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Where and When to Refuel:
A Revealed Preferences Approach to Local Gasoline Markets

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Abstract

This paper provides a systematic analysis of German car drivers' refuelling behaviour. A dataset combining population-representative individual-level GPS-tracking and survey information with data on fuel prices is used to identify 922 refuelling stops between April and December 2023. Besides a discussion of the conducted data processing and cleaning steps, the paper provides insights into German fuel price developments and the competition situation of gas stations. The analysis of the identified refuelling trips shows that drivers most often refuel during shopping trips or on the way home and during times that are known for relatively low prices. The choice between available gas stations is predominantly based on proximity to the direct route, as drivers avoid detours even at the expense of higher costs. In the context of competition policy and market regulation, the findings suggest that the catchment area of gas stations is smaller than often assumed when defining the competition among gas stations. Nevertheless, the high density of gas stations in Germany provides consumers with a considerable choice set and gas stations with a competitive environment even in small geographic areas.

Keywords: Gasoline markets, Refuelling, Consumer choice

JEL classification: D12, R41, R48

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1. Introduction

Gasoline markets are under continuous scrutiny of competition authorities both at the national and international level, triggered by suspected impacts of mergers, tacit collusion, and market concentration on prices. Recent examples include concerns on incomplete pass-through of fuel discounts introduced as a response to the drastically increased fuel prices due to Russia's war in Ukraine in 2022 and skyrocketing fuel prices because of the 2026 Iran war. In the context of the latter, the higher increase of fuel prices in Germany compared to other countries gave rise to the assumption of market power and collusion at the German gasoline market.

A fundamental issue of antitrust policy analyses is the definition of markets, which should be based on estimated demand and supply substitutability. While market definitions commonly refer to both product market and geographic market definitions, only geographic market delineation matters for gasoline markets due to the lack of product differentiation. In this context, the decisive issue is the ability and preference of car drivers to substitute fuel purchases between gas stations, given the necessary time to drive to an alternative provider. Out of various approaches to define geographic market boundaries such as the elasticity-based SSNIP-test and analyses of price correlation and cointegration, the most straightforward and common approach to define spatial gasoline markets is the use of iso-distances (i.e., mapping fixed-radius circles around a provider, often paired with isochrone measures based on driving times). For example, the German antitrust authority (Bundeskartellamt, BKartA) has used calculated driving times of 30 minutes in urban areas and 60 minutes in rural areas from a gas station to alternative stations by means of a GIS-based accessibility model until recently (BKartA, 2011; BBSR, 2020). This model assumes shortest path travel distances and times under free-flow conditions with road link-specific speed profiles by mode (car and lorry) and road categories.

The aforementioned approaches involve either some degree of arbitrariness in defining fixed-radius circles or, as for the accessibility model, rely on theoretical driving times. In order to represent consumer behaviour with more realism, the use of consumer cards (Doshi et al., 2024) has become popular to estimate average distances or travel times of consumers by categories of goods. The BKartA has recently followed a similar approach for the delineation of spatial gasoline markets by analysing 5-digit postal code information from customer cards to derive the catchment area of gas stations (BKartA, 2022). With this revised approach, the BKartA uses driving times of 20 to 30 minutes around gas stations to define their catchment area. However, even though this approach moves the theoretical distances and driving times for refuelling closer to real observations of drivers' gas station choices, it relies on the assumption of home-based refuelling trips as well as on theoretical driving times and does not provide conclusive evidence on the real refuelling behaviour of consumers.

This paper addresses this gap by analysing where, when, and at which price car drivers refuel their vehicles. It controls for circumstances such as whether drivers refuel on their way from or to home as compared to trips with other purposes, and uncovers whether they ponder additional driving time in exchange for lower prices. Our analysis is based on a unique dataset combining GPS-tracked geo-locations and time stamps of refuelling stops obtained for a representative sample of German individuals with gasoline and diesel prices for the total of 17,000 gas stations in Germany. The data cover the time between April and December 2023, which was characterised by a relatively stable development of fuel prices and lower average prices than in 2022.

The contribution of our paper is threefold. First, we contribute to the ongoing discussion on local market delimitation by analysing observed distances and travel times for origin-destination pairs of individuals' refuelling trips. Second and related to this, we identify the purpose of the trip consumers use to refuel their vehicle and challenge the assumption of home-based refuelling alternative approaches rely on. Third, we analyse price consciousness and responsiveness of car drivers by identifying whether they choose stations with lower prices over neighbouring stations within a pre-defined buffer, and to what degree they detour from the nearest station. Furthermore, we contribute to the discussion on the temporal dimension of price sensitivity by analysing the day of week and the time of day of consumers' refuelling trips.

The remainder of the paper is organised as follows. Section 2 summarises the findings from available research. Section 3 explains the processing and derivation of the dataset. Section 4 provides a descriptive analysis of the dataset, the German fuel market, and the fuel price development in 2023. Section 5 presents empirical results on the observed refuelling trips, individuals' refuelling behaviour, and gas station choice. Section 6 draws conclusions and describes approaches for further research.

