZIP Code. If the defendant is initially scheduled to appear for their initial court appearance after their residence ZIP Code is impacted by a natural disaster then the likelihood of the bench warrant on their traffic citation issued post FTP or FTA instance increased by approximately 2.8 percentage points. Relative to the pre-natural disaster mean, this is a sizable increase of approximately 34.1 percent. Thus, defaults on low-level traffic LFOs are a contributing factor towards pipeline-to-prison (Pager et al., 2022).

5.6 Policy Implications

In this subsection, I examine if short-term financial help in the aftermath of natural disasters affects the likelihood of defendants impacted by natural disasters defaulting on their legal financial obligations (LFOs). As shown in Section 5.4, liquidity constraints tightening when the defendant's residence ZIP Code is affected by a natural disaster is the likely mechanism leading to the defendants defaulting on their legal debt. Thus, programs that help relax these constraints may impact the default likelihood.

Federal Emergency Management Agency (FEMA) provides vital financial assistance through its housing assistance program, part of the Individuals and Households Program (IHP), to homeowners and renters affected by federally declared disasters. This aid can include temporary help with rent, other needs assistance (ONA) for uninsured costs like damaged personal property or childcare, and direct housing assistance such as transportable housing units, repairs to multi-family homes, or permanent housing construction.

To qualify for FEMA assistance, individuals must meet certain general criteria. They need to confirm that the disaster-affected property was their primary residence and that their disaster-related expenses aren't already covered by other sources, such as insurance or other programs. If applicants have insurance, FEMA will require proof of their settlement or a denial letter before determining the amount of assistance they can receive based on the difference between losses and coverage from other sources.

Using ZIP Code-level data, I categorize defendants who are residents of ZIP Codes where at least one household received FEMA assistance as being potential beneficiaries of FEMA's housing assistance program. In Figure 6 and Table A14, I show that those defendants who are not potentially exposed to housing assistance drive the increase in the likelihood of defendant's default on their LFOs. Defendants who are residents of ZIP Codes without any housing assistance program approval are approximately 4.2 percentage points more likely to have an FTP or FTA instance in the immediate aftermath of the natural disaster impacting their residence ZIP Code.

The estimates in this section demonstrate the potential beneficial effects of short-term financial assistance in preventing a rise in legal debt defaults in the event of the defendant's residence ZIP Code being impacted by a natural disaster.

6 Discussion and Conclusion

In this paper, I examine if natural disaster exposure affects the likelihood of defendants defaulting on their legal financial obligations (LFOs). 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 4 percentage point increase in the FTP or FTA likelihood is approximately 16% 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 court appearance date associated with each traffic citation.

Heterogeneity analysis suggests that the increase in FTP or FTA likelihood is driven by the less wealthy and non-White defendants. I also provide evidence for defaults on LFOs originating from low-level traffic violations are a contributory factor towards pipeline-to-prison as there is an increase in the likelihood that the defendant is arrested when their residence ZIP Code is struck by a natural disaster before they are scheduled to appear in the court for their initial appearance. I show that cognitive demands that potentially increase after natural disasters are not a likely mechanism leading to FTP or FTA likelihood increase and provide evidence for liquidity constraints to explain the change in this likelihood.

I also show that the total fines and fees assessed for traffic citations increase when the initial court appearance date is after the defendant's ZIP Code is affected by a natural disaster. Back-of-the-envelope calculation suggests that this increase in total fines and fees is approximately $29.33 million for all traffic citations where the initial appearance date is after the natural disaster.

Taken together, the estimates in this paper suggest that there is potential merit to considering 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 Garin, Koustas, McPherson, Norris, Pecenco, Rose, Shem-Tov and Weaver (2025); Mueller-Smith (2015). Furthermore, as climate change is expected to make natural disasters more frequent, intense, and longer, these interventions are likely to become even more relevant.

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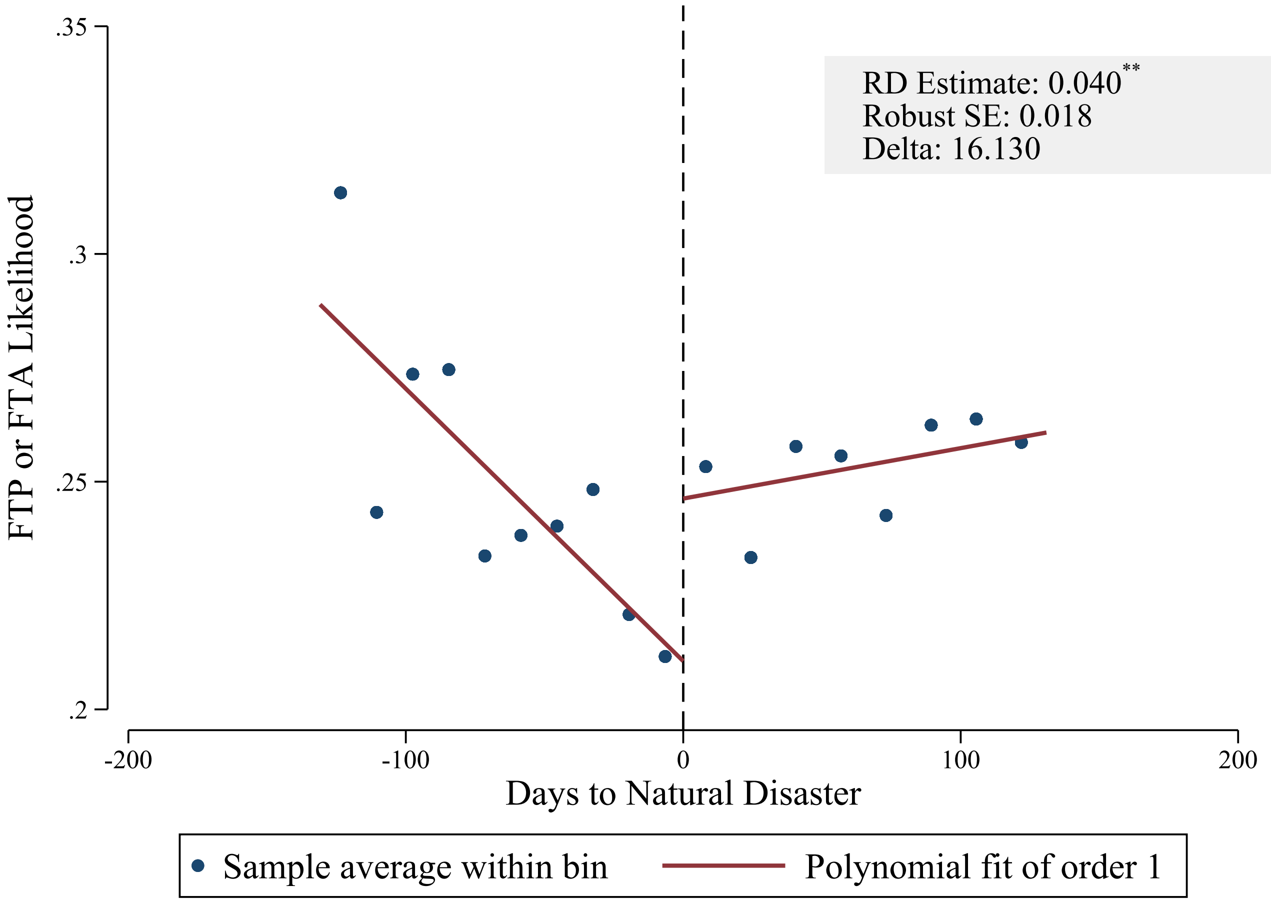
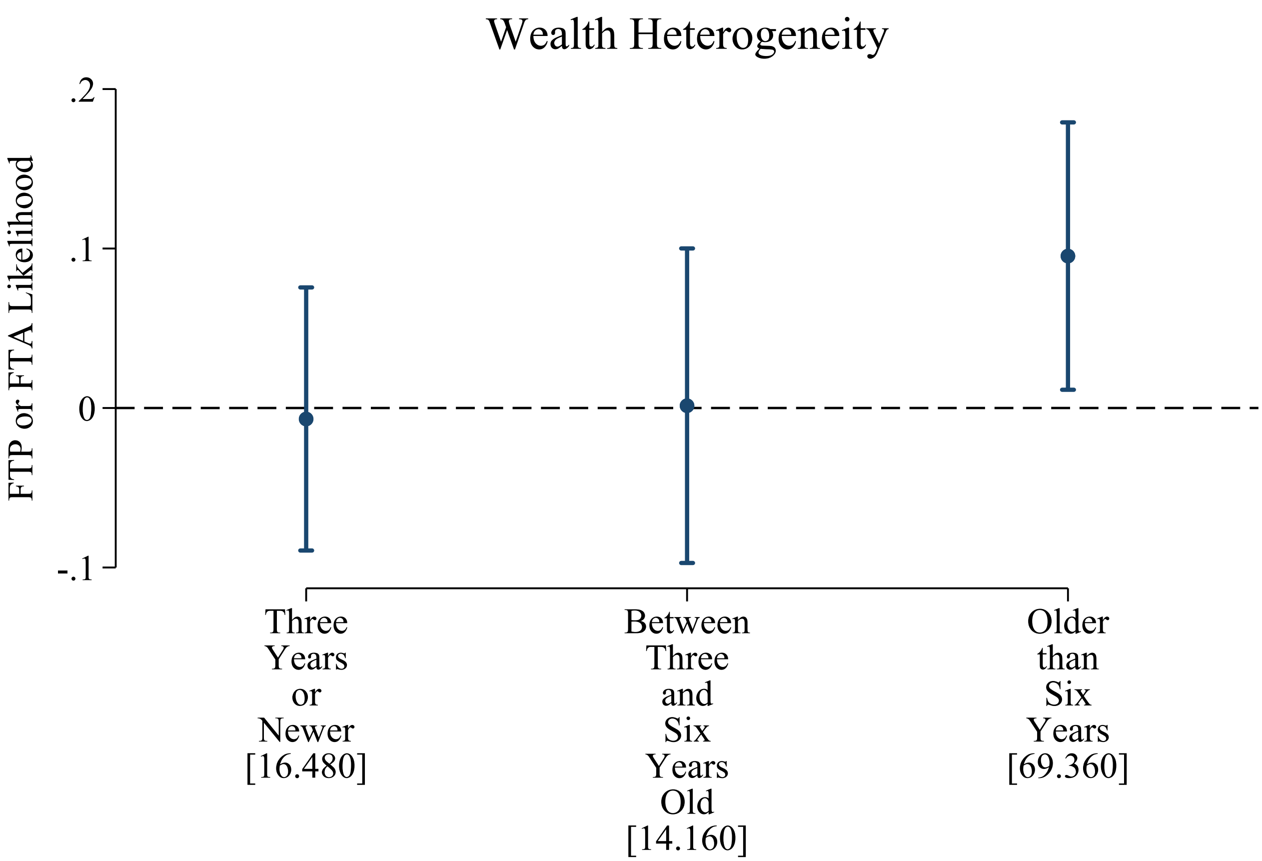
Figure 1: Effect of Natural Disaster on Legal Debt Default



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.

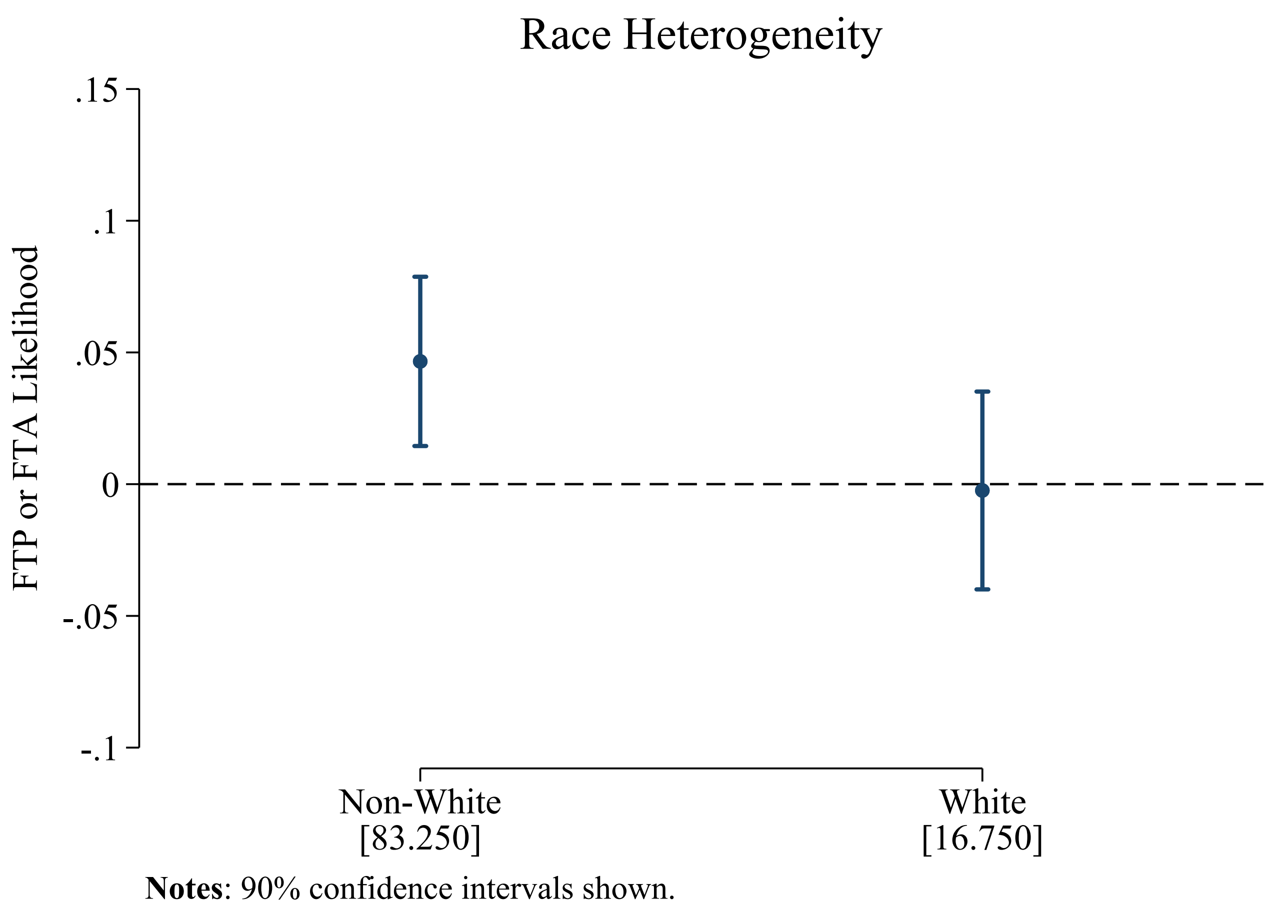
Figure 2: Heterogeneity: Pre-determined Defendant Characteristics



Notes: 90% confidence intervals shown.

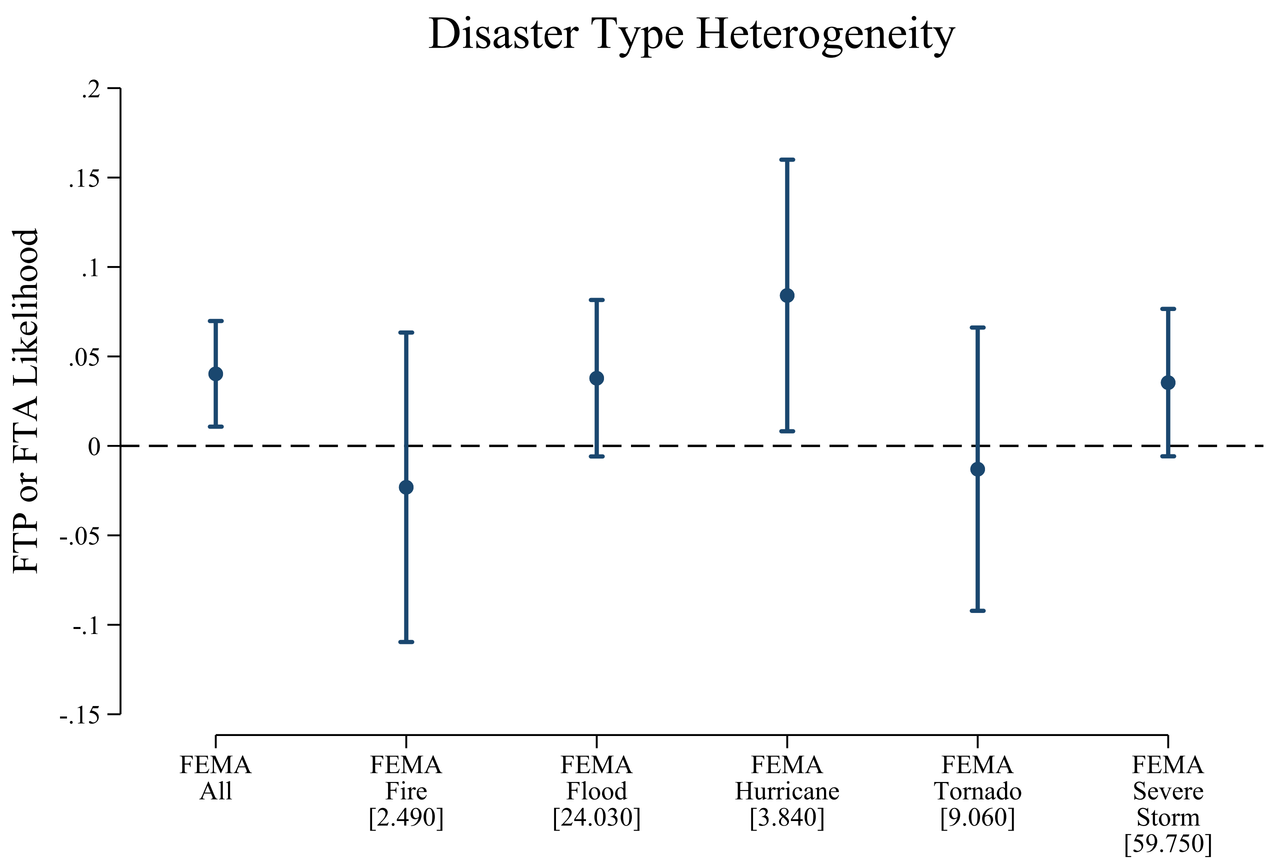
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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 3: 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.

