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DISCUSSION PAPER

// ILONA TSANKO

Consumers' Response to Price Increases: Evidence From Gasoline Markets

Consumers' response to price increases: Evidence from gasoline markets *

Ilona Tsanko†

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Abstract

Understanding how consumers respond to price increases is key when designing price-related policies. Using microdata on vehicle usage and paid fuel prices, I analyze consumers' response, focusing on three channels of mitigation: distance driven, fuel efficiency, and search. On average, consumers mitigate 38 percent of a price increase through these channels. Reducing distance driven is the primary channel of mitigation. Increased search efforts mitigate up to 11 percent of a price increase. Response levels vary significantly with newer vehicles' owners mitigating up to 88 percent of a price increase, while older vehicle owners achieve can mitigate up to 45 percent.

Keywords: Demand response, Gasoline prices, Consumers search, Fuel consumption

JEL Codes: D12, Q41, L91, L98

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†ZEW - Leibniz Centre for European Economic Research, Univeristy of Zürich, and MaCCI. E-mail: ilona.tsanko@gmail.com

1 Introduction

Skyrocketing energy prices following the Russian invasion of Ukraine in February 2022 prompted governments to introduce policies to help consumers cope with increased prices. Examples from Germany are: temporary value added tax reductions, temporary fuel tax reductions and energy-price lump sum payments. How do consumers react to price increases is a key question when designing such polices.

I use high-frequency data on vehicles' refueling behavior of German consumers and their fuel expenses which allows me to empirically decompose consumers' response into the three potential channels: (i) reducing the distance driven, (ii) driving more fuel efficiently, and (iii) searching for lower prices.[1] To evaluate consumers' search effort, I combine the fuel expenses data with the universe of fuel prices in Germany. This allows me to locate consumers positioning within the national price distributions. I construct a novel consumer search measure which tracks how consumers' positions within the national price distributions change when these distributions are exogenously shifted. I then estimate consumers' response using a single differences model and an instrumental variable (IV) model. For the single differences model, I take advantage of the exogenous shock to gasoline prices the Russian invasion of Ukraine induced.[2] I find that, on average, in the short-term, a one percent increase in prices paid by consumers reduces the distance driven by 0.26 percent, and it increases fuel efficiency by an average of 0.04 percent. I document that in addition to these changes in behavior, consumers also increase their search effort to reduce their paid prices. On average, a one percent increase in prices, reduces consumers' positions in the national price distribution by 0.62 percent. Heterogeneity in these estimates is high, with owners of newer vehicles showcasing higher levels of response than owners of older vehicles. To understand the role each of these channels plays in consumers' behavior as a whole, I utilize the estimated magnitudes of the channels to evaluate how consumers responded to the fuel price increases following the Russian invasion of Ukraine. I find that the primary channel by which consumers mitigated the price increase was by reducing the distance driven. On average, this channel accounted for mitigating 27.7 percent of the impact of the price increase on fuel expenses. Search mitigated on average 5.6 percent of the impact of the price increase, while increasing

[1] I use the term search to describe consumers' efforts to purchase fuel at lower prices. This may include, for example, strategically timing purchases to avoid expensive stations, such as those along highways, or refraining from refueling during peak price periods like morning rush hours. It could also involve actively comparing prices and selecting the most competitively priced stations available at a given moment. Given the high intraday volatility of German gasoline prices as is illustrated in figure C.4 such efforts can result in significant savings.

[2] On February 24th, 2022, Russia invaded Ukraine. As one of the top three oil producers, Russia's invasion triggered a 58 percent increase in crude oil prices, resulting in higher retail gasoline prices around the globe.

fuel efficiency was responsible for an average mitigation of 4.4 percent of the impact. These findings vary greatly by vehicle cohort groups. The high heterogeneity is also reflected in the overall proportions of price increase mitigation, with owners of newer gasoline vehicles able to mitigate up to 88 percent of the impact of the price increase, while owners of older gasoline vehicles could only mitigate 45 percent of the impact. This result is important when designing public policy for transportation markets with equity in mind, as it is lower-income households that are more likely to own older vehicles and, as I demonstrate, bear a higher percentage of the burden of increased prices.

Retail gasoline markets offer a great environment for understanding consumer reactions to price increases. This is owing to the homogeneous nature of gasoline, its essential role in everyday household life, and its limited storability, which closely links purchases to usage. Moreover, retail gasoline markets are of high importance for policymakers, as transportation markets are at the heart of economic activity, which manifests itself by the wide array of policies aimed at them.

This paper is closely related to three strands of literature. First, it contributes to the emerging literature investigating public policies aimed at alleviating the inflationary burdens faced by consumers following the aftermath of the COVID-19 pandemic and the Russian invasion of Ukraine (Dertwinkel-Kalt and Wey, forthcoming; Schmerer and Hansen, 2023; Dovern et al., 2023). The literature has mainly focused on the supply side response to public policies. As most policy measures focused on providing relief to consumers, this paper empirically quantifies the demand side response. Secondly, this paper contributes to the vast literature on price elasticies in gasoline markets. In particular, it closely relates to the work of Levin et al. (2017) and Knittel and Tanaka (2021). Levin et al. (2017) use daily gasoline prices aggregated at the city level to demonstrate that relaying on aggregated data results in less elastic price elasticities for gasoline. Knittel and Tanaka (2021) employ similar data to the one I am using to investigate the effect of gasoline prices on fuel efficient driving in the Japanese gasoline market. I extend this literature first by evaluating the complete behavioral response of consumers to price increases. In addition to measuring fuel efficient driving and demand for travel, I extend the previous literature by measuring consumer search behavior. I show that search is a also a channel consumers use to mitigate price increases. Secondly I document the heterogeneity in consumers' elasticities, which is of importance when designing public policy to address fuel consumption or to alleviate the inflationary pressures faced by consumers. Thirdly, this paper relates to the burgeoning search literature. Search activity and its determinants in retail gasoline were documented by Lewis and Marvel (2011) and Byrne and de Roos (2017). Using website visits, both papers show that consumers search more (less) when prices go up (down). To my knowledge, it has yet to be documented how increased search activity materializes into real monetary savings. This paper provides estimates for the monetary value of search activity in gasoline markets. The relationship between price dispersion and search in gasoline markets has been analyzed by Pennerstorfer et al. (2020); Lach and Moraga-González (2017); Chandra and Tappata (2011); Lewis (2008). A significant challenge in the literature is to empirically estimate the relationship between price dispersion and the actual prices paid by consumers. This paper is one of the first to empirically relate the price distribution to the prices paid by consumers in gasoline markets.

The rest of the paper is organized as follows: section 2 introduces the German market for retail fuels. Section 3 presents the data. Section 4 presents the empirical strategy employed in this paper and its estimation results. Lastly, section 5 concludes and discusses the findings.

2 Industry background

2.1 German retail fuel market

For passenger vehicles, diesel and gasoline fuels are two separate markets. On the short term, consumers cannot substitute between the two fuels: a diesel vehicle cannot be driven with a gasoline fuel and vice versa. Diesel vehicles are more expensive than gasoline vehicles, yet their marginal cost of driving is lower. In 2019, in Germany, the average annual kilometers driven by a diesel vehicle were 19,200 kilometers, while a gasoline vehicle was driven on average for 10,800 kilometers.[3] Hence, drivers who travel longer distances tend to purchase diesel vehicles, as they are willing to accept a higher fixed cost in order to mitigate variable fuel expenses. The gasoline market consists of two main products: E5 and E10. E5 is regarded by consumers as standard gasoline, which contains 5 percent ethanol (hence the name E5). E10 was introduced in 2011 as a less polluting alternative to E5.[4] Even though E10 is cheaper than E5, its market share is below 25 percent of gasoline sales, as illustrated in figure C.7 in the appendix. The main reasons for its lower market shares are consumers' perception that E10 damages the engine and its lower fuel-efficiency compared to E5.[5]

[3]Source: Verkehr in Zahlen 2022/2023, Federal Ministry for Digital and Transport.

[4]E10 contains a higher share of ethanol (10 percent), which reduces the amount of oil burned by the engine and hence subsequent emissions. The lower share of oil in the E10 grade results in E10 being cheaper than the E5 grade. Whether it is cheaperin terms of total fuel costs is unclear, as some claim that the fuel consumption of vehicles increases as a result of E10 usage.

[5]Source: `https://www.adac.de/news/umfrage-e10-tanken/`

2.2 Retail fuel price increase

On February 24th 2022, Russia invaded Ukraine. Following the invasion, there has been a sharp increase in energy prices, with crude oil prices increasing by 58 percent. In Germany, the high reliance on Russian oil[6] has resulted in retail gasoline prices increasing by 30 percent, to levels unseen before.[7] Figure C.5 in the appendix illustrates the sharp increase in prices. The surge in gasoline prices is driven by the supply side, making it exogenous to consumer demand. Additionally, the shock was unforeseen by consumers: despite escalating tensions on the Russian-Ukrainian border in the months leading up to the invasion, the timing and occurrence of a Russian attack remained uncertain. Even if consumers had anticipated the attack, their limited ability to store fuels prevented them from avoiding the higher prices. These two characteristics of the price shock are essential for my identification strategy.

2.3 Policy intervention

On June 1st, the German government implemented a wide set of measures to alleviate the burden of rising energy prices on consumers. Among the measures was a fuel tax reduction equivalent to 35.16 euro cents per liter for gasoline, and 16.71 euro cents per liter for diesel (after VAT). The tax reduction was in force for three months until August 31st. The tax reduction was fully passed through to consumers (Dovern et al., 2023; Schmerer and Hansen, 2023; Seiler and Stöckmann, 2023; Fuest et al., 2022). In addition to the reduction in fuel taxes, the government introduced a subsidized public transportation ticket. It is unclear whether the subsidized public transportation ticket has led to substitution between driving and using public transportation. To my knowledge, empirical evidence exploring this potential substitution pattern is currently unavailable. Therefore, in the analysis, I will focus on the time period before the policy intervention, namely December 2021 to May 2022.

3 Data

I combine data from two main data sources. The data on vehicle related expenses origins from Spritmonitor, an German based application (app) that helps drivers track their vehicles related costs. The sample consists of app users who were active during 2022. For each user, I observe their vehicle type (brand, model and production year) as well as their vehicle's

[6] According to the Federal Office of Economics and Export Control, Germany received around 34 percent of its crude oil imports from the Russian Federation in 2021.

[7] `https://presse.adac.de/meldungen/adac-ev/verkehr/spritpreise-im-februar-so-hoch-wie-nie.html`; `https://www.rnd.de/wirtschaft/benzin-und-dieselpreise-2022-tanken-war-noch-nie-so-teuer-47-cent-mehr-fuer-diesel-RAZPSJO547S2TCEQFUD52IOWNQ.html`

related costs and refueling instances. I focus on refueling observations of combustion engine vehicles which took place between 2019 and 2022 for the subset of users who were using the app before and after the Russian invasion of Ukraine. For each user-vehicle pair,[8] I observe data on the refueling date, the odometer reading, the quantity of fuel purchased and the total cost of the refuel instance. These allows me to infer the actual price paid by simply dividing the cost by the quantity. Since the data is user generated, I clean the data from unreasonable and incomplete observations. The final dataset contains 1,001,623 observations for 17,333 users with an average of 57.59 observations per user-vehicle pair.[9] I complement the vehicle usage data with data on vehicles' list prices obtained from the website of the General German Automobile Club (ADAC) which provides an auto catalog for the German market. The second dataset is of the universe of gasoline prices in Germany. In Germany, gasoline stations are required to report price changes in real-time to the Market Transparency Unit at the German Federal Cartel Office. The Market Transparency Unit then provides this data to price comparison websites, which subsequently make it accessible to the public. Tankerkönig is such price comparison website, which provides access to the whole historic price data for research purposes.[10] I use the data on the price changes to form a panel data which documents the prices of gasoline (E5 and E10 grades) and diesel at 30 minutes intervals.

Table 1 presents summary statistics for the vehicle usage data for the years 2019 to 2022 for the subset of users who were active in the app three months before and after the Russian invasion. In addition to the summary statistics for the whole sample, I present a breakdown of the values by the vehicle production year (cohort). Users spend on average 63 euros per refuel, the average observed fuel price is 1.52 (averaging over all fuel types) and the daily kilometers driven are about 74 kilometers. Breaking down the values by vehicle production cohort highlights the differences between the components affecting the vehicle expenses:[11] Owners of newer vehicles, on average, pay 15 percent higher fuel prices than owners of older vehicles. Conversely, fuel consumption values of newer vehicles are, on average, 12 percent lower than those of old vehicles.

[8] A small number of users (167) are tracking costs for multiple vehicles.

[9] Additional details on the data preparation process are in appendix A.1.

[10] https://creativecommons.tankerkoenig.de/.