2. Literature Overview

Gasoline markets belong to the best-researched markets in economic literature due to characteristics such as a high degree of product homogeneity, price-conscious consumers, high market transparency (at least in most developed countries), low information search costs, and low product innovation. Motivated by competition and antitrust policy, a large body of literature analyses the impact of market structure, market concentration, vertical integration, collusion and mergers on prices as well as the dynamics of prices ("rockets and feathers" phenomenon) and

Edgeworth cycles. More recently, the pass-through of newly introduced, increased, reduced, or removed taxes on gasoline has generated a stream of studies. A recent example is Genakos & Kampouris (2026), who use the framework of pass-through analysis to define spatial gasoline markets, arguing that defining spatial markets by distance or time metrics might lead to too narrow market definitions due to undetected substitutability.

Most of the existing studies on gasoline markets focus on the supply side, while less research is available on consumer behaviour, representing the demand side of the market, apart from an established body of literature on fuel price elasticities. This holds in particular for research on refuelling behaviour at the level of individuals, which would allow conclusions on the spatial, temporal and individual-specific determinants of refuelling decisions and gas station choice. The subsequent summary of available literature focuses on research that analyses the choice of gas stations and the driving patterns related to refuelling. We will not review the comprehensive literature on fuel price elasticities as this is not the subject of this paper.

Most studies on gas station choice are motivated by the interest to transfer findings from gasoline and diesel markets to electric charging infrastructure. The majority of studies is survey-based, using household interviews to ask car drivers about gas stations they frequent (i.e., asking about their perceived choice set) and the respective trip distances and times from home, work, and other locations. Examples include Plummer et al. (1998) for Minnesota, Bunzeck et al. (2010) for the Netherlands, and Brey et al. (2016) for Spain. Another survey-based stream of research applies the concept of intercept surveys by asking drivers while refuelling, with the advantage of maximising response rates and minimising inaccurate memory of trip details. The pioneering work for this type of studies goes back to the 1980s with Sperling & Kitamura (1986), Kitamura & Sperling (1987), and Dingemans, Sperling, & Kitamura (1986). After a long phase of less research interest in the topic, Kuby et al. (2013), Kelley & Kuby (2013), and Pramono & Oppewal (2013, 2021) have revitalised this strand, triggered by an interest in comparing refuelling behaviour of individuals driving conventional vehicles with that of users of alternative fuel (CNG, propane, hydrogen, biodiesel) or electric vehicles. Over the last decade, an emerging stream of studies uses GPS and/or customer card data in revealed preference (RP) studies. For example, Dorsey et al. (2025) analyse the gas station choice of 105 drivers in South-East Michigan observed over 40 days between April 2009 and May 2010 through vehicles equipped with on-board units recording data on time and location of every trip during the experiment.

A major result from this rather small body of research is that a large share of refuelling stops is done on trips that anchor (start and/or finish) at home, with 43 to 52% starting from home and 35 to 39% ending at home. Less conclusive results are found on work trips with 19 to 28% of refuelling trips starting from work and 13 to 33% ending at work. Based on ranking questions on the purpose of trips with a refuelling stop, Plummer et al. (1998) find a share of 69% of work-related trips, corresponding to Pramono & Oppewal (2021) reporting that 64% of interviewed drivers refuelled during work/study-related trips. The available literature provides evidence on a rather low share of special-purpose refuelling trips, ranging between 5% (Kuby et al., 2013) and 10% (Dingemans et al., 1986). Furthermore, Kitamura & Sperling (1987) find that drivers tend to refuel most often at the beginning or end of the trip. This is confirmed by Brey et al. (2016) with 57% of drivers refuelling close to origin or destination of their trips and 28% along the way. Most of these studies find that drivers tend to behave economically rationally, valuing the time inconvenience of approaching gas stations that are farther away.

While absolute distances and driving times to gas stations are highly country specific, some empirical findings can be generalised and compared to the results presented in this paper. Kitamura & Sperling (1987) find that 60 and 40% refuelled within a driving time of 0-5 minutes from their origin and destination, respectively (28% of the trips were so short that the refuelling stop was within 5 minutes from both the origin and the destination). Bunzeck et al. (2010) confirm this finding in their study, with 58% of drivers refuelling within the first 5 minutes after departure and another 25% within 5-10 minutes. Dorsey et al. (2025) find that excess time and excess distance of choosing an alternative gas station over a closer one are right-skewed, i.e. towards shorter and faster detours. This is reflected in a high value of time indicating that drivers strongly avoid deviating far from their route to refuel. In addition, almost 90% of refuelling stops occur at stations that drivers passed previously, indicating that familiarity and information play an important role.

For Germany, studies on refuelling behaviour or preferences in gas station choice are rare. The German Mobility Panel (MOP; Kantar, 2023) contains a survey module on passenger car types, distance driven, and refuelling diaries for all cars of the respective households. The refuelling diary contains information on refuelling dates, quantities, the cost of fuel purchased, and odometer readings. However, as the time of day as well as geographic information on the route and refuelling stop are missing, this database cannot be used for an analysis of gas station choice. Tsanko (2024) uses data of the Spritmonitor app car drivers can install to track vehicle-related costs. These data comprise the type of vehicle, refuelling dates, odometer readings, and the quantity and price of fuel purchased. Based on this data, Tsanko (2024) analyses how consumers respond to price increases through three channels (distance driven, fuel efficiency, and price search), with reducing distance driven being the primary channel of price mitigation.