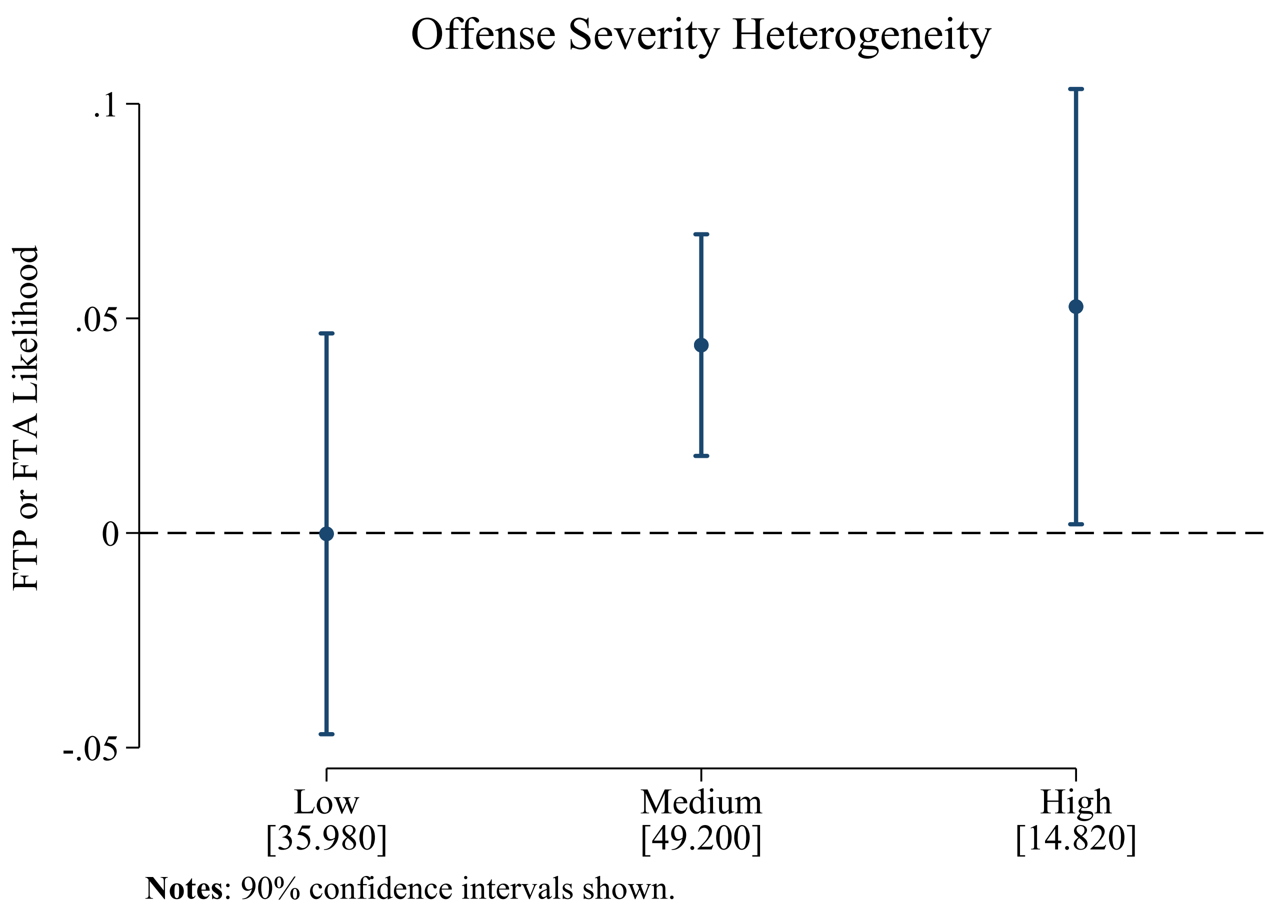
Figure 4: Heterogeneity: Disaster Type



Notes: 90% confidence intervals shown.

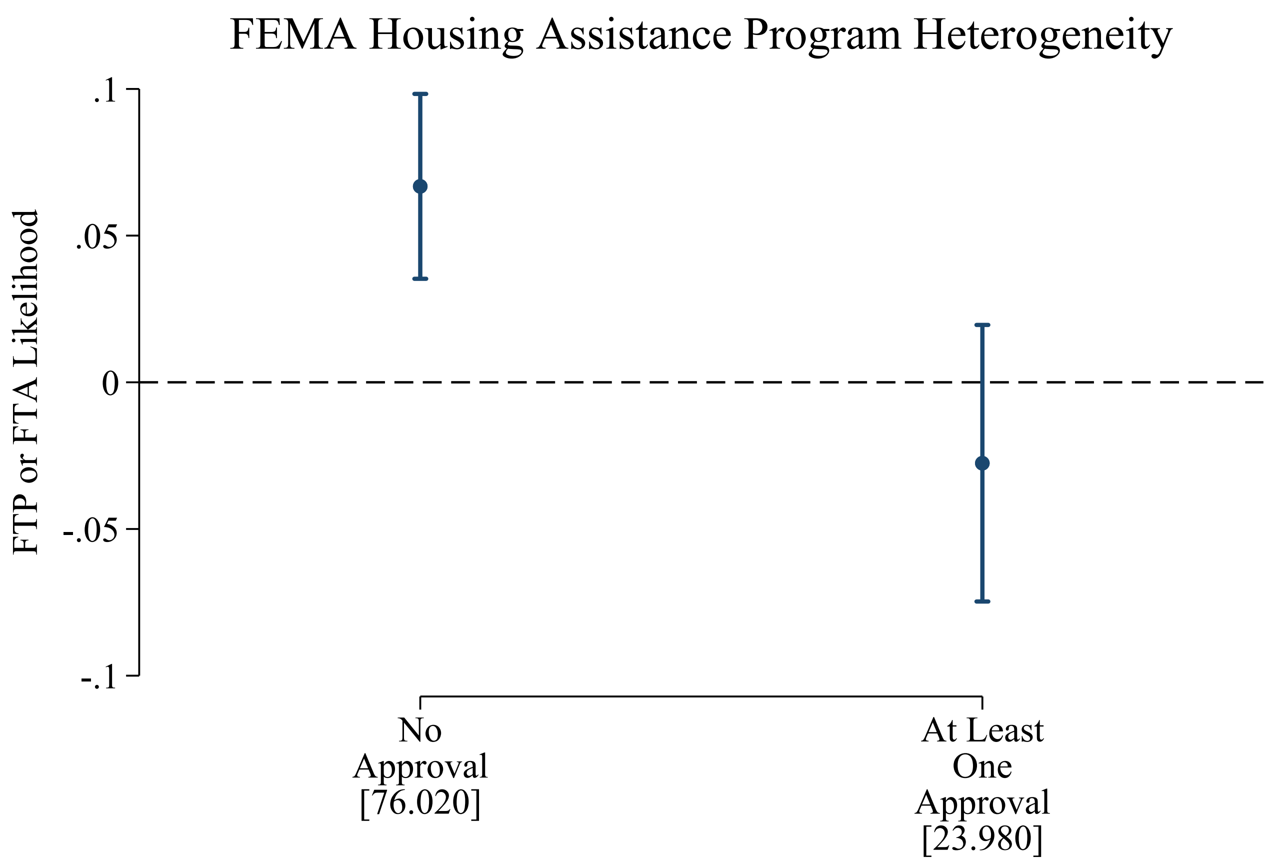
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters in estimates labeled "FEMA" are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Data on natural disasters in estimates labeled "NOAA Damage Assessment Toolkit" are derived from the National Oceanic and Atmospheric Administration (NOAA)'s Damage Assessment Toolkit dataset. Data on natural disasters in estimates labeled "NOAA Storm Prediction Center" are derived from the National Oceanic and Atmospheric Administration (NOAA)'s Storm Prediction Center dataset. 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 5: Heterogeneity: Offense Severity



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. 90% 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 6: Heterogeneity: FEMA Housing Assistance Program



Notes: 90% confidence intervals shown.

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 the FEMA Housing Assistance Program are used to categorize ZIP Codes with at least one household with approved FEMA assistance. Default options, as documented in Calonico et al. (2017) are used. 90% 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 1: Summary Statistics

	All	Control	Treatment
Outcomes			
$\mathbb{1}$ (FTP or FTA Citation)	0.262	0.274	0.229
	(0.439)	(0.446)	(0.420)
Individual Variables			
Age (in 20 years)	1.771	1.746	1.792
	(2.669)	(2.999)	(2.479)
Male	0.480	0.425	0.561
	(0.500)	(0.494)	(0.496)
Non-White	0.831	0.835	0.827
	(0.375)	(0.372)	(0.378)
ZIP Code-level Variables			
Fraction Urban	0.589	0.574	0.533
	(0.386)	(0.383)	(0.387)
Fraction White	0.713	0.716	0.724
	(0.158)	(0.155)	(0.154)
Fraction Working Age	0.650	0.649	0.649
	(0.039)	(0.039)	(0.039)
Adjust Gross Income (AGI) Per-capita ($100)	0.234	0.232	0.234
	(0.109)	(0.107)	(0.108)
Natural Disaster Variables			
$\mathbb{1}$ (Major Disaster)	0.826	0.781	0.905
	(0.379)	(0.413)	(0.293)
$\mathbb{1}$ (Emergency)	0.174	0.219	0.095
	(0.379)	(0.413)	(0.293)

Notes: The number of observations in the column labeled “All” is $1,105,327$. The number of observations in the column labeled “Control” is $610,716$. The number of observations in the column labeled “Treatment” is $348,815$. 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 2: Effect of Natural Disaster on Legal Debt Default – Main Effect

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
$\mathbb{1}$ (FTP or FTA)	130.92	0.040	0.02	[0.01, 0.08]	261	0.26	0.08
$\mathbb{1}$ (FTP)	144.25	0.015	0.14	[-0.01, 0.04]	289	0.09	0.05
$\mathbb{1}$ (FTA)	112.71	0.047	0.00	[0.02, 0.08]	225	0.20	0.07

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 in each row 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.

Table 3: Payment Plan, Extension or Deference, and Arrests

	$\mathbb{1}$ (Payment Plan or Extension/Deferment)	$\mathbb{1}$ (Payment Plan)	$\mathbb{1}$ (Extension/Deferment)	Total Fines
	(1)	(2)	(3)	(4)
RDD Estimate	0.04762***	0.03934***	0.04243***	64.53955**
	(0.00956)	(0.00900)	(0.00914)	(28.06049)
$\frac{\text{Coefficient}}{\text{Pre-treatment Mean}} \times 100$	22.9	22.0	27.5	23.7
N	731	731	731	731

Note: Heteroskedasticity robust standard errors in parentheses. (* p<.10 ** p<.05 *** p<.01). 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. Each observation in all columns is at the day-level. Day-level observations are based on the initial appearance date of the citation and the date of the beginning of the natural disaster. Column headers denote the outcome variable.

Table 4: Default on Payment Plans Enrolled before Natural Disaster

	Estimator	Robust Inference		Number of	Dep. Var.	Dep. Var.
		p-value	95% CI	Observations	Mean	SD
$\mathbb{1}$ (FTP)	0.020	0.07	[-0.00, 0.04]	4,938	0.20	0.37

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. Empirical specification includes fixed-effects for the year-week during which the defendant is scheduled to initially appear in the court and their residence county. Robust standard errors are reported.

Table 5: Pipeline-to-Prison

	$\mathbb{1}\,(\text{Arrested})$	$\mathbb{1}\,[\text{Arrested}\vert$ $\mathbb{1}\,(\text{FTP or FTA})]$
	(1)	(2)
RDD Estimate	0.00953^{***}	0.02759^{***}
	(0.00302)	(0.00939)
$\frac{\text{Coefficient}}{\text{Pre-treatment Mean}} \times 100$	57.8	34.1
N	731	731

Note: Heteroskedasticity robust standard errors in parentheses. (* p<.10 ** p<.05 *** p<.01). 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. Each observation in all columns is at the day-level. Day-level observations are based on the initial appearance date of the citation and the date of the beginning of the natural disaster. Column headers denote the outcome variable.

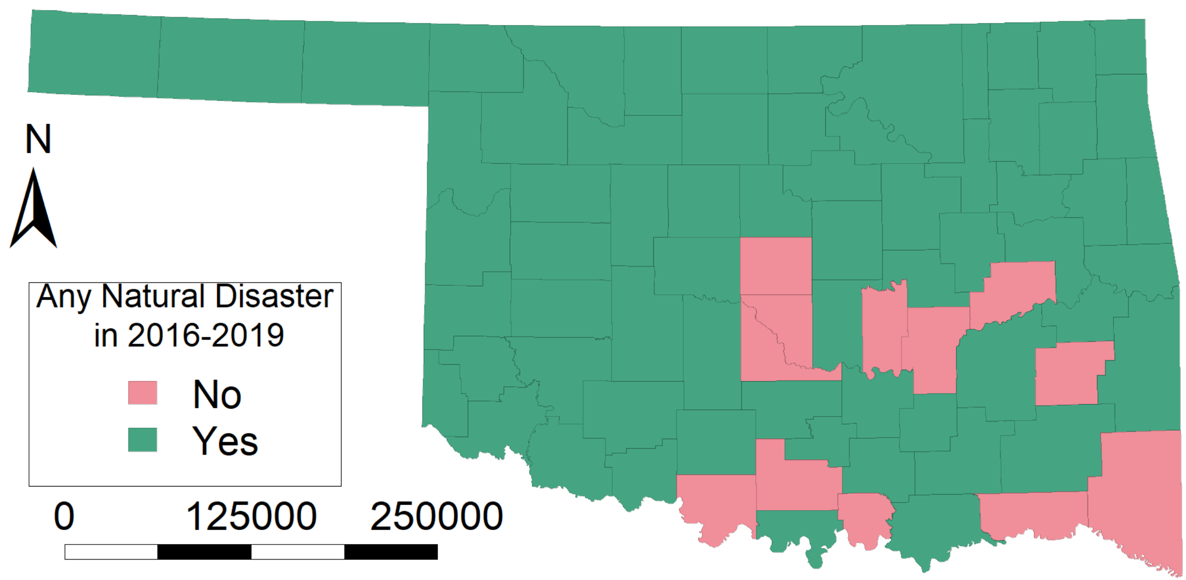
Online Appendix for The *Marshalsea* Underwater: Natural Disasters and Legal Debt Defaults

Tejendra P. Singh

May, 2025

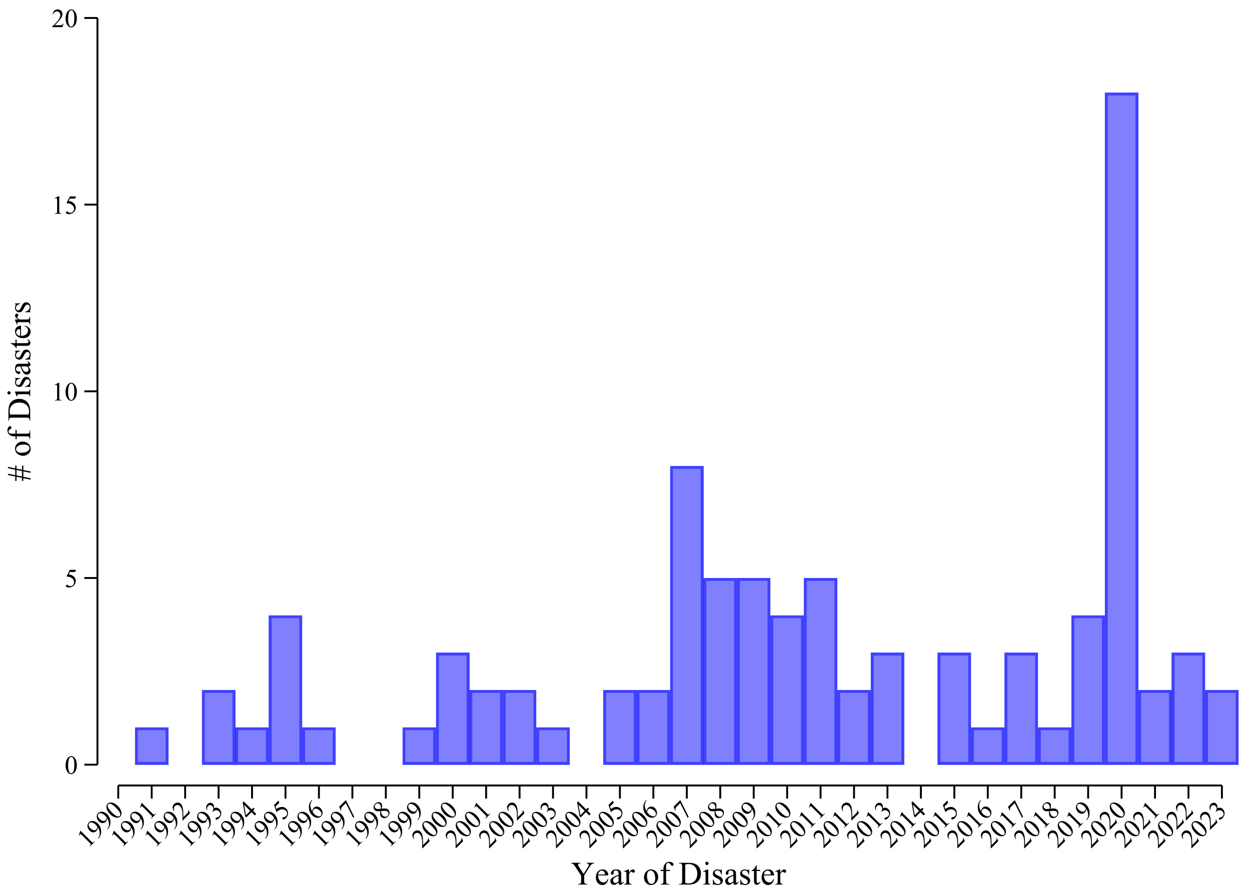
A Figures and Tables

Figure A1: Oklahoma Counties with at least One Natural Disaster During the Sample Years



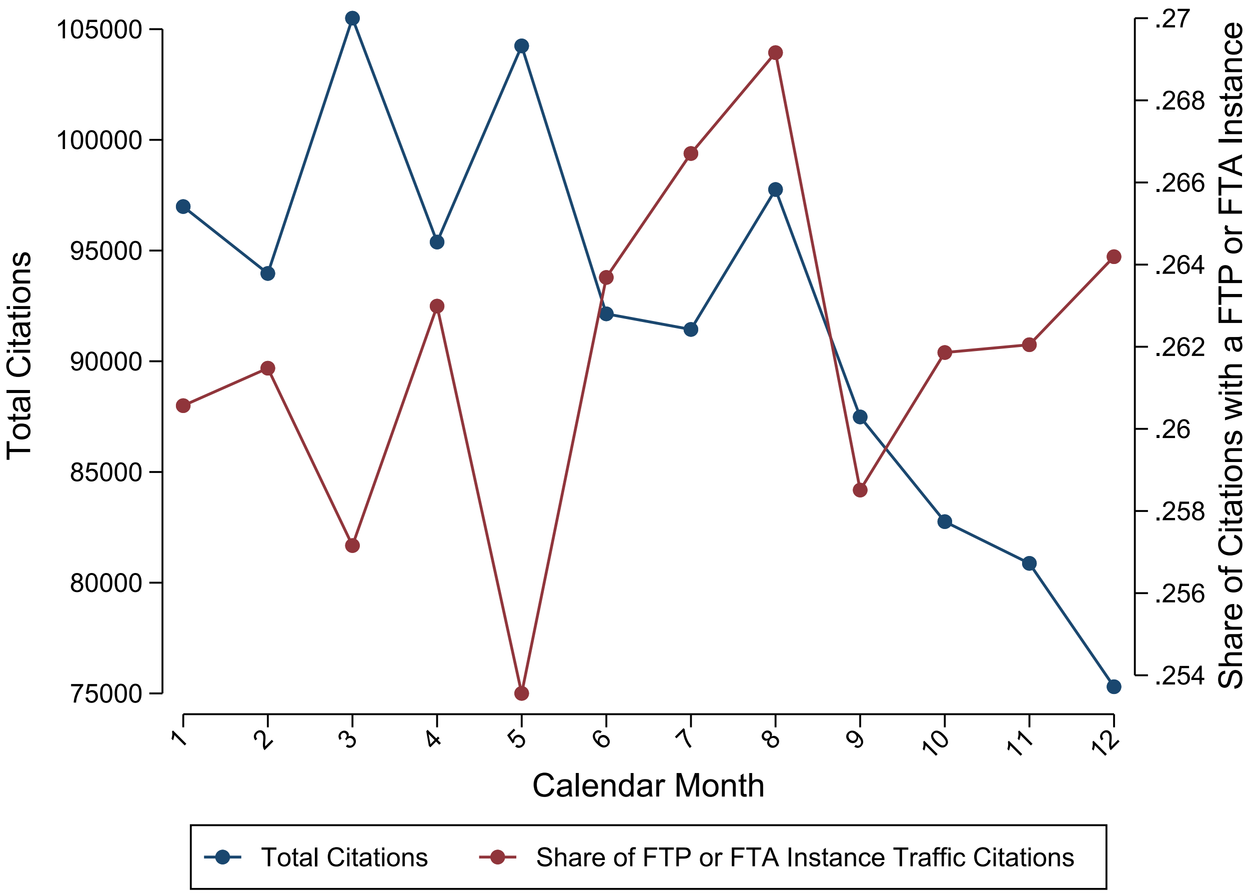
Note: Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Natural disasters only for years 2016 to 2019 are kept in the analytical sample. County shapefiles data are derived from United States Census Bureau.

