Short-term Impact of Wildfire on Retail Gasoline Prices†

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Highlights

- We examine the impact of the 2024 Park Fire in California on local gasoline prices.
- Our analysis includes station-level gas prices, weather information, road closures, distance to the event (edge of fire or closed road) and unaffected (control) stations outside the fire area.
- We find a decline in gas prices in the affected area during the fire period.

Abstract

As wildfires become increasingly frequent and intense due to multiple factors such as a changing climate and the accumulation of dry vegetation , understanding their economic effects on critical commodities is essential to evaluate their economic consequences beyond immediate property damage. This study assesses the short-term impact of the 2024 Park Fire on local retail gasoline prices in Northern California, using high-frequency station-level data. A generalized difference-in-differences approach and event study reveal that stations within 20 miles of the wildfire experienced a roughly nine-cent-per-gallon price drop compared to more distant controls—an outcome contrasting with the price spikes typically observed after hurricanes and floods. This study contributes to the literature by demonstrating how natural disasters, particularly wildfires, can influence fuel markets in unexpected ways, highlighting the importance of monitoring post-disaster price changes.

Keywords: Natural Disasters, Wildfire, Retail Fuel Markets

JEL classifications: Q41, Q54, R11, R32

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Introduction

Wildfires are one of the most pressing challenges in the contemporary United States—not only for their environmental and public safety impacts but also for their far-reaching economic consequences. Wildfires are an increasingly prominent and destructive force, particularly in the western United States where their size, intensity, and frequency continue to escalate (Miller & Safford, 2012). Data from the National Interagency Fire Center indicates a slight decrease in the number of fires annually in the US, yet there is a marked increase in the millions of acres consumed by these fires each year. Fire weather seasons have lengthened in the western US attributable to a changing climate (Jolly et al., 2015; Abatzoglou & Williams, 2016). Fuel accumulation (Mercer et al., 2008) and the expansion of the wildland-urban interface (Radeloff et al., 2018) contribute to these trends. While many wildfires remain small in terms of the area burned, certain "extraordinary" fires have profound economic impacts, causing significant disruptions across various sectors.

Much of the extant literature has focused on the general economic impacts of wildfires—ranging from property losses (Gibbons et al., 2012; Huang & Skidmore, 2024; Penman et al., 2015; Syphard et al., 2012; Wang et al., 2021; Xu & Kooten, 2013) to productivity declines (Breedt et al., 2013; Stephenson et al., 2013). However, there remains a significant gap in our understanding of how wildfires affect commodity prices, particularly retail gasoline prices. Gasoline is critical during emergencies for evacuations, powering generators, and supporting public safety, yet its price behavior under wildfire conditions is relatively understudied.

By contrast, hurricanes and floods have been extensively analyzed for their dramatic supply-side impacts (see Beatty et al., 2021; Blair & Rezek, 2008; Fink et al., 2010; Lewis, 2009; Montgomery et al., 2007). For instance, in response to Hurricane Katrina in 2005, wholesale gasoline prices surged as oil production and refining capacity were directly affected, leading to nationwide price shocks (Beatty et al., 2021; Blair & Rezek, 2008). Such events prompted robust policy responses, including the activation of anti–price gouging statutes designed to shield consumers from exploitative pricing. However, economic literature is less developed when it comes to the impacts of wildfires on fuel costs.

This study seeks to bridge this gap by focusing on the economic repercussions of wildfires, specifically how they influence gasoline prices. In this article, we examine the impact of a wildfire event on prices at nearby retail gasoline stations. We specifically focus on the Park Fire incident, which began on July 24th, 2024, and was fully contained on September 27th, 2024, in Butte and Tahama counties in Northern California. Burning 429,603 acres, it ranks as the fourth largest wildfire in California's recorded history (Freedman, 2024). This fire is categorized as a 'megafire,' a term for wildfires that consume over 100,000 acres (40,500 hectares), according to the U.S. Interagency Fire Center (National Geographic Society, n.d.).[1] Although the cause of the Park Fire was traced to an unusual act of arson, the rapid spread was exacerbated by several climatic contributing factors including high temperatures, strong winds, and a large amount of dry vegetation that had accumulated due to unusually wet winter and spring seasons followed by a hotter-than-normal summer (Leonard & Sacks, 2024).

Our empirical findings suggest that contrary to expectations of price gouging in the aftermath of natural disasters, gasoline prices around the Park Fire declined. Several hypotheses could explain this outcome. For instance, the observed decrease may result from reduced local travel demand, either due to displaced residents or deterred tourists, or from adjustments in station-level inventory management driven by anticipated supply disruptions. Alternatively, broader market expectations regarding commodity availability could also influence consumer behavior. Regardless of the precise underlying mechanism, these findings are notable as they underscore how wildfire-induced disruptions in consumer markets can significantly diverge from patterns typically observed in other disaster contexts, highlighting the importance of context-specific analyses when evaluating disaster-related economic impacts.

From a policy standpoint, understanding these divergent behaviors is critical. While anti–price gouging laws are a potentially important safeguard in disaster-prone regions, the findings suggest that policymakers also need to address the unique market dynamics associated with wildfires. These may involve measures to stabilize supply chains, support local businesses through emergency loan programs, and systematically track both demand fluctuations and environmental stressors. In doing so, communities may be better prepared not only to prevent adverse price

[1] Other wildfire experts expand the definition of a megafire beyond “acres burned” to mean wildfires that have an unusually large impact on people and the environment (National Geographic Society, n.d.). Tedim et al. (2018) defines extreme wildfire events based on how fire spreads out and how difficult to suppress them. Redefining the term ‘megafire’ is an area of debate (Linley et al., 2022; Stoof et al., 2024).

swings but also to ensure that critical commodities such as gasoline remain accessible in high-risk fire zones.

The rest of the paper is structured as follows: Section 2 outlines the workings of the U.S. retail gasoline market and how wildfires could potentially affect prices. Section 3 details the station-level retail gas and environmental data used for estimation. Section 4 describes the difference-in-differences and event study empirical models employed. Section 5 presents the results of our analysis, and Section 6 concludes with a summary of findings and discussion of the study's limitations.

Background & Framework

U.S. Retail Gasoline Market

Gasoline prices that consumers pay at the pump reflect the supply chain process that starts from crude oil futures and extends to retail sales.[2] Crude oil is distilled at refineries and transformed into gasoline, a process where costs can vary by season and region. California, with the highest retail gasoline prices in the continental United States, faces unique price pressures due to its prolonged warm climate and stringent environmental standards. During summer, gasoline formulations—designed to evaporate at higher temperatures to reduce emissions—are costlier to produce, and California’s extended warm season requires longer use of this summer blend. Additionally, California mandates a specialized blend to meet the specific average carbon intensity requirements aimed at reducing the carbon intensity of transportation fuels under Low Carbon Fuel Standard regulations. This specific blend, known as CARBOB (California Reformulated Gasoline Blendstock for Oxygenate Blending), is sold in California's spot markets as unfinished gasoline and can be costly and complex to produce (U.S. Energy Information Administration, 2015; OPIS, 2024). Once ethanol is added at the wholesale rack terminal, this blend is transformed into CARB RFG (California Air Resources Board Reformulated Gasoline), which is then transported to retail stations. At these terminals, fuel distributors, often referred to as jobbers, purchase the fuel and

[2] As of September 2024, the average composition of U.S. gasoline prices is as follows: crude oil accounts for approximately 53% of the price, refining costs and profits constitute 11%, distribution and marketing represent about 20%, and federal and state taxes make up 16% (U.S. Energy Information Administration, 2024).

then distribute it by truck to retailers and other end users.[3] Jobbers often incorporate these compliance costs into the wholesale prices, significantly influencing the final retail prices of gasoline (OPIS, 2024).

In terms of distribution and marketing, price heterogeneity exists between branded and unbranded retailers (Beatty et al., 2021; Hurtado & González, 2024). Branded retailers enter long-term contracts with major suppliers, specifying the quantity and frequency of fuel deliveries.[4] These contracts often require purchases from designated racks and jobbers, ensuring branded retailers a guaranteed fuel supply, particularly during supply disruptions, along with marketing support (OPIS, 2024). Furthermore, branded gasoline includes a proprietary additive package to enhance fuel performance. This combination of factors often results in higher retail prices for branded gasoline compared to unbranded alternatives. According to Beatty et al. (2021), branded stations in Florida and Louisiana charged an average of four cents per gallon more than unbranded retailers. Unbranded retailers on the other hand are not affiliated with a major oil company brand, e.g., Chevron, Shell, 76, Valero, and ARCO. They include small independent retailers as well as big box retailers.[5] According to the U.S. Energy Information Administration (2015), about 79% of retailers in California as of December 2014, are associated with a major brand, with less competition from unbranded retailers.

Other factors that affect the final retail price differences include the specific type of refined product used. We focus on conventional regular gasoline with an octane rating between 85 and 87, influenced by vapor pressure regulations which relate to the fuel's volatility and the emission of volatile organic compounds (VOCs). Moreover, retail gasoline prices and the strategic location of fueling stations are influenced by market-specific factors such as local labor costs, other operational costs, expected margins, and the intensity of local competition. These factors collectively determine the disparities in retail gasoline pricing.