3. Dataset Construction Process

The baseline dataset used in this project is the same as the one described in Gaus & Link (2025) based on the GPS tracking panel GIM Traces provided by the market research company *GIM Gesellschaft für innovative Marktforschung*. The roughly 5,000 participants were representatively drawn from the German population by age, gender, household size, and region and have agreed to install a smartphone app for geolocation tracking. The tracked mobility information was matched with data on socio-economic characteristics (age, gender, education, household income, household size, number of children), travel behaviour, and availability of transport modes (possession of a car, bike, motorcycle, etc.; access to public transport) which were collected within three survey waves in June, September, an December 2023[1], respectively. The collected data consists of 3.97 million trips conducted by a total of 5,317 GIM Traces participants (3.39 million trips by 5,259 participants after initial cleaning) between April and December 2023 – with information on start and end locations and time, distance and duration travelled, transport mode (walk, bicycle, car, public transport), and trip purpose (identified based on points of interest (POIs) at the destination) – and 2,920 individuals that responded to at least one of the three survey waves. A detailed description of the data cleaning and processing, addition of information such as region types, weather, and access to railway stations, and a descriptive analysis of the dataset at various stages is presented in Gaus & Link (2025).

The second source of data is Tankerkönig, an authorised consumer information service providing a database on each price change for retail prices of (all) around 17,000 gas stations in Germany.[2] Further station characteristics provided by Tankerkönig, such as station name, brand affiliation, address, and geo-coordinates, allowed us to localise each station precisely.[3] Additionally, OpenStreetMap (OSM) data were used to obtain the location of car wash facilities and identify gas stations with a car wash. However, it must be noted that OSM identifies only 4,431 car wash facilities in Germany while the Federal Association of Gas Stations and Commercial Car Washes (BTG) reports 18,250 facilities (Pawlik, 2025). Analyses using the OSM data must therefore be treated with caution, as a large share of gas stations with a car wash is not identified as such.

[1] Each wave focused on the current month and the two previous months, so that the overall dataset covers monthly data from April 2023 to December 2023.

[2] As a response to suspected market collusion of major companies, the BKartA established the market transparency unit (MTU) in 2013. Since then, gas stations have been obliged to report price changes in real-time to the MTU. Privately operated websites and mobile apps have been given access to the MTU database to report information to consumers. The data obtained from Tankerkönig is available under the Creative-Commons-License (CC BY 4.0) at https://creativecommons.tankerkoenig.de.

[3] Further information such as the availability of a store, café, or toilet could have provided additional insights, but are unfortunately not collected or published in a meaningful way.

To analyse individuals' refuelling behaviour, the tracking dataset with 3.39 million trips was matched with the list of gas stations based on geo-coordinates. In a first step, the tracking dataset was reduced to 241,718 trips that were done by car and followed by another car trip starting at the end location of the previous trip no more than 20 minutes after the previous trip ended. In the second step, 8,980 refuelling stops were identified as those stops that took place within 25 meters of a gas station. Consequently, the initial refuelling dataset consists of 8,980 observations of two consecutive trips describing a journey from a starting location A (origin) to an end location B (destination) with a stop at gas station G in-between. In a third step, Open-RouteService (ORS; HeiGIT, 2008) was used to calculate driving routes, times, and distances for the direct route from A to B (i.e., without refuelling).[4] The fourth step determined the choice set of all reasonably available gas stations among the route from A to B. To do so, buffers of increasing size were placed around the direct route until the actually chosen gas station was included in the buffer. The choice set was then defined as all gas stations in a buffer double the size of the one necessary to include the chosen gas station, meaning that it was generally assumed that drivers would accept double the observed detour. This algorithm was supplemented by a minimum acceptable buffer of 3km and a maximum acceptable buffer of 50km (trips where the observed detour was more than 50km were dropped based on the assumption that the detour is unlikely to be only for refuelling purposes). The fifth step matched the route-specific buffer zones around the direct routes with the gas station locations, identifying a gas station choice set for each route. Two types of information were added for each available gas station: a route (i.e., travel times and distances) from origin A to destination B via the respective gas station was calculated using ORS, and the price of E5 gasoline, E10 gasoline, and diesel as reported by the gas station at the time of the start of the journey[5] was added from the Tankerkönig data.

Multiple cleaning steps finalise the dataset construction process: observations without reported fuel prices, with unrealistically low (<1.00€/l) fuel prices, with fuel prices that were reported more than 12 hours before the journey (and therefore unlikely to still be accurate), and refuelling stops shorter than 3 minutes[6] were dropped. Consistency between the observed behaviour and the calculated travel times and distances is ensured by dropping observations with

[4] Routes were optimised by travel times (i.e., fastest routes) without accounting for congestion, providing best-case travel times.

[5] Alternatively, the price at the hypothetical arrival time at the gas station can be used. As this introduces additional uncertainty due to differences between calculated and actual travel times, we rely on departure time prices instead. In addition, as the majority of trips is relatively short (cf. section 5.1), departure time prices and hypothetical arrival time prices are identical in 80% of the dataset.