Figure A2: Temporal Variation in Natural Disasters in Oklahoma



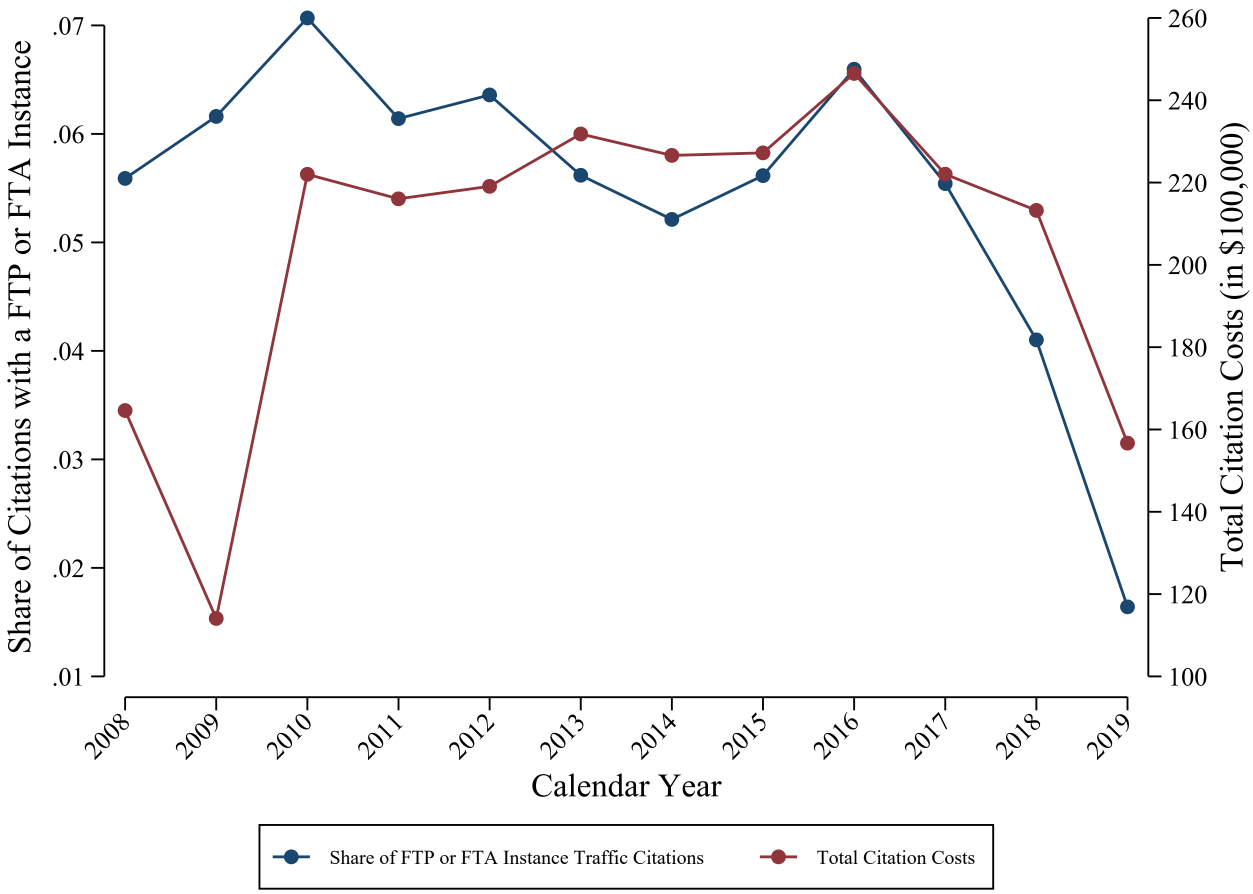
Note: Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. The year on the horizontal axis corresponds to the year in which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

Figure A3: Monthly Trends: Total Citations and Share of Citations with a FTP Instance



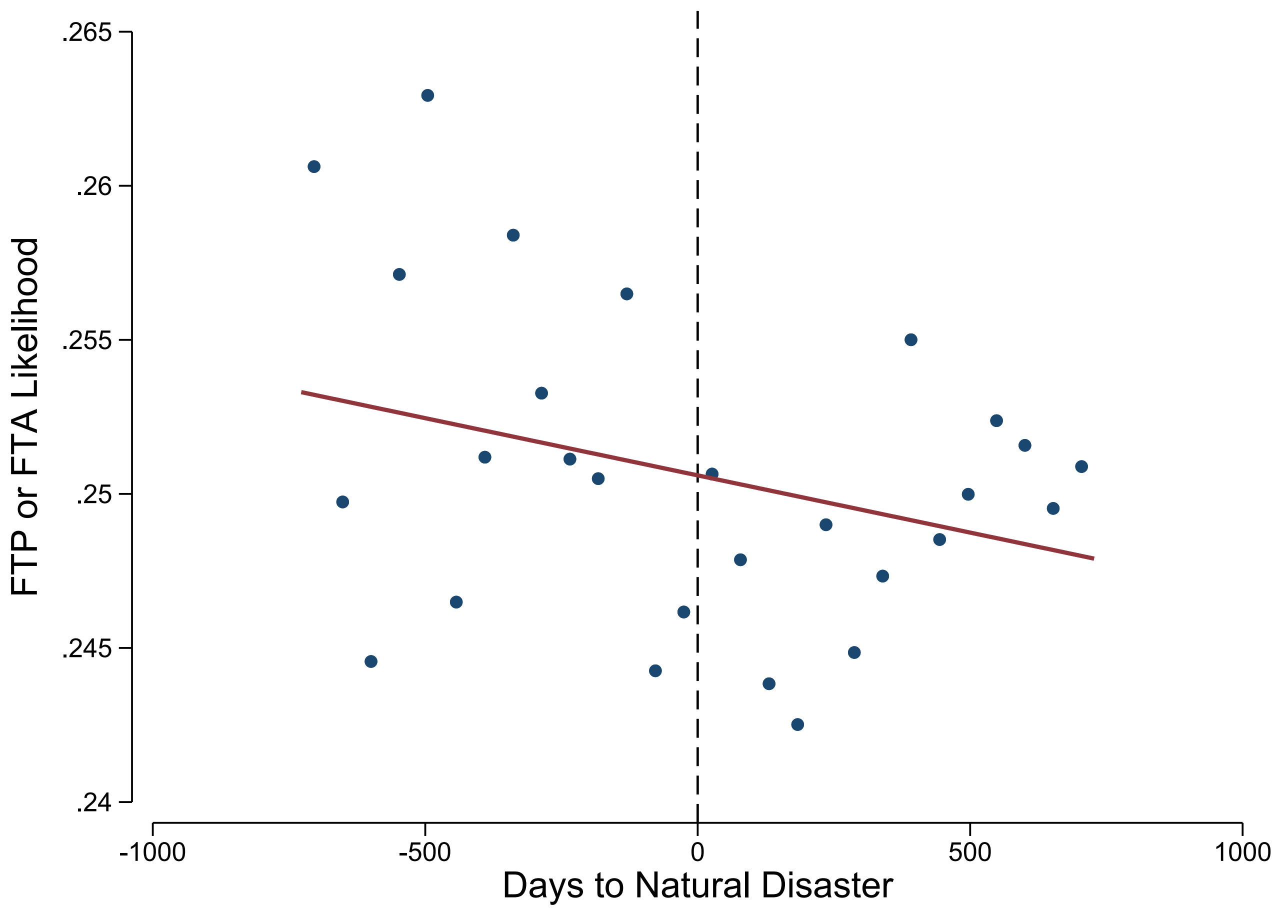
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN).

Figure A4: Temporal Variation in Share of FTP or FTA Citations and Total Costs in Oklahoma



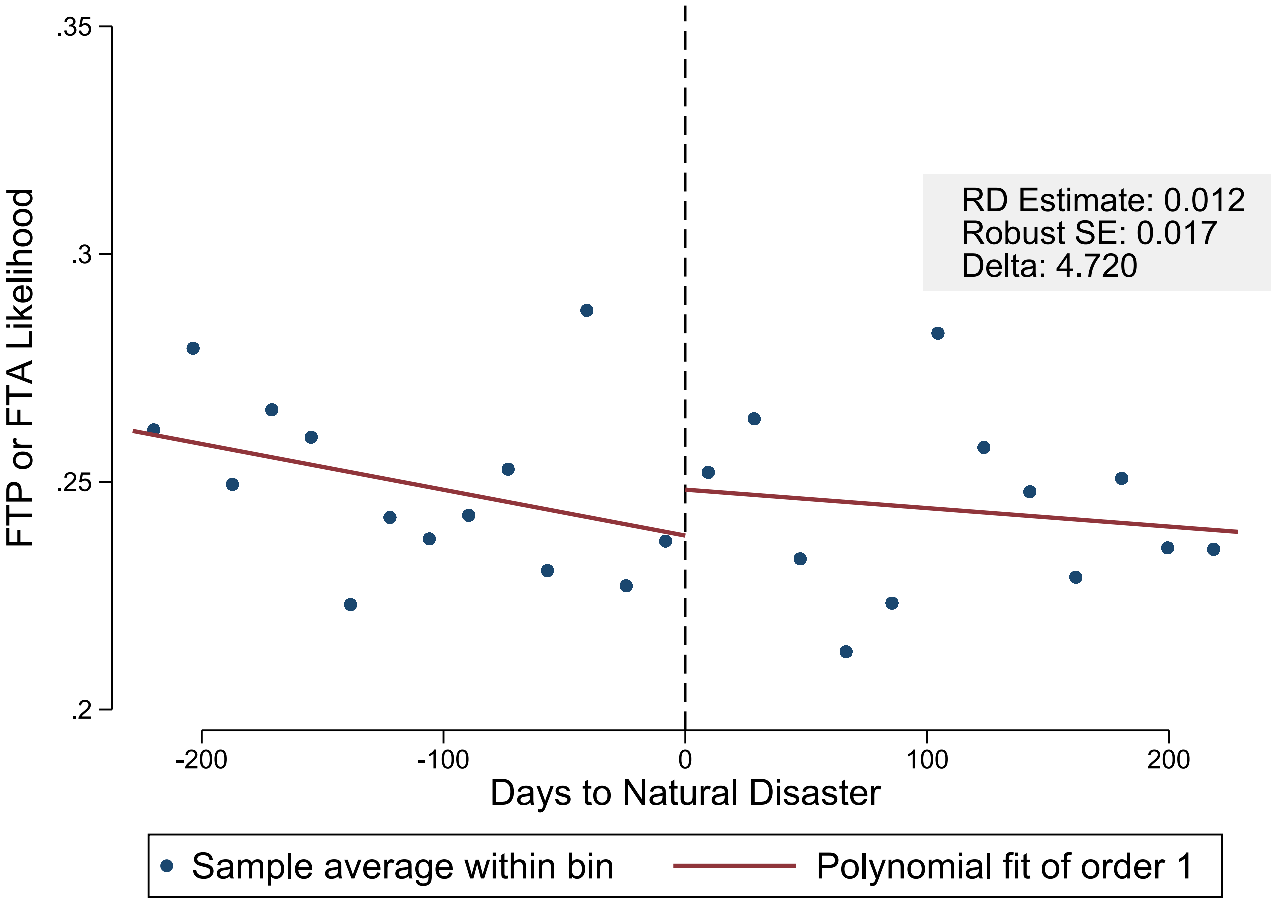
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). The classification of traffic citation having an instance of failure to pay (FTP) or failure to appear (FTA) is derived from Gaebler et al. (2023). Total costs include administrative costs.

Figure A5: Trend Break Binscatter



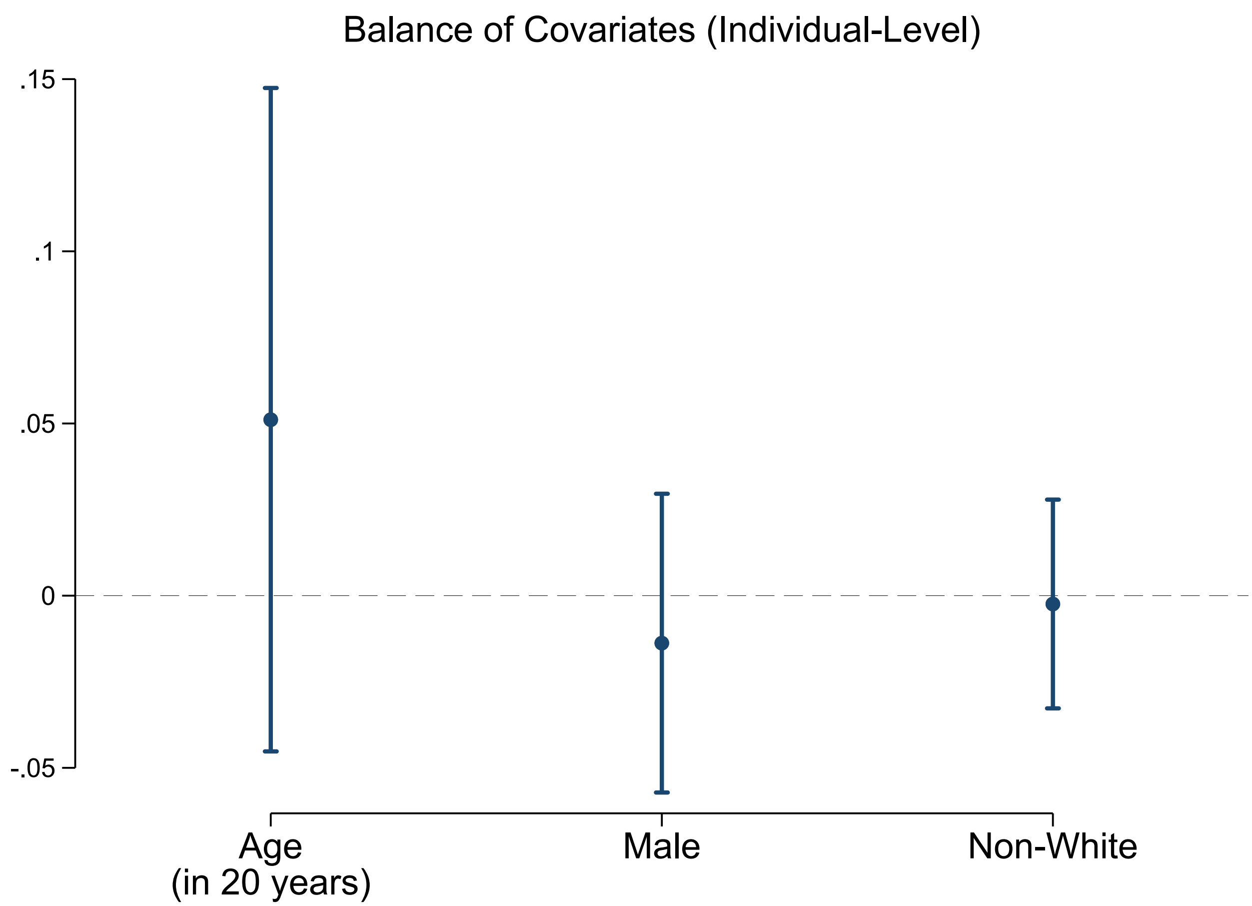
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Default options, as documented in Cattaneo et al. (2025) are used. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster. Only those ZIP-codes that are unaffected by the natural disaster constitute analytical sample.