[3] After being traded in the spot market, gasoline is transported via pipelines to fuel storage terminals. The points where jobbers' trucks are loaded with fuel are called loading racks, a stage in the supply chain known as the rack market. In California, there are 14 rack markets and 50 fuel terminals as of 2024, according to OPIS (2024).

[4] Most branded contracts default to a 10-year term, although the exact duration is often subject to negotiation (OPIS, 2024).

[5] Warehouse retailers, which aim to sell gasoline in large volumes at low margins, typically offer lower prices to draw consumers to their stores. This factor could significantly influence the variation in gasoline prices. Warehouse retailers are excluded from the analysis due to the insufficient number of big box retailers in the study region.

Influence of Wildfires on Gasoline Market Dynamics

Wildfires often cause extensive damage to road networks, which are essential for the transportation of gasoline. When roads are damaged or blocked, the supply chain is disrupted, leading to delays and increased costs of fuel delivery. These disruptions can create temporary shortages and drive-up gasoline prices. Wildfires can inflict severe damage on critical infrastructure such as roads, pipelines, and refineries, which are essential for maintaining a stable gasoline supply. Moeltner et al. (2013) discuss how wildfire-induced damage to transportation networks can exacerbate supply chain vulnerabilities, leading to increased transportation costs and potential price spikes in affected areas. This is further supported by Tanner (2018) who explores the economic costs associated with wildfires in heavily urbanized areas, showing that infrastructure damage can lead to significant disruptions in fuel supply. These supply constraints, especially during emergencies, can create conditions conducive to price gouging, particularly in regions where alternative fuel sources are limited. However, the immediate impact of such disruptions may be mitigated for branded retailers who often have long-term contracts ensuring a steady supply, shielding them from short-term supply shocks.

We hypothesize that in areas affected by wildfires, gasoline demand may initially increase due to evacuations and emergency responses (Hess & Greenberg, 2011). Yet, as road closures and widespread smoke deter travel, demand is likely to wane. The decline in demand may be further exacerbated by decreased recreational activity in the affected areas, as residents and visitors avoid traveling near the wildfire zones. For instance, during the Park Fire, the upper Bidwell Park—recognized as one of the largest municipal parks in the U.S.—sustained damage and was closed (Ramos et al., 2024). Such closures not only disrupt local infrastructure but also significantly alter visitor patterns and potentially reduce the associated economic welfare (Bawa, 2017). This complex interaction of factors suggests that gasoline demand can vary significantly during and after wildfire incidents, influenced by both the immediate needs of the population and the longer-term impact on recreational habits and local travel.

The interplay between supply constraints and variable demand during wildfire complicates the economic landscape. While demand may surge initially, it is typically countered by disrupted supply chains and infrastructure damage. Du & Hayes (2011) suggest that disruptions similar to those caused by wildfires could significantly increase gasoline prices, as supported by Heinen et al. (2019) who found that emergencies such as hurricanes and floods lead to substantial price increases. There is concern that spikes often result from opportunistic behavior by sellers aiming to maximize profits during crises, causing thirty-five states to pass anti-gouging legislation (National Conference of State Legislatures, 2022). A limitation of our study is the inability to fully dissect the contributing factors and mechanisms behind our observed price changes.

Data

Retail gasoline stations and prices

We collected daily retail gasoline prices and station locations from GasBuddy.com using web scraping.[6] All prices refer to regular unleaded gasoline with an octane level of 85-87. GasBuddy enables users to submit real-time prices and locations for gas stations and convenience stores in the U.S. and Canada through a mobile app and its website. The platform incentivizes users to report real-time prices by offering points, which can be redeemed for entries into daily drawings for monetary prizes on gasoline purchases, thereby encouraging frequent and accurate reporting. Also, GasBuddy employs automated algorithms to detect obvious errors. Data scraping was conducted daily at 6:00 PM Eastern Standard Time, typically requiring six hours to complete, starting from March 11th, 2024, to October 13th, 2024, except for a pause from September 21st to 26th due to technical issues. To address this gap, we incorporated three-day moving averages and weekly average prices into the model. Each price report is timestamped to indicate the exact time and date of submission, which we cross-referenced with our data collection timestamps to confirm accuracy. Our raw dataset comprises 7,578 unique gas stations in California, with an average of 4,210 stations reporting valid prices daily, resulting in a total of 863,241 observations.

We geocoded the addresses of each station using the `geocode` function from the `tidygeocoder` package version 1.0.5 (Cambon et al., 2021), using the ArcGIS parameter method for precise location data. For stations where address-based geocoding was unsuccessful or coordinates were missing, we supplemented the data with longitude and latitude coordinates

[6] According to GasBuddy's terms of service, user-submitted retail gas price data is public, as GasBuddy does not claim ownership of it (link: https://www.gasbuddy.com/disclaimer/usa). Nonetheless, we requested and received permission from GasBuddy to use its data for the study (request #1527604). See the Appendix for further details on the web scraping procedure.

directly from the Google Maps interface on GasBuddy's website. We also matched the FIPS code with the coordinates to classify the gas stations into their counties.

Based on the gas station locations, time-invariant variables for each gas station are incorporated into the dataset. We categorized each station as either branded or unbranded according to the station name associated with it. The classification of branded companies follows the list provided by Oil Price Information Service (OPIS).[7] To address the transportation cost by location of the station, we use distance to the nearest petroleum refinery. Petroleum refineries' location data was sourced from the EIA U.S. Energy Atlas (U.S. Energy Information Administration, n.d.) and is calculated in miles. Competition among the nearby retailers is measured by the number of other gas stations within 1 mile of each station. Given the diverse coordinate systems of our geographic data, a transformation was necessary for consistent spatial analysis. Therefore, all geographic data were standardized to the World Geodetic System 1984 (WGS-84) using the 'sf' package version 1.0.14 in R (Pebesma, 2018), ensuring precise spatial alignment across all variables.

Control variables representing climate conditions were incorporated using data from the National Oceanographic and Atmospheric Administration (NOAA) Daily Summaries by County. This dataset provides daily observations on weather parameters, including average wind speed, wind direction (the direction of the fastest 2-minute wind), precipitation, and average, maximum, and minimum temperatures. To ensure the reliability of our climate measures, we first filtered out any climate stations that did not record at least 80% of daily observations for each variable during the study period. Subsequently, we matched each gas station in our study area to the nearest climate station located within a 30-mile radius, thereby ensuring that the climatic data used in our analysis accurately reflects the local weather conditions experienced by each gas station. These filters resulted in XXXXX observations.

Impact of wildfire

The impact of a wildfire on local gasoline prices depends, in part, on the proximity of gas stations to both the wildfire and any resulting road closures. To quantify this, we employed geographic

[7] According to OPIS, branded fuel brands include 76, Alon, Amoco, Arco, BP, Cenex, Chevron, Citgo, Conoco, Diamond Shamrock, Exxon, Getty, Gulf, Irving, Lukoil, Marathon, Mobil, Phillips 66, Shell, Sinclair, Sunoco, Tesoro, Texaco, and Valero. Stations not associated with these brands are considered unbranded in our analysis (link: https://www.opisnet.com/product/pricing/retail-fuel-prices/brand-power-ranking-report/).

polygon data from the National Interagency Fire Center (n.d.) and California Department of Forestry and Fire Protection (CAL FIRE; www.fire.ca.gov) to calculate the distance from each gas station to the wildfire perimeter. To capture the temporal dynamics of the event, we obtained eighteen daily shapefiles of the Park Fire, covering the period from July 24th to August 18th, 2024, which document the progressive expansion of the fire. For each of these dates, we calculated the distance from each gas station to the Park Fire, ensuring that the wildfire polygon coordinates were converted to the WGS-84 system for consistent spatial analysis.

Additionally, Road closures related to the Park Fire incident are recorded in daily status updates. From these reports, we identify the specific road numbers and locations, as well as the duration of closures during the Park Fire incident. All related road closures were lifted by August 22nd, 2024. Our analysis focuses exclusively on highways classified as motorways, trunks, and primary roads in OpenStreetMap (OSM).[8] For each gas station, we compute the distance to the nearest road closure in miles.

Final sample

Our final sample is constructed combining daily prices, climate variables, time invariant characteristics and distances to the wildfire related variables. To assess the impact of the Park Fire, we categorized gas stations into treated and control groups based on their proximity to the fire. The treated group includes stations within 20 miles of the Park Fire, while the control group comprises stations located 20 to 40 miles away, specifically north of Butte and Tehama Counties.[9] We excluded stations in the southern parts of these counties due to their proximity to the major metropolitan areas, especially Sacramento County. This exclusion helps mitigate unobserved variations in retail gasoline price fluctuations that are influenced by higher population density and urban factors, distinguishing significantly from the more rural areas covered by the treated group.

Figure 1 displays maps of California highlighting the Park Fire and shows the locations of all retail gas stations in our dataset. Stations within the treated and control groups are marked red

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[8] Motorway is defined as a restricted access major divided highway, normally with 2 or more running lanes plus emergency hard shoulder. Trunk is the most important roads in a country's system that aren't motorways. Primary is the next most important road after trunk in a county's system, which often links to larger towns (link: https://wiki.openstreetmap.org/wiki/Key:highway).