[6] In contrast to some other countries, gas stations in Germany require customers to enter the station building and pay at a cashier. The share of automatic filling stations in Germany is estimated at around 7% (Birger, 2024) and neglected for our analysis. It can therefore be ruled out that stops shorter than 3 minutes are refuelling stops.

an observed travel distance shorter than 66% of the calculated distance or an observed travel distance significantly longer than the calculated travel distance (more than 5km longer for trips shorter than 2.5km; more than 3 times the calculated travel distance for trips longer than 2.5km). Gas stations among highways were eliminated, as they have much higher prices (while offering additional services such as restaurants) and can in most situations not be considered as competing with non-highway gas stations.[7] Finally, comparability of trips across the dataset is maintained by restricting the sample to trips with a calculated direct travel time (between origin A and destination B) of no more than 1 hour and no more than 150 available gas stations.[8]

While the remaining dataset consists of 4909 refuelling trips, a meaningful analysis requires information obtained through the surveys, dropping the usable dataset to (depending on the variables of interest) around 922 observations. For example, individuals with a company car or a job that requires them to be mobile (e.g., bus driver, postman) were dropped, as they have systematically different mobility and refuelling patterns. The subsequent analysis therefore focuses on the restricted dataset with all relevant information available.

4. Dataset Discussion

4.1. Fuel Market Observations

We start with a general analysis of the development of fuel prices and the spatial distribution of gas stations. In the context of fuel prices, it should be noted that station operators were free in price setting during the observation period, except an obligation to meet minimum sales targets for E10 gasoline. This regulatory setting has been changed in April 2026 to the restriction that price increases are only permitted once a day at noon (price decreases are permitted at any time of day). We assume that our empirical findings for 2023 also hold for this new regulatory scheme, except hourly patterns of fuel price changes and refuelling behaviour (cf. section 5.1).

Figure 1 visualises the development of daily average fuel prices for E5, E10, and diesel throughout the observation period.[9] It shows stable prices for gasoline from April to end of July, followed by a slight increase over the summer months until end of September and a continuous decrease in prices until December. The difference between E5 and E10 gasoline is almost

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[7] This is in line with the approach of BKartA and the German Monopolies Commission defining highway gas stations as a separate market.

[8] These thresholds ensure that few particular outliers are eliminated while maintaining the overall characteristics of the dataset and distributions of the variables. In addition, few refuelling trips with only one available gas station were dropped in order to keep the focus on the competitive situation of gas stations and the gas station choice of individuals.

[9] As the Tankerkönig database registers fuel prices only when they are changed, gas stations with frequent price changes are overrepresented. However, the overall size of the dataset makes this distortion negligible, as is confirmed by a comparison with the ADAC fuel price statistics (ADAC, 2026).

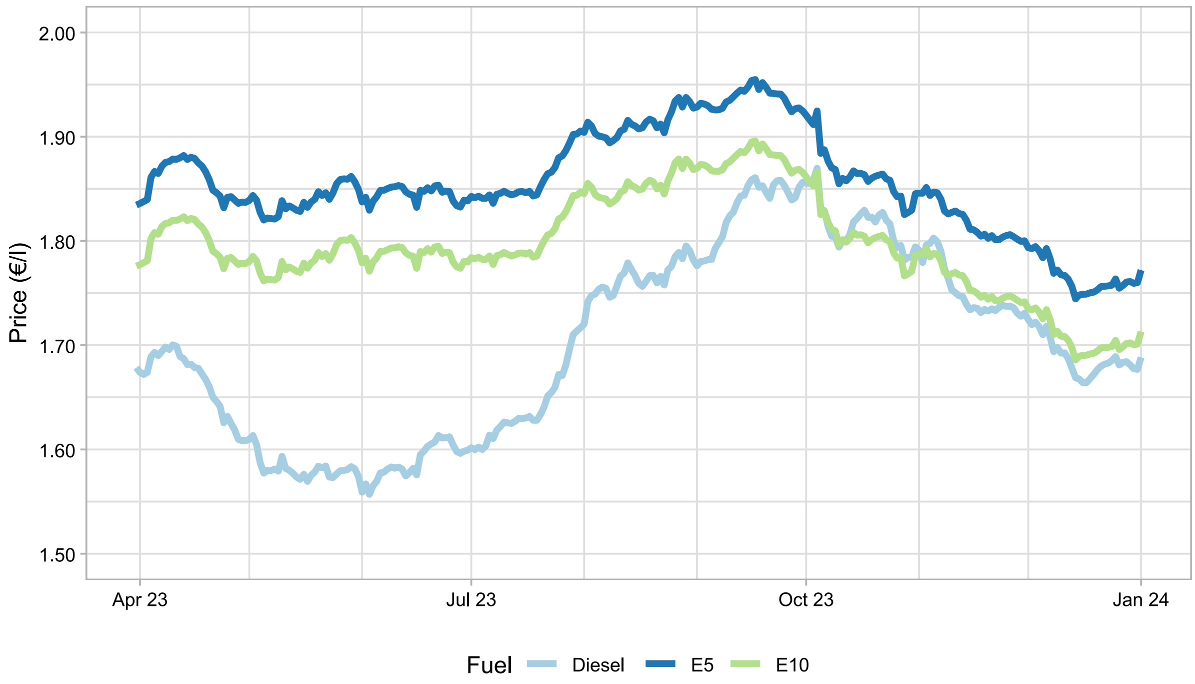

Figure 1: Fuel Price Development during the Observation Period (April-December 2023)

constant around 0.06€/l. The price of diesel shows slightly higher fluctuations, with a considerable decrease in May and a stronger increase in July and August compared to gasoline prices. While diesel is subject to a lower tax than gasoline and diesel prices are traditionally lower than those of gasoline, the prices of E10 and diesel were almost identical between October and December 2023.