Figure A6: Trend Break RDD Estimate



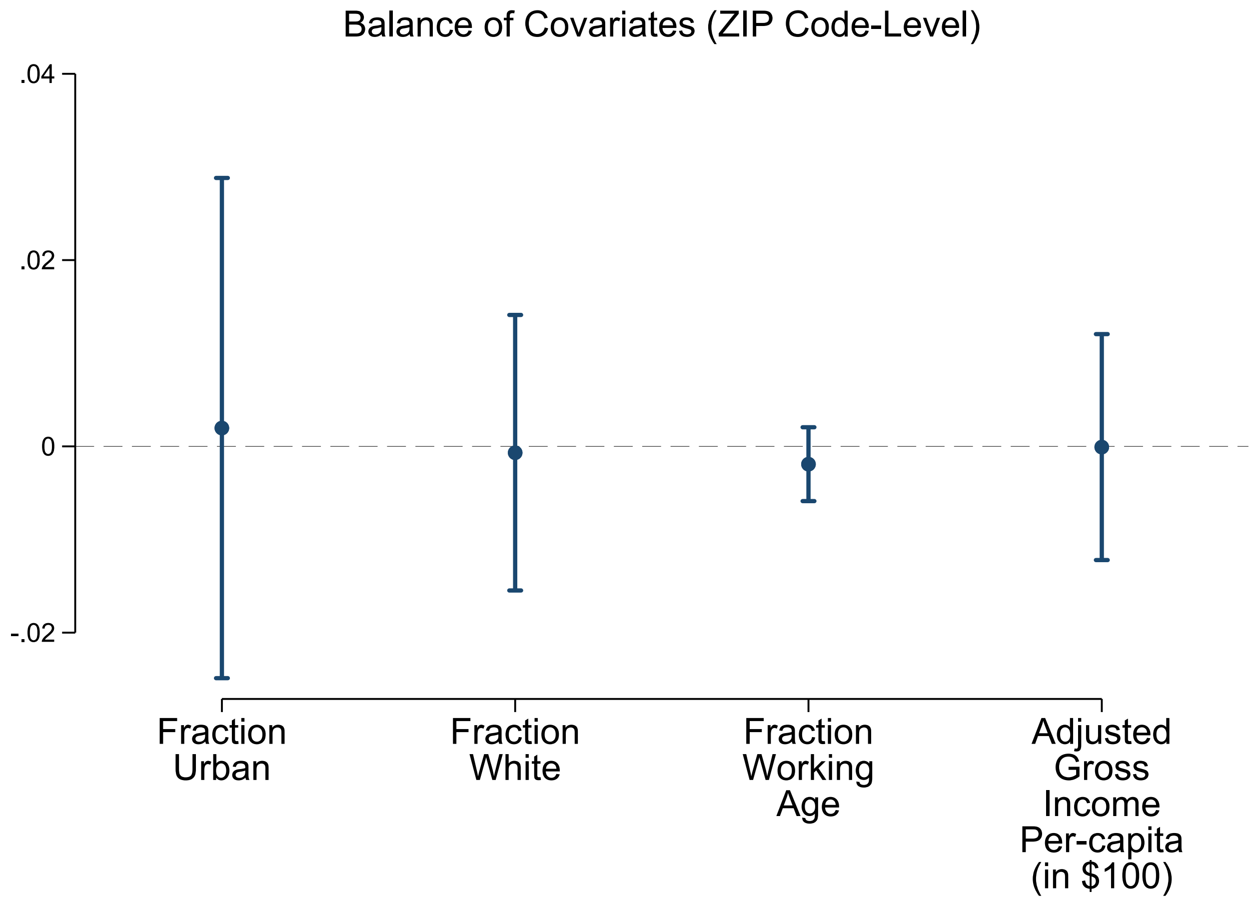
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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. Only those ZIP-codes that are unaffected by the natural disaster constitute analytical sample.

Figure A7: Effect of Natural Disaster on Pre-determined Defendant Characteristics



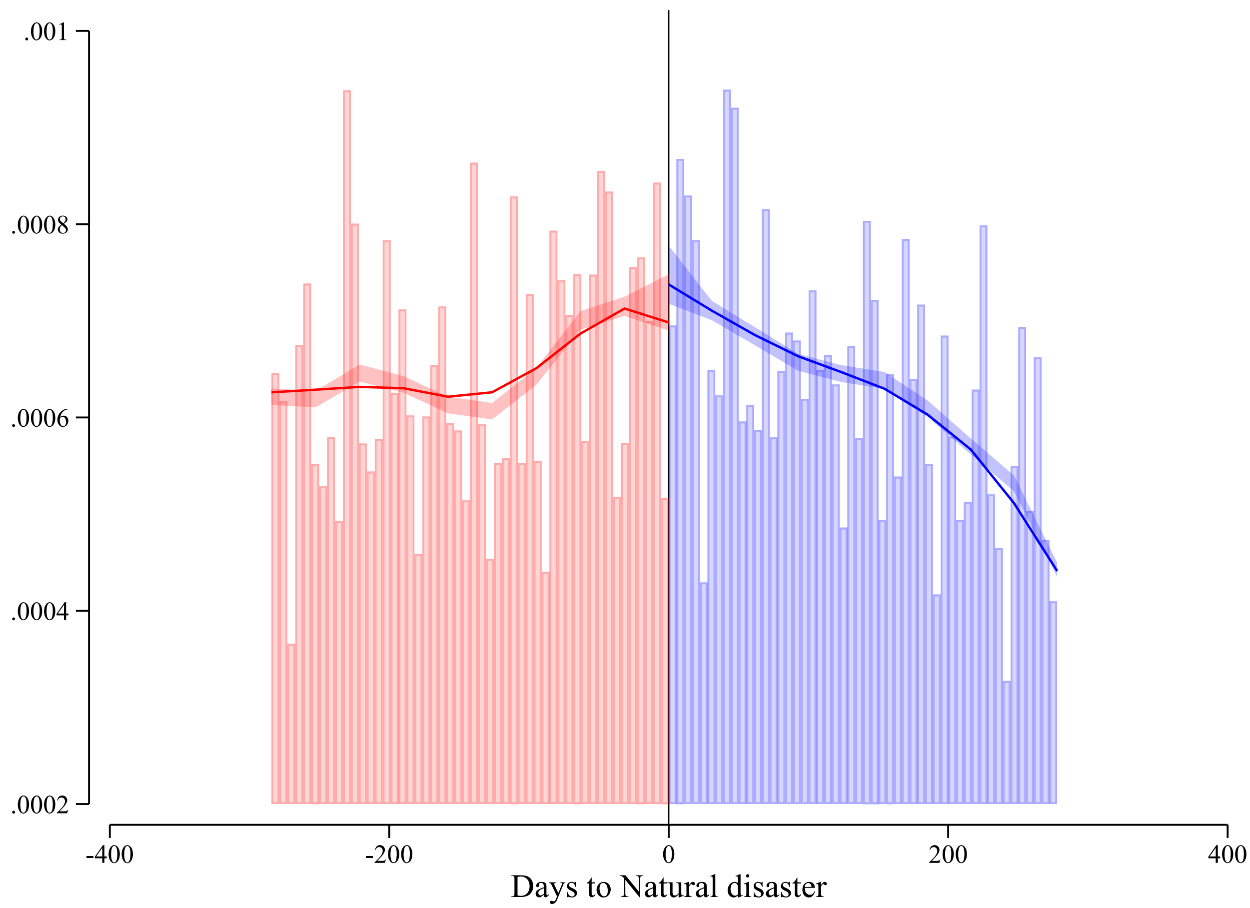
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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 A8: Effect of Natural Disaster on Pre-determined ZIP Code Characteristics



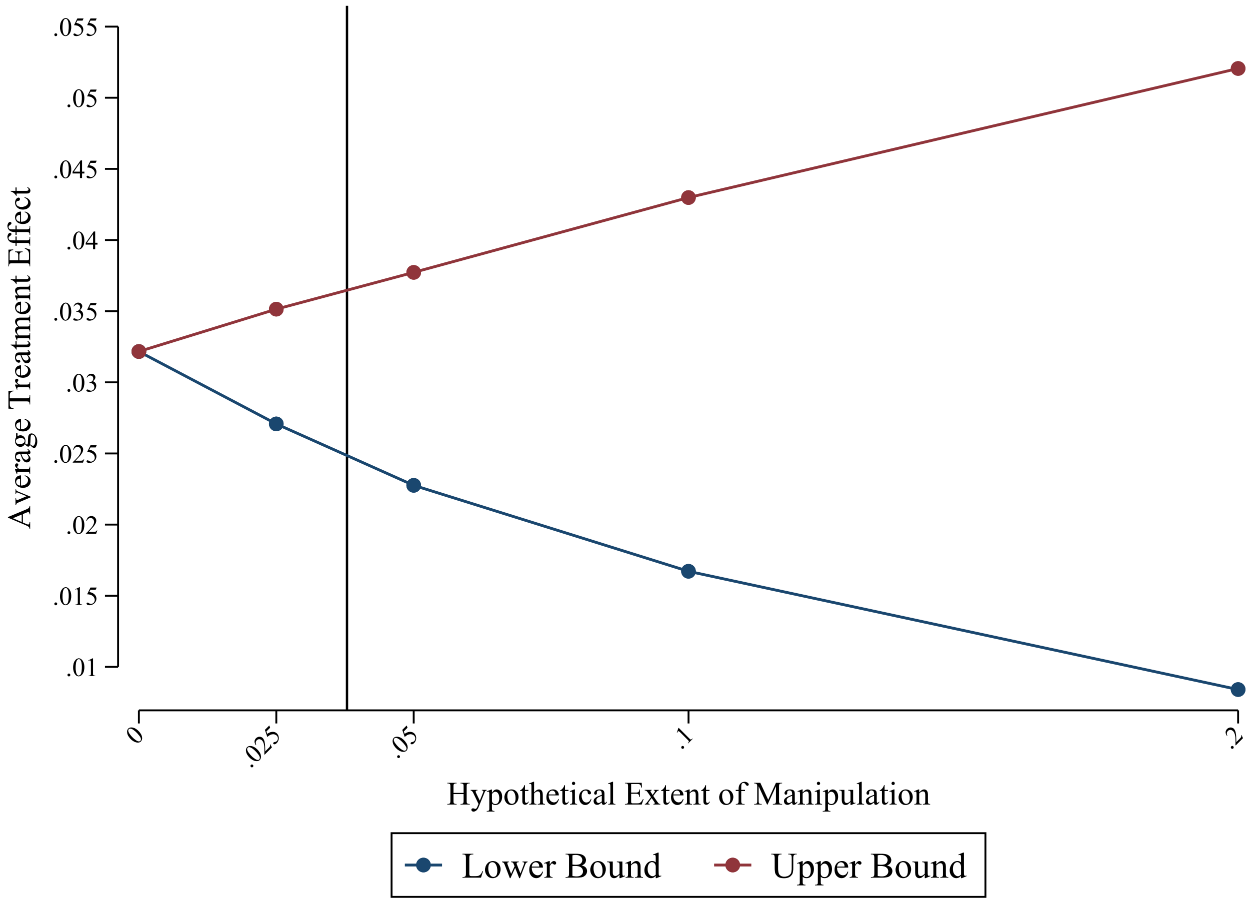
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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 A9: Traffic Citation Density Relative to the Natural Disaster Date



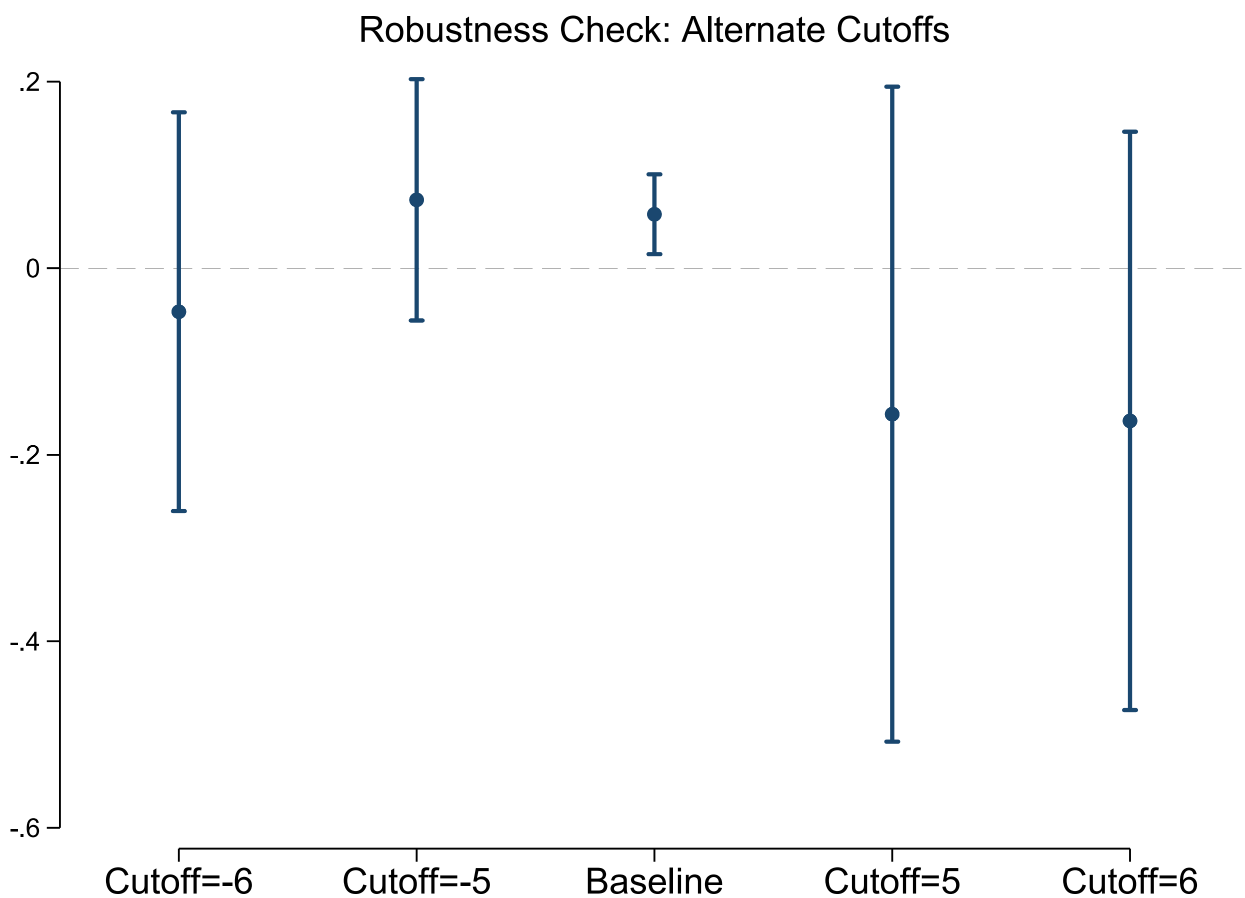
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. The optimal bandwidth used for density estimators is 94.774 to the left of the cutoff and 92.666 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 0.2305. 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 A10: Fixed-manipulation Inference based on Gerard et al. (2020)



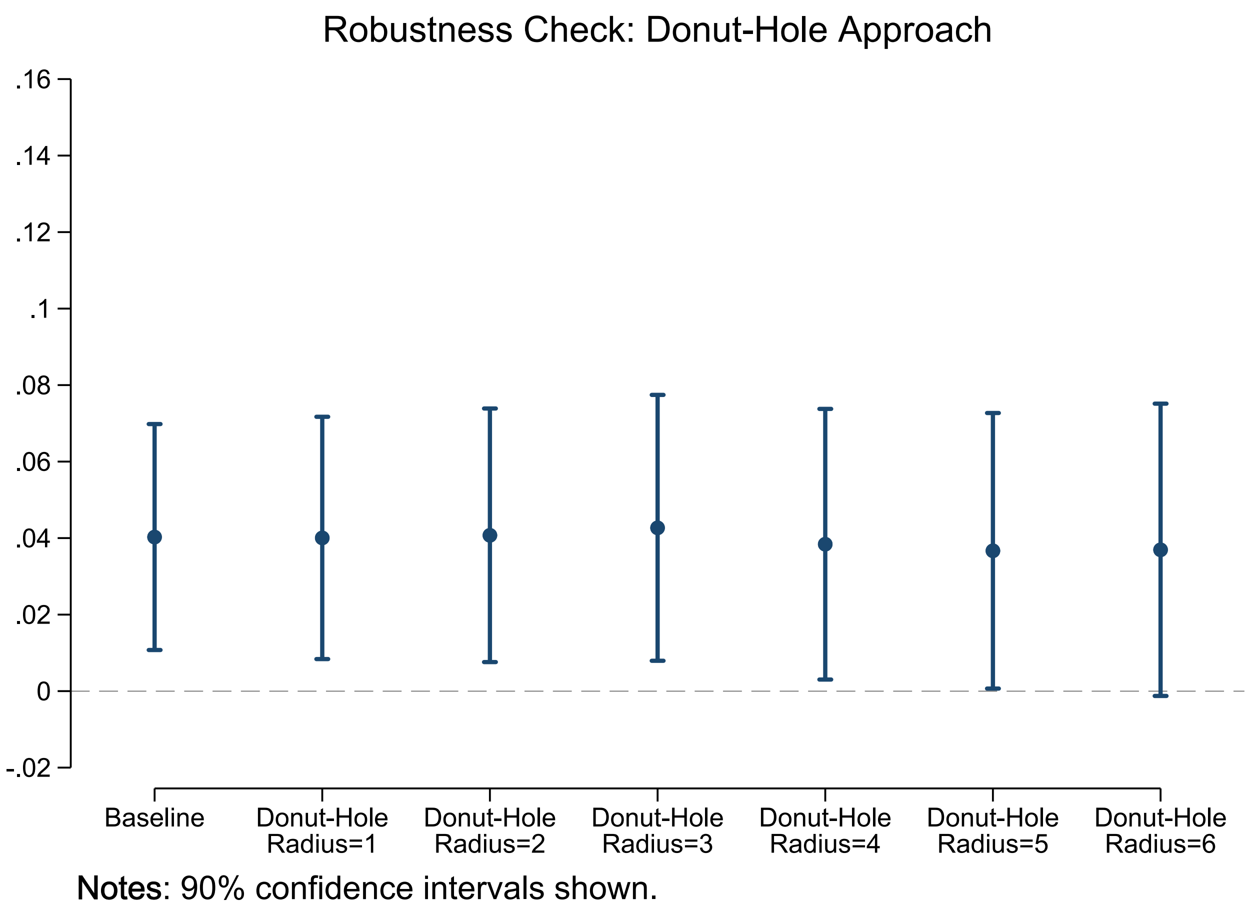
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Bins are based on the initial appearance date of the citation and the date of the beginning of the natural disaster. The figure displays point estimates of bounds based on Gerard et al. (2020) for the average treatment effect under fixed levels of the degree of manipulation. The solid vertical line corresponds to the point estimate in Table 2 for the extent of manipulation.