[9] The 20-mile and 40-mile distance thresholds used to classify the treated and control groups were chosen based on the threshold that yielded the most optimal p-value for establishing parallel pre-treatment trends. See the Appendix for further details.

and grey, respectively, to illustrate their proximity to the Park Fire and associated road closures. Consequently, the final dataset for our analysis is an unbalanced panel, comprising 32,116 retail gasoline price observations over 217 days across 148 stations, with some missing data left as is. Three-days moving averages, daily prices and weekly averages mitigate the volatile daily retail gasoline prices and missing prices (see Figures 3 and 4 for trends).

Table 1 shows the summary statistics for these 148 gas stations. The average retail gasoline price for the sample period was $4.70 per gallon with wide range over the period. From the daily average price trends of treated and control groups in Figure 2, average prices increased until the middle of April to around $5.30 per gallon and trended downward to around $4.30 per gallon until August, then increased to 40 cents in September before decreasing again. The treatment group (89 gas stations) had slightly higher average prices than the control group of 59 stations, however prices were broadly similar. Prices exhibit heterogeneity of branded and unbranded stations, where branded stations have around 40 cent/gallon higher prices than unbranded, on average.

Geographically, the average distance to the wildfire from the stations was around 17 miles, with distances spanning from as close as 1.89 miles to as far as 38.67 miles, showing a wide distribution. The average distance to the closest petroleum refinery was much greater at 151 miles. The proximity to road closures had an average of 14.54 miles, with minimum distance of just 0.024 miles, highlighting the immediate impact of the wildfire on some stations. On average, gas station had three competing stations within a mile, varying from none to 11, indicating heterogeneity in levels of local market competition.

Climate variables indicate that the average daily temperature is approximately 22.73°C, with maximum and minimum temperatures averaging 30.85°C and 14.25°C, respectively. Precipitation, used as a control variable for environmental conditions, averages 1.23 mm per day but exhibits substantial variability (SD = 4.59 mm) and is highly skewed toward lower values, with a maximum of 67.1 mm recorded on a single day. Additionally, average wind speed is 2.61 m/s, reaching up to 8.4 m/s under certain conditions. Wind direction, measured in degrees as the direction of the fastest 2-minute wind, averages 183.66° (SD = 91.33°), indicating that winds typically originate from the south (with 180° representing a south wind); however, the high variability suggests a wide range of wind directions over the study period.

Empirical Strategy

In this section we explain our empirical strategy for assessing the impact of the Park Fire on nearby gasoline prices, drawing on methodologies used in prior research such as the study by (Beatty et al., 2021), which examined the effects of hurricane landfalls on retail prices. We start with a generalized difference-in-differences (DID) analysis under common assumptions. Then we only use treatment groups to use event study models with fewer assumptions.

A difference-in-differences approach allows for straightforward interpretation under established assumptions. Using simple DID structure where we only use two groups (treated and control) and two time periods (pre- and post-wildfire), the validity of the model relies on several critical assumptions. First of all, the stable unit treatment value assumption (SUTVA) (Imbens & Rubin, 2015) requires both groups to have stable composition for repeated cross-sectional design, with no spillover effects from the treatment to the control group or vice versa. Also, the parallel trend assumptions (PTA) restricts the average counterfactual prices for the treated stations at the post-wildfire period had they not been subject to the treatment (wildfire event), but it does not directly affect restrictions on the prices in pre-wildfire periods (Marcus & Sant'Anna, 2021). However, this PTA is by definition untestable since the counterfactual conditional expectation is unobservable (Cunningham, 2021). Lastly, we should consider the assumption of homogeneous treatment effects across both groups and over time as discussed in (De Chaisemartin & D'Haultfœuille, 2020).

The DID model specification we use in our analysis is presented as follows:

$$\begin{aligned} Price_{ict} = \beta_1 + \beta_2 Post_t + \beta_3 Treated_i + \beta_4 \mathrm{Post_t} \times Treated_i + \delta X_{ict} + \lambda_{\mathrm{i(c)}} \\ + \theta_m + \pi_{d(w)} + \epsilon_{ict} \end{aligned} \tag{1}$$

where dependent variable $Price_{ict}$ is retail gasoline price at station i in county s on date t. The dummy variable for the post-wildfire period, $Post_t$ is set to one on and after July 24, 2024, and zero otherwise. The dummy variable for stations close to the wildfire, $Treated_i$ is set to one if the station is treated (withing 20 miles from the wildfire) and zero otherwise. The coefficient of the interaction term between the Post and Treated variables is the average treatment effect of wildfire on retail gasoline prices. The vector X_{ict} represents control variables including precipitation, distances to the closest road closure, refinery, and the number of competitors. To control seasonal patterns of gasoline prices, we use month fixed effects (θ_m) and day of the week fixed effects ($\pi_{d(w)}$). Station (i) level fixed effects (λ_i) may capture station-specific costs that are not captured in other controls. We also regress the same model using county level fixed effect (λ_c) to account for different demographic or time-invariant economic factors varying across counties, while ϵ_{ict} is an error term.

We estimate model (1) using daily, moving averages daily, and weekly prices as the dependent variable. For the weekly price sample, the day of the week fixed effects (π_d) are omitted due to aggregation.

To reinforce the validity of our DID approach given the critical importance of the PTA, we incorporate an event study. While event studies do not directly test the PTA, they show that groups were comparable before the treatment, supporting the assumption's credibility (Cunningham, 2021). Our event study approach, influenced by (Sun & Abraham, 2021) and (Beatty et al., 2021), allows for varied treatment effects, as long as their patterns are consistent over time. This method helps us robustly analyze the dynamic impacts of wildfires on gasoline prices without requiring uniform treatment effects across all groups and times. The event study model specification we use in our analysis is presented as follows:

$$Price_{it} = \beta_1 + \sum_{k=-L}^{-1} \beta_k Lead_k + \sum_{m=0}^{M} \gamma_m Lag_m + \delta X_{it} + \lambda_i + \theta_m + \pi_d + \epsilon_{it} \tag{2}$$

$$\begin{aligned} Price_{it} = \beta_1 + \sum_{k \neq -1} \beta_k \mathbf{1}\{Week2Treat_{it} = k \text{ and } Treated_{it} = 1\} + \delta X_{it} + \lambda_i + \theta_m \\ + \pi_{\mathrm{w}} + \epsilon_{it} \end{aligned} \tag{3}$$

where specified controls are the same as in equation (1). The $Lead_k$'s are indicator variables for pre-treatment periods, where k indicates the number of periods before the treatment (wildfire). The Lag_m's are indicators for post-treatment periods, where m represents the number of periods after the treatment (wildfire). The dynamic treatment effects before and after the wildfire are captured by β_k and γ_m.

We limit our event study sample to gas stations located within 20 miles of the Park Fire and analyze weekly gasoline prices for these stations during eight weeks before and after the event. The event dates are defined by 18 fire layers that capture key milestones in the wildfire's progression, as detailed in Table 2. For example, 35 stations were within 20 miles of the initial fire on July 24th, and an additional 29 stations were added to the impact zone the following day as the fire expanded. As the wildfire progressed, more stations were incorporated, resulting in seven distinct event dates for the treated group. Stations initially outside the 20-mile radius are included as the wildfire expanded, enabling us to capture a staggered impact over time and preventing perfect collinearity between lead and lag variables.

To standardize our findings, we normalize our coefficients relative to a week before the wildfire event, $Lead_{-1}$, as the baseline level is otherwise unidentifiable. This normalization helps clarify the incremental impact of the wildfire on gasoline prices, relative to the immediate pre-event period.

For the event study analysis, we aggregate gasoline price data at the weekly level. We chose weekly aggregation to balance temporal granularity with statistical reliability, given that nearby gas stations often exhibit strongly correlated price movements. Weekly aggregation helps to smooth out short-term fluctuations while preserving meaningful trends in price responses. However, this approach may also obscure some short-term dynamics that occur within a week. For further details on these trade-offs, see the Appendix.

Results

The estimation results from our generalized difference-in-differences (DID) model, as specified in Equation (1), are detailed in Tables 3 and 4. Table 3 presents the results using station-level fixed effects, which capture idiosyncratic, time-invariant characteristics unique to each gas station. Table 4, on the other hand, employs county-level fixed effects, accounting for broader geographic and demographic factors that might influence gasoline prices across different counties.

In our analysis of the average treatment effects of wildfire on retail gasoline prices, we observed statistically significant reductions across all samples. Detailed in columns (1) and (2) of Table 3, gas stations near the Park Fire decreased their prices by approximately 9.5 cents per gallon following the event. This decline was slightly smaller in the moving average prices, showing a decrease of about 8.9 cents per gallon. Additionally, the weekly price data in column (3) also exhibited a significant reduction, with prices dropping by 7.8 cents per gallon post-wildfire.

When using county fixed effects, as shown in Table 4, the price reductions were still statistically significant but of a smaller magnitude. Columns (1) and (2) indicate that the average treatment effect on daily prices was around 5 cents per gallon lower, and for weekly prices in column (3), the effect was approximately 5.9 cents per gallon lower.