Figure 2 displays the intra-day fuel price development as the average prices by hours. As has been found in previous descriptive work (ADAC, 2023), prices are relatively high in the morning with fluctuations until noon, before gradually falling until the evening. The lowest prices are registered between 8 and 10 PM, followed by a price increase over night. The lower prices between 3 and 5am in our sample can be explained by the Tankerkönig dataset only registering price changes and by the fact that we cannot control for the opening hours of gas stations. While this distorts the descriptive pattern of fuel prices during the night, it is a minor issue for the analysis of refuelling behaviour, as the share of refuelling trips during the night is small (cf. section 5.1). Figure 2 furthermore points out that the average intra-day development is identical among the three fuel types E5, E10, and diesel.

To understand the competitive situation of gas stations in Germany, Table 1 provides descriptive statistics of the number of competing gas stations within 500m, 1km, 5km, and 10km around a gas station. On the one hand, it shows that immediate agglomerations of gas stations are rare, with more than half of the gas stations having no competition within 500m and 75% of the stations having no more than 2 competitors within 1km. On the other hand, gas

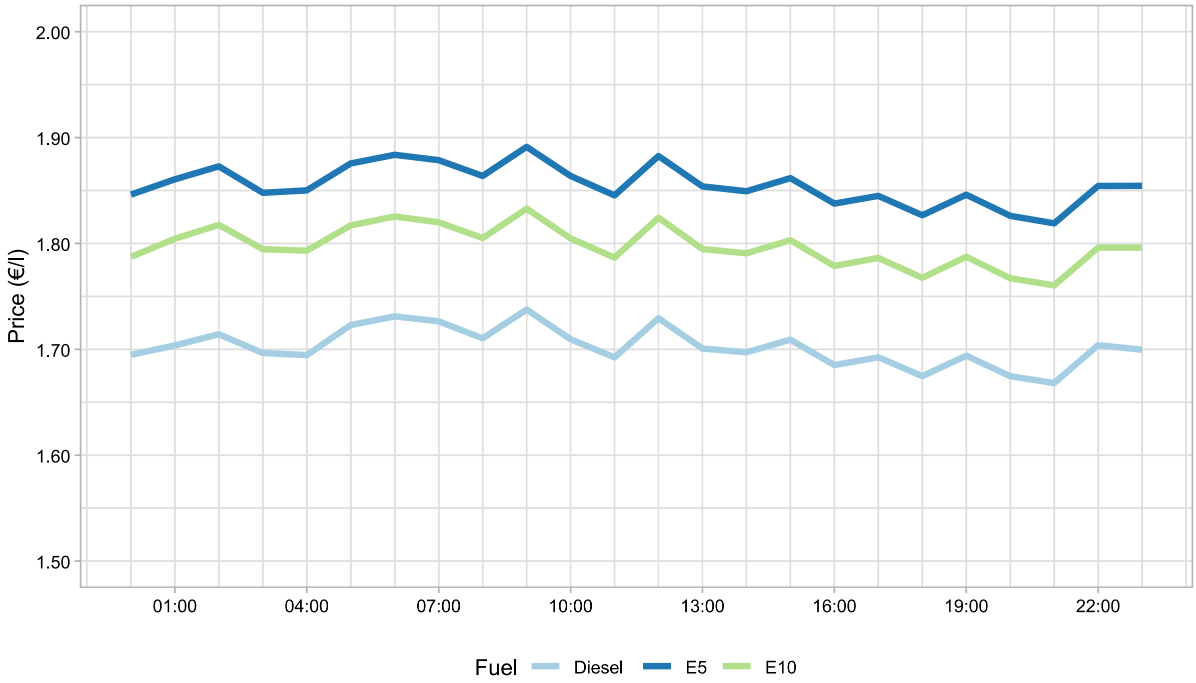

Figure 2: Intra-Day Fuel Price Development (Average of April-December 2023)

stations in Germany compete with an average of 11 gas stations within 5km and 34 gas stations within 10km, underlining that consumers usually have a reasonably large set of alternative gas stations to choose from. Extreme cases of up to 69 gas stations within 5km and 177 stations within 10km can be found in the cities of Berlin, Hamburg, and Munich.

Finally, it must be noted that we do not have information on the type of vehicles that were refuelled (i.e., the type of fuel that was purchased) in our sample due to the GPS-tracking-based nature of the data. Generally, three fuel types – E5 gasoline, E10 gasoline, and diesel – play a role for combustion engine cars in Germany, with gasoline being used by the majority (62.7%) of cars. 29.6% of the cars registered in Germany on January 1st, 2023, use diesel, while 7.7% rely on other methods such as gas, batteries, and hybrid solutions (KBA, 2023). As hybrid vehicles include plug-in hybrid engines, which usually combine a gasoline combustion engine with a battery-powered electric engine, the actual share of cars relying on gasoline or diesel can be expected to be above 95%. The decision between E5 (gasoline with up to 5% ethanol) and E10 (gasoline with up to 10% ethanol) – which is less environmentally damaging and cheaper than E5 – is a personal one in most cases: Cars built in 2011 and later can usually work with both fuel types with essentially no differences. Nevertheless, E5 accounted for 68% of gasoline consumption in Germany in 2024, compared to 27% for E10 (the remaining 5% being special gasoline products such as Super Plus; BAFA, 2024, as cited in BDBE, 2024). Based on these numbers, it can be estimated that E5 was purchased in roughly half of the observed refuelling trips, E10 in 20% of the cases, and diesel in 30%.