Figure A11: Robustness Check: Alternate Cutoff Values



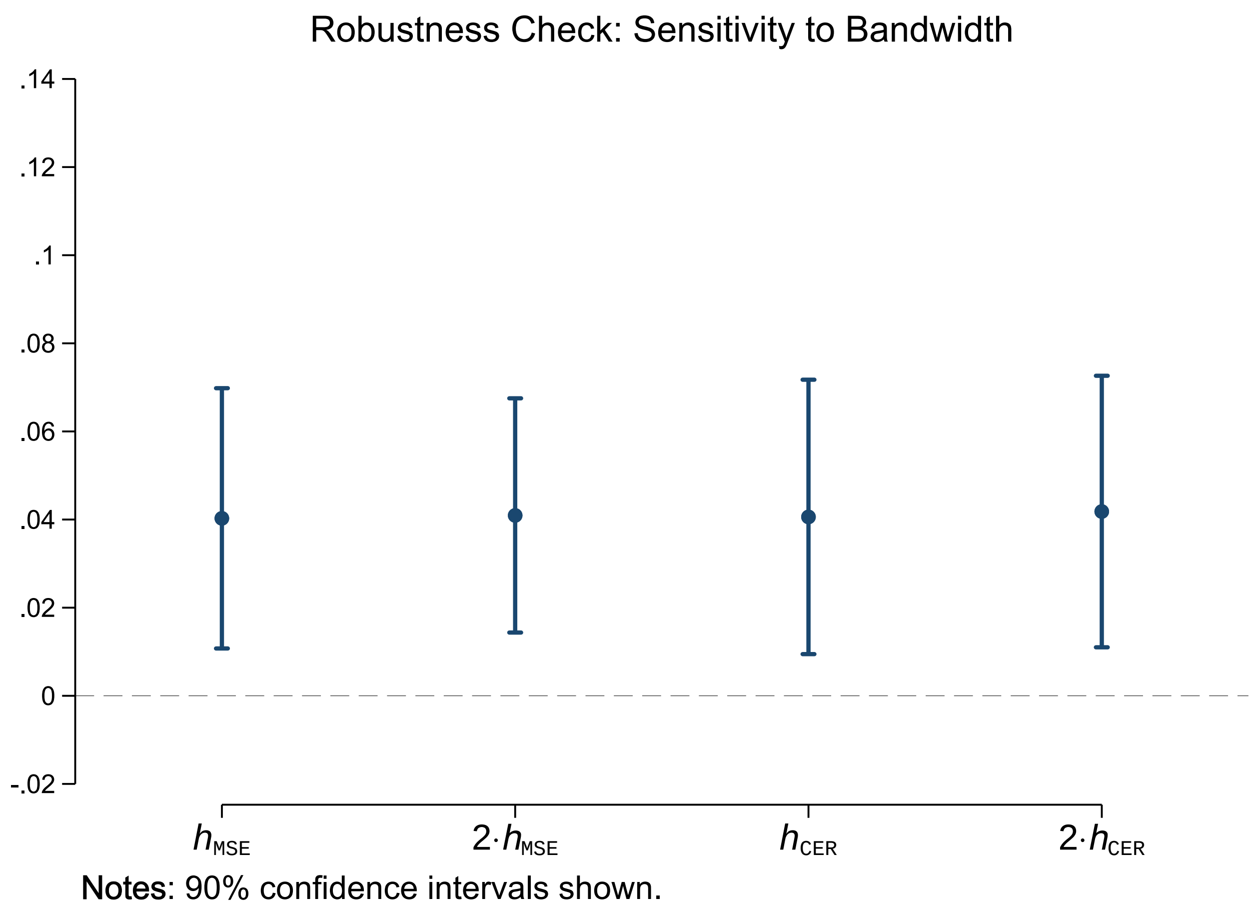
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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 A12: Robustness Check: Donut-Hole Approach



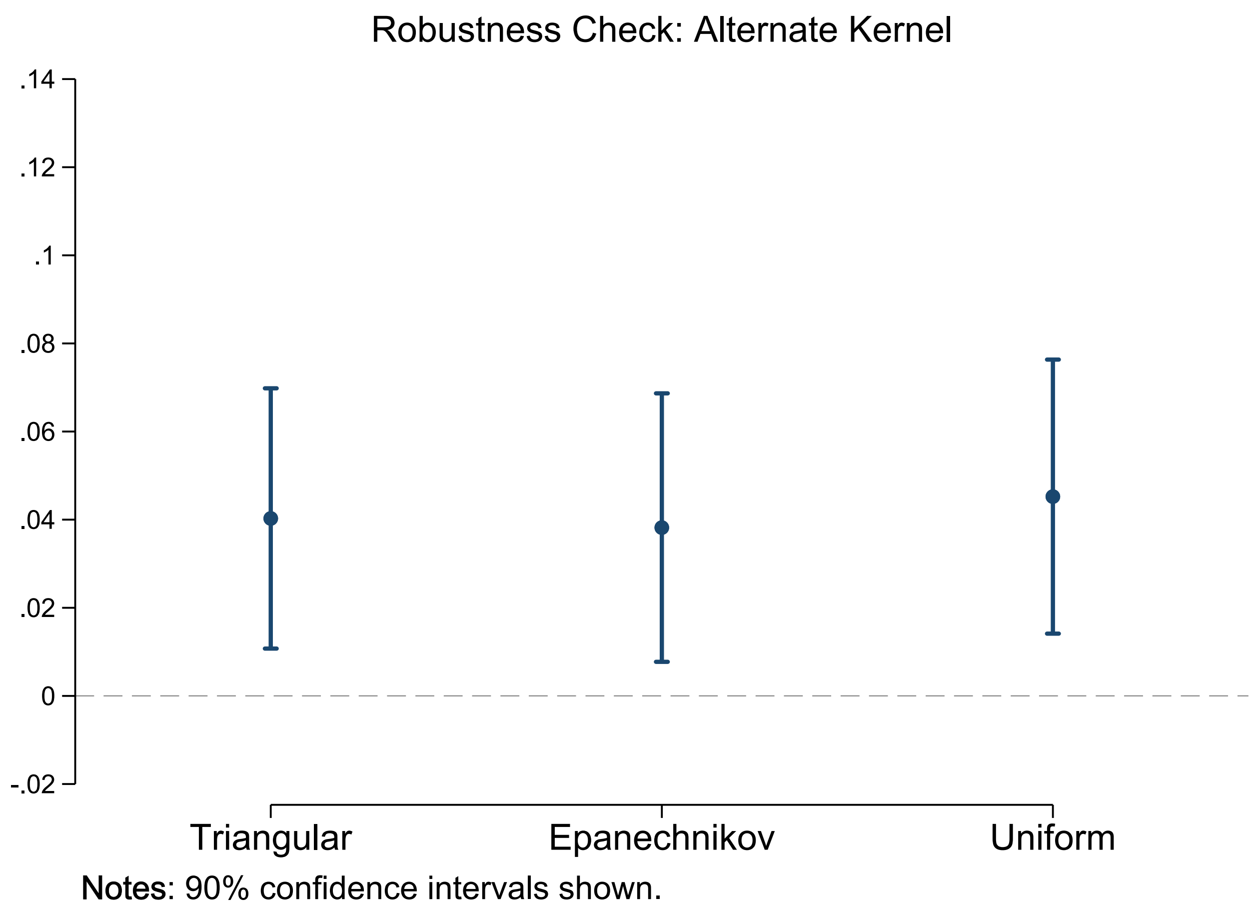
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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 A13: Robustness Check: Alternate Bandwidth



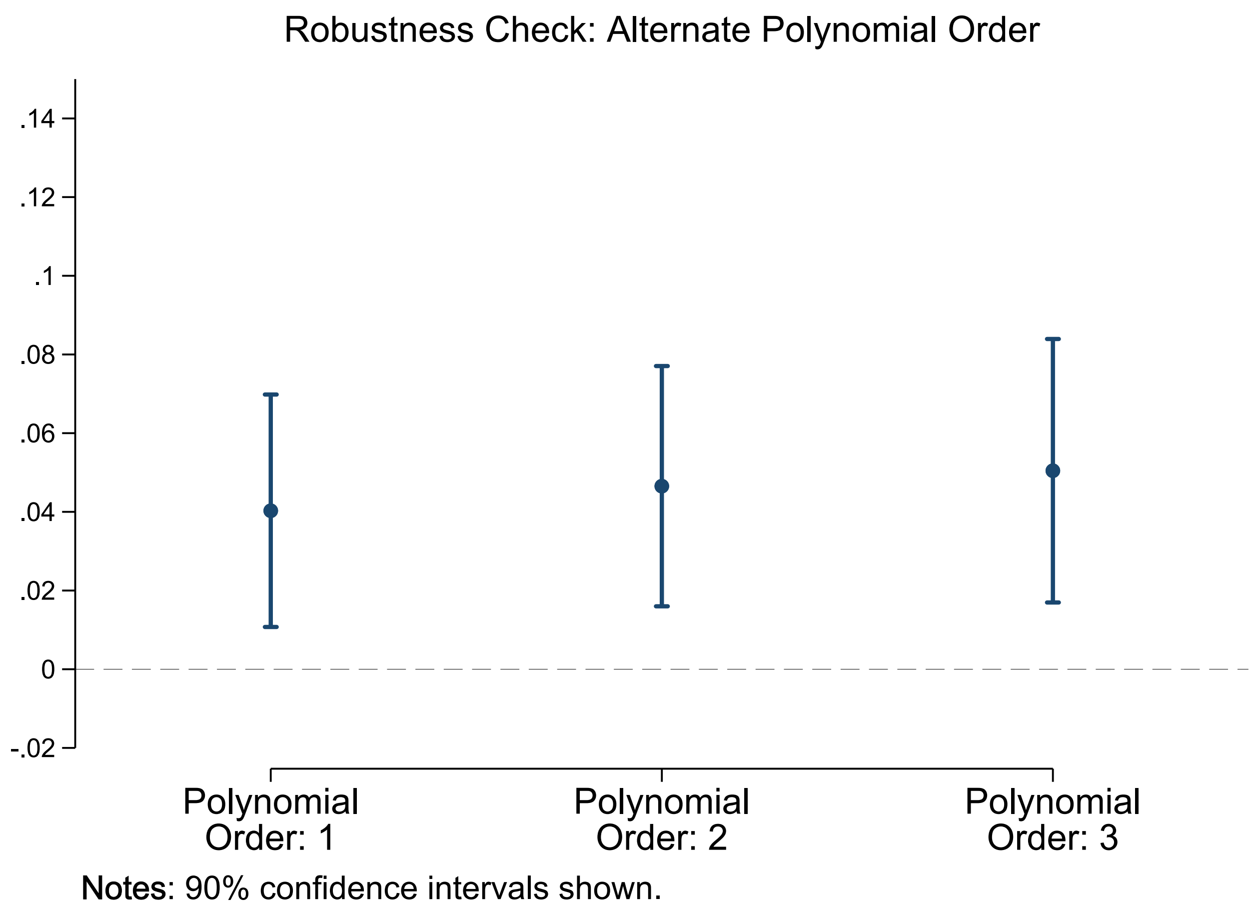
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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 A14: Robustness Check: Alternate Kernel



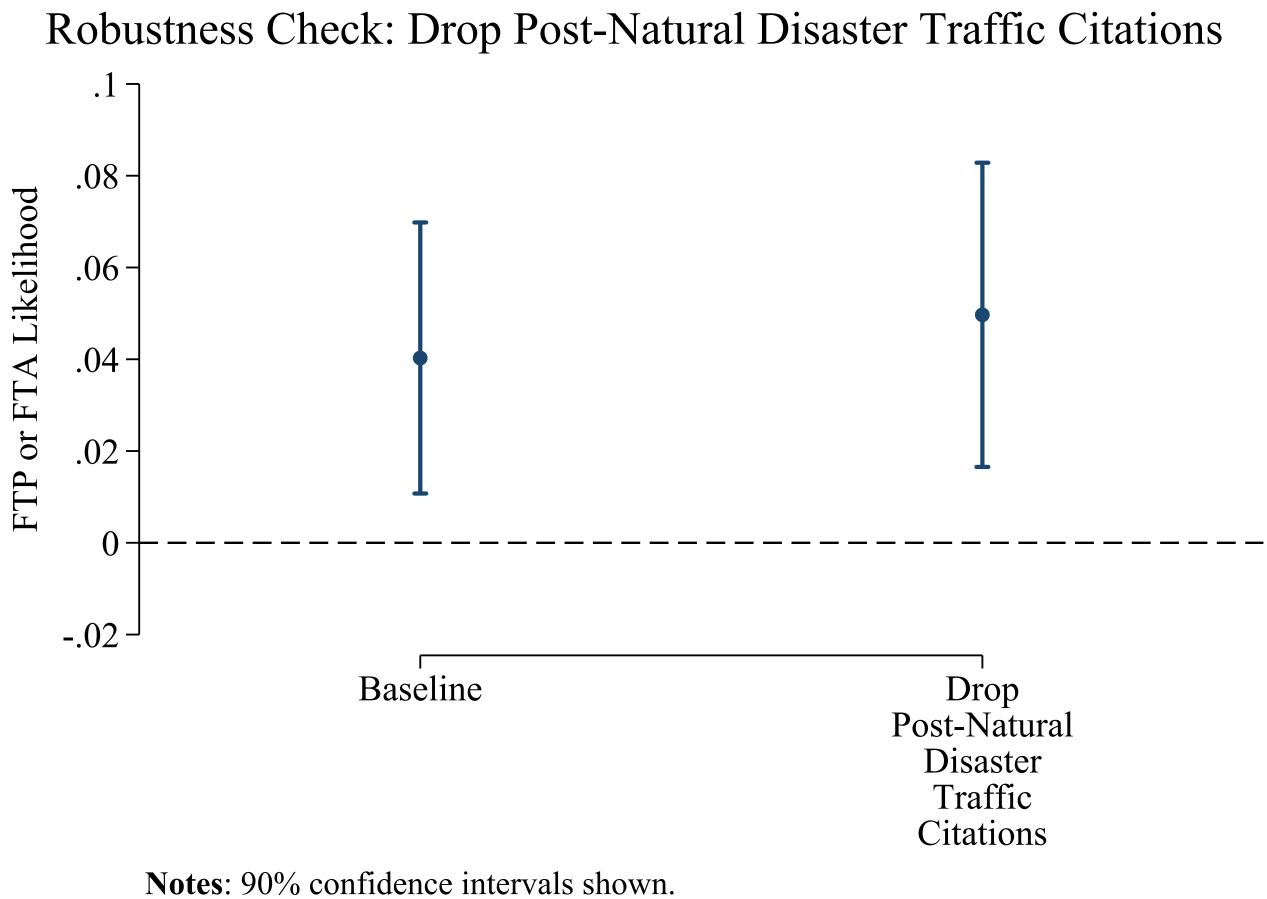
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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 A15: Robustness Check: Alternate Polynomial Order



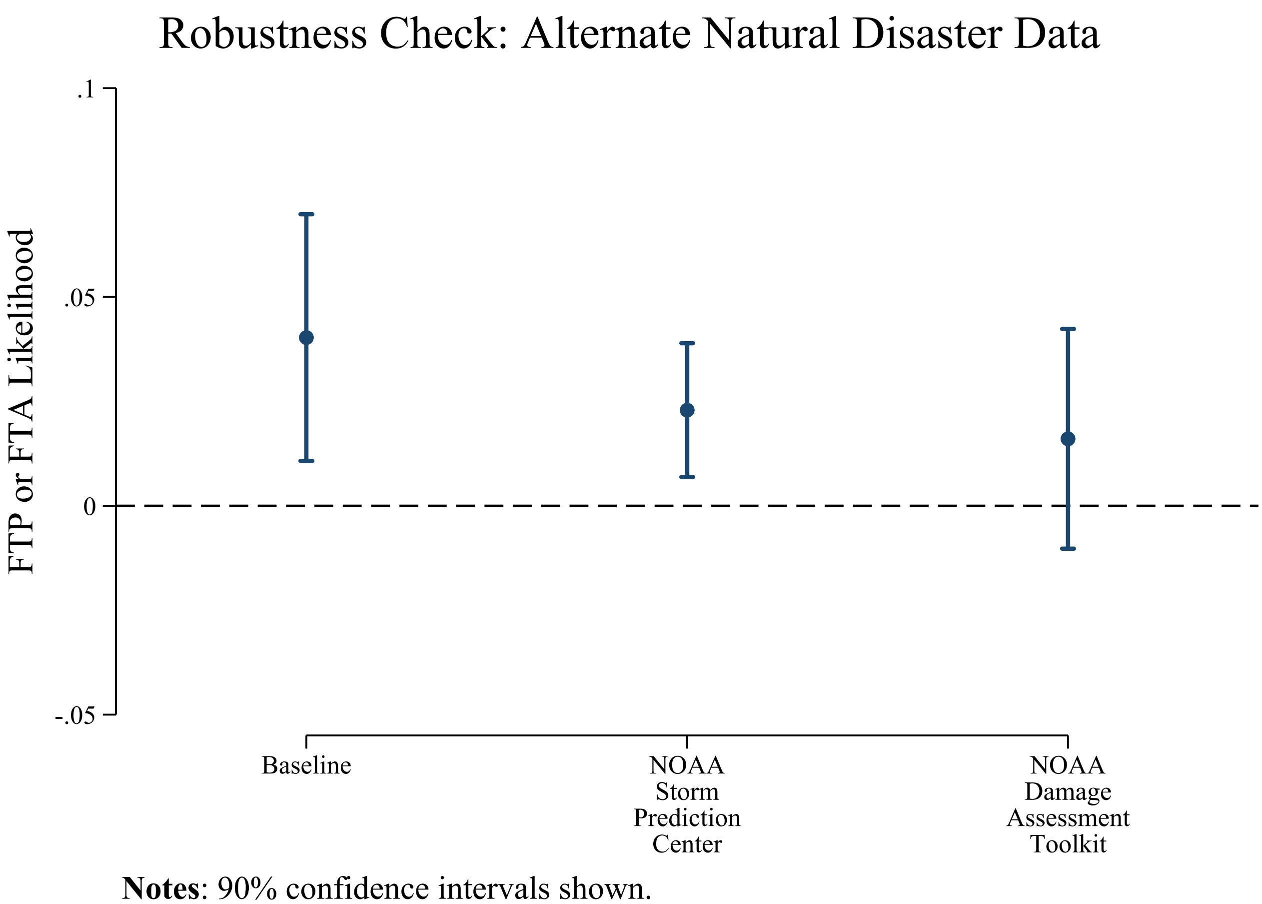
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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 A16: Robustness Check: Drop Post-Natural Disaster Traffic Citations