Our analysis reveals that distance to road closures significantly impacts gasoline prices under county fixed effects, with a one-mile increase linked to price increases of 2.2 to 3.0 cents per gallon. This suggests as a hypothesis that stations near closures face reduced demand due to accessibility constraints, forcing them to lower prices to attract customers, while customers of those farther away experience less inconvenience so station managers can maintain higher prices. This pattern suggests that proximity to road closures directly correlates with lower gasoline prices, likely due to reduced accessibility and decreased demand. Stations closer to closures may offer lower prices to counteract decreased consumer traffic, whereas those farther away face less change in demand and maintain higher prices. The lack of statistical significance in the station fixed effects model suggests that the impact of supply disruptions is more noticeable at the county level.

Figure 5 presents the results from the event study regression of Equation (2) using weekly price data. The vertical dashed line marks the reference week—one week prior to the fire—for each treated station. Prior to the fire (weeks −5 to −1), gasoline prices hover slightly above the reference period, with no strong upward or downward trend, indicating the absence of significant pre-trends. Immediately following the fire, however, prices drop below the baseline by about 7.2 cents per gallon, initiating a pronounced downward trajectory that persists for several weeks. The most substantial decline, approximately 21 cents per gallon, occurs within the first three weeks post-event, and the tight confidence intervals suggest these reductions are statistically significant. This finding supports the hypothesis that wildfire-induced disruptions to local demand and supply chains can temporarily reduce retail gasoline prices.

After around week +3, prices begin to rebound, and by weeks +5 or +6, they approach pre-fire levels. The widening confidence intervals in these later weeks indicate greater uncertainty in the estimates as the market adjusts. Overall, these results point to a short-lived but notable impact of the Park Fire on gasoline prices: a sharp initial decline followed by a gradual return to baseline levels. This pattern illustrates how local gasoline markets can respond to wildfire-related disruptions, underscoring the event's potential influence on short-term pricing dynamics.

Integrating results across both models clearly indicates a decline in retail gasoline prices following the wildfire, challenging the typical expectation of price gouging post-natural disasters. Contrary to prior studies that documented price increases after disasters (Blair & Rezek, 2008; Lewis, 2009), our findings reveal a decrease in retail gasoline prices near the wildfire. One possible explanation may involve consumer behavior, if demand suddenly falls or if consumers anticipate imminent supply disruptions, or it may reflect strategic station management decisions, such as clearing inventory before the next delivery or mitigating fire-related risks.

Nonetheless, it is important to note that our study lacks control variables that could serve as proxies for actual gasoline demand, such as traffic data. Without these variables, we cannot definitively attribute the price reductions solely to decreased demand or station manager behavior. Overall, these results highlight the complex interplay of retail gasoline market expectations, the direct impact of the wildfire event, and market adjustments, providing a nuanced understanding of economic dynamics in the wake of natural disasters.

Other Determinants of Retail Gasoline Prices

The distance to the nearest refinery significantly affects gasoline prices—except in the station-level weekly model—highlighting the role of transportation costs in fuel distribution. In both station and county fixed effects models, each additional mile from a refinery is associated with an increase of 0.3 to 0.5 cents per gallon This finding is consistent with fuel market theory: as distances increase, logistical expenses—such as those for fuel transport, storage, and distribution—rise, and these higher costs are ultimately passed on to consumers.

Brand affiliation plays a significant role in shaping retail gasoline pricing, as evidenced by both the station-level and county-level fixed effects models. Our results consistently show that branded stations charge higher prices than their unbranded counterparts, with premiums ranging from 13 to 15 cents per gallon in the station-level models and from 42 to 44 cents per gallon in the county-level models. This notable price differential can be attributed to the enhanced value provided by branded stations, including better facilities, and improved fuel efficiency. These factors contribute to a perception of higher quality among consumers, which, in turn, supports higher pricing and fosters customer loyalty.

Market competition also influences retail gasoline prices, albeit to a lesser extent. While station-level models do not reveal a statistically significant effect of local competition, county-level estimates indicate that each additional competitor within a mile is associated with a price reduction of approximately 0.7 to 0.9 cents per gallon. This finding implies that competitive pressures are more effectively captured at the broader regional level, where higher market density drives price competition (Liu, 2020). The absence of a strong competitive effect at the individual station level may stem from site-specific factors that enable some retailers to sustain price premiums despite local competition.

In addition, climate variables play a crucial role in gasoline price dynamics. For instance, precipitation is positively correlated with gasoline prices—each extra millimeter of rainfall raises prices by 0.1 to 1.4 cents per gallon—likely due to delivery disruptions and increased transportation costs. Temperature effects are mixed, with higher maximum temperatures reducing prices by 0.4 to 0.6 cents per gallon, possibly reflecting increased travel and competitive pressure, while minimum temperatures exhibit inconsistent effects, suggesting seasonal variations in fuel demand.

Finally, stronger wind conditions are associated with lower gasoline prices—reductions of up to 4.1 cents per gallon—which may result from curtailed travel and suppressed fuel demand, whereas wind direction shows a minor negative effect in county-level models, indicating that specific wind patterns might disrupt fuel transportation.

Collectively, these results underscore the multifaceted nature of gasoline pricing, where refinery distance, brand affiliation, competition, and weather-driven supply and demand factors interact to shape retail prices. Thus, a complete picture of factors influencing pricing requires consideration of a broad array of contributing factors.

Conclusion

In this study, we investigate the short-term impact of Park Fire on retail gasoline prices of nearby gas stations. We find that contrary to common expectations of price gouging following natural disasters, our analysis reveals a statistically significant decrease in gasoline prices across all examined models. Specifically, we observed an approximate 9 cents per gallon decrease in daily gasoline prices at stations near the wildfire, with smaller yet significant reductions noted when employing county-level fixed effects. These findings demonstrate that major disaster events do not always lead to price increases for essential commodities such as fuel, showing that market dynamics in the context of wildfires might differ from those observed in other types of natural disasters.

These findings have several implications for policymakers and emergency management. While anti–price gouging laws remain a safeguard in a number states, policymakers could also focus on maintaining stable fuel supplies through improved data collection and monitoring systems that capture changes in both demand and environmental conditions. Furthermore, enhanced disaster recovery support for fuel retailers is critical to ensuring continuous access to gasoline during and after wildfire events. Measures such as small business loans offered through the Small Business Administration Disaster Loan Program and targeted supply chain interventions have proven effective in past crises (Watson, 2024). The aftermath of the 2018 Camp Fire shows how combining flexible regulations with financial aid can help restore fuel services quickly. By temporarily easing fuel transport and quality rules, authorities ensured that emergency responders and essential businesses had the fuel they needed, preventing a fuel shortage (FMCSA, 2018). At the same time, disaster loans and grants provided gas station owners with the funds needed to rebuild, helping stabilize the local economy (LaMalfa, 2018; University of California, Division of Agriculture and Natural Resources, n.d.).

However, it is important to note a limitation in our study: the absence of direct measures of gasoline demand, such as traffic data, prevents a definitive conclusion regarding the causative factors behind the observed price reductions. Future research would benefit from incorporating such variables to better isolate the effects of reduced demand from other potential influences. Additionally, our study lacks comprehensive environmental data which could shed more light on the impacts of wildfire and associated smoke. Factors such as wind direction, air quality, and smoke severity could significantly influence both the wildfire's spread and consumer behavior in the affected areas. Integrating this data could deepen our understanding of how wildfires influence local gasoline markets.

Overall, our findings contribute to the broader understanding of economic impacts of wildfires on local markets and other implications for policy. Similar to findings in other studies such as Beatty et al. (2021), we found no evidence of price gouging in the face of natural disaster emergencies. Nevertheless, the generalizability of our results is limited by the focus on a single region and event. Future studies could strengthen our conclusions through comparative analyses with other states without anti-price gouging laws, regions with different landscapes, or different wildfire events. Such studies could ascertain if the effects we observed are consistent across various scenarios or are unique to the specific conditions of the Park Fire, thereby enhancing strategies for managing and mitigating wildfire impacts on essential commodities.

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Tables

Table 1 Summary statistics

	Mean	SD	Min	Max	N	Obs.
Dependent Variable						
Price ($/gal)	4.701	0.467	3.680	5.990	148	32,116
- Treated	4.703	0.458	3.680	5.900	89	19,313
- Control	4.698	0.482	3.770	5.990	59	12,803
- Branded	4.919	0.414	3.690	5.990	80	17,360
- Unbranded	4.505	0.424	3.680	5.790	68	14,756
Control Variables						
Distance to wildfire (mi)	16.985	9.722	1.885	38.674	148	32,116
Distance to closest refinery (mi)	150.763	25.229	114.841	198.969	148	32,116
Distance to road closure (mi)	14.535	11.190	0.024	38.666	148	32,116
Number of stations within 1 mi	3.284	2.584	0	11	148	32,116
Average temperature (°C)	22.727	7.335	-3.8	37.1	148	32,116
Maximum temperature (°C)	30.853	8.540	0	48.9	148	32,116
Minimum temperature (°C)	14.249	6.205	-8.3	29.4	148	32,116
Precipitation (mm)	1.190	4.576	0	67.1	148	32,116
Average wind speed (m/s)	2.607	1.225	0.5	8.4	148	32,116
Wind direction (°)	183.659	91.328	10	360	148	32,116

Table 2 Number of treated gas stations by event dates and weeks

Event Dates	Event Weeks	Number of Treated Stations
2024-07-24	30	35
2024-07-25	30	29
2024-07-26	30	8
2024-07-27	30	6
2024-07-29	31	1
2024-07-30	31	6
2024-08-05	32	4

Note: This table reports the number of treated gas stations by event date and the corresponding event week. The counts represent gas stations located within a 20-mile radius of the wildfire perimeter, as determined for each event date.