[11] All mean-comparison tests (t-tests) between the groups for fuel price, daily liters consumed, fuel consumption and daily kilometers driven, but three are significant at the 1 percent level. The difference in mean daily liters for vehicles produced between 1980-2005 and those produced between 2016-2020 is significant at the 5 percent level, and the other two (difference in mean fuel prices for vehicles produced between 1980-2005 and those produced between 2016-2020 and difference in mean fuel consumption for vehicles produces between 2006-2015 and those produced between 2021-2022) are significant at the 10 percent level.

Table 1: Summary statistics of vehicle usage data

	All	1980-2005	2006-2015	2016-2020	2021-2022
Fuel price (euro)	1.52	1.53	1.49	1.53	1.77
	(0.36)	(0.30)	(0.34)	(0.38)	(0.24)
Days	15.39	16.06	16.31	14.64	12.39
	(12.15)	(13.53)	(12.65)	(11.50)	(9.71)
Daily liters	5.23	5.35	4.94	5.41	6.38
	(6.88)	(7.21)	(6.52)	(7.03)	(8.36)
Fuel consumption (l/100 km)	7.22	8.05	7.14	7.16	7.11
	(1.95)	(2.58)	(1.91)	(1.83)	(1.88)
Daily km	74.26	69.29	70.88	77.17	89.47
	(92.71)	(90.45)	(88.31)	(95.68)	(107.42)
Share of E10 fueling	0.13	0.11	0.10	0.15	0.22
	(0.34)	(0.31)	(0.30)	(0.36)	(0.42)
Share of E5 fueling	0.39	0.53	0.34	0.41	0.42
	(0.49)	(0.50)	(0.47)	(0.49)	(0.49)
Share of diesel fueling	0.48	0.37	0.56	0.43	0.36
	(0.50)	(0.48)	(0.50)	(0.50)	(0.48)
Gasoline	0.54	0.64	0.45	0.59	0.66
	(0.50)	(0.48)	(0.50)	(0.49)	(0.47)
Price (in 2015 Euro values)	29,439.95	26,698.25	28,782.18	29,660.17	30,670.05
	(12,331.99)	(15,983.09)	(13,124.94)	(11,993.71)	(11,308.91)
Production year	2,013.99	2,000.99	2,011.55	2,017.99	2,021.00
	(5.72)	(4.22)	(2.77)	(1.36)	(0.04)
No. observations	1,001,620	79,730	412,406	484,813	24,671
No. user-vehicle	17,333	1,564	6,988	8,059	722
No. refuels	57.79	50.98	59.02	60.16	34.17

Notes: The table presents means and standard deviations for key variables from the vehicle usage data for the whole sample and for vehicles' production cohort groups separately. The price variable is available for only 72 percent of the sample.

Despite newer vehicles having the lowest fuel consumption values among the groups, the average daily liters consumption of these drivers is higher by about 20 percent than that of other owners. This is due to newer vehicles owners driving, on average, almost 29 percent more kilometers per day compared to older vehicle owners. The average vehicle's price in the sample is about 29,400 Euros in 2015 values and the average vehicle cohort is 2014. As expected, the average vehicle price (in 2015 euro values) increases with vehicles cohort. About 54 percent of the vehicles in the sample are fueled by gasoline and the rest are fueled by diesel. This corresponds well to the German fleet of combustion engine vehicles, where 56 percent of the vehicles are gasoline fueled, while the rest 44 percent are diesel fueled.[12]. The majority of gasoline refuels are of E5 type. The share of E10 refuels out of all gasoline refuels in the sample is 13 percent, which is in line with the total market share of E10 in the German market. Interestingly, despite newer vehicle owners paying higher fuel prices, a greater proportion of them – 22 percent - use E10 gasoline for their vehicles, which is on average 3 percent cheaper than E5 gasoline. This could be due to the perception that E10 fuels are not compatible with older vehicles. In appendix A.1, I investigate further the representativeness of the vehicle usage data.

Table 2 presents summary statistics for the universe of fuel prices in Germany in 30 minutes intervals between November 22nd 2021 and May 30th, 2022.[13] The table splits the summary statistics to values before and after the invasion which occurred on Feb. 24th 2022. The table presents mean, standard deviation and a decomposition of the standard deviation into a between and within terms where SD-between captures the standard deviation between stations: $\sqrt{(\frac{1}{NT-1}\sum_i^N(\bar{x}_i-\bar{x})^2)}$ and SD-within captures the standard deviation within stations: $\sqrt{(\frac{1}{NT-1}\sum_i^N\sum_t^T(x_{it}-\bar{x}_i)^2)}$ where N is the total number of stations, T the total number of refuels, and $\bar{x}_i=\frac{1}{T}\sum_t^T x_{it}$ and $\bar{x}=\frac{1}{NT}\sum_i^N\sum_t^T x_{it}$.

Table 2 shows a clear increase in fuel prices following the Russian invasion on February 24th, 2022. Comparing the three months before and after the invasion reveals an average price increase of 20 percent for the E5 and 29 percent for diesel. While the variation across stations remained relatively stable post-invasion, the within-station variation increased by over 40 percent. This suggests that temporal price variation within stations has increased after the war, while the variation between stations remained unchanged. Gasoline and diesel prices in Germany show high price volatility. The average station changed its gasoline and diesel prices approximately 14 times a day. This pattern seems to not be affected by the invasion.

[12] Source: Verkehr in Zahlen 2022/2023, Federal Ministry for Digital and Transport.

[13] In Germany there are about 14,894 gasoline stations, and intraday price volatility is high: stations change prices, on average, 14 times a day. Given the sheer amount of data, some aggregation of the data is necessary to facilitate computational processing. Additional details are found in appendix A.2

Table 2: Summary statistics of Gasoline prices pre and post-invasion

	Before invasion				After invasion			
	Mean	SD	SD between	SD within	Mean	SD	SD between	SD within
Price e5 (euro)	1.72	0.08	0.05	0.07	2.08	0.11	0.05	0.10
Price e10 (euro)	1.67	0.08	0.05	0.07	2.02	0.12	0.05	0.10
Price diesel (euro)	1.58	0.08	0.05	0.07	2.05	0.15	0.05	0.14
Daily price changes e5	14.23	6.14	5.73	2.59	14.21	6.23	5.61	2.83
Daily price changes e10	13.82	6.47	6.09	2.54	13.79	6.56	5.99	2.79
Daily price changes diesel	14.12	5.74	5.33	2.51	14.08	5.89	5.20	2.88
No. observations	52,468,302				53,545,444			
No. stations	14,887				14,894			
No. half-hour periods observed	3,524.44				3,595.10			

Notes: The table presents means and standard deviation of gasoline prices and daily number of price changes for the time period from November 22, 2021, to May 31,2022, separately for periods before and after the invasion that occurred on February 24, 2022. Additionally, I present a further decomposition of the standard deviations into between-stations and within-stations components.

4 Evaluating consumers' response

4.1 Evaluating consumers' search

The high volatility in the German gasoline market, as observed in table 2, allows consumers to reduce their fuel expenses by strategically choosing their location and timing for purchases. In such a dynamic environment, assessing a policy intervention without accurate knowledge of the prices consumers actually pay can prove to be extremely challenging. The prices paid by consumers are influenced by two primary factors: their geographic location, which which determines the prices available to them, and their endogenous search effort, which is usually unobserved. Since I do not have access to information regarding consumers' geographic locations, a main challenge in identifying search efforts lies in determining why consumers pay lower prices. Is a consumer situated at the lower end of the national price distribution because she lives near a particularly inexpensive gasoline station (location effect) or is it because she invests an effort in finding the cheapest price available in her area (search effort)? To disentangle the location effect from consumers' search effort, I am using an exogenous shock to gasoline prices – the Russian invasion of Ukraine. Under the assumption that the invasion led to an increase in fuel prices but did not affect the positioning of stations in the national price distribution, this exogenous shock will allow me to quantify changes in consumers search efforts due to the price increase.

To empirically quantify the search effort, I construct a measure of consumers' positions in the national fuel price distribution. To do so, I use the universe of fuel price changes in Germany to construct daily price distributions of fuel prices available in the country during a day by fuel type (E5, E10 and diesel).[14] I define consumers' positions as the quantiles within the daily price distribution to which their paid price corresponds. As long as the invasion solely led to increases in fuel prices without affecting the stations' positions within the distribution, any observed changes in consumers' positions following the invasion are likely to be a result of changes in consumers' search efforts.

4.2 National price distributions

I construct the national price distribution using all prices observed across Germany during single day period. Prices vary greatly throughout the day.[15] I assume consumers are aware of these patterns and consider them when choosing when to refuel. As a robustness check, I construct weekly distributions that consider the variation in prices across different days of the week, for example weekends versus weekdays.[16] To construct the daily national distributions, I use the dataset of fuel price changes in Germany to construct a day long grid of fuel prices at 30 minutes intervals. I then compute the empirical distribution of prices and their various quantiles using each daily grid. This approach offers the advantage of accounting for the duration for which the price was available. For instance, the density of available prices for a couple of hours will be higher than the density of prices available for only 30 minutes. Then, I match each observed paid price with their corresponding quantile (position) in the national daily distribution.

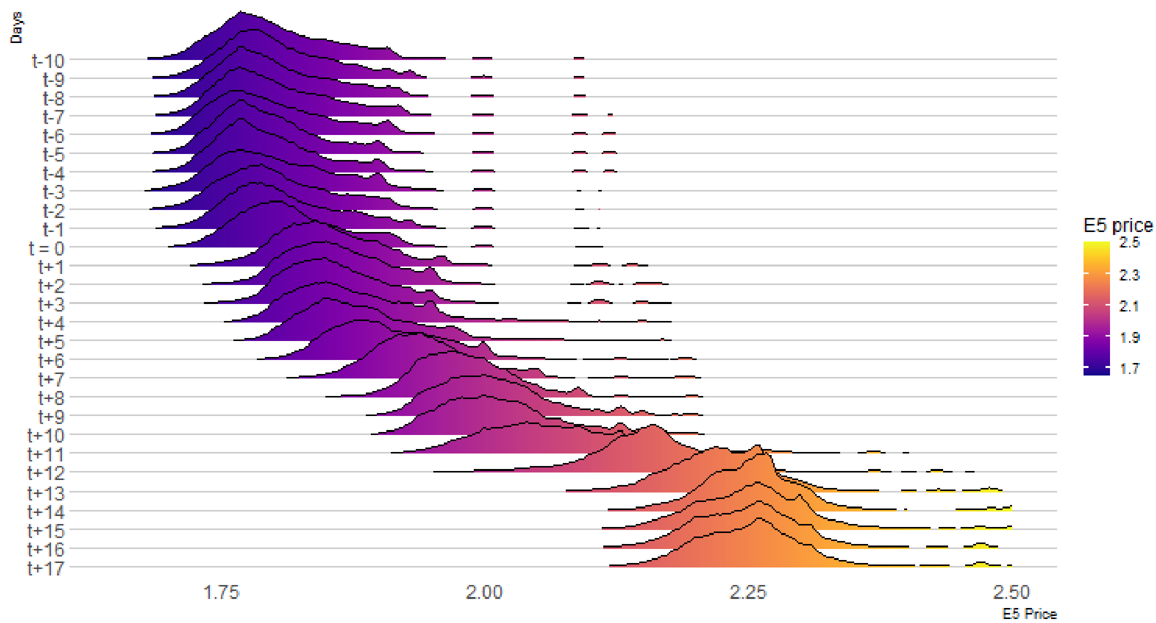
To demonstrate the distributions and their shifts following the invasion, Figure 1 illustrates the daily national price distribution for E5 over a 28 day period from February 14th, 2022 to March 13th 2022. The figure shows the rightward shift in the price distributions following the invasion (at t=0). Figure C.10 in the appendix illustrates the weekly price distributions in a similar manner. Table 3 shows the estimated effects of the invasion on both the mean prices and various quanitles of the national price distribution. The comparison is made between one week periods before and after the invasion. The values in table 3 represent the coefficients on a dummy variable for the period after the invasion, estimated by an OLS

[14]As a robustness check, I also conduct the analysis with weekly price distributions.

[15]See illustrations in appendix A.2 and figure C.5.

[16]Using weekly distributions for the analysis implies the assumption that drivers are not only well-informed about the cheapest times of day to refuel but also well-informed about which days of the week offer cheaper fuel prices. This is a stronger assumption than in the daily distribution case. Widespread belief suggests that weekends are usually more expensive than weekdays, yet I couldn't confirm this notion using the data. This implies that it may not be straightforward for consumers to accurately know which day of the week is actually cheaper.

Figure 1: Daily National price distributions for E5



Notes: The figure presents the daily national price distribution for E5 gasoline over 28 days period starting at 14th February 2022 until 13th March 2022. 't' represents the position of each day relative to the day of the invasion, denoted as t=0.

regression and unconditional simultaneous quanitle regressions of prices on a constant and the invasion dummy (Koenker and Bassett, 1978). These coefficients indicate an increase in gasoline prices, measured in euros, following the invasion. The invasion led to almost equal price increases across the entire price distribution. This suggests that invasion induced a location shift in the distributions, while keeping their scale relatively constant.