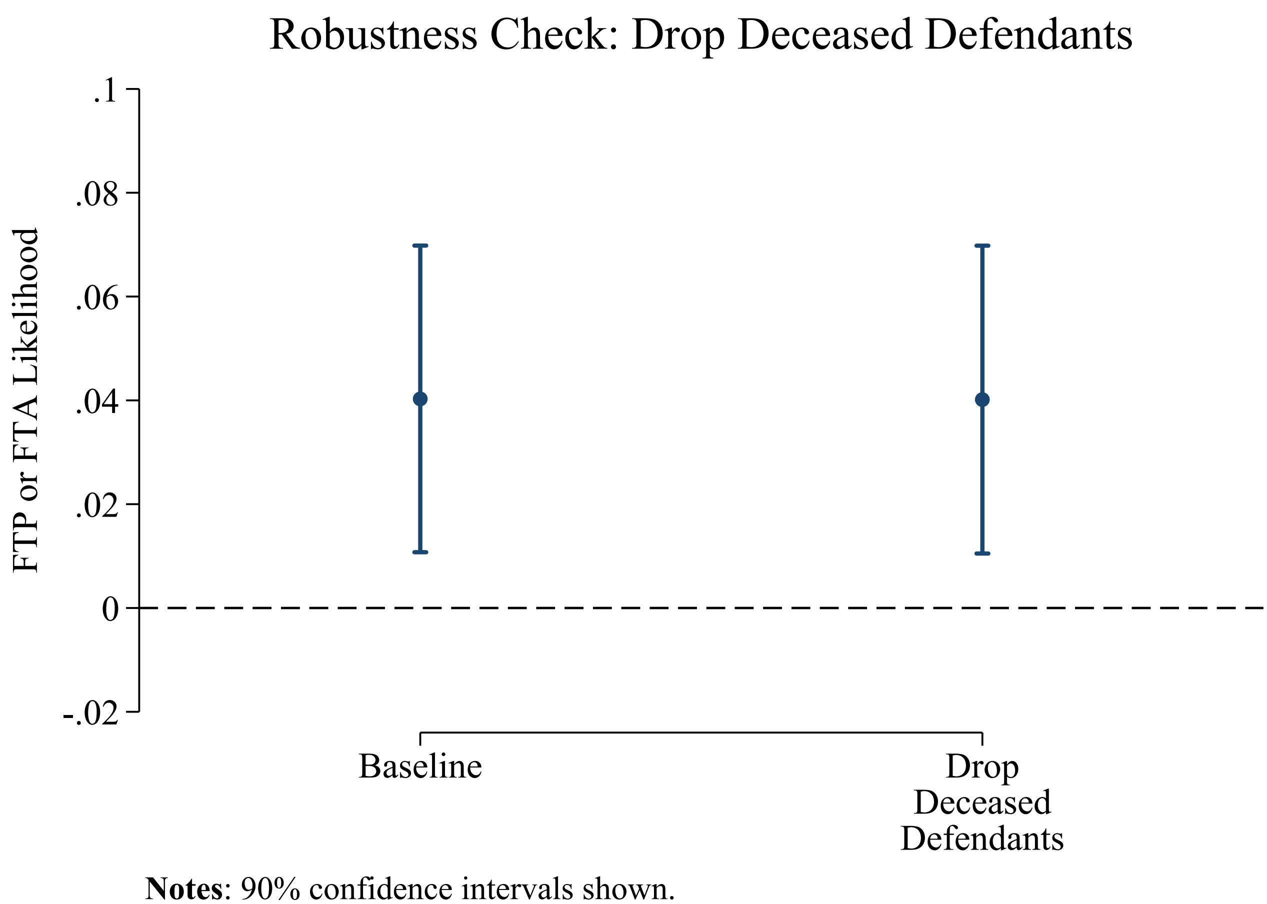
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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 A17: Robustness Check: Alternate Natural Disaster Data



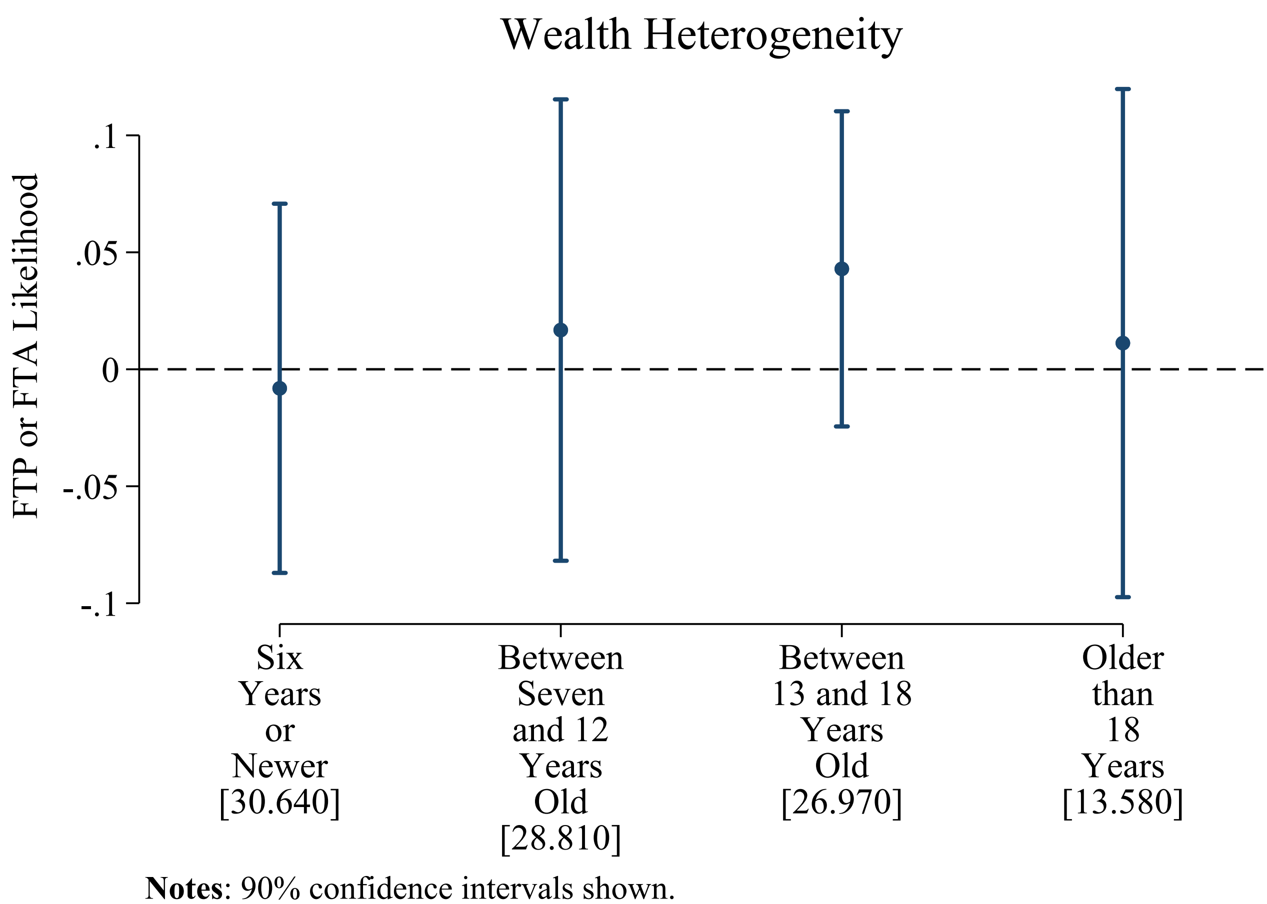
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters in estimates labeled "FEMA" are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Data on natural disasters in estimates labeled "NOAA Damage Assessment Toolkit" are derived from the National Oceanic and Atmospheric Administration (NOAA)'s Damage Assessment Toolkit dataset. Data on natural disasters in estimates labeled "NOAA Storm Prediction Center" are derived from the National Oceanic and Atmospheric Administration (NOAA)'s Storm Prediction Center dataset. 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 A18: Robustness Check: Drop Deceased Defendants



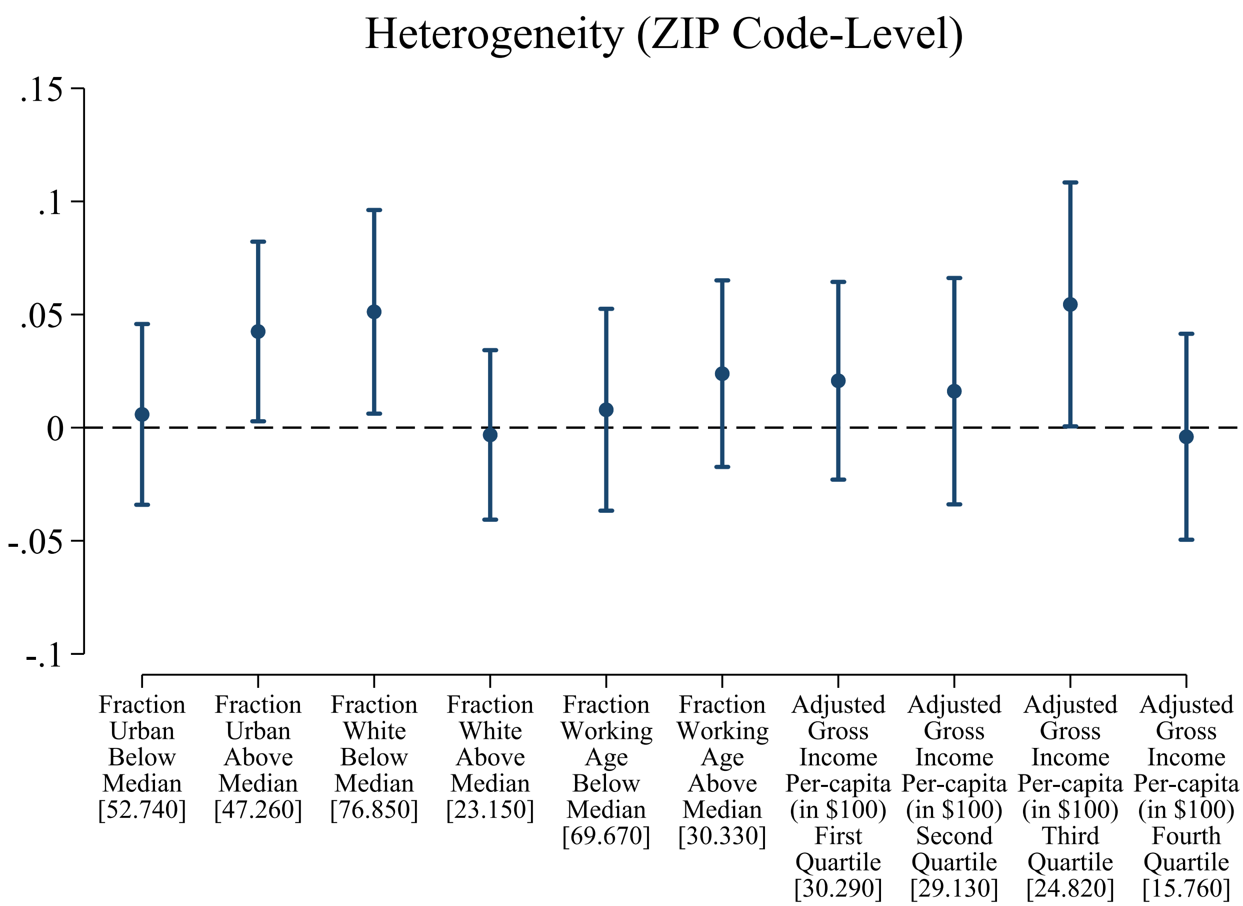
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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 A19: Heterogeneity: Alternate Vehicle Model Year Categories



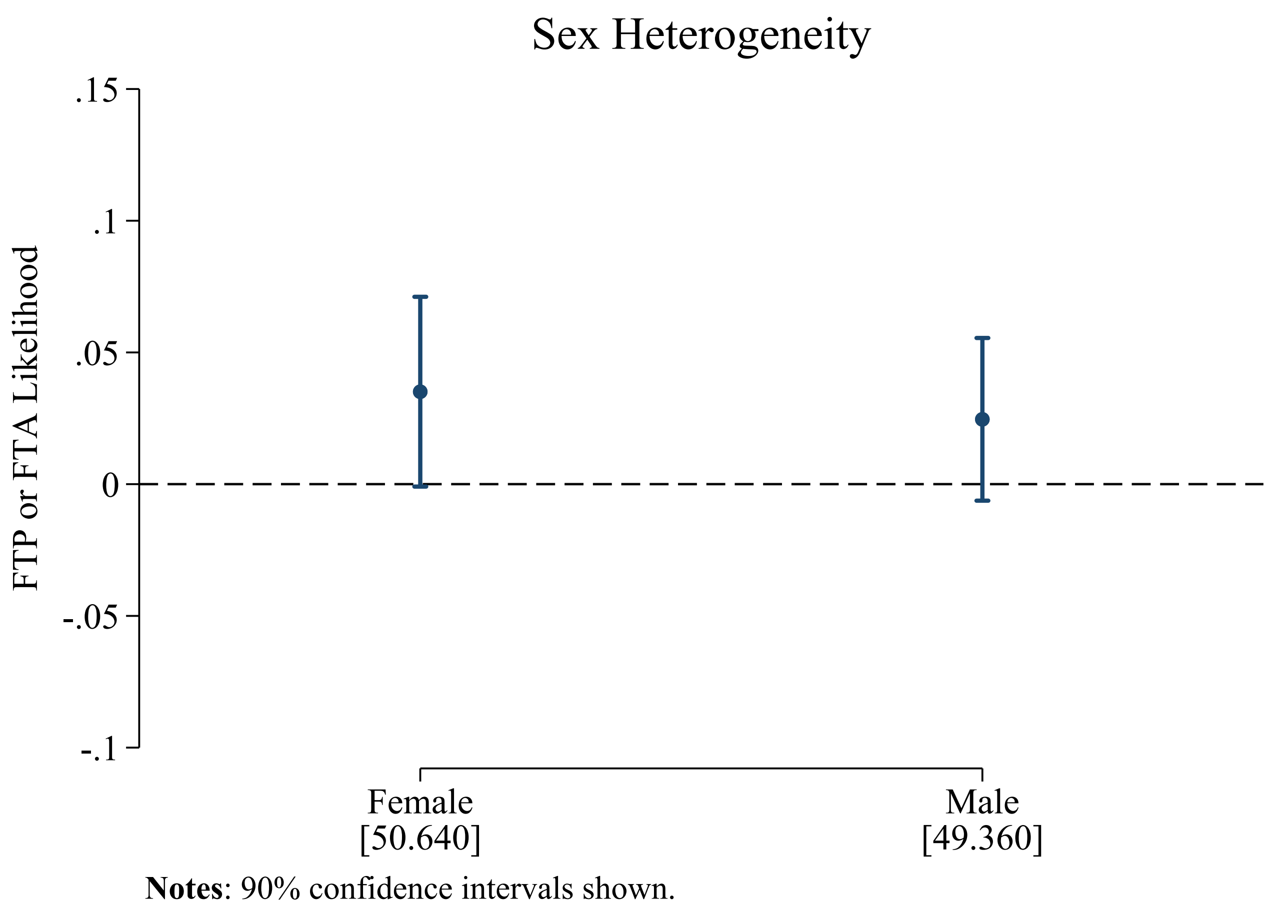
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Default options, as documented in Calonico et al. (2017) are used. 90% 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 A20: Heterogeneity: Pre-determined ZIP Code Characteristics



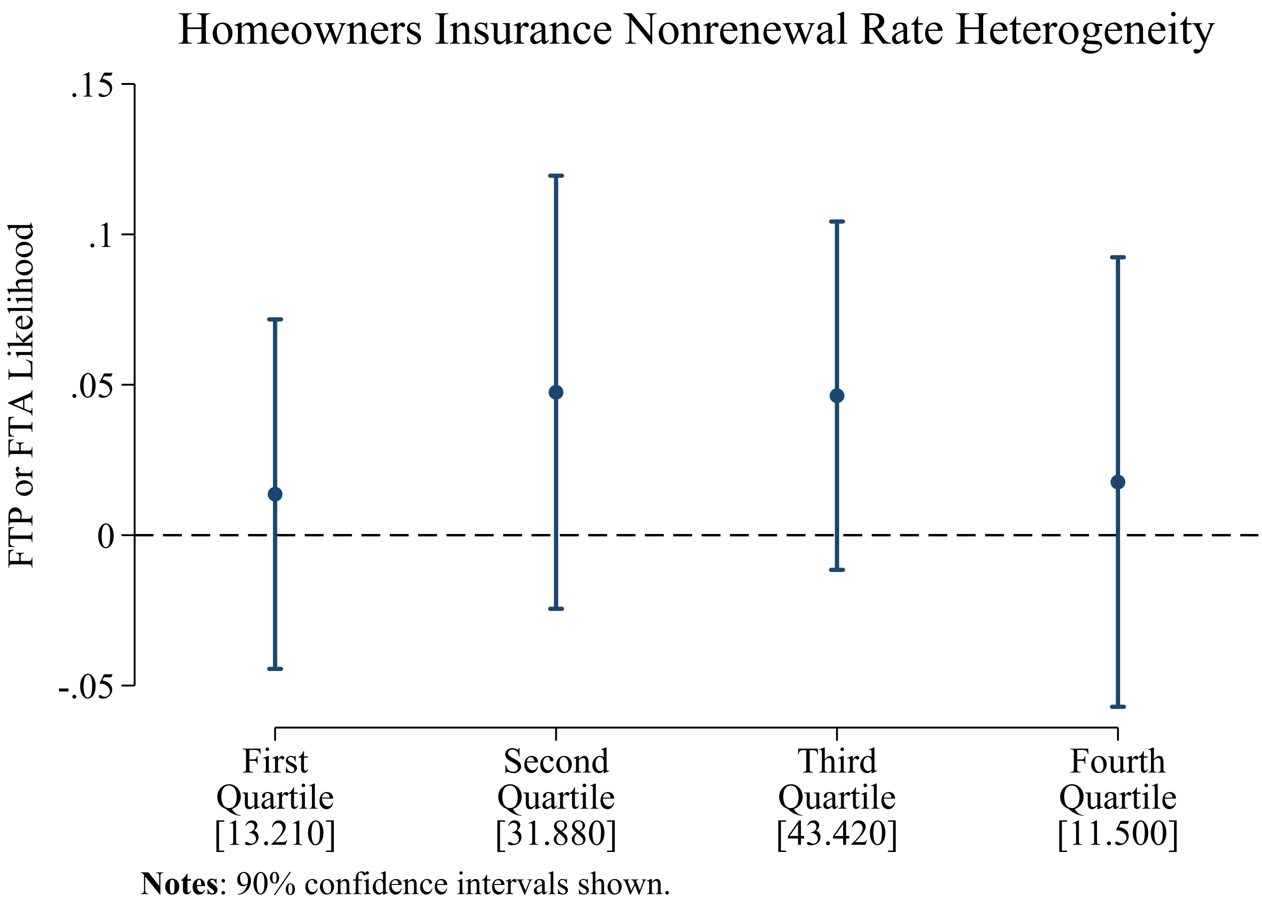
Note: Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the 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.

Figure A21: 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 A22: Heterogeneity: Home Insurance Availability



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. 90% 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. Home insurance availability categories are derived from the non-renewal data obtained from the Department of Treasury.