Table 3 Difference-in-Differences Analysis – Station fixed effects

	Daily price	Moving Ave Daily price	Weekly price
	(1)	(2)	(3)
Post	-0.065***	-0.052***	-0.046*
	(0.016)	(0.012)	(0.027)
Treated	0.212***	0.192***	0.210***
	(0.041)	(0.031)	(0.071)
Post X Treated	-0.095***	-0.089***	-0.078***
	(0.011)	(0.008)	(0.016)
Average Temperature	0.0001	0.0005	-0.002
	(0.002)	(0.001)	(0.003)
Maximum Temperature	-0.005***	-0.004***	-0.006***
	(0.001)	(0.001)	(0.002)
Minimum Temperature	0.001	0.001	0.007***
	(0.001)	(0.001)	(0.003)
Precipitation	0.001**	0.001***	0.014***
	(0.001)	(0.0004)	(0.002)
Average Wind Speed	-0.011***	-0.008***	-0.041***
	(0.002)	(0.002)	(0.007)
Wind Direction	0.00002	-0.00001	-0.0003***
	(0.00002)	(0.00002)	(0.0001)
Road Closure Distance	0.006	0.004	0.005
	(0.009)	(0.008)	(0.020)
Refinery Distance	0.003*	0.004**	0.004
	(0.002)	(0.002)	(0.004)
Branded	0.128*	0.149***	0.126
	(0.070)	(0.058)	(0.138)
Competition	0.032	0.026	0.039
	(0.034)	(0.029)	(0.071)
Constant	3.893***	3.834***	3.916***
	(0.152)	(0.130)	(0.317)
Observations	5,366	9,190	2,074
N	118	119	131
T	1-206	2-210	1-31
R2	0.890	0.886	0.901
Adjusted R2	0.887	0.884	0.894
Residual Standard Error	0.155	0.155	0.148
	(df = 5227)	(df = 9050)	(df = 1928)
F-Statistics	307.163***	505.916***	121.408***
	(df = 138; 5227)	(df = 139; 9050)	(df = 145; 1928)

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 4 Difference-in-Differences Analysis – County fixed effects

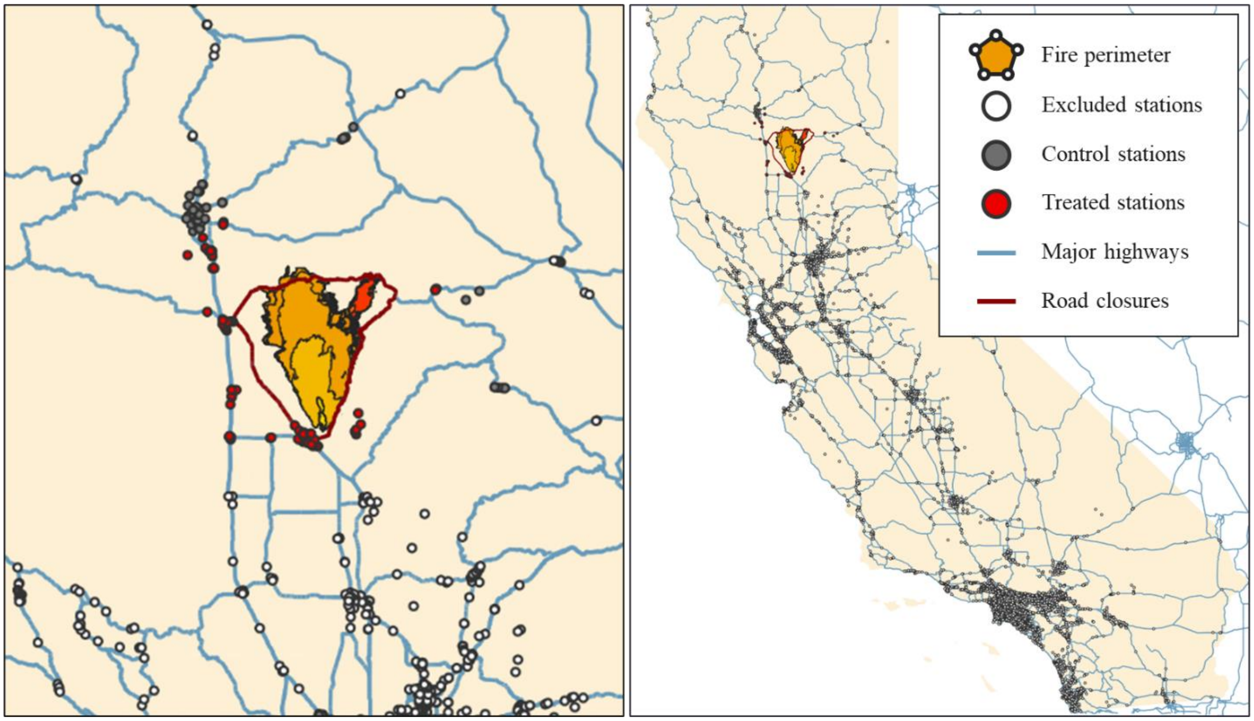
	Daily price	Moving Ave Daily price	Weekly price
	(1)	(2)	(3)
Post	-0.094***	-0.082***	-0.089**
	(0.026)	(0.020)	(0.045)
Treated	0.241***	0.195***	0.168***
	(0.016)	(0.012)	(0.027)
Post X Treated	-0.049***	-0.046***	-0.059**
	(0.017)	(0.013)	(0.025)
Average Temperature	0.0005	0.001	0.003
	(0.002)	(0.002)	(0.004)
Maximum Temperature	-0.001	-0.001	0.001
	(0.001)	(0.001)	(0.003)
Minimum Temperature	-0.006***	-0.006***	-0.011***
	(0.002)	(0.001)	(0.004)
Precipitation	0.001	0.001*	0.013***
	(0.001)	(0.001)	(0.003)
Average Wind Speed	-0.003	-0.001	-0.023*
	(0.003)	(0.002)	(0.012)
Wind Direction	0.00003	-0.00002	-0.0004***
	(0.00004)	(0.00003)	(0.0002)
Road Closure Distance	0.030***	0.025***	0.022***
	(0.002)	(0.001)	(0.003)
Refinery Distance	0.004***	0.005***	0.005***
	(0.001)	(0.001)	(0.002)
Branded	0.438***	0.421***	0.430***
	(0.007)	(0.005)	(0.011)
Competition	-0.007***	-0.009***	-0.008***
	(0.001)	(0.001)	(0.002)
Constant	3.857***	3.756***	3.942***
	(0.127)	(0.096)	(0.218)
Observations	5,366	9,190	2,074
N	118	119	131
T	1-206	2-210	1-31
R2	0.700	0.693	0.706
Adjusted R2	0.698	0.692	0.702
Residual Standard Error	0.254 (df = 5335)	0.253 (df = 9159)	0.247 (df = 2049)
F-Statistics	414.166*** (df = 30; 5335)	687.925*** (df = 30; 9159)	204.878*** (df = 24; 2049)

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Figures

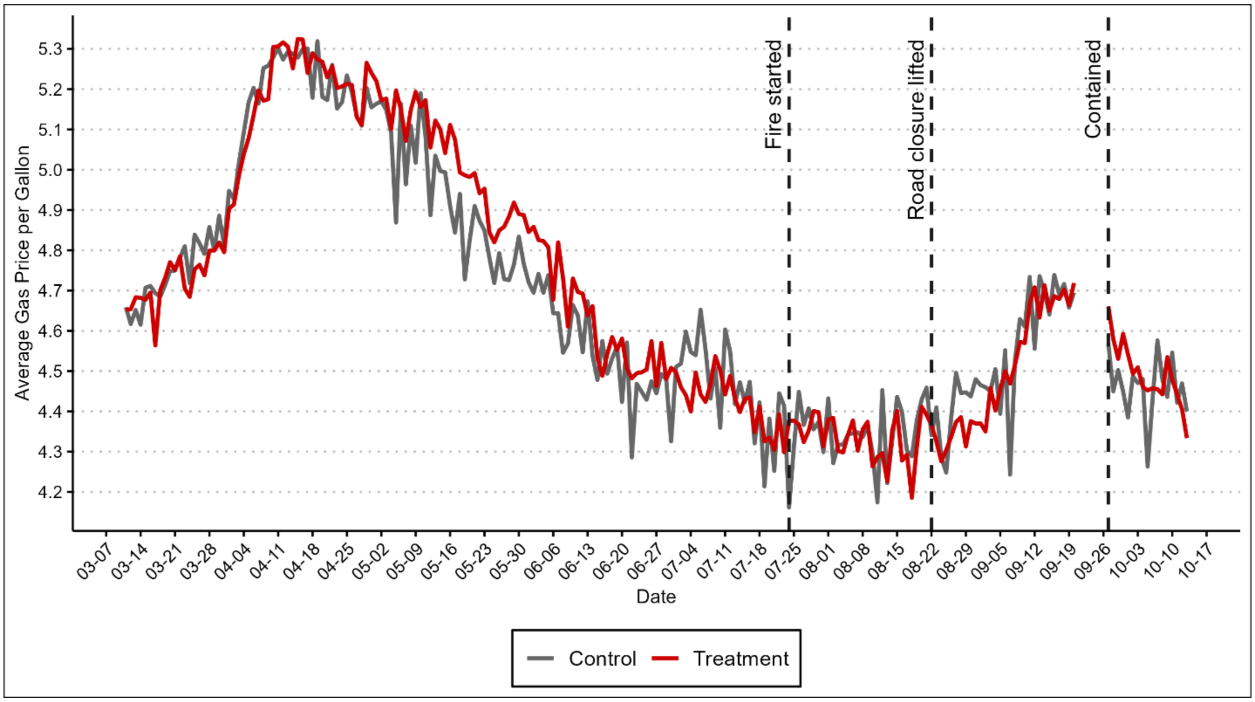
Figure 1 Park Fire impact zones on gas stations