Table 3: The impact of the invasion on gasoline prices by quantiles

	mean	q05	q10	q25	q30	q50	q70	q75	q90	q95
E5	0.373	0.370	0.370	0.380	0.371	0.380	0.380	0.380	0.360	0.360
E10	0.372	0.370	0.370	0.380	0.380	0.380	0.370	0.370	0.360	0.350
Diesel	0.551	0.550	0.560	0.560	0.560	0.560	0.560	0.560	0.540	0.535

Notes: The table shows the estimated coefficients on the invasion dummy obtained from two sets of regressions: an OLS regression of fuel prices on a constant and a dummy for the time period after the invasion, unconditional simultaneous quantile regressions of fuel prices on a constant and the invasion dummy. Both sets estimated on each fuel type separately. All regressions include hour of the day and day of the week fixed effects. The pre-invasion period spans from January 24, 2022, to January 31, 2022, while the post-invasion period covers March 21, 2022, to March 28, 2022. Regressions are ran on the 30 minute interval prices panel. Standard errors are omitted. All coefficients are significant at the 1 percent level.

To evaluate the plausibility of the assumption of no rank reversals across stations, I am estimating the following equation for each station in the dataset separately:

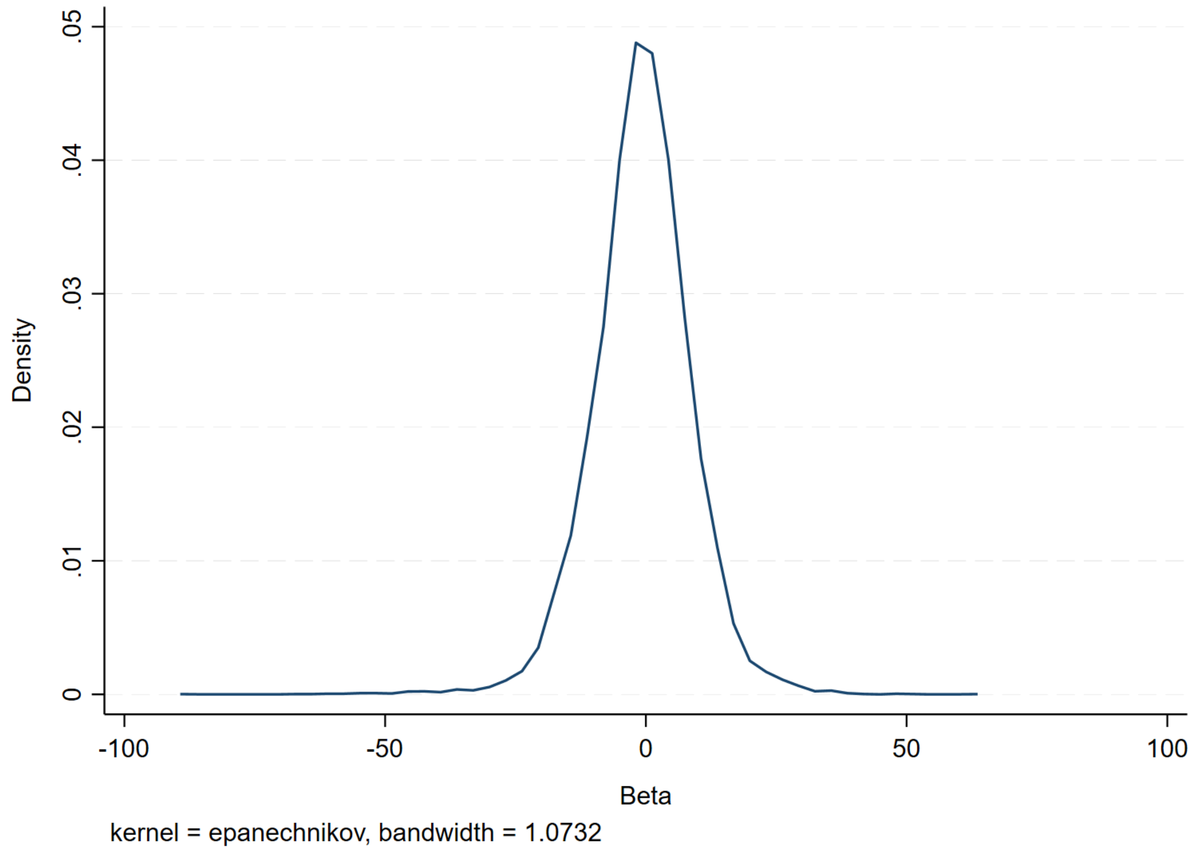
$$\text{quantile}_{ift} = \beta_{cons_{if}} + \beta_{invasion_{if}} * \text{Invasion}_t + \xi_{ift} + \epsilon_{ift} \tag{1}$$

quantile_{ift} is the quantile of the national price distribution where station's i price of fuel f (E5, E10, diesel) is positioned at. β_{cons} is a constant term, capturing the average quantile the station is positioned at. Invasion_t is a dummy that equals one on all dates following the invasion and zero otherwise. ξ_{ift} is a set of hour of day and day of week fixed effects, capturing systemic deviations from the station's mean quantile based on time of day. ϵ_{ift} is the error term. The coefficient $\beta_{invasion_i}$ is station-fuel specific and captures deviations from the average quantile after the invasion. A significantly nonzero $\beta_{invasion_i}$ indicates a rank reversal for station i, while if the assumption of no rank reversal holds, $\beta_{invasion_i}$ should equal to zero. I estimate equation 1 separately for each station and fuel type (E5, E10 and diesel) using the 30 minute prices grid for the fourteen week period before and after the invasion.
Figure 2 plots the kernel density of the estimated station level $\beta_{invasion_i}$ coefficients for E5 gasoline. The distribution is concentrated around zero, suggesting the invasion did not induce rank reversals among most stations in Germany. These results support the validity of the no rank reversals assumption in the study's settings. The results for diesel and E10 prices are similar and are presented in figure C.8 in the appendix.

4.3 Measuring changes in consumers' search

To gain an initial understanding of the possible scale of consumers' search efforts, I compare the regression results provided in table 3 with the results from a similar regression estimated on the prices by paid consumers in the usage data. Table 4 presents the estimated mean effect of the invasion on consumers' paid prices, comparing the week period beginning January 24th, 2022 before the invasion with the week starting March 27th, 2022 after the invasion. Table 4 indicates that the invasion led to a 43 Euro cent increase in paid prices for E5 consumers (average national price increased by 37 Euro cents), a 35 Euro cent increase for E10 (average national price increased by 37 Euro cents) and a 46 Euro cent increase for diesel consumers (average national price increased by 51 Euro cents). Notably, the increases for E10 and diesel fuels are lower than those reported in table 3 for the national price distribution. This suggests a rise in consumers' search efforts.

Figure 2: Distribution of rank-reversal estimates for E5



Notes: The figure plots the distribution of the estimated $\beta_{invasion}$ coefficients from the estimations of equation 1 conducted separately for each station, for the time period from November 22, 2021, to May 30, 2022.

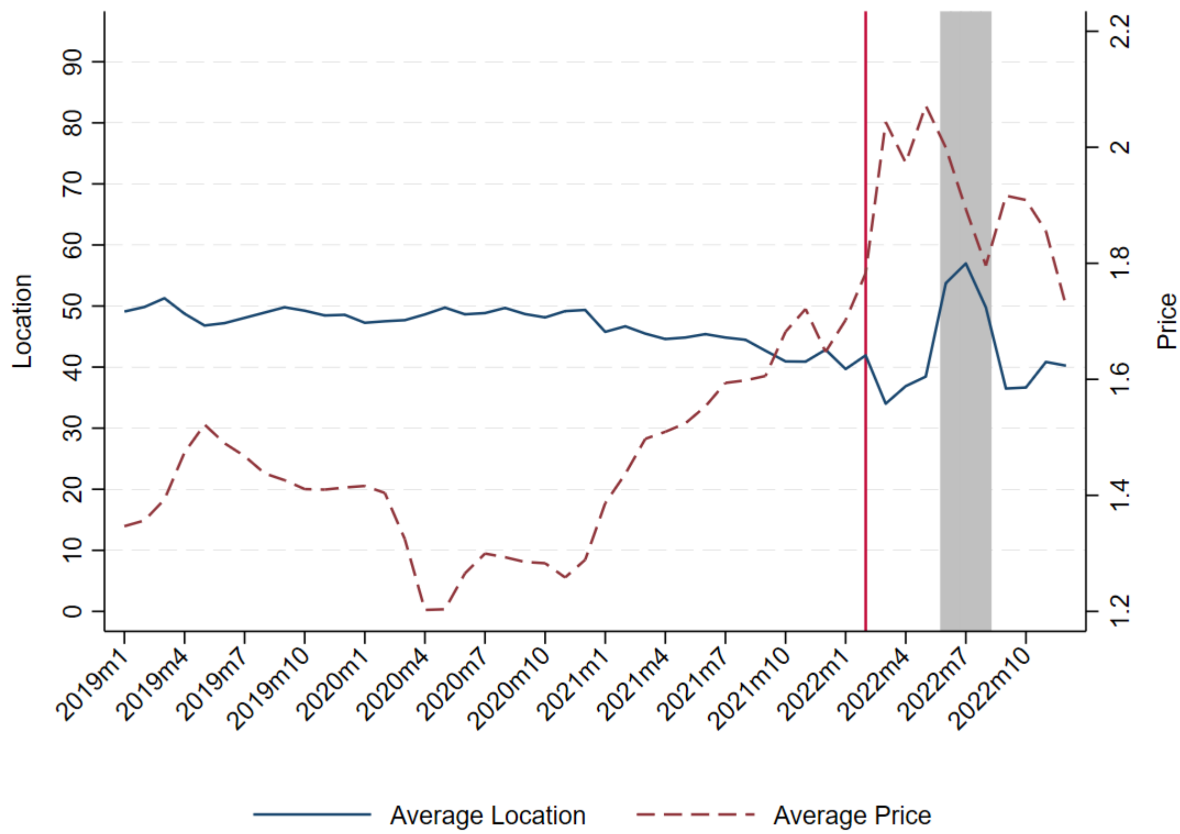
Table 4: The impact of the invasion on paid prices

	E5	E10	Diesel
Invasion	0.429	0.348	0.457
	(0.004)	(0.004)	(0.004)
R-squared	0.586	0.532	0.679
Observations	7,362	7,595	7,687

Notes: The table shows the estimated coefficients on the invasion dummy from an OLS regression of consumers' paid fuel prices on a constant and a dummy for the dates after the invasion estimated for different fuel types separately. The pre-invasion period is the week long period from January 24, 2022, to January 31, 2022, and the post-invasion period is the week long period from March 21, 2022, to March 28, 2022. Standard errors are clustered by user-vehicle pairs.

To systematically evaluate consumers' search efforts, I construct a measure of consumer position within the national price distribution. I match the observed paid prices to their

Figure 3: Evolution of consumers positions and E5 paid prices



Notes: The figure presents the average position of E5 consumers and the average E5 price paid for the years 2019 to 2022, using the sub-sample of consumers who have been using the app since at least 2019. The gray shaded area represents the three month period during which the government was offering measures to help commuters. Consumers' positions are measured as the quantile in which their paid price is positioned in the daily national price distribution, ranging from the 5th to the 95th quantile in intervals of 5.

corresponding quantiles in the corresponding daily national price distribution. Figure 3 plots the development of the average position of E5 consumers, and the average price they paid. The graph shows a negative correlation between price and position. Periods characterized with higher average prices corresponds to periods with lower average positions on the price distribution. In other words, during periods of higher prices, consumers tend to pay prices in the lower parts of the price distributions, suggesting increased search efforts. The gray shaded area in the figure corresponds to the period from 1st of June 2022 and Augst 31th, 2022, during which the government lowered the gasoline tax by 29.55 Euro cents and the diesel tax by 14.04 Euro cents. The tax reduction was almost fully passed through to consumers (Dovern et al., 2023; Schmerer and Hansen, 2023; Fuest et al., 2022).[17] During the

[17]In addition to the reduction in fuel taxes, the government introduced a subsidized public transportation

government intervention period, the average paid price has decreased. Even more pronounced is the significant increase in consumers' positions within the daily distributions during the policy intervention. This increase in the average position suggests that the policy intervention led to reduced search effort. Nonetheless, this increase in average location was temporary, and as the intervention ended, the average position returned to its previous levels.