Table A1: Effect of Natural Disaster on Pre-determined Characteristics

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
Defendant Characteristics							
Age (in 20 years)	183.16	0.051	0.30	[-0.05, 0.15]	367	1.84	0.38
Male	96.85	-0.014	0.53	[-0.06, 0.03]	193	0.43	0.12
Non-White	161.69	-0.002	0.88	[-0.03, 0.03]	323	0.86	0.07
Zip Code Characteristics							
Fraction Urban	115.41	0.002	0.89	[-0.02, 0.03]	231	0.68	0.07
Fraction White	182.61	-0.001	0.93	[-0.02, 0.01]	365	0.73	0.04
Fraction Working Age	119.35	-0.002	0.34	[-0.01, 0.00]	239	0.66	0.01
Adjusted Gross Income Per-capita (in $100)	140.36	-0.000	0.99	[-0.01, 0.01]	281	0.25	0.02

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 A2: Robustness Checks

	Optimal	RD	Robust Inference		Number of	Dep. Var.	Dep. Var.
	Bandwidth	Estimator	p-value	95% CI	Observations	Mean	SD
Baseline							
Baseline	130.92	0.040	0.02	[0.01, 0.08]	261	0.26	0.08
Artificial Cutoff Values							
Cutoff= -6	80.07	-0.028	0.53	[-0.11, 0.06]	86	0.26	0.08
Cutoff= -5	77.63	0.029	0.61	[-0.08, 0.14]	82	0.26	0.08
Cutoff= 5	48.21	-0.025	0.68	[-0.14, 0.09]	53	0.26	0.08
Cutoff= 6	69.64	-0.139	0.25	[-0.38, 0.10]	75	0.26	0.08
Donut-Hole Approach							
Donut-Hole Radius= 1	129.76	0.040	0.04	[0.00, 0.08]	256	0.26	0.08
Donut-Hole Radius= 2	129.40	0.041	0.04	[0.00, 0.08]	254	0.26	0.08
Donut-Hole Radius= 3	126.67	0.043	0.04	[0.00, 0.08]	246	0.26	0.08
Donut-Hole Radius= 4	131.35	0.038	0.07	[-0.00, 0.08]	254	0.26	0.08
Donut-Hole Radius= 5	129.80	0.037	0.09	[-0.01, 0.08]	248	0.26	0.08
Donut-Hole Radius= 6	132.40	0.037	0.11	[-0.01, 0.08]	252	0.26	0.08
Alternate Bandwidth							
$2 \cdot h_{MSE}$	261.83	0.041	0.01	[0.01, 0.07]	523	0.26	0.08
$1 \cdot h_{CER}$	90.94	0.041	0.03	[0.00, 0.08]	181	0.26	0.08
$2 \cdot h_{CER}$	181.88	0.042	0.03	[0.01, 0.08]	363	0.26	0.08
Alternate Kernel							
Epanechnikov	121.17	0.038	0.04	[0.00, 0.07]	243	0.26	0.08
Uniform	102.49	0.045	0.02	[0.01, 0.08]	205	0.26	0.08
Alternate Polynomial Order							
Polynomial Order: 2	236.64	0.047	0.01	[0.01, 0.08]	473	0.26	0.08
Polynomial Order: 3	324.70	0.050	0.01	[0.01, 0.09]	649	0.26	0.08

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 A3: Robustness to Dropping Traffic Citations Issued Post-Natural Disaster

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
Baseline	130.92	0.040	0.02	[0.01, 0.08]	261	0.26	0.08
Drop Post-Natural Disaster	150.71	0.050	0.01	[0.01, 0.09]	285	0.26	0.08

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A4: Robustness to Using Alternate Natural Disaster Data

	Optimal	RD	Robust Inference		Number of	Dep. Var.	Dep. Var.
	Bandwidth	Estimator	p-value	95% CI	Observations	Mean	SD
Baseline	130.92	0.040	0.02	[0.01, 0.08]	261	0.26	0.08
NOAA Storm Prediction Center	167.34	0.023	0.02	[0.00, 0.04]	335	0.21	0.05
NOAA Damage Assessment Toolkit	176.79	0.016	0.32	[-0.02, 0.05]	353	0.22	0.08

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A5: Robustness to Dropping Deceased Defendants

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
Baseline	130.92	0.040	0.02	[0.01, 0.08]	261	0.26	0.08
Drop Deceased Defendants	129.44	0.040	0.03	[0.00, 0.08]	259	0.26	0.08

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A6: Wealth Heterogeneity

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
Three Years or Newer	181.90	-0.007	0.89	[-0.11, 0.09]	357	0.26	0.23
Between Three and Six Years Old	217.47	0.001	0.98	[-0.12, 0.12]	419	0.30	0.25
Older than Six Years	231.60	0.095	0.06	[-0.00, 0.20]	434	0.35	0.26

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A7: Wealth Heterogeneity: Alternate Vehicle Model Year Categories

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
Six Years or Newer	223.16	-0.008	0.87	[-0.10, 0.09]	445	0.29	0.22
Between Seven and 12 Years Old	181.74	0.017	0.78	[-0.10, 0.13]	349	0.45	0.23
Between 13 and 18 Years Old	219.58	0.043	0.29	[-0.04, 0.12]	434	0.39	0.23
Older than 18 Years	155.67	0.011	0.87	[-0.12, 0.14]	290	0.47	0.26

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A8: Pre-determined ZIP Code Characteristics Heterogeneity

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
Fraction Urban Below Median	175.49	0.006	0.77	[-0.03, 0.05]	351	0.22	0.15
Fraction Urban Above Median	136.05	0.042	0.04	[0.00, 0.08]	273	0.22	0.15
Fraction White Below Median	142.43	0.051	0.03	[0.01, 0.10]	285	0.22	0.15
Fraction White Above Median	203.70	-0.003	0.87	[-0.04, 0.03]	407	0.22	0.15
Fraction Working Age Below Median	154.60	0.008	0.73	[-0.04, 0.05]	309	0.22	0.15
Fraction Working Age Above Median	179.61	0.024	0.26	[-0.02, 0.07]	359	0.22	0.15
Adjusted Gross Income Per-capita (in $100) First Quartile	173.80	0.021	0.35	[-0.02, 0.06]	347	0.22	0.15
Adjusted Gross Income Per-capita (in $100) Second Quartile	146.17	0.016	0.53	[-0.03, 0.07]	293	0.22	0.15
Adjusted Gross Income Per-capita (in $100) Third Quartile	153.76	0.054	0.05	[0.00, 0.11]	307	0.22	0.15
Adjusted Gross Income Per-capita (in $100) Fourth Quartile	218.54	-0.004	0.86	[-0.05, 0.04]	437	0.22	0.15

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A9: Race Heterogeneity

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
Non-White	128.49	0.047	0.02	[0.01, 0.08]	257	0.25	0.10
White	273.17	-0.002	0.92	[-0.05, 0.04]	547	0.22	0.15

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A10: Sex Heterogeneity

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
Female	164.27	0.035	0.11	[-0.01, 0.08]	329	0.27	0.10
Male	149.54	0.025	0.19	[-0.01, 0.06]	299	0.24	0.10

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A11: Homeowners Insurance Nonrenewal Rate Heterogeneity

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
First Quartile	186.72	0.014	0.70	[-0.06, 0.08]	367	0.21	0.21
Second Quartile	113.11	0.047	0.28	[-0.04, 0.13]	227	0.27	0.20
Third Quartile	161.11	0.046	0.19	[-0.02, 0.12]	323	0.29	0.19
Fourth Quartile	199.14	0.018	0.70	[-0.07, 0.11]	398	0.28	0.21

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A12: Disaster Type Heterogeneity

	Optimal	RD	Robust Inference		Number of	Dep. Var.	Dep. Var.
	Bandwidth	Estimator	p-value	95% CI	Observations	Mean	SD
FEMA All	130.92	0.040	0.02	[0.01, 0.08]	261	0.26	0.08
FEMA Fire	243.92	-0.023	0.66	[-0.13, 0.08]	462	0.25	0.26
FEMA Flood	183.69	0.038	0.15	[-0.01, 0.09]	367	0.26	0.15
FEMA Hurricane	137.96	0.084	0.07	[-0.01, 0.17]	275	0.27	0.21
FEMA Tornado	260.77	-0.013	0.79	[-0.11, 0.08]	448	0.19	0.20
FEMA Severe Storm	180.27	0.035	0.16	[-0.01, 0.08]	361	0.26	0.11

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A13: Offense Severity Heterogeneity

	Optimal	RD	Robust Inference		Number of	Dep. Var.	Dep. Var.
	Bandwidth	Estimator	p-value	95% CI	Observations	Mean	SD
Low	171.50	-0.000	0.99	[-0.06, 0.06]	343	0.28	0.12
Medium	139.35	0.044	0.01	[0.01, 0.07]	279	0.21	0.08
High	211.59	0.053	0.09	[-0.01, 0.11]	423	0.43	0.15

Note: Dependent variable in each row is an indicator variable for whether the defendant has an Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 in each row 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.

Table A14: FEMA Housing Assistance Program Heterogeneity

	Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference 95% CI	Number of Observations	Dep. Var. Mean	Dep. Var. SD
No Approval	155.04	0.067	0.00	[0.03, 0.10]	311	0.21	0.08
At Least One Approval	175.91	-0.028	0.34	[-0.08, 0.03]	351	0.23	0.16

Note: The dependent variable in each row is an indicator variable for whether the defendant has a Failure to Pay (FTP) or Failure to Appear (FTA) instance. 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 the FEMA Housing Assistance Program are used to categorize ZIP Codes with at least one household with approved FEMA assistance. Estimates in each row 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.

B Data Exhibit

In this section, I present an example of traffic citation data that I scraped from the Oklahoma State Court Network (OSCN) website. Figure B1 shows how the parties, attorneys, and events information are reported on the website. Counts and citation information reporting format for the county of interest from the data example is presented in Figure B2. Figures B3 to B6 show the docket associated with the traffic citation. All personally identifiable information of the defendant has been redacted.

Figure B1: Traffic Citation Example: Overview, Parties, Attorneys, and Events

IN THE DISTRICT COURT IN AND FOR OKLAHOMA COUNTY, OKLAHOMA

State of Oklahoma v. [redacted]	**No. TR-2017-9[redacted]** **(Traffic)** Filed: 05/01/2017 Closed: 01/16/2019 Judge: Pipes, Robert Trent

PARTIES

[redacted] Defendant
Oklahoma Highway Patrol, ARRESTING AGENCY
STATE OF OKLAHOMA, Plaintiff

ATTORNEYS

None

EVENTS

Event	Party	Docket	Reporter
Friday, June 2, 2017 at 9:00 AM PAID	[redacted]	James B. Croy	

Source: Oklahoma State Court Network (OSCN).

Figure B2: Traffic Citation Example: Counts and Citation

COUNTS

Parties appear only under the counts with which they were charged. For complete sentence information, see the court minute on the docket.

Count # 1. Count as Filed: S11, SPEEDING 11-14 mph over, in violation of 47 O.S. 11-801(B)(C)(F)
Date of Offense: 04/08/2017

Party Name	Disposition Information
[redacted]	**Disposed: CONVICTION, 01/16/2019. Nolo Contendere Plea** Count as Disposed: SPEEDING 11-14 mph over(S11) Violation of 47 O.S. 11-801(B)(C)(F)

CITATION INFORMATION

Arresting Agency: Oklahoma Highway Patrol
Location of Offense: JKT EB /.2 W ROCKWELL AVE
North Location:
East Control: 649
County: Oklahoma
Citation Number: M626264
License Class: D
License Endorsements:
Employer:
Violation Type: Operation
Vehicle Make: SUBA
Vehicle Model: 2014
Vehicle Body Style:
Vehicle Color: GRY
Vehicle Tag: 737LKU
Vehicle Tag Year: 2017
Vehicle Tag Issuer: Oklahoma
Commercial Vehicle:No
Hazardous Material: No
Accident: No
Personal Injury: No
Property Damage: No
Fatality: No
Bond Amount: $250.25
Information Date: N/A
Comments: N/A

Source: Oklahoma State Court Network (OSCN).

Figure B3: Traffic Citation Example: Docket

DOCKET

Date	Code	Description	Party	Count	Amount
05-01-2017	[TR]	TRAFFIC FILING - SPEEDING 11-14 MPH OVER Document Available at Court Clerk's Office	[redacted]	#1	
05-01-2017	[TEXT]	OCIS HAS AUTOMATICALLY ASSIGNED JUDGE CROY, JAMES B. TO THIS CASE.			
06-02-2017	[CTDFTA]	DEFENDANT FAILED TO APPEAR; BENCH WARRANT TO ISSUE INITIAL BOND AMT $250.25	[redacted]		
06-07-2017	[NOSe]	NOTICE OF ABILITY TO SUSPEND ELECTRONICALLY TRANSFERRED TO THE ADMINISTRATIVE OFFICE OF THE COURTS.	[redacted]	#1	$ 10.00
06-07-2017	[NOSPSe]	NOTICE OF SUSPENSION ELECTRONICALLY TRANSFERRED TO THE ADMINISTRATIVE OFFICE OF THE COURTS FOR TRANSMISSION TO DPS.	[redacted]		
06-14-2017	[BWIFAP]	BENCH WARRANT ISSUED FAILED TO APPEAR AND PAY, JUDGE: DONALD EASTER - BOND AMOUNT: $442.33 COUNT 1 - SPEEDING 11-14 MPH OVER COMMENT: ATTENTION BOOKING DEPARTMENT: DEFENDANT MAY BE RELEASED UPON A CASH PAYMENT IN FULL OR SET FOR THE COST DOCKET. WARRANT RECALLED 1/16/2019, WARRANT ISSUED ON 6/14/2017	[redacted]		$ 50.00
06-14-2017	[CBWF1]	CLERK'S BENCH WARRANT FEE {TITLE 22 O.S.966A}	[redacted]		$ 5.00
06-14-2017	[OCISR]	OKLAHOMA COURT INFORMATION SYSTEM REVOLVING FUND	[redacted]		$ 25.00
06-15-2017	[SFC]	CASE SENT FOR COLLECTION. BATCH ID: 20170615-6499 - COLLECTION ID: 122137	[redacted]		$ 102.08
06-15-2017	[SFCSF]	REDUCTION IN BENCH WARRANT FEE TO SHERIFF (10%)	[redacted]		$ -5.00
06-15-2017	[SFCCC]	ADDITION OF 10% FOR WARRANT COLLECTION	[redacted]		$ 5.00
11-05-2018	[TEXT]	ADMINISTRATIVELY REASSIGNED BY AOC MIS PER HELP DESK CONTACT 77990			

Source: Oklahoma State Court Network (OSCN).

Figure B4: Traffic Citation Example: Docket

01-16-2019 [**COSTT**] TRAFFIC COSTS	[redacted]	#1	$ 88.00
01-16-2019 [**OCISR**] OKLAHOMA COURT INFORMATION SYSTEM REVOLVING FUND	[redacted]	#1	$ 25.00
01-16-2019 [**DPSFEE**] DPS PATROL VEHICLE FUND FEE ASSESSMENT	[redacted]	#1	$ 20.00
01-16-2019 [**FINE**] FINES PAYABLE TO COUNTY	[redacted]	#1	$ 20.00
01-16-2019 [**DACPAT**] DA COUNCIL PROSECUTION ASSESSMENT FOR TRAFFIC	[redacted]	#1	$ 20.00
01-16-2019 [**SSFCHS**] SHERIFF'S SERVICE FEE FOR COURT HOUSE SECURITY	[redacted]	#1	$ 10.00
01-16-2019 [**TCARF**] TRAUMA CARE ASSISTANCE REVOLVING FUND	[redacted]	#1	$ 10.00
01-16-2019 [**CLEET**] CLEET PENALTY ASSESSMENT	[redacted]	#1	$ 9.00
01-16-2019 [**PFE7**] LAW LIBRARY FEE	[redacted]	#1	$ 6.00
01-16-2019 [**AFIS**] AFIS FEE	[redacted]	#1	$ 5.00
01-16-2019 [**SSF**] SHERIFF'S SERVICE FEE ON ARRESTS	[redacted]	#1	$ 5.00
01-16-2019 [**FOREN**] FORENSIC SCIENCE IMPROVEMENT ASSESSMENT	[redacted]	#1	$ 5.00
01-16-2019 [**CHAB**] C.H.A.B. STATUTORY FEE	[redacted]	#1	$ 3.00
01-16-2019 [**AGVSU**] ATTORNEY GENERAL VICTIM SERVICES UNIT	[redacted]	#1	$ 3.00
01-16-2019 [**CCADMIN**] COURT CLERK ADMINISTRATIVE FEE ON COLLECTIONS	[redacted]	#1	$ 8.50
01-16-2019 [**DCADMIN**] DISTRICT COURT ADMINISTRATIVE FEE	[redacted]	#1	$ 12.75
01-16-2019 [**CONVICTED**] NOLO PLEA	[redacted]	#1	

Source: Oklahoma State Court Network (OSCN).

Figure B5: Traffic Citation Example: Docket

01-16-2019 [EAA]

ENTRY OF APPEARANCE/ NOLO PLEA
Document Available at Court Clerk's Office

01-16-2019 [NOWS]

NOTICE OF WITHDRAWAL OF DEPARTMENT OF PUBLIC SAFETY SUSPENSION - COPY TO DPS, COPY TO FILE/GAVE COPY TO DEFT.
Document Available at Court Clerk's Office

01-16-2019 [BWR]

BENCH WARRANT RECALLED, WARRANT ISSUED ON 6/14/2017

01-16-2019 [ADJUST] $ 8.50

ADJUSTING ENTRY: MONIES DUE TO AC09-CARD ALLOCATION

01-16-2019 [ACCOUNT] $ -8.50

ADJUSTING ENTRY: MONIES DUE TO THE FOLLOWING AGENCIES REDUCED BY THE FOLLOWING AMOUNTS:
TR-2017-9014: AC88 SHERIFF'S SERVICE FEE FOR COURT HOUSE SECURITY -$0.25
TR-2017-9014: AC79 OCIS REVOLVING FUND -$1.25
TR-2017-9014: AC78 OKLAHOMA DEPARTMENT OF HEALTH/TRAUMA CARE FUND -$0.25
TR-2017-9014: AC77 DA COUNCIL PROSECUTION ASSESSMENT FEE -$0.50
TR-2017-9014: AC75 FORENSIC SCIENCE IMPROVEMENT ASSESSMENTS -$0.13
TR-2017-9014: AC71 DPS PATROL VEHICLE REVOLVING FUND -$0.50
TR-2017-9014: AC69 CHILD ABUSE MULTIDISCIPLINARY FEE -$0.08
TR-2017-9014: AC67 DISTRICT COURT REVOLVING FUND -$0.32
TR-2017-9014: AC31 COURT CLERK REVOLVING FUND -$0.47
TR-2017-9014: AC23 LAW LIBRARY FEE CIVIL AND CRIMINAL -$0.15
TR-2017-9014: AC22 SHERIFF'S SERVICE & INCARCERATION FEE -$0.13
TR-2017-9014: AC21 AFIS FUND -$0.13
TR-2017-9014: AC14 FINES -$0.50
TR-2017-9014: AC11 CLEET PENALTY ASSESSMENT -$0.23
TR-2017-9014: AC08 SHERIFF FEES -$1.13
TR-2017-9014: AC07 ATTORNEY GENERAL VICTIM SERVICES UNIT -$0.08
TR-2017-9014: AC01 CLERK FEES -$2.40

01-16-2019 [ACCOUNT]

ADJUSTING ENTRY TO COSTS DUE TO CARD CALCULATION:
MONIES DUE TO AC09-CARD ALLOCATION ($2.56) AND MONIES ADJUSTED IN CCA CASE

Source: Oklahoma State Court Network (OSCN).