(a) Focused map near the Park Fire (b) California map



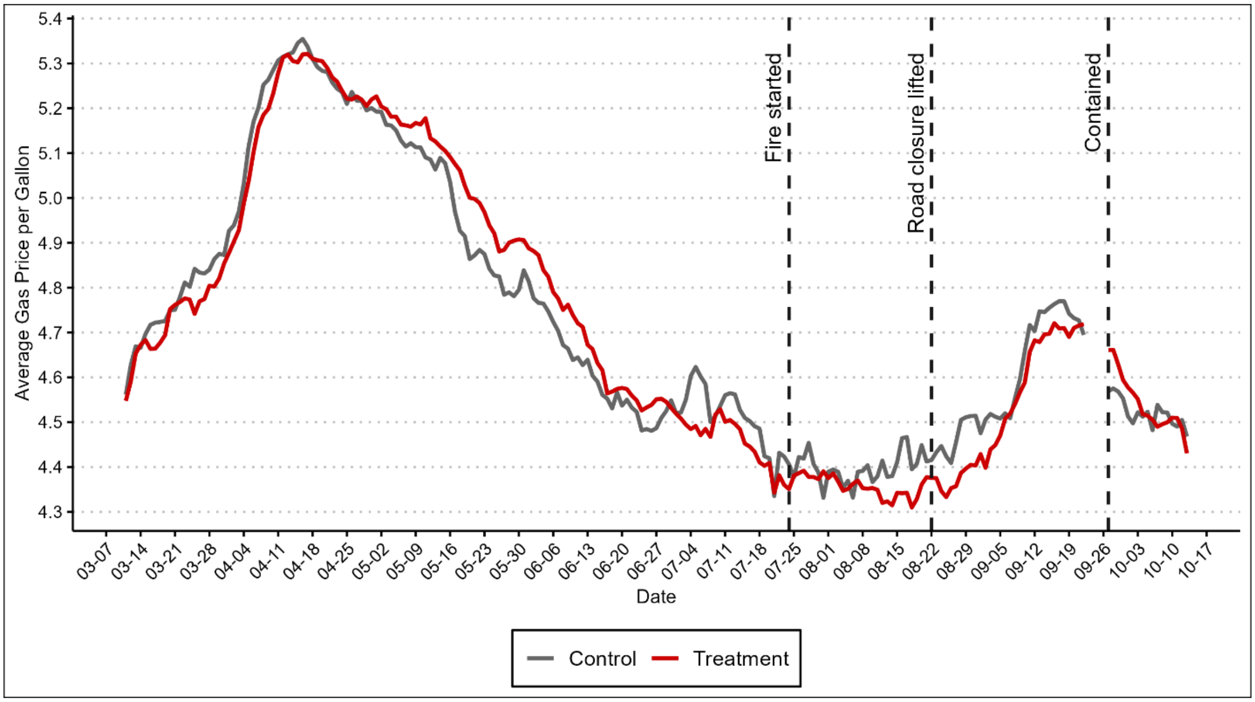
Note: This map depicts the progression of the Park Fire between July 24, 2024 (the smallest *yellow* polygon) and August 18, 2024 (the largest *red* polygon), with intermediate date fire boundaries shown in varying intensities of *orange*. The *blue* lines represent major highways, while the *red* lines indicate road closures resulting from the fire. The dots mark retail gas station locations: *grey* dots are control-group stations, *red* dots are treated-group stations, and *white* dots indicate gas stations that were in the initial sample but ultimately not included in the analysis.

Figure 2 Average daily gasoline price trend of sample stations (March 11 – October 13)



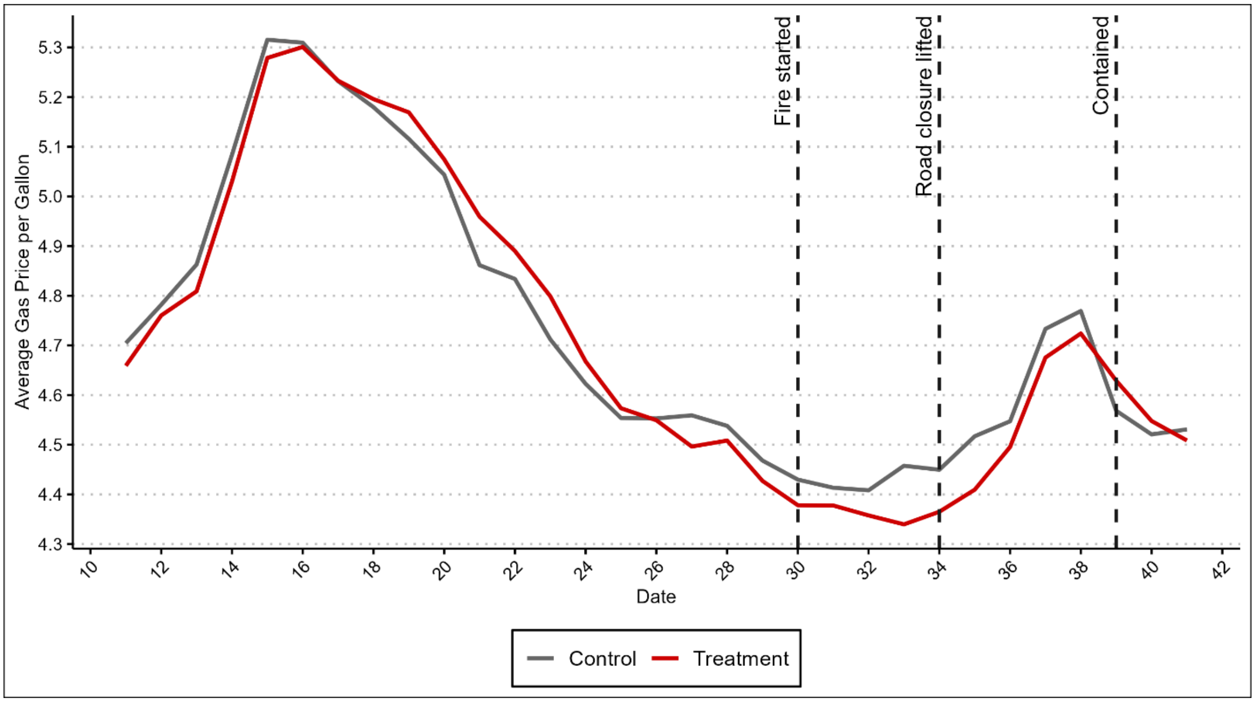
Note: This figure compares average daily gas prices for the Treatment group (*red*) and the Control group (*grey*) over the period from March 11th to October 13th, 2024. The vertically dashed lines indicate key events related to the fire: the date it started (July 24th), the date the road closure was lifted (August 22nd), and the date the fire was contained (September 27th). Due to technical issues, data for September 21st – 26th are missing.

Figure 3 Moving average daily gasoline price trend of sample stations (March 11 – October 13)