Table 1: Competitive Situation of Gas Stations (Number of Competitors within Radius)

	Min	25%	Median	Mean	75%	Max
500m	0	0	0	0.64	1	23
1km	0	0	1	1.25	2	24
5km	0	3	7	11.33	16	69
10km	0	12	21	33.89	45	177

4.2. Socio-economic Characteristics

As mentioned, a detailed analysis of the socio-economic characteristics of the collected dataset is presented in Gaus & Link (2025). An overview of the main characteristics is provided in the first column of Table 2. The dataset used in this application differs from the overall dataset in multiple important ways, as its basic unit of observation is refuelling trips rather than individuals. To get an understanding of the socio-economic distributions, we compare two perspectives: The second column of Table 2 presents the data based on refuelling trips (i.e., individuals with multiple refuelling trips are counted multiple times); the third column focuses on the included individuals, counting each individual once independent of its number of refuelling trips.

It must be noted that the dataset cannot cover the complete refuelling behaviour of individuals due to multiple reasons. As the initial dataset is based on GPS tracking, there is a considerable share of unobserved trips (e.g., when people leave their phone at home, run out of battery, deactivate GPS functionalities, etc.) and inconsistently tracked trips (e.g., partly missing data). In addition, the algorithm used to detect refuelling trips based on geo-coordinates is unlikely to capture all possible refuelling trips due to its focus on eliminating false positives (i.e., minimizing the number of trips classified as refuelling that did not actually have this purpose). The subsequent data cleaning eliminates further trips. While the dataset allows discussing the general refuelling behaviour of the total sample and its subgroups by treating each refuelling trip as an independent observation, we refrain from analysing individual-specific and repetition-related aspects such as habits and inertia.

As Table 2 shows, the sample – both based on refuelling observations and based on individuals – differs from the overall dataset and from the German population (based on the representative distributions provided by SOEP, 2022) in multiple aspects. While these differences should be kept in mind, it is important to note that the refuelling data does not represent the overall population by definition. As individuals self-select into car ownership and refuelling, differences between the total population and the group regularly refuelling a car can be expected. However, the lack of research on refuelling and car use behaviour impedes formulating an expectation about the characteristics of the "refuelling population", as – to the best of our knowledge – no adequate sample exists for a comparison.

Table 2: Socio-economic Characteristics of the Sample

	Full recorded Survey	Sample (Refuelling Trips)	Sample (Individuals)	SOEP (2022)[1]
Age (mean)	47.49	45.11	44.50	44.0
Gender (% male)	50.12	49.78	46.13	50.6
Household size (mean)	2.43	2.65	2.57	3.1
Occupation (%)				
Full-time worker	55.60	77.11	74.67	38.6
Part-time worker	16.39	19.52	21.41	19.1
In education[2]	4.88	3.36	3.91	3.4
At home/not occupied	8.61	0.00	0.00	24.8
Retired	14.51	0.00	0.00	13.9
Income groups (%)				
<1000€	6.57	1.00	2.14	5.2
1000-2000€	18.45	15.04	13.94	18.0
2000-3000€	25.83	26.88	27.88	21.4
3000-4000€	20.37	23.23	20.91	17.5
>4000€	20.84	27.10	27.08	30.9
NA	7.94	6.75	8.04	7.0
Access to car as driver (%)	82.57	97.93	96.58	-
Frequency of car use as driver (%)				
At least daily	48.10	72.45	68.36	-
At least weekly	30.17	22.28	26.01	-
At least monthly	2.51	2.58	1.07	-
Less than monthly	19.22	2.69	4.55	-
Region type of home county (%)[3]				
Urban	46.24	52.23	48.95	-
Rural	53.76	47.77	51.05	-
Observations	2920	922	383	32,022

[1] Sample consists of individuals older than 15 years.- [2] School, university, apprenticeship, job training.- [3] Based on Küpper, 2016 (cf. Gaus & Link, 2025).

Nevertheless, it seems reasonable that the share of workers (both full- and part-time) is higher than in the overall population, as these groups have regular commute trips, higher average daily mobility distances, and a higher car mode share than other groups. The higher share of workers also explains the slight upward skewness of the income distribution. Retirees are known to be less mobile than other groups, in particular concerning car mobility (MiD, 2025), explaining their absence in the refuelling trip sample. While our sample shows a deviation from the real population in this aspect (even groups with less mobility have to refuel occasionally), we can reasonably assume that the data represents the large majority of refuelling trips.

It is unsurprising that almost all participants with observed refuelling trips use their car on a daily or at least weekly basis. However, it must also be noted that around 3% of the sample state to not have access to a car as a driver. Besides potential data errors (e.g., incorrect survey answers or wrong mode assignment), these participants could be car passengers in the observed refuelling trips.

Finally, little difference is found between the sample based on refuelling trips and the individual-based distributions. This suggests that despite the strongly unbalanced panel structure – around half of the individuals are observed only once, 18% more than 3 times and at maximum 19 times – individuals observed more often do not appear to systematically differ from participants with few observed refuelling trips. We can thus assume that our data are not biased due to systematic differences in capturing refuelling trips across population groups and that we can draw generally valid conclusions from the assembled dataset.