Table 5: Consumers' positions pre and post-invasion

	All	1980-2005	2006-2015	2016-2020	2021-2022
E5					
Pre					
Mean	41.8	39.4	42.2	41.6	46.0
SD	(33.1)	(32.0)	(33.5)	(32.8)	(34.2)
Median	35	30	35	35	40
Post					
Mean	37.0	37.4	37.8	36.4	36.7
SD	(32.5)	(31.8)	(32.8)	(32.3)	(33.1)
Median	25	25	25	25	25
E10					
Pre					
Mean	36.2	36.1	37.0	35.6	38.5
SD	(30.5)	(30.8)	(30.7)	(30.3)	(31.2)
Median	25	25	30	25	30
Post					
Mean	33.7	34.1	34.1	33.5	33.9
SD	(30.2)	(29.7)	(30.0)	(30.1)	(31.2)
Median	25	25	25	25	25
Diesel					
Pre					
Mean	37.8	35.6	36.8	38.9	41.3
SD	(32.3)	(31.0)	(32.0)	(32.6)	(32.4)
Median	30	25	25	30	35
Post					
Mean	31.8	28.3	30.8	32.8	35.8
SD	(30.0)	(28.2)	(29.7)	(30.3)	(31.2)
Median	20	15	20	20	25

Notes:The table shows mean standard deviations and medians of consumers' positions in the daily national price distribution, separating the six month period around the invasion (December 2021 to May 2022) to before and after invasion.

To further illustrate the constructed measure of consumers positions, table 5 shows the means, standard deviations and median positions of consumers in the daily national price distributions by fuel type and vehicle cohort for the period from December 2021 to May 2022. The positions are measured in ventiles[18] of the daily national price distributions. During this

ticket. It remains unclear whether this subsidy led to a substitution between driving and using public transportation. To my knowledge, empirical evidence exploring this potential substitution pattern is currently unavailable.

[18]I divide the order distribution into 20 equal parts, ventiles values ranging from the 5th to the 95th quantile in intervals of 5.

six months period around the invasion, drivers paid prices below the median national price (the mean and median positions are below 50 which corresponds to the median national price). As expected from the fuel price summary statistics presented in table 1, prior the invasion, owners of newer vehicles were positioned in higher parts of the national price distribution compared to owners of older vehicles. Interestingly, following the invasion, the differences between the groups diminished, and for E5 consumers they became statistically insignificant (except for the 2016-2020 cohort). The table also show that the distribution of drivers' positions in the sample is skewed to the right (the median is lower than the mean values), indicating that most drivers in the sample are concentrated in lower parts of the distributions. Table D.1 in the appendix illustrates the average prices associated with different quantiles in the daily national price distributions before and after the invasion.

4.4 Empirical setup

To evaluate consumers' response to price increases, I estimate the following model:

$$\ln(Y_{it}) = \alpha + \beta_{invasion} * \text{Invasion}_t + \delta_i + \epsilon_{it} \tag{2}$$

α is a constant, δ_i are user-vehicle fixed effects, and ϵ_{it} is an independent and identically distributed random shock specific to each user-vehicle pair. Invasion is a dummy variable that takes the value of one for dates after the invasion (24th of February 2022). Y_{it} are the outcome variables of interest, which includes the consumer's quantile in the daily national price distribution, consumers' paid price, fuel consumption (measured in liters per 100 kilometers driven), daily kilometer driven, and number of days between refuels. $\beta_{invasion}$ will capture any changes in the outcome variables following the invasion which exceed the average deviation of consumers from their mean position in the sample. These average deviations are captured by the user-vehicle fixed effects. For consumers' position in the daily national price distribution, a negative $\beta_{invasion}$ coefficient suggests that consumers shifting down the price distribution, suggesting increased search efforts and lower prices paid compared to their previous position in the national price distribution. Conversely, a positive coefficient suggests that consumers are shifting up the price distribution, implying reduced search efforts and as a result they pay higher prices compared to their previous position in the national price distribution. Notice that moving down the price distribution does not imply paying lower prices than before the invasion, as those prices are not available anymore. Instead it implies that consumers pay lower prices compared to the prices available after the invasion at their previous position in the national price distribution.

Equation 2 is a single difference model which is different from the traditional difference in differences model, since it does not control for time trends. This is due to the lack of a control group unaffected by the invasion. As a control, I rely on drivers' behavior during the three months period prior the invasion. This design recovers the casual impact of the invasion on consumers' behavior, under the assumption of no time trends in search effort – meaning there are no time-related development in consumers' positions between the pre-invasion and post-invasion periods. This assumption does not hold if consumers change their search over time, for example due to learning. Another threat to identification is the existence of other confounding events occurring during the three months after the invasion which might be correlated with search effort. For example a release of a new mobile application for fuel price search. However, the drivers in the sample had already been using the app for at least six months prior the six month period used to estimate equation 2, making it unlikely for additional learning to occur among these drivers. Moreover, I couldn't identify any other events during the same period of time that might impede the identification of the search efforts. Nevertheless, to address these concerns, I estimate in addition to equation 2 the following IV model which is similar to the IV model estimated in Knittel and Tanaka (2021) using the full usage sample period from 2019 to 2022:

$$\ln\left(\text{price paid}_{it}\right) = \alpha + \beta_z * Z_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{3}$$

Equation 3 serves as the first stage of the IV model, where α is a constant (not to confuse with the α from equation 2), and Z_{it} is a vector of instruments, namely the national average fuel price at day t[19]. δ_i are user-vehicle fixed effects, γ_t are time fixed effects which include month of the year and a dummy variable set to one during the months when the German government implemented lockdowns to curb the spread of COVID-19. ϵ_{it} are user-vehicle specific independent and identically distributed random shocks. In the second stage, I regress the outcome variable of interest on the fitted values of $\ln\left(\widehat{\text{price paid}_{it}}\right)$ obtained from the regression results of equation 3:

$$\ln\left(Y_{it}\right) = \beta_0 + \beta_{price} * \ln(\widehat{\text{price paid}}_{it}) + \delta_i + \gamma_t + \epsilon_{it} \tag{4}$$

where β_0 is a constant.

[19]To clarify, the national average fuel price is calculated using the universe of fuel prices in Germany, not just the average prices paid by the drivers in the sample.

4.5 Results

4.5.1 Consumers' search

I begin with presenting the results for consumer search response to increases in prices. To estimate equation 2 with the outcome variable $ln(position)$, I estimate the ventiles[20] of the daily national price distribution and match them to consumers' paid prices to identify consumers' positions in the price distribution.

Table 6: The impact of the invasion on consumers' search

	All	1980-2005	2006-2015	2016-2020	2021-2022
E5					
ln(location)					
Invasion	-0.219	-0.140	-0.209	-0.236	-0.287
	(0.011)	(0.031)	(0.019)	(0.015)	(0.046)
ln(paid price)					
Invasion	0.170	0.176	0.169	0.169	0.167
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)
Observations	57,639	6,792	18,930	28,548	3,369
E10					
ln(location)					
Invasion	-0.128	-0.078	-0.119	-0.125	-0.217
	(0.016)	(0.049)	(0.030)	(0.022)	(0.066)
ln(paid price)					
Invasion	0.176	0.176	0.176	0.176	0.170
	(0.001)	(0.004)	(0.002)	(0.001)	(0.005)
Observations	25,804	1,720	7,186	14,825	2,073
Diesel					
ln(location)					
Invasion	-0.234	-0.259	-0.248	-0.220	-0.200
	(0.010)	(0.039)	(0.015)	(0.015)	(0.049)
ln(paid price)					
Invasion	0.235	0.233	0.235	0.236	0.236
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)
Observations	76,895	4,924	33,570	35,386	3,015

Notes: The table shows the estimated invasion coefficients from an OLS regression with fixed effects transformation on the logarithm of consumers' position and the logarithm of paid prices. The first column displays the results when using the entire sample, while the remaining columns show the results obtained from estimating the model on vehicles' cohorts subsets. The regressions were ran using the observations from the period December 2021, to May 2022. Standard errors are clustered by user-vehicle pairs.

Table 6 presents the estimation results of equation 2 for two outcome variables: the logarithm of consumers' position in the daily national price distribution and the logarithm of paid price. Across specifications, I employ a fixed effects transformation and cluster the standard errors

[20] I divide the order distribution into 20 equal parts, ventiles values ranging from the 5th to the 95th quantile in intervals of 5.

at the user-vehicle level. The table presents the results for the entire sample and for the model being estimated at vehicle production cohort subsets.

The results show that the position of E5 consumers decreased on average by 22 percent after the invasion,[21] compared to consumers' positions prior to the invasion. Hence consumers have increased their effort to search for lower prices after the invasion. The positions of diesel consumers in the daily national price distribution experienced a decrease of 23 percent. This slightly stronger reaction could be due to diesel consumers being more price sensitive than E5 consumers.[22] The impact of the price increase on E10 consumers' search efforts is smaller and equal to a reduction of 13 percent in consumers' position. Notice that E10 is a substitute for E5 and its price per liter is, on average, 3 percent cheaper.[23] Although it is plausible that consumers in the sample have substituted their E5 purchases with E10, using the data I cannot reject the hypothesis that consumers after the invasion were as likely as before the invasion to purchase E10. As a robustness check, in figure C.9 in the appendix, I present the results of a random inference analysis, where I re-estimate the the model while randomizing the date of the invasion and the six month periods surrounding it. The results of this analysis reaffirm the significance of the findings.

Paid prices for E5, E10, and diesel have increased by 17, 17.6, and 23 percent respectively. These figures are about 8 percent lower than the average increases observed nationally, which corresponds to 20.5, 21 and 29 percent respectively.

Table 6 reveals high heterogeneity in search efforts across different vehicle cohorts. For gasoline fuels (E5 and E10), owners of newer vehicle appear to reduce their positions the most, therefore experiencing lower increases in paid prices following the invasion. Conversely, owners of older vehicle reduce their positions to a lesser extent and bear a higher percentage of the price increase. This relationship is reversed for diesel vehicle, suggesting that the behavior of diesel vehicle owners differs from that of gasoline owners.

Table 7 presents the results of the IV model described in equation 4. A one percent increase in paid price leads, on average, to a 0.71 percent reduction in E5 consumers' positions in the price distribution.[24] This relationship varies across fuel types, with diesel drivers decreasing their position by 0.58 percent and E10 consumers reducing their position by 0.51 percent

[21] Precisely, in a log-linear model the a one unit increase in X multiplies Y by e^{β}. For small values of β, $e^{\beta} \approx 1 + \beta$, therefore I use $100 \cdot \beta$ as an approximation for the expected percentage change in Y for a unit increase in X. The precise effect will be of magnitude 24.5 percent ($e^{\beta} = e^{0}.219 = 1.245$).

[22] As I mention in 2.1, diesel vehicles are more expensive than gasoline vehicles yet their fuel costs are lower.

[23] As mentioned in 2.1, E10 is about 3 percent cheaper than E5 and should be less harmful to the environment. However, consumers perceive E10 as potentially harmful to the engine.

[24] Precisely, in a log-log model the proportional change in Y associated with a p percent change in X equals to $e^{\log([100+p]/100)*\beta}$ hence a one percent increase in prices will lead to $e^{\log(1.01)*\beta} = 1.0071 = 0.71$ percent increase in positions.

for one percent increase in paid prices. The estimated magnitude of search efforts in the IV model is lower than the one estimated using the single differences model. Between December 2022 and May 2022, average national prices for E5, E10 and diesel increased by 20.5, 21 and 29 percent respectively. For these price increases, the IV model yields positions reductions of 14.5, 10.77 and 16.85 percent respectively. The differences are likely stem from the significant magnitude of the price increases following the invasion, which made the price increases less salient among drivers.

Table 7: The effect of prices on consumers' search - IV model

	All	1980-2005	2006-2015	2016-2020	2021-2022
E5					
ln(paid price)	-0.711	-0.464	-0.724	-0.753	-0.070
	(0.028)	(0.078)	(0.046)	(0.040)	(0.263)
Observations	393,008	41,864	140,717	200,048	10,379
E10					
ln(paid price)	-0.513	-0.499	-0.446	-0.561	0.103
	(0.048)	(0.163)	(0.080)	(0.065)	(0.356)
Observations	129,764	8,733	40,831	74,704	5,496
Diesel					
ln(paid price)	-0.581	-0.768	-0.630	-0.508	-0.347
	(0.022)	(0.104)	(0.030)	(0.034)	(0.146)
Observations	478,852	29,133	230,858	210,064	8,797

Notes: The table shows the estimated coefficient on the logarithm of paid prices β_{price} obtained by estimating the IV model using 2SLS with fixed effects transformation. The dependent variable is the logarithm of consumers' position. The first column shows the results for the entire sample, the subsequent columns shows the results for vehicle cohorts subsets. The regressions were ran using the observations from the whole period of the sample: 2019 to 2022. Standard errors are clustered by user-vehicle pairs.

In terms of heterogeneity across vehicles cohort, the results from both models show similar patterns except for owners of the newest gasoline vehicles: the IV model suggest they do increase their search efforts following small changes in prices. Again, these differences between the models could be attributed to the significant price increases following the invasion, which even owners of the newer vehicles could not ignore.