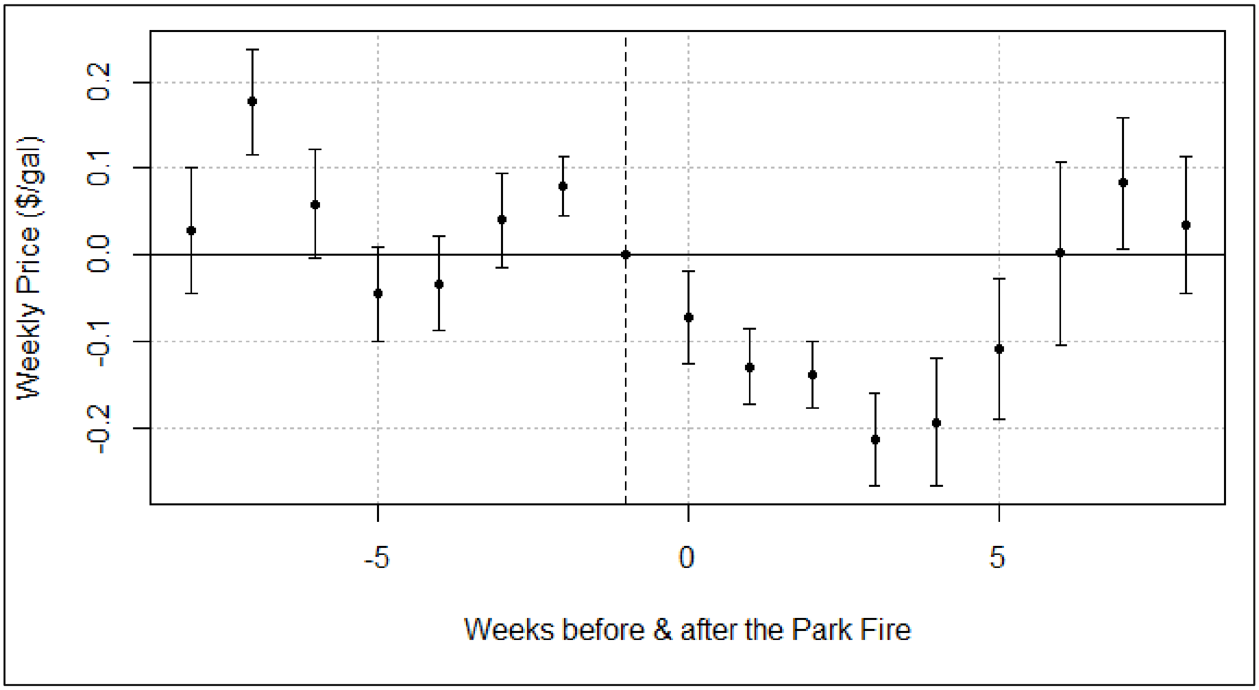
Note: This figure compares three-days moving average daily gas prices for the Treatment group (*red*) and the Control group (*grey*) over the period from March 11th to October 13th, 2024. The vertically dashed lines indicate key events related to the fire: the date it started (July 24th), the date the road closure was lifted (August 22nd), and the date the fire was contained (September 27th). Due to technical issues, data for September 23 – 26 are missing.

Figure 4 Average weekly gasoline price trend of sample stations (week 10 – 41, 2024)



Note: This figure compares average weekly gas prices for the Treatment group (red) and the Control group (grey) over the period from week 11 (March 11–17) to 41 (October 7–13) of 2024. The vertically dashed lines indicate key events related to the fire: the week it started (week 30, July 22–28), the date the road closure was lifted (week 34, August 19–25), and the date the fire was contained (week 39, September 23–29).

Figure 5 Event study analysis: Weekly prices



Note: This figure displays event study estimates from Equation (2) using weekly gasoline price data. The dashed vertical line marks the reference week—one week prior to the Park Fire—for each treated station. Each point represents the estimated difference in price relative to that reference period, with vertical bars indicating 95% confidence intervals.

Appendix

1. Web scraping procedure from GasBuddy

In this study, we collected station-level retail gasoline prices from GasBuddy, an online platform that reports user-submitted fuel price information. To begin, we conducted a zip code-based search on GasBuddy's website. For each query, the site generated a list of nearby gas stations sorted by their lowest reported price. Each station's entry included its brand name, street address, the most recently updated price for regular unleaded fuel, the time since that price was posted (in minutes, hours, or days), the username of the individual who submitted the price, and a unique web link containing a station-specific ID.

Given that a single station can appear in multiple zip code results, data cleaning was required to remove duplicate records. We used the station ID embedded in the station-specific web link to identify unique listings and consolidate information on each station. Additionally, to convert GasBuddy's relative "time posted" format into an absolute timestamp (i.e., the date and time the price was reported), we subtracted the elapsed time from our known data-collection timestamp.

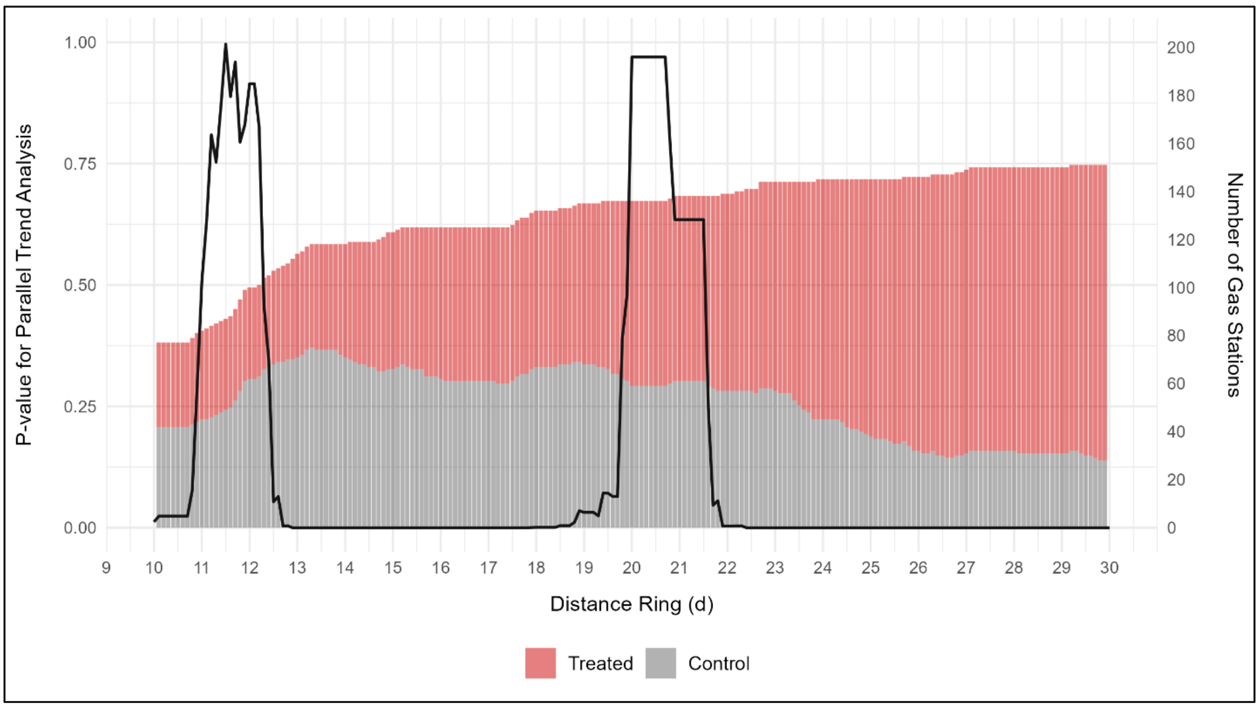
After retrieving and merging records across all U.S. zip codes, we retained only the most recent data for each station on each day. The resulting dataset thus represents an unbalanced panel of daily gas station observations. It includes station identifiers, brand affiliation, geographical coordinates (derived from street addresses or from the website's interface), posted retail prices, and posted dates. These data provided the basis for our empirical analyses of retail gasoline pricing and its interaction with wildfire events.

2. *Robustness Check: Determination of the Optimal Distance Threshold*

To assess the validity of our parallel trends assumption and ensure robust treatment group classification, we conducted a robustness check to determine the optimal distance threshold (d) for defining the affected (treated) gas stations. We varied d from 10 to 30 miles in increments of 0.1 mile. For each candidate d, we defined the treated group as stations within d miles of the wildfire and the control group as those located between d and $2 * d$ miles. We then restricted the sample to the pre-treatment period ($Post = 0$) and estimated a regression of gasoline prices on date interacted with the treatment indicator. In this specification, the p-value associated with the interaction term serves as a diagnostic for the plausibility of parallel pre-treatment trends, the higher the p-value, the less evidence there is of a pre-existing trend difference between the groups.

We implemented this procedure separately for daily and weekly price data. We computed the p-value for each candidate d, and we selected the optimal d as the one that maximized this p-value. This procedure yielded an optimal distance threshold of 20 miles. Figure A.1 plots the p-values from our parallel trends test against different distance rings. Overlaid is a stacked bar chart showing the number of gas stations in the treated group and control group at each distance ring. By examining these two metrics together, we can see how the choice of distance threshold influences both the statistical evidence for parallel pre-treatment trends and the sample size available for robust estimation.