5. Refuelling Trips: Descriptive Analysis

5.1. Observed Refuelling Behaviour

In total, we observed 922 refuelling trips by 383 individuals, suggesting an average of 2.41 trips per individual with the mentioned strongly skewed distribution. Figure 3 displays the distribution of the observed refuelling trips by month, day of week, and time of day, while Table 3 provides an overview of descriptive statistics.

First, Figure 3 shows a decline of observed refuelling stops in particular for the last three months of our observation period. To some extent this is due to expected lower mobility after the summer holidays between June and September. In addition, we face the common problem of panel attrition that is particularly prevalent in data collected via smartphone apps. This is less of a problem for the analysis presented in this paper, as we can assume that panel attrition is random and does not introduce a systematic bias. Furthermore, we are interested in the characteristics of refuelling stops and the comparison between chosen and alternative gas stations rather than in providing absolute figures on refuelling behaviour with respect to individuals.

Second, Figure 3 points out that individuals show an economically rational behaviour with respect to the time pattern of refuelling (cf. section 4.1). This holds for the time of day, with an observed peak at 6 PM and a smaller peak around noon, corresponding well with the observed fuel prices and ADAC recommendations on low-price periods. It must be noted that the introduction of the “Austrian model” – permitting only one price increase per day at noon, while allowing price decreases at any time – in April 2026 most likely changed the observed time of day patterns. However, as our results illustrate rational behaviour of drivers, it can be assumed that drivers respond rationally to the changed timings of price changes.

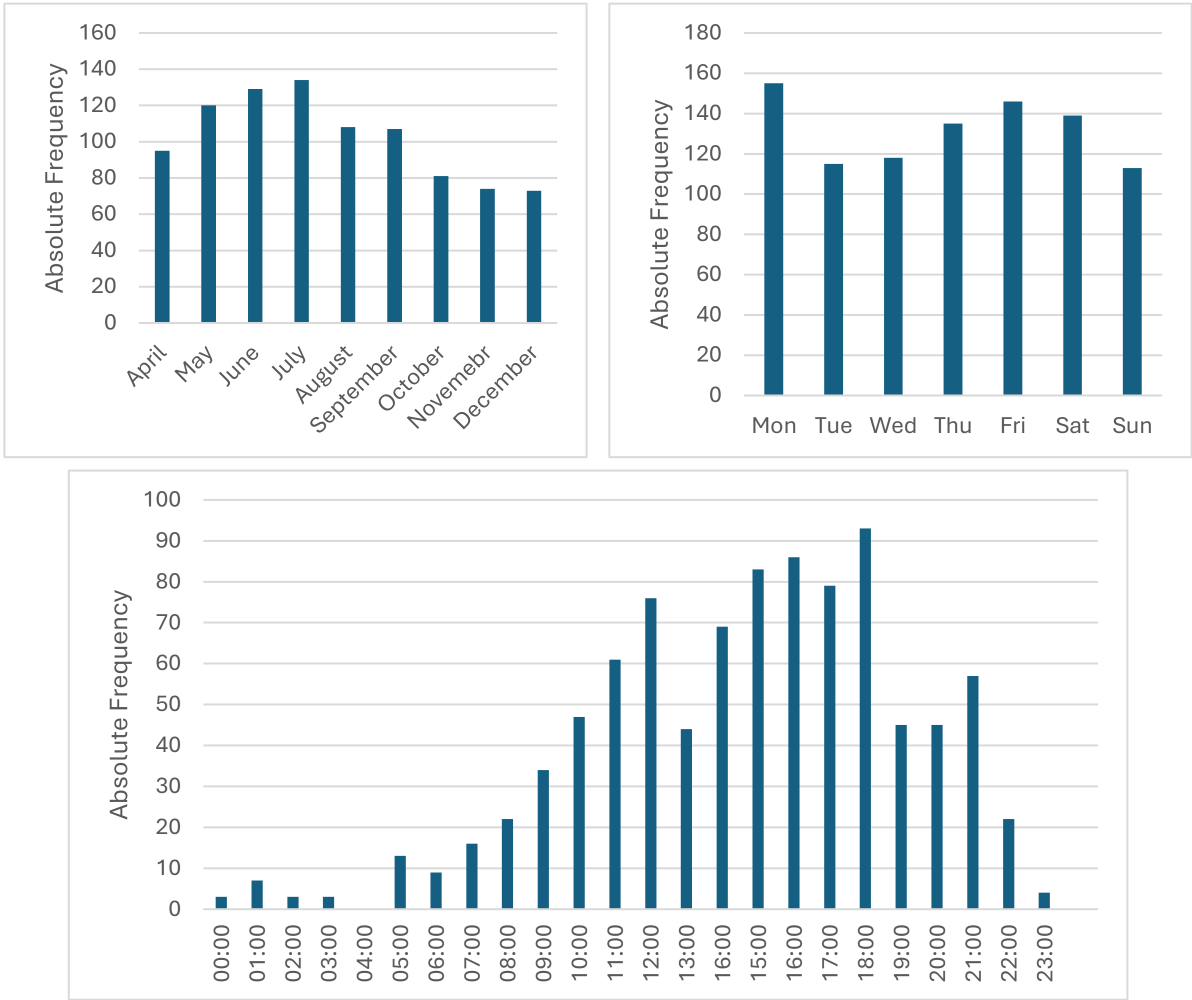

Figure 3: Distribution of Observed Refuelling Trips by Months, Day of Week, and Time of Day

Third, even though there is no comparatively clear recommendation with respect to the day of week, common sense and experience signals to avoid refuelling on Sundays, which is reflected in the behaviour of our sample. As a consequence, a particularly high share of refuelling trips is observed on Mondays and Fridays, i.e. before and after the weekend. An intuitive explanation for this observation is that people tend to make longer trips during the weekend and refuel ahead of these or need to refuel afterwards.