To demonstrate the monetary impact of the estimated effect, I illustrate the impact using the results of the single difference model for diesel consumers. According to table 5 the average consumer's position prior the invasion corresponds to the 38th percentile. Table 6 indicates that diesel consumers decreased their position by an average of 23.4 percent post-invasion, resulting in a them positioning at the 29th percentile of the daily national price distribution. Prior to the invasion, the average diesel price at the 38th percentile of the daily national price distribution was 1.565 Euros, post-invasion it increased to 2.017 Euros. The average diesel price corresponding to the 29th percentile post-invasion is 1.996 Euros. Hence diesel consumers managed to reduce their paid prices by 1.8 Euro cents which is equivalent to approximately 5 percent of the price increase following the invasion.

Table 8 presents the results of of performing the aforementioned exercise on E5 and diesel fuel, both for the entire sample and individually for two vehicle cohorts: the oldest and the newest.

Table 8: The benefits of search after the invasion

	All	1980-2005	2021-2022
E5			
Monetary benefits (Euro cents)	1.5	1.1	2.2
Percentage out of price increase	7%	5%	11%
E10			
Monetary benefits (Euro cents)	0.5	0.2	1.3
Percentage out of price increase	2%	1%	6%
Diesel			
Monetary benefits (Euro cents)	1.5	2.1	1.6
Percentage out of price increase	5%	7%	6%

Notes: The table shows the calculated benefits of increased search efforts post-invasion. These values are calculated by using the pre-invasion mean positions from table 5 to estimate consumers' mean positions after the invasion, based on the estimated coefficients on the invasion dummy from the single differences model (which are presented in table 6). For each position, the corresponding prices before and after the invasion were determined to calculate the monetary benefits and their proportion out of the price increase experienced at the original pre-invasion position.

Drivers of newer vehicles who consume E5 were able to avoid 11 percent of the price increase experienced in their pre-invasion position, by shifting down the price distribution after the invasion, while drivers of older vehicles who consume E5 were able to avoid 5 percent of of the price increase experienced in their pre-invasion position. For diesel consumers, the difference is much smaller between the groups with drivers of older vehicles avoiding 7 percent of the price increase and drivers of newer vehicles avoiding 6 percent of the price increase.

4.5.2 Consumers' driving behavior

Table 9 presents the results of the IV model for consumers' driving behavior using fuel consumption (liters per 100 kilometer driven), daily kilometer driven and number of days between refuels as dependent variables. Fuel consumption decreases, on average, by 0.05 percent for a one percent increase in price paid for E5 fuel, for diesel the reduction is of 0.03 percent magnitude. This decrease could be due to drivers consciously adopting more fuel efficient driving practices, , such as reducing travel speeds on highways. Additionally, drivers may avoid driving in cities where vehicles tend to consume more fuel due to frequent braking. Drivers reduce travel distance on average by 0.23 percent to 0.3 percent for a one percent increase in paid prices. Combining these results, a one percent increase in paid prices leads, on average, to a 0.67 to 0.75 percent increase in fuel expenses. This is due to reductions of 0.25 to 0.33 percent in liters consumed.[25]

The reduction in the vehicle's fuel consumption accounts for over 15 percent of the decrease in fuel expenses, with the remaining portion attributed to reductions in the distances consumers travel. These results relate closely to previous elasticities estimated by Levin et al. (2017) and Knittel and Tanaka (2021), both of whom also used similar granular data.

Table 9: The impact of price increases on consumers' driving behavior

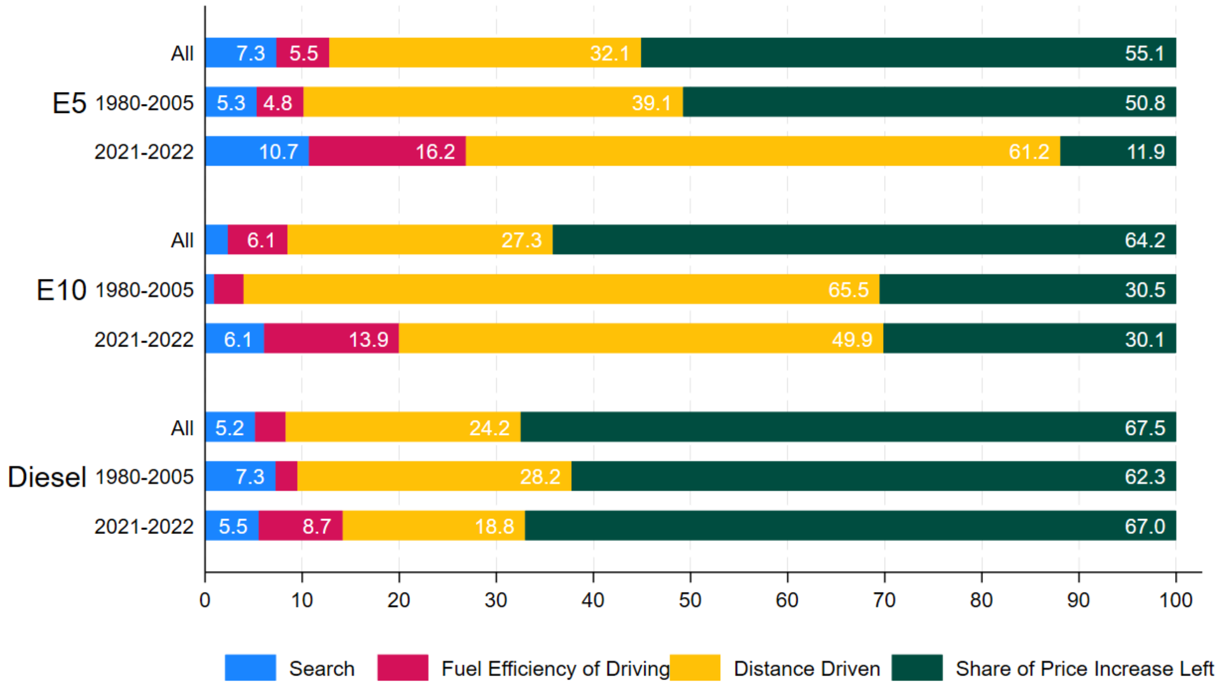
	All	1980-2005	2006-2015	2016-2020	2021-2022
E5					
ln(l/100 km)	-0.051	-0.046	-0.046	-0.054	-0.146
	(0.003)	(0.009)	(0.004)	(0.004)	(0.025)
ln(daily km)	-0.299	-0.371	-0.282	-0.302	-0.553
	(0.016)	(0.055)	(0.027)	(0.022)	(0.146)
ln(days)	0.245	0.361	0.224	0.244	0.328
	(0.016)	(0.056)	(0.026)	(0.022)	(0.156)
Observations	393,006	41,864	140,716	200,048	10,378
E10					
ln(l/100 km)	-0.060	-0.030	-0.058	-0.062	-0.131
	(0.005)	(0.017)	(0.008)	(0.006)	(0.037)
ln(daily km)	-0.267	-0.649	-0.225	-0.254	-0.470
	(0.027)	(0.107)	(0.044)	(0.036)	(0.218)
ln(days)	0.186	0.573	0.147	0.173	0.122
	(0.027)	(0.105)	(0.044)	(0.037)	(0.229)
Observations	129,762	8,733	40,832	74,701	5,496
Diesel					
ln(l/100 km)	-0.030	-0.021	-0.029	-0.031	-0.082
	(0.002)	(0.008)	(0.002)	(0.002)	(0.014)
ln(daily km)	-0.230	-0.263	-0.241	-0.219	-0.178
	(0.009)	(0.040)	(0.013)	(0.013)	(0.080)
ln(days)	0.167	0.208	0.168	0.167	0.135
	(0.009)	(0.041)	(0.014)	(0.013)	(0.087)
Observations	478,852	29,133	230,858	210,064	8,797

Notes: The table shows the estimated coefficients on the logarithm of paid prices, β_{price} obtained from estimating the IV model using 2SLS with fixed effects transformation. The dependent variables are fuel consumption (in liters per 100 kilometers), daily kilometers driven and days between refuels. The first column shows the results for the entire sample, the subsequent columns show the results from estimating the model on vehicles' cohorts subsets. The regressions were ran using the observations from the whole period of the sample: 2019 to 2022. Standard errors are clustered by user-vehicle pairs.

Breaking down the results by vehicle cohorts shows that owners of newer vehicles respond stronger to increases in paid fuel prices. A one percent increase in paid E5 prices leads to a 0.15 percent reduction in fuel consumption and a 0.55 percent reduction in distance

[25] Given that expense $=$ price $*$ fuel consumption $*$ distance, it follows that $\Delta \ln(\text{expense}) = \Delta \ln(\text{price}) + \Delta \ln(\text{fuel consumption}) + \Delta \ln(\text{distance})$

Figure 4: Proportions of post-invasion price increase mitigated by each channel



Notes: The figure illustrates the proportion of post-invasion price increase mitigated by each action channel (search, fuel efficiency of driving, and distance driven) for the entire sample, as well as for owners of old and new vehicles separately.

traveled by drivers, resulting in a nearly 0.7 percent reduction in total liters consumed. For comparison, owners of older vehicles are only able to decrease total liters consumption by 0.42 percent. This suggest that owners of newer vehicles are better able to substitute or forgo a larger proportion of their vehicle trips compared to owners of older vehicles. Moreover, the results show that owners of newer vehicles can drive their vehicle more fuel efficiently when provided with the right incentives. Overall, these results indicate that fuel costs for owners of newer vehicles increase by only 0.3 percent for every one percent increase in paid prices, whereas for older vehicle owners, this increase is almost double. This result is important for designing public policy for transportation markets with equity considerations, as lower-income households are more likely to own older vehicles.

Figure 4 summarizes the paper's results, it demonstrates how consumers responded to the post-invasion price increases. Among the three channels, reducing distance driven emerges as the primary channel through which consumers mitigate most of the price increase. On average, reducing distance driven accounts for mitigating 28 percent of the price increase.[26]

[26] Note that to measure consumers behavioral response as a whole, I perform this exercise using prices before search rather than actual paid prices. Therefore, the values for fuel efficiency of driving and distance

On average, search mitigates a larger proportion of the post-invasion price increases (5.6 percent) compared to driving more fuel efficiently (4.4 percent). The role of search in mitigating the price increase varies considerably from 11 percent for newer vehicles drivers who purchase E5 to one percent for older vehicles drivers who purchase E10. Similarly, the proportion of the price increase mitigated by driving more fuel efficiently among the groups, from 16 percent for newer vehicles drivers who purchase E5 to 2 percent for older vehicles drivers who purchase diesel. Newer vehicle drivers purchasing E5 can mitigate the highest proportion of the post-invasion price increase, reaching 88 percent. For diesel consumers, the differences in the mitigated proportions are more nuanced. On average, they are able to mitigate about 34 percent of the post-invasion price increase.

5 Discussion and conclusions

This paper evaluates how consumers respond to price increases in gasoline markets, considering both search and driving behavior. I find that consumers not only adjust their driving behavior, but also search more intensively when prices increase. The response is stronger among owners of newer vehicles, who are also more likely to have higher incomes than owners of older vehicles. Owners of newer vehicles were able to mitigate up to 88 percent of the gasoline price increase following the Russian invasion of Ukraine. This is nearly double the average mitigation rate for E5 fuels, which is 45 percent. For gasoline fuels, owners of newer vehicle exhibited a stronger response across all channels – search, driving more fuel efficiently and reducing demand for vehicle travel. These results combined with the observation that, on average, owners of newer vehicles consume more fuel liters per day, are important for designing environmental policy to reduce fuel consumption. In the short term, the burden of increased fuel prices falls primarily on owners of older vehicles because their demand for vehicle travel is less elastic, their search efforts returns lower benefits, and their ability to drive more fuel efficiently is limited. I document that consumers tend to search more intensively when facing price increases. While the monetary benefits of increased search effort may appear modest, reaching up to 2.2 Euro cents per liter, its role in mitigating price increases is at least as significant as driving more fuel efficiently.

Given these results, the policy intervention by the German government to temporarily reduce fuel taxes has benefited lower income households the most, as it is these households who often own older vehicles and are less capable of mitigating the impact of price increases following the invasion.

The data used in the study consists of consumers who make efforts to learn their fuel costs

driven were adjusted align with prices before search.

and are potentially more price sensitive than the average fuel consumer. Therefore, they might have a higher incentive than the average driver to search for lower prices. However, the results indicate that the group paying higher fuel prices (owners of newer vehicle) and therefore possibly investing less in search, increases their search efforts the most following price increases. They also adjust their driving behavior more strongly than other user groups in the sample. These findings suggest that the effects for the general populations might be of a higher magnitude. The analysis is done under the assumption that gasoline stations have already adjusted their prices to account for potential changes in consumers behavior. If gasoline stations failed to anticipate and account for these changes in their prices, the benefit of search is overestimated.