Figure B6: Traffic Citation Example: Docket

01-16-2019 [ACCOUNT]

RECEIPT # 2019-4520654 ON 01/16/2019.
PAYOR: [redacted] TOTAL AMOUNT PAID: $ 442.33.
LINE ITEMS:
TR-2017-9014: $95.60 ON AC01 CLERK FEES FOR [redacted]
TR-2017-9014: $2.92 ON AC07 ATTORNEY GENERAL VICTIM SERVICES UNIT FOR [redacted]
TR-2017-9014: $43.87 ON AC08 SHERIFF FEES FOR [redacted]
TR-2017-9014: $8.50 ON AC09 CARD ALLOCATIONS FOR [redacted]
TR-2017-9014: $8.77 ON AC11 CLEET PENALTY ASSESSMENT FOR [redacted]
TR-2017-9014: $19.50 ON AC14 FINES FOR [redacted]
TR-2017-9014: $4.87 ON AC21 AFIS FUND FOR [redacted]
TR-2017-9014: $4.87 ON AC22 SHERIFF'S SERVICE & INCARCERATION FEE FOR [redacted]
TR-2017-9014: $5.85 ON AC23 LAW LIBRARY FEE CIVIL AND CRIMINAL FOR [redacted]
TR-2017-9014: $18.03 ON AC31 COURT CLERK REVOLVING FUND FOR [redacted]
TR-2017-9014: $12.43 ON AC67 DISTRICT COURT REVOLVING FUND FOR [redacted]
TR-2017-9014: $2.92 ON AC69 CHILD ABUSE MULTIDISCIPLINARY FEE FOR [redacted]
TR-2017-9014: $19.50 ON AC71 DPS PATROL VEHICLE REVOLVING FUND FOR [redacted]
TR-2017-9014: $4.87 ON AC75 FORENSIC SCIENCE IMPROVEMENT ASSESSMENTS FOR [redacted]
TR-2017-9014: $19.50 ON AC77 DA COUNCIL PROSECUTION ASSESSMENT FEE FOR [redacted]
TR-2017-9014: $9.75 ON AC78 OKLAHOMA DEPARTMENT OF HEALTH/TRAUMA CARE FUND FOR [redacted]
TR-2017-9014: $48.75 ON AC79 OCIS REVOLVING FUND FOR [redacted]
TR-2017-9014: $102.08 ON AC87 WARRANTS COLLECTIONS FOR [redacted]
TR-2017-9014: $9.75 ON AC88 SHERIFF'S SERVICE FEE FOR COURT HOUSE SECURITY FOR [redacted]

01-16-2019 [SFCU]

UPDATE OF CASE INFORMATION, SENT TO COLLECTION AGENCY. BATCH ID: 20190116-8566 - COLLECTION ID: 122137

01-17-2019 [ABST] #1

ABSTRACT SENT TO D.P.S.

01-18-2019 [O]

ORDER RECALLING COST BENCH WARRANT FAILED TO APPEAR AND PAY JUDGE COLLINS
Document Available at Court Clerk's Office

01-23-2019 [RETBW]

WARRANT RETURNED 1/23/2019, WARRANT ISSUED ON 6/14/2017
COMMENT: ATTENTION BOOKING DEPARTMENT: DEFENDANT MAY BE RELEASED UPON A CASH PAYMENT IN FULL OR SET FOR THE COST DOCKET./RECALLED/CLEARED 1-18-19
Document Available at Court Clerk's Office

Source: Oklahoma State Court Network (OSCN).

C Difference-in-Differences Analysis

In this appendix section, I examine the robustness of the main estimates reported in Table 2 using a different identification strategy. I leverage variation in natural disaster exposure across ZIP Codes in the analytical sample to estimate how the likelihood of defaulting on legal financial obligations (LFOs) evolves in the post-natural disaster period relative to the pre-natural disaster period in ZIP Codes affected by the natural disaster when compared to non-natural disaster exposed ZIP Codes. In Figure C1, I report estimates from the following event-study specification.

$$y_i = \alpha_d + \sum_{\tau=-4, i \neq -1}^{7} \beta_\tau \cdot \mathbb{1}\left\{Date_i - NaturalDisaster_d \in Bin_\tau\right\} + \epsilon_i \tag{3}$$

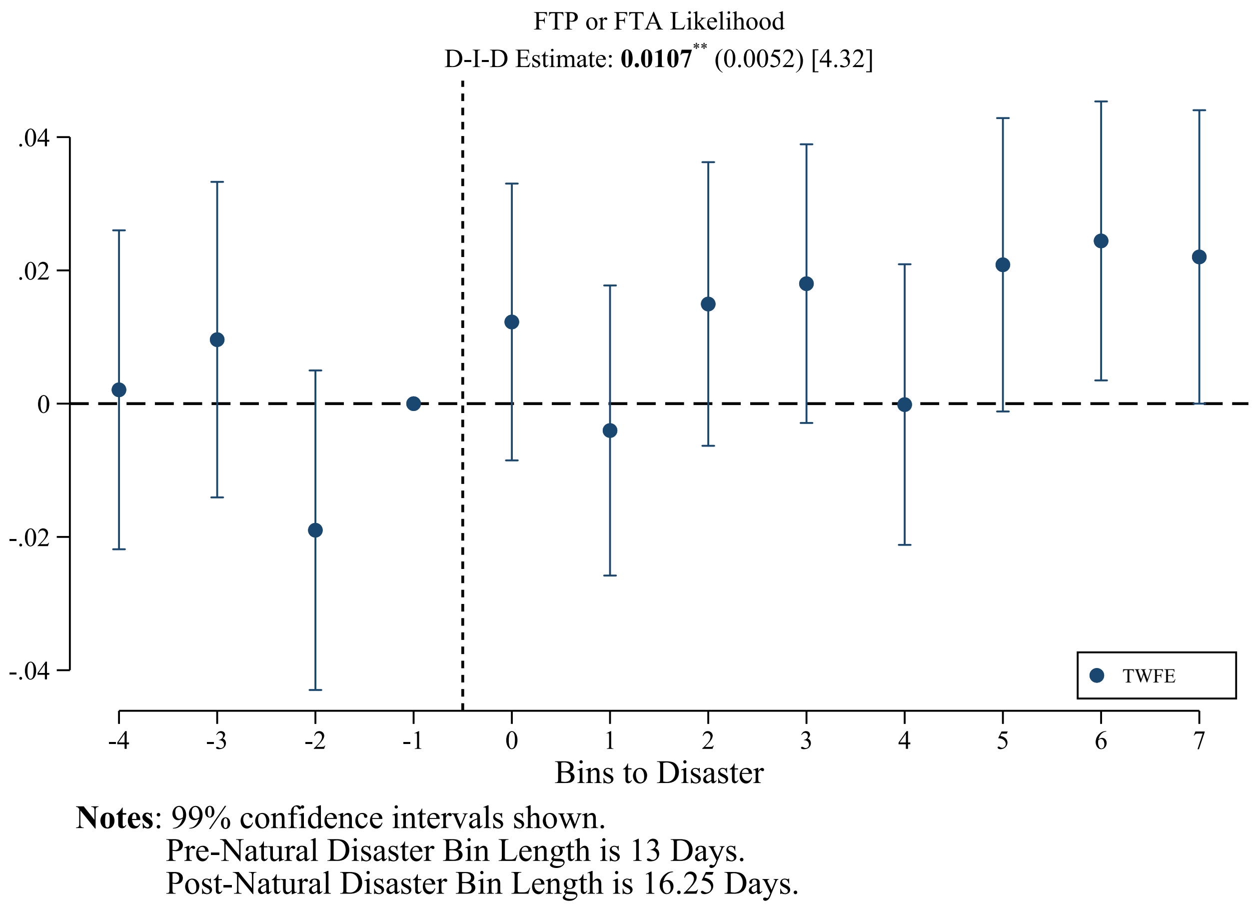
In Equation 3, y_i is the outcome of interest for defendant i. The main outcome of interest is an indicator variable for whether the defendant i defaults on their legal debt, i.e., they have either failure to pay (FTP) or failure to appear (FTA) instance. $Date_i$ refers to the day on which the defendant 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. Thus if a traffic citation is exposed to multiple natural disasters, each natural disaster uniquely contributes to the analytical sample.

$\mathbb{1}\left\{Date_i - NaturalDisaster_d \in Bin_\tau\right\}$ in Equation 3 is an indicator variable for the difference between the initial court appearance date for the defendant i and the date of a natural disaster striking their residence ZIP Code to be in the bin Bin_τ where τ varies from -4 to 7, i.e., four bins before the beginning of the natural disaster and eight bins after. For comparability reasons, I use the same length for the bins before and after the natural disaster as those used for estimates reported in Figure 1. Furthermore, I average the traffic citations across a given natural disaster to have the same analytical sample as that used for estimates reported in Table 2 and Figure 1. α_d accounts for unobservable characteristics that are common across all the defendants for natural disaster d. The control group in the estimation of specification in Equation 3 are those defendants whose residence ZIP Code is never impacted by a natural disaster during the sample period, i.e., from 2016 to 2019.

Reassuringly estimates from the specification in Equation 3 reported in Figure C1 show that there is no evidence that the ZIP Codes with at least one natural disaster and those that have no natural disaster between 2016 and 2019 are trending differentially before the natural disaster. Furthermore, there is evidence from the estimates derived from Equation 3 that natural disasters in the defendant's residence ZIP Code increase FTP or FTA likelihood. In particular, the point estimates from modifying specification in Equation 3 by replacing indicators for individual bins with a single post-natural disaster indicator variable show that relative to pre-natural disaster period defendants who reside in ZIP Codes affected by the natural disaster approximately one percentage points more likely to have an FTP or FTA instance on their traffic citations relative to their counterparts who reside in ZIP Codes that are never impacted by a natural disaster during the sample period.

It is worth emphasizing that the asymmetry in the point estimates reported in Figure C1 and those reported in Figure 1 is due to different estimands of the two approaches. In Figure 1 the estimand is the local average treatment effect which is the causal effect for those defendants who have an initial court appearance date very close to the natural disaster striking their residence ZIP Code. Estimand in Figure C1 is the average treatment effect on the treated which is the causal effect for those defendants who were ever exposed to the natural disaster during the sample period.

Figure C1: Event-study Estimates



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 specification also includes fixed-effects for natural disasters. Bin indicator values are based on the initial appearance date of the citation and the date of the beginning of the natural disaster. The length of the bin pre-natural disaster is 13 days and it is 16.25 days post-natural disaster. 99% confidence intervals are reported as spike bars.

D Judge Fixed-effects Estimation

Dockets data scraped from the Oklahoma State Court Network (OSCN) also contains information on the presiding judge for each traffic citation. I use the information on the presiding judge that is initially assigned to each traffic citation to examine if there is any influence of this assignment on the likelihood of defendants either failing to pay (FTP) or failing to appear (FTA) when their residence ZIP Code is affected by a natural disaster. By showing that my main estimates reported in Table 2 are not sensitive to accounting for the initial presiding judge assignment, I alleviate concerns regarding strategic FTP or FTA decision by the defendant.

For this analysis, I augment the specification in Equation 1 by also including judge fixed-effects. Thus, the specification is as follows.

$$\begin{aligned} y_i = &\alpha_h + \tau_h \cdot \mathbb{1}\left\{Date_i > NaturalDisaster_d\right\} + \beta_h^- \cdot (Date_i - NaturalDisaster_d) \\ &+ \beta_h^+ \cdot \mathbb{1}\left\{Date_i > NaturalDisaster_d\right\} \cdot (Date_i - NaturalDisaster_d) + \boldsymbol{\gamma}_{j(i)} + \epsilon_i \end{aligned} \tag{4}$$

In Equation 4, $\boldsymbol{\gamma}_{j(i)}$ is a vector of presiding judge fixed-effects. All other parameters are the same as that in Equation 1. The estimates from the specification in Equation 4 are in the second column of Table D1. The first column of Table D1 reports estimates from the first row of Table 2 for comparison. The estimates in the second column of Table D1 imply that in the immediate aftermath of the defendant's residence ZIP Code being impacted by a natural disaster, the likelihood of an FTP or FTA instances increased by approximately 3.1 percentage points. This increase is similar to the baseline estimate reported in the first column. Indeed, I cannot reject the null hypothesis that the two estimates are the same statistically. The estimates in the second column of Table D1 suggest an increase over the pre-disaster mean of FTP or FTA likelihood of approximately 14% in the immediate of the natural disaster.

Overall, the baseline estimates reported in Table 2 are not impacted by accounting for the identity of the presiding judge assigned to the traffic citation.

Table D1: Judge Fixed-effects Estimation

	Baseline	Judge Fixed-Effects
	(1)	(2)
RDD Estimate	0.04028**	0.03148***
	(0.01796)	(0.00795)
$\frac{\text{Coefficient}}{\text{Pre-treatment Mean}} \times 100$	15.6	14.4
N	261	15,679

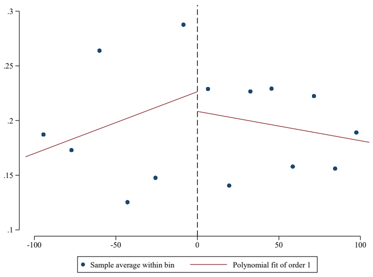
Note: Heteroskedasticity robust standard errors in the first column and clustered at the judge-level in the second column are in parentheses. (* p<.10 ** p<.05 *** p<.01). Data on traffic citations are derived from the Oklahoma State Court Network (OSCN). Data on natural disasters are derived from the Federal Emergency Management Agency (FEMA)'s disaster declarations summaries dataset. All disaster declarations for fire management assistance are dropped from the analytical sample. Each observation in all columns is at the day-level. Day-level observations are based on the initial appearance date of the citation and the date of the beginning of the natural disaster. Column headers denote the outcome variable.

E Sub-Experiment Estimation

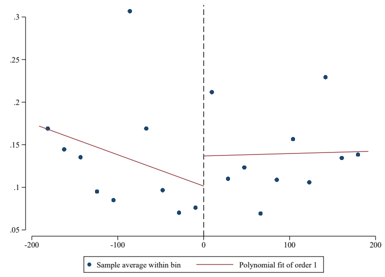
Estimates from the specification in Equation 1 for each natural disaster in the analytical sample with enough mass for reliable estimates and inference are reported in Figure E1.

Figure E1: Individual Disaster Estimates

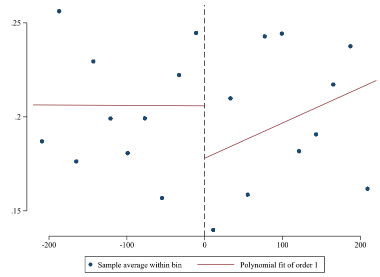
(a) DR-4274-OK



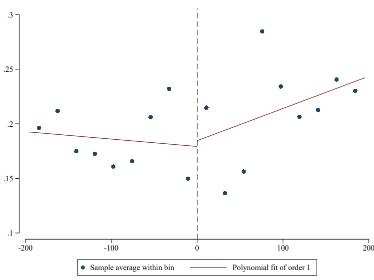
(b) DR-4299-OK



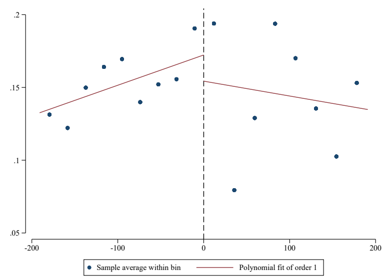
(c) DR-4315-OK



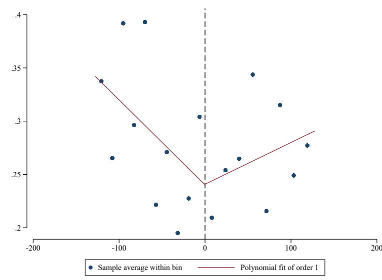
(d) DR-4324-OK



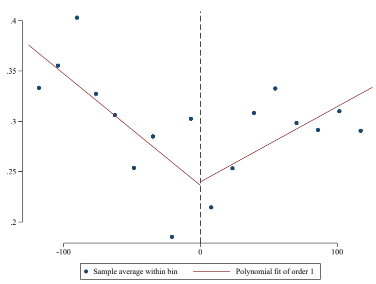
(e) DR-4373-OK



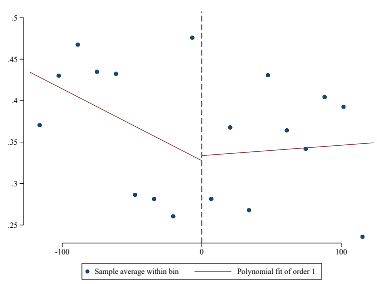
(f) DR-4438-OK



(g) DR-4453-OK



(h) EM-3411-OK



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. Estimates in all panels are labeled using the unique FEMA natural disaster identifier.

F Back-of-the-Envelope Calcuations

I use the estimates from the fourth column of Table 4 to provide an estimate of the total increase in fines for all traffic citations that are impacted by a natural disaster in my analytical sample. The total number of traffic citations affected by a natural disaster in my analytical sample is $454,522$. Note that this count differs from the one reported in the footnote of Table 1. This difference arises due to two reasons. First, not all ZIP Codes have associated observable covariates from the American Community Survey (ACS) 5-year sample data. Second, not all defendants' names could be matched to the Rosenman et al. (2023) data on race and ethnicity.

Recall that the marginal effect of natural disaster exposure on total fines from Table 4 is approximately $65. Thus, the average increase in total fines projected over all the traffic citations impacted by a natural disaster in the defendant's residence ZIP Code is given by the product of the marginal effect and count of natural disaster affected traffic citations. This estimate is approximately $29.33 million.