Figure A.1 Parallel Trends Test with Sample Distribution: P-Values and Gas Station Counts by Distance



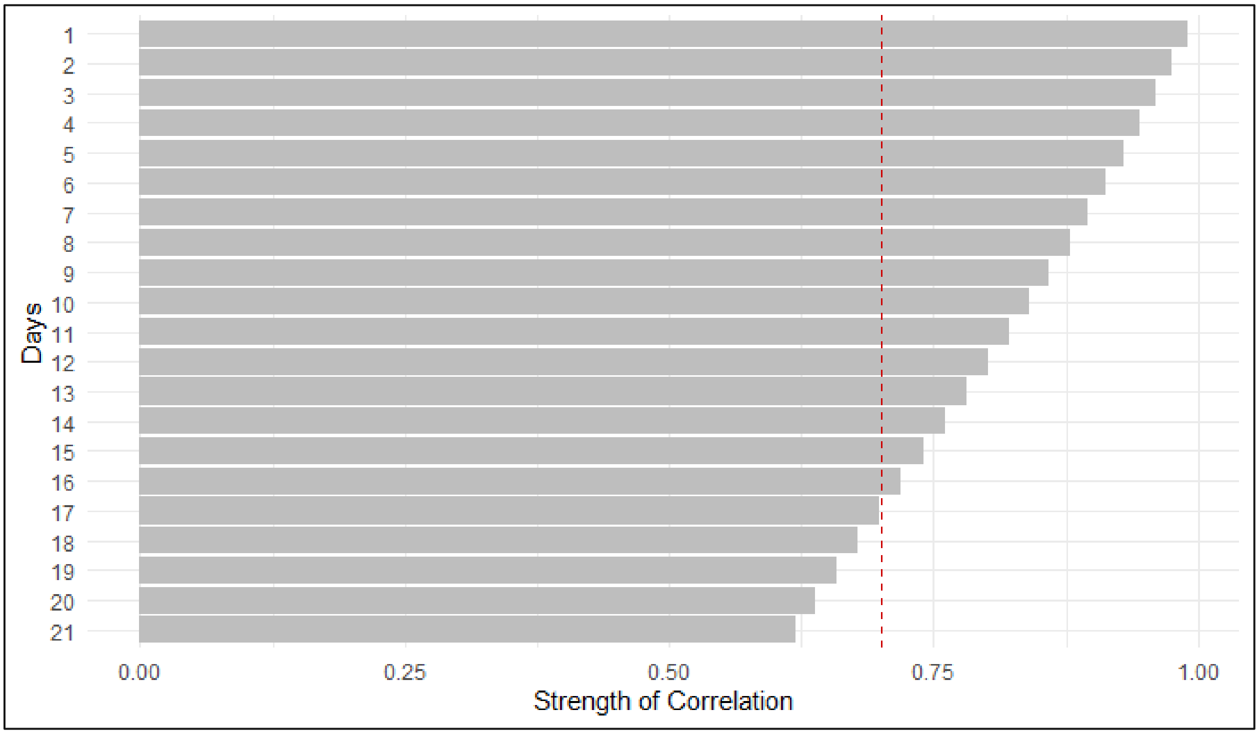
Note: This plot simultaneously displays two elements. The *black* line represents the p-value for the interaction effect in our regression model (with the primary y-axis ranging from 0 to 1), indicating the statistical significance of the treatment effect over different distance rings (x-axis). Overlaid on this, the stacked bar chart shows the number of gas stations, with the *red* segment representing the "Treated" group (stations within the threshold distance) and the *grey* segment representing the "Control" group (stations between the threshold and twice that distance). The secondary y-axis provides the actual counts of gas stations.

Smaller thresholds (e.g., 11–12 miles) do maintain relatively high p-values in the plot, yet they result in a much smaller sample of stations. Although the parallel trends assumption is not necessarily violated at these shorter distances, the reduced sample size undermines the statistical power and broader generalizability of the analysis. Therefore, we selected a 20-mile threshold to ensure both an adequate number of stations and robust results.

3. Rationale for Weekly Data Aggregation in the Event Study

To determine an appropriate temporal scale for the event study, we investigated the day-to-day correlation structure of gasoline prices. A correlogram in Figure A.2 shows that prices reported on consecutive days are highly correlated, and this correlation remains quite strong for more than a week. Such persistent autocorrelation complicates the use of daily data, as even modest day-to-day movements often reflect routine price adjustments rather than meaningful signals of market response. By aggregating prices to a weekly frequency, we smooth out these short-term fluctuations and mitigate the noise introduced by closely spaced data points.

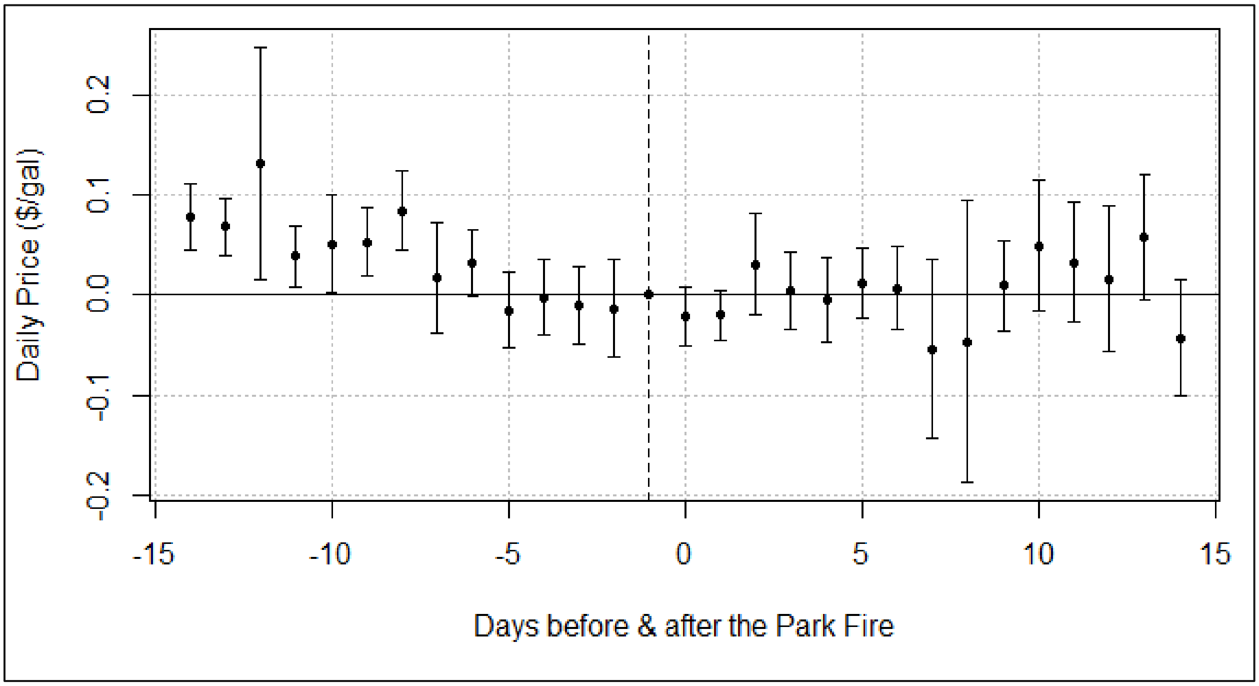
Figure A.2 Average correlation by days



Note: The horizontal axis measures the strength of the correlation (0 to 1), while the vertical axis lists the number of days lagged. Each bar shows how closely today's price correlates with the price observed *n* days earlier. The dashed vertical line at 0.7 indicates a high threshold of correlation as a reference.

Weekly aggregation thus strikes a balance between retaining sufficient variation to capture meaningful price responses to the event while reducing the confounding effects of autocorrelation. However, it is important to note that this approach can blur rapid, within-week price changes that might otherwise be observable in higher-frequency data. Consequently, while the weekly frequency provides clearer, less noisy estimates for the event study analysis, they may not fully capture short-term price dynamics. For comparison, Figures A.3 and A.4 present the event study results using daily and moving-average daily prices.

Figure A.3 Event study analysis: Daily prices



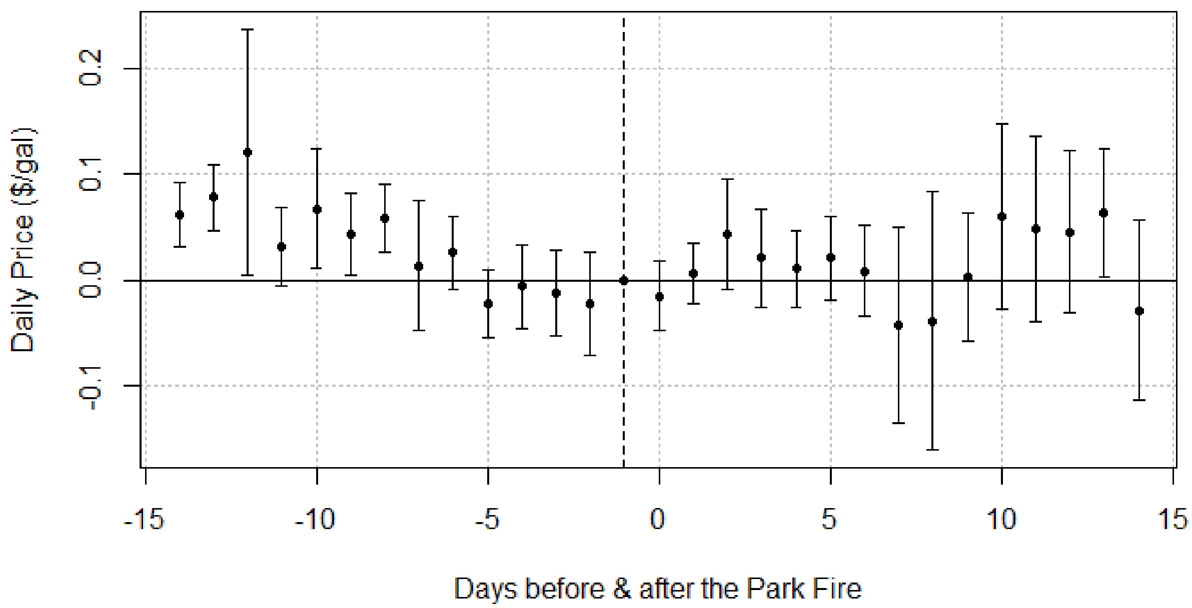


Figure A.4 Event study analysis: Moving averages daily prices