The German gasoline market exhibits high price volatility; therefore searching in this market can greatly influence the prices consumers pay. Future research involving different markets and industries will provide insights into whether the documented findings are unique to the German gasoline market or more widespread.

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Appendix

A Data preparation

A.1 Vehicle usage data

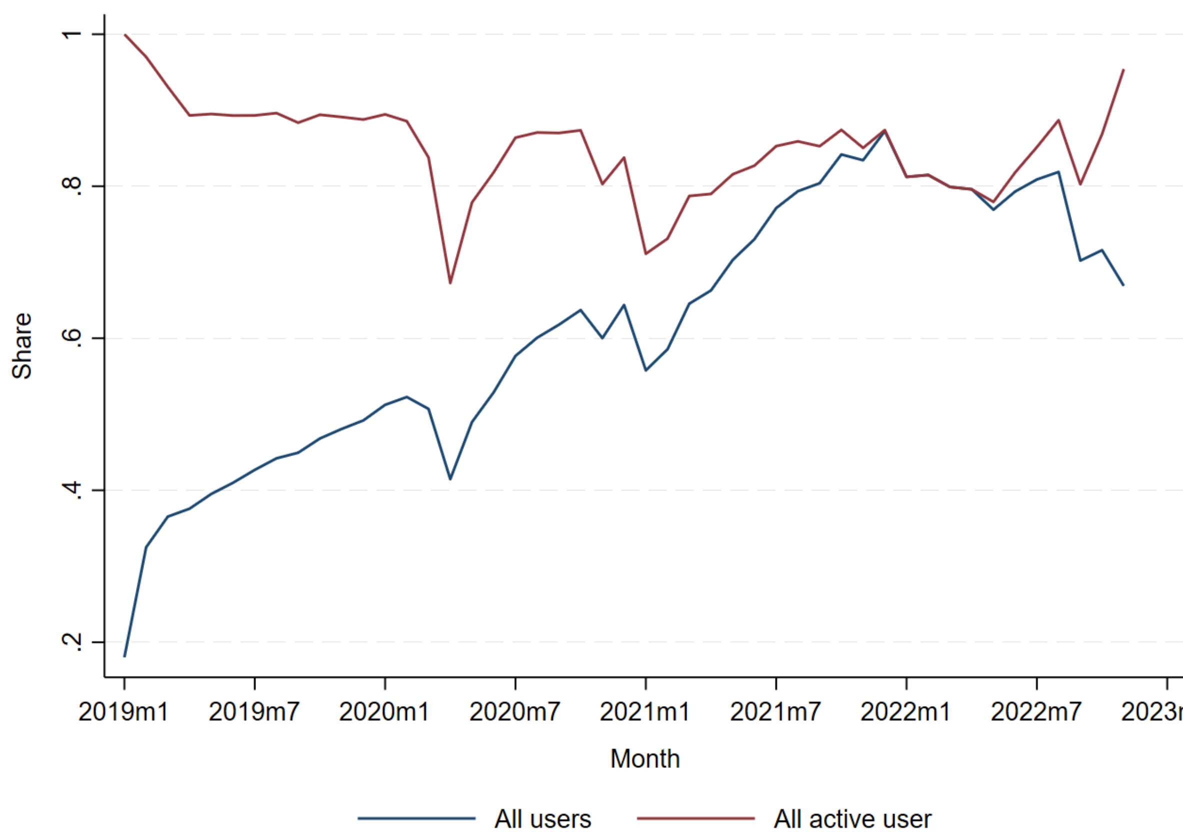
The app data consists of users' logged data on their refueling instances and self-reported data on their vehicles, namely: brand, model, trim, fuel type (diesel or gasoline), production year, horsepower, and gear type. An observation in the sample consists of a user-vehicle pair,[27] the date of their refueling instance, odometer value, type of fuel bought, amount of liters purchased, and the price paid per liter, in addition they can record, their driving style (aggressive, conservative or normal), the type of tires they use (winter, summer, all-year), and the type of roads they used (city,secondary roads, highways). I retain observations on vehicles which were produced between 1980 and 2022 and which are fueled solely by gasoline or diesel (plug-in hybrids are excluded). I identify observations as erroneous entries and remove them if: (i) fuel consumption values are twice the size of the last two refueling occurrences and subsequent two refueling occurrences, or (ii) fuel consumption or distance values are 50 percent above the user's corresponding 95th percentile value and 50 percent below the user's corresponding 5th percentile value. Additionally, I remove observations with fuel prices below (above) the lowest (highest) fuel price observed at the refueling date in Germany. Lastly, I retain observations which have non-missing values for the variables of interest: total fuel expense, odometer, and quantity purchased.

The panel dataset is not balanced: users gradually join the sample between 2019 and 2022, with 50 percent of users in the sample beginning to record their vehicle usage during the first 9 months of 2019. Additionally, 90 percent of the users in the sample start using the app before July 2021. After joining the app, all users continue to record their usage until April, 2022. About 5 percent of the sample stopped recording their usage between April 2022 and July 2022. Users may also have some inactivity spells during which they do not record vehicle usage. I define a gap as a calendar month in which no activity was recorded. The average gap in the sample is of 1.5 months, with approximately 82 percent of users recording at least one gap period. The unbalanced nature of the panel might be a threat to identification if users' decision whether to record their usage is correlated with price levels. For example, users may record their usage during periods of high prices and stop recording during periods of low prices. Figure C.1 plots users activity over the sample period. The figure plots the proportion of users who record their usage out of all users in the sample ("All users") and

[27] Users can log multiple vehicles on their account.

the proportion of users who record their usage out of all users who have joined the app by that month ("All active users"). Decreases in app usage occur primarily coincide with the COVID-19 lockdown periods in Germany, particularly in spring 2020, and winter 2021. During these months, highway activity in Germany decreased due to government imposed measures to restrict. The average activity rate among all active users is 85 percent.

Figure C.1: App usage rates over time



Notes: The figure plots the share of users who log their activity during each month in the sample, both out of all users included in the sample ("All users") and out of all users who have joined the app by that month ("All active users").

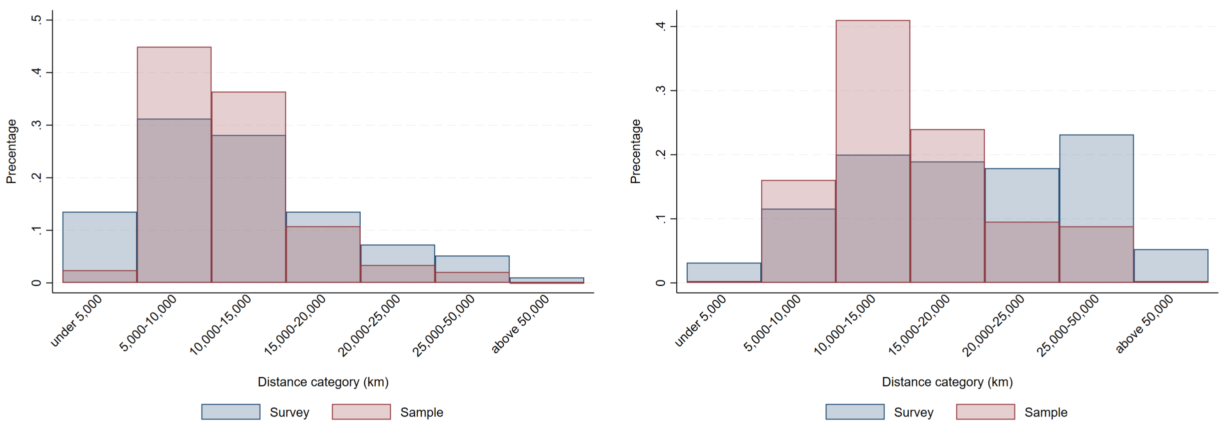
Another concern regarding the data is how well it represents the population of drives in Germany. To gauge the representativeness of the data, I compare the sample with two other data sources: the Mobility in Germany 2017 (MiD) survey (Nobias and Kuhnimhof, 2018), which is a representative cross sectional survey commissioned by the Federal Ministry for Transport and Digital Infrastructure,[28] and the Traffic in Kilometers statistics prepared and published by the Federal Motor Transport Authority (Federal Motor Transport Authority,

[28]More information about the survey can be found here: `https://www.mobilitaet-in-deutschland.de/archive/publikationen2017.html`

2023). Figure C.2 presents the results of the comparison. The distribution of vehicle age and the distances traveled by gasoline vehicles in the sample closely mirror those of the German population. Owners of diesel vehicles in the sample tend to travel shorter distances annually compared to the general German population.

Figure C.2: Distribution of annual distance driven

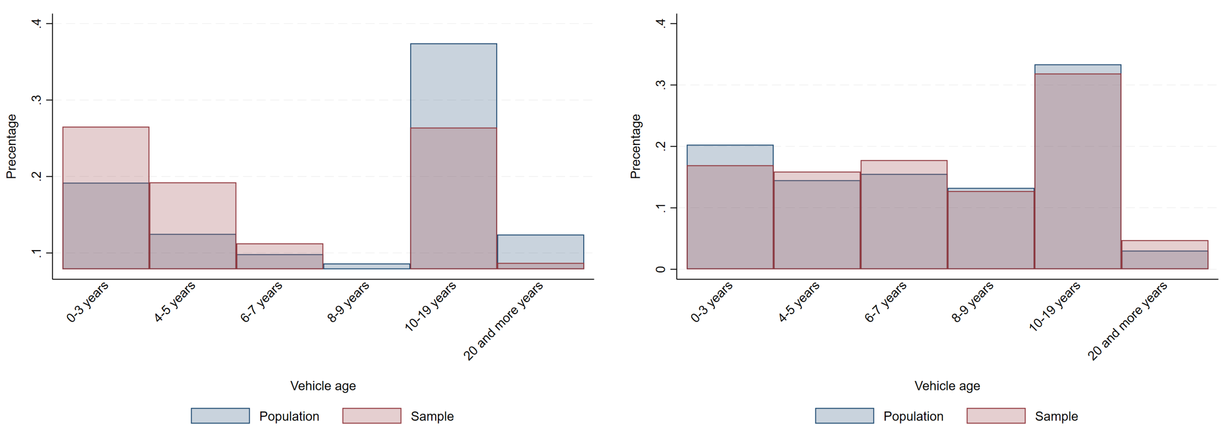
(a) Gasoline vehicles (b) Diesel vehicles



Notes: The figure plots histograms of annual distance traveled using the results of the Mobility in Germany 2017 (MiD) survey ("Survey") and the sample from the vehicle usage app data ("Sample").

Figure C.3: Distribution of vehicles' age

(a) Gasoline vehicles (b) Diesel vehicles

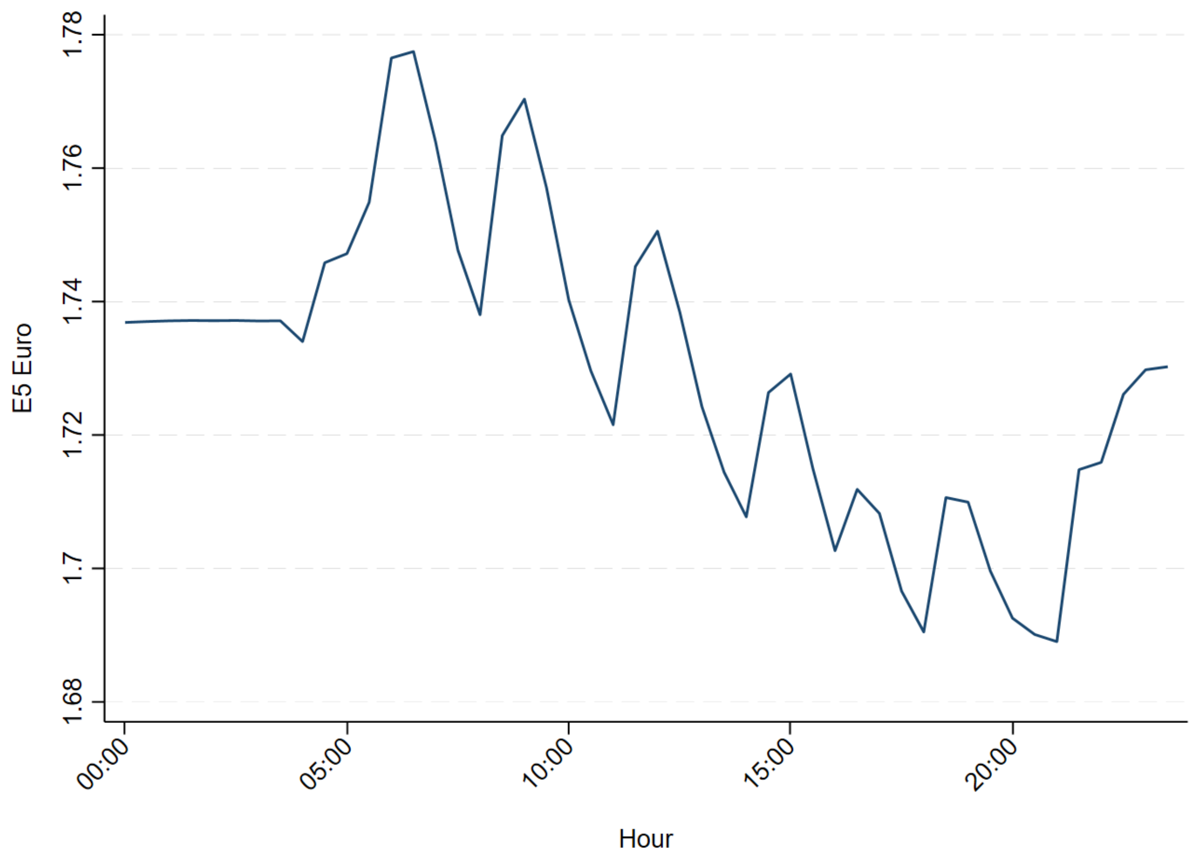


Notes: The figure plots histograms of vehicles' age using the Federal Motor Transport Authority official statistics ("Population") and the sample from the vehicle usage app data ("Sample").

A.2 Gasoline prices

In Germany, gasoline stations are required to report price changes in real-time to the Market Transparency Unit at the German Federal Cartel Office. The data is publicly available through third-party data providers. The data consists of the exact time a price change have occurred: date and time, and the new fuel prices by station. In addition to prices, I observe for each station their geographic location, brand affiliation and their opening hours. I use all price changes which took place between 2019 and 2022 to construct a panel data of all gasoline prices in Germany at 30 minute intervals.[29] During each 30-minute interval, I remove stations from the panel that are closed. I use the panel to calculate quantiles of the empirical daily cumulative distribution of prices for each fuel type (E5, E10, and diesel).

Figure C.4: Example of a daily price cycle



Notes: The figure plots the evolution of the national average E5 prices on November 23, 2021.

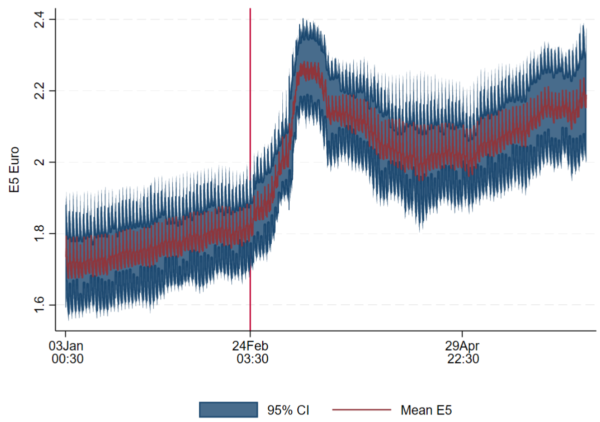
[29]It is feasible to construct such panel at more granular intervals, but the CPU and RAM-memory costs are significant due to the large number of gasoline stations in Germany, nearly 15,000. The advantages of such a detailed panel for constructing daily price distributions appear limited, as stations typically maintain their posted prices for at least 30 minutes.

Figure C.4 presents an example of a daily price cycle observed in Germany. The figure plots the evolution of E5 prices in Germany on November 23rd 2021 averaged across all stations nationwide. The figure illustrates the typical pattern of prices raising during the early morning hours. These increases typically reflect changes in wholesale prices that occurred the previous day. The morning hours usually exhibit the highest observed prices of the day. In the following hours stations undercut each other until the evening rush hours, when the cheapest prices of the day are observed. Prices increase again in the late evening hours, when some stations close their shops for the day. The figure shows that that consumers can reduce significantly their fuel costs by fueling during cheaper times of the day. For example, on November 23rd, 2021, the difference between the highest average price and the lowest was 8.8 Euro cents per liter. In addition to the inter-temporal variation, there is also high variation in prices across stations, with branded stations (such as Shell, Aral and Total) charging higher prices than unbranded stations.

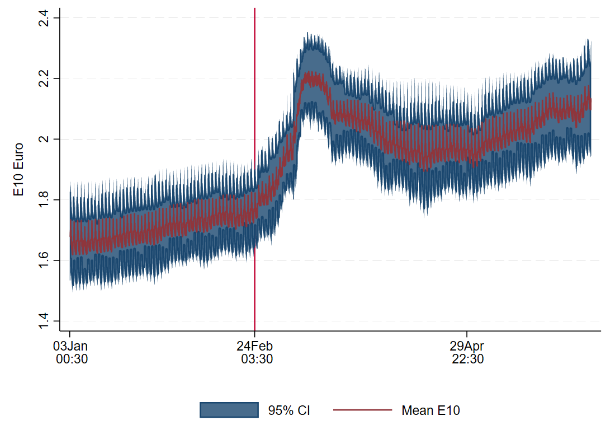
B The impact of the invasion on gasoline prices

Figure C.5: Development of fuel prices around the invasion

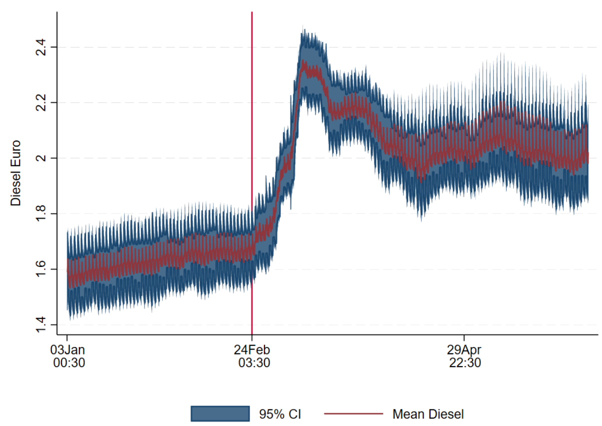
(a) Development of E5 Prices



(b) Development of E10 Prices



(c) Development of Diesel Prices

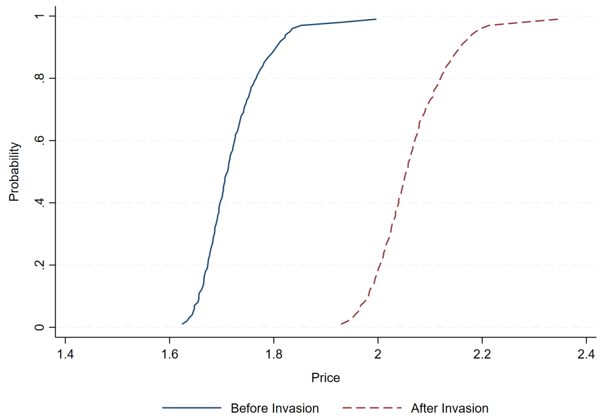


Notes: The figure presents the average and 95 percent confidence interval of fuel prices in Germany in 30 minute interval between January 3rd, 2022, and April 29th, 2022.

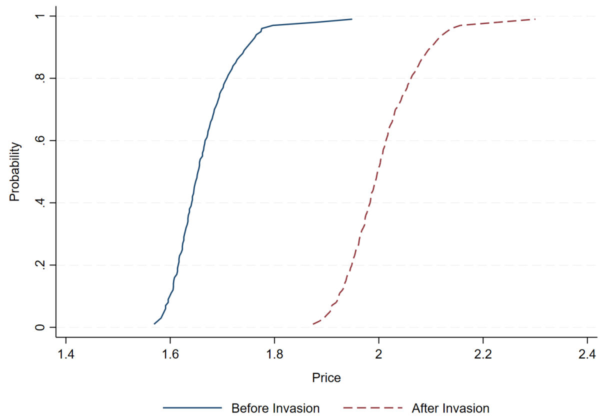
Figure C.5 plots the evolution of fuel prices in 30 minute intervals during the weeks preceding and following the invasion. The figure illustrates clearly the immediate effect the invasion had on fuel prices: in a matter of hours since the invasion, gasoline prices rapidly increased. The figure illustrates the high cyclical nature of the German retail gasoline markets: prices vary significantly throughout the day, resulting in the erratic movements of the mean. The wide confidence intervals illustrates the high spread of prices across stations nationwide.

Figure C.6: Cumulative distributions of fuel prices

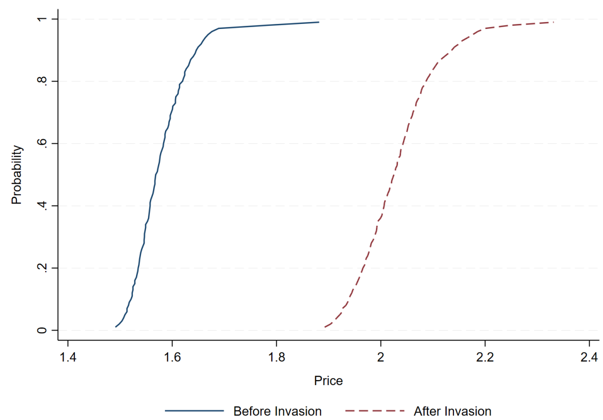
(a) Cumulative distributions E5 Prices



(b) Cumulative distributions of E10 Prices



(c) Cumulative distributions of Diesel Prices



Notes: The plot shows the cumulative distributions of national fuel prices during the period November 11th, 2021, to May 31st, 2022, separately for the time period before and after the invasion.

Figure C.6 illustrates the impact of the invasion on the prices distributions by plotting the cumulative price distribution fourteen weeks before and after the invasion. The figure further illustrates that the invasion created primarily a shift in the distributions' positions rather than a change in scale.

C Additional tables

Table D.1: Prices corresponding to consumers' positions pre and post-invasion

	E5		E10		Diesel	
	Pre	Post	Pre	Post	Pre	Post
Quantile						
10	1.659	1.993	1.602	1.935	1.530	1.952
	(0.057)	(0.085)	(0.057)	(0.085)	(0.056)	(0.118)
20	1.676	2.015	1.618	1.960	1.543	1.979
	(0.055)	(0.089)	(0.056)	(0.089)	(0.057)	(0.123)
30	1.689	2.034	1.631	1.977	1.556	2.002
	(0.055)	(0.090)	(0.056)	(0.090)	(0.056)	(0.128)
40	1.700	2.051	1.645	1.994	1.566	2.021
	(0.056)	(0.092)	(0.053)	(0.090)	(0.056)	(0.130)
50	1.715	2.066	1.656	2.009	1.577	2.039
	(0.053)	(0.092)	(0.054)	(0.090)	(0.055)	(0.128)
60	1.728	2.082	1.670	2.025	1.593	2.057
	(0.053)	(0.092)	(0.056)	(0.094)	(0.055)	(0.127)
70	1.746	2.100	1.688	2.042	1.609	2.076
	(0.054)	(0.092)	(0.053)	(0.091)	(0.055)	(0.127)
80	1.770	2.126	1.713	2.067	1.631	2.101
	(0.054)	(0.091)	(0.054)	(0.089)	(0.057)	(0.125)
90	1.811	2.163	1.754	2.105	1.660	2.152
	(0.050)	(0.086)	(0.047)	(0.087)	(0.060)	(0.123)

Notes: The table shows the average prices and the standard deviations corresponding to each quantile in the daily national price distributions. The values were separately calculated for before and after the invasion using the six months period from December 1, 2021, to May 31, 2022.

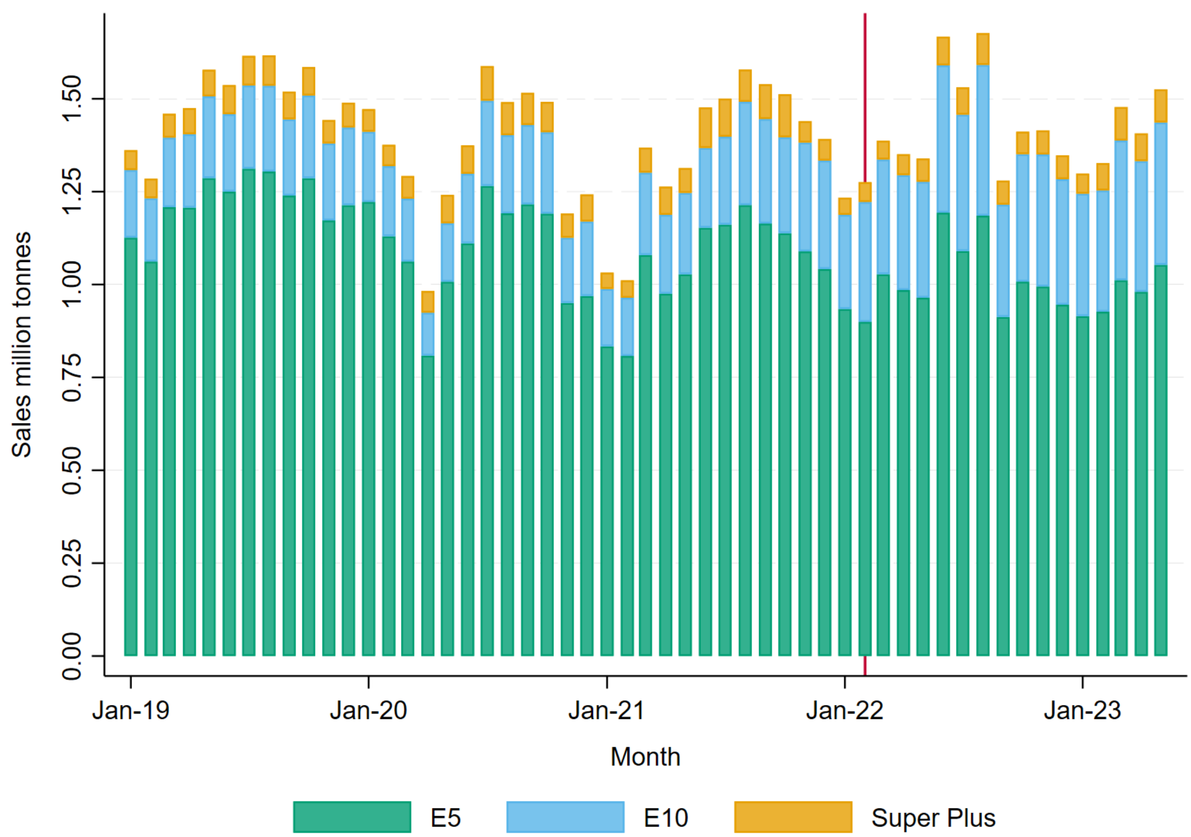
Table D.2: The impact of the invasion on consumers' search - weekly distributions

	All	1990-2005	2006-2015	2016-2020	2021-2022
E5					
ln(location)					
Invasion	-0.137	-0.047	-0.127	-0.156	-0.202
	(0.011)	(0.031)	(0.019)	(0.015)	(0.046)
ln(paid price)					
Invasion	0.170	0.176	0.169	0.169	0.167
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)
Observations	57,639	6,792	18,930	28,548	3,369
E10					
ln(location)					
Invasion	-0.033	-0.001	-0.022	-0.026	-0.142
	(0.016)	(0.048)	(0.030)	(0.022)	(0.067)
ln(paid price)					
Invasion	0.176	0.176	0.176	0.176	0.170
	(0.001)	(0.004)	(0.002)	(0.001)	(0.005)
Observations	25,804	1,720	7,186	14,825	2,073
Diesel					
ln(location)					
Invasion	-0.114	-0.120	-0.128	-0.101	-0.101
	(0.010)	(0.039)	(0.015)	(0.015)	(0.050)
ln(paid price)					
Invasion	0.235	0.233	0.235	0.236	0.236
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)
Observations	76,895	4,924	33,570	35,386	3,015

Notes: The table shows the estimated invasion coefficients from an OLS regression with fixed effects transformation on the logarithm of consumers' position in the weekly national price distribution and the logarithm of paid prices. The first column displays the results when using the entire sample, while the remaining columns show the results obtained from estimating the model on vehicles' cohorts subsets. The regressions were ran using the observations from the period December 2021, to May 2022. Standard errors are clustered by user-vehicle pairs.

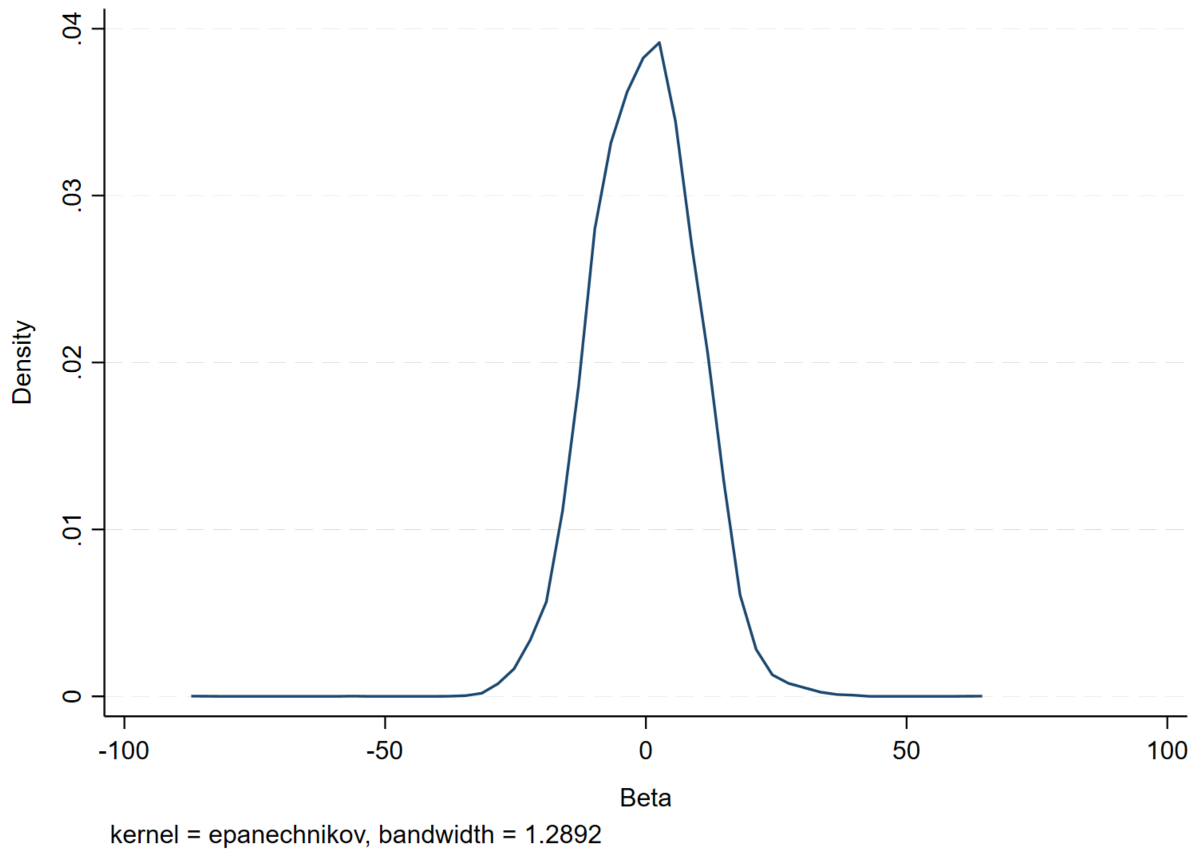
D Additional figures

Figure C.7: National gasoline sales by gasoline type



Notes: The figure displays gasoline sales in Germany between 2019 and 2022 by gasoline type: E5, E10, and super-plus. The data was compiled using the official monthly petroleum data published by the Federal Office of Economics Affairs and Exports Control (Federal Office for Economic Affairs and Export Control, 2019-2023).

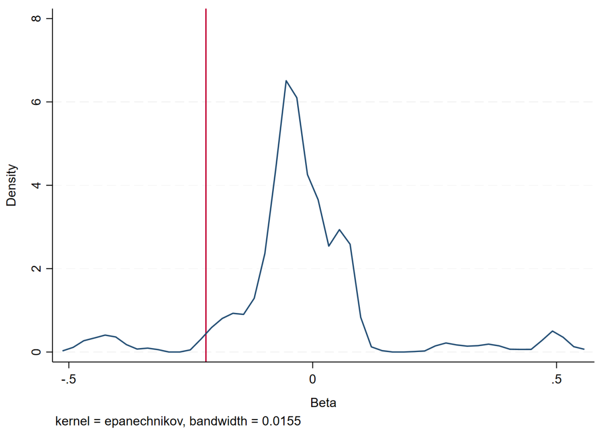
Figure C.8: Distribution of rank-reversal estimates for diesel



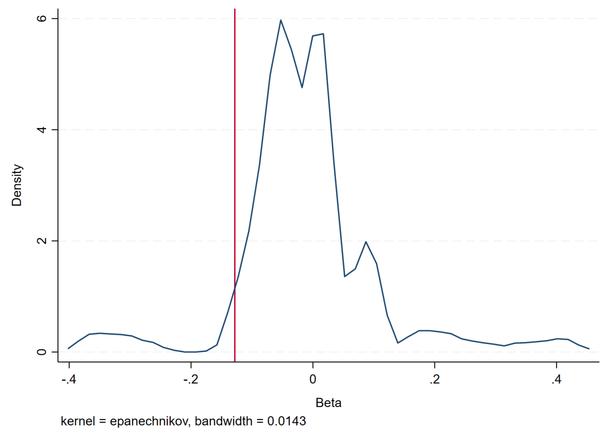
Notes: The figure plots the distribution of the estimated $\beta_{invasion}$ coefficients from the estimations of equation 1 conducted separately for each station, for the time period from November 22, 2021 to May 31, 2022.

Figure C.9: Results of random inference analysis

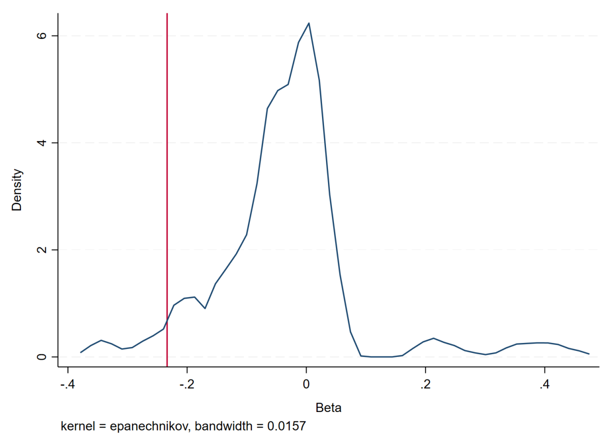
(a) E5



(b) E10

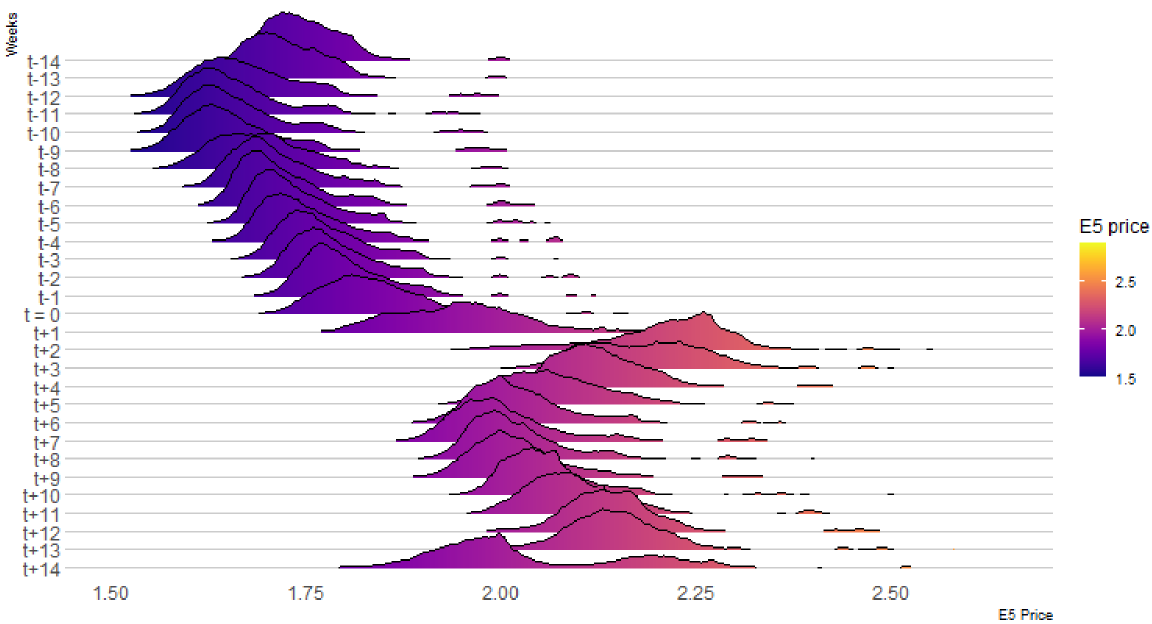


(c) Diesel



Notes: The figure plots the $\beta_{invasion}$ coefficients obtained from a random inference analysis conducted through 1,000 repetitions. The invasion date and the subsequent six months period around it were randomly assigned using the full sample period of 2019 to 2022. Equation 2 was then re-estimated using the randomly assigned time periods and invasion date. The vertical line corresponds to the estimated impact of the invasion estimated by the equation 2 using the six months period around the true invasion date. The corresponding P-values for rejecting the hypothesis that the true impact of the invasion on prices is zero are E5: 0.049, E10: 0.054 and Diesel: 0.039.

Figure C.10: Weekly national price distributions for E5



Notes: The figure presents the weekly national price distribution for E5 gasoline over the 29 week period starting at 15th November 2021 until 6th June 2022. 't' represents the position of each week relative to the week of the invasion, denoted as t=0.

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ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de