Table 3 reports descriptive statistics of the main characteristics of the observed refuelling trips. As mentioned before, the "panel" structure of the dataset is extremely unbalanced, with 48% of the individuals being observed once, 20% twice, and only 18% more than three times. Consequently, we treat the refuelling trips as independent observations in this study and refrain from analysing individual-specific behaviour. Unsurprisingly, our sample is characterised by a large share of relatively short trips and few long trips. This is in line with the distribution observed in the initial dataset (Gaus & Link, 2025) and other studies (MiD, 2025). A comparison of the observed trips with the calculated direct routes from origin to destination (without refuelling stops) reveals that detours are rather short on average: At the median, the refuelling trip

Table 3: Characteristics of Observed Refuelling Trips

	Minimum	Mean	Median	Maximum	SD
Number of refuelling stops per individual	1.00	2.41	2.00	19.00	2.27
Total trip distance (Observed, km)[1]	1.16	16.27	10.46	98.46	16.21
Direct trip distance (Calculated, km)[1]	0.00[a]	14.39	8.61	108.07	16.99
Distance before refuelling as % of total trip distance[1]	1.10	48.31	49.51	98.97	27.56
Detour distance (km)[2]	-24.26	1.88	0.67	50.23	6.06
Detour time (min)[2]	-19.26	8.17	5.67	251.70	13.53
Duration of refuelling stop (min)	3.02	7.59	6.34	19.93	3.76
Diesel price at chosen station (€/l)	1.48	1.68	1.68	1.96	0.10
E5 price at chosen station (€/l)[3]	1.63	1.85	1.85	2.07	0.07
Number of alternative gas stations	2.00	17.76	11.00	139.00	19.86

[1] As travel distances and times are highly correlated (ρ=0.89) and show the same patterns, we focus on distances to not overburden the table.- [2] Difference between observed distance (with refuelling) and calculated direct distance (without refuelling).- [3] E10 prices are distributed identically and 0.06€/l lower than E5 prices.- [a] A direct distance between origin and destination of 0km is recorded for special-purpose refuelling trips (i.e., returning to the origin after refuelling).

is 0.67km or 5.67 minutes longer than the direct route. While there are some (positive and negative) outliers, this is a clear sign that consumers commonly rely on gas stations within a relatively small area around the direct route and that the competitive environment of gas stations is rather limited in space. The observations with negative detour distances can be attributed to the travel time-based optimisation of ORS, suggesting that individuals prefer shorter routes over best-case fastest routes in some cases (e.g., smaller, but more direct roads instead of congested main roads during rush hour; cf. Ringhand & Vollrath, 2019). Potential explanations for the negative detour times are that individuals know shortcuts on their regular routes that are not applied by routing algorithms and that real-life speeds in off-peak hours might be higher than the average (uncongested) speeds ORS relies on. In contrast to previous literature (cf. section 2), we cannot confirm a tendency to refuel at the beginning or the end of the trip. Instead, refuelling locations are almost uniformly distributed along the observed trips.

Table 3 furthermore points out that individuals spend an average of 7.59 minutes at the gas station, which seems reasonable for a refuelling stop (even though the distribution is clearly influenced by the set minimum of 3 minutes and maximum of 20 minutes). Despite the common choice of gas stations along the direct route, individuals can on average choose from 17.76 gas stations (median: 11) due to the high gas station density in Germany. This adds to the impression that gas stations are subject to strong competition even if their spatial competitive area is defined rather narrowly. Finally, Table 3 outlines the distribution of prices individuals paid at their chosen gas stations. While this is particularly relevant in a comparison between chosen and non-chosen stations (section 5.2), a comparison with section 4.1 shows that the minimum and maximum prices are considerably below the lowest and above the highest average price, respectively. The observed refuelling decisions cover a wide price range, suggesting that the fuel price has a heterogeneous role in individuals' gas station choice.

An interesting addition is the brand distribution of the chosen gas stations, visualised in Figure 4.[10] It shows a clear preference for brand gas stations: While 58% of all gas stations in Germany are not part of Aral, Shell, Total, Esso, or Jet, they are chosen only in 39% of the observed refuelling stops. Aral, Shell, and Jet are chosen 45, 75, and 154% more often than their share in the total number of gas stations suggests, respectively, while Esso is chosen only half as often and Total's choice share corresponds to its station share. The prices recorded in our dataset point out that non-brand and Jet stations are on average around 0.03€/l cheaper than other brands both for gasoline and diesel. While Jet might increase its market share due to these lower prices, Aral and Shell seem to benefit from additional services. On the one hand, gas stations of the two brands often offer cafés, small stores, and toilets. In addition, 20% of Aral stations and 23% of Shell stations are assigned a car wash, compared to 14-17% for the other stations. While the lack of reliable data on these facilities prevents a more detailed analysis, it seems reasonable to assume that they add to the two brands' market shares. In addition, awareness of customer loyalty programs might differ between brands. Shell is known for its well-established customer loyalty program ("ClubSmart"), besides offering discounts to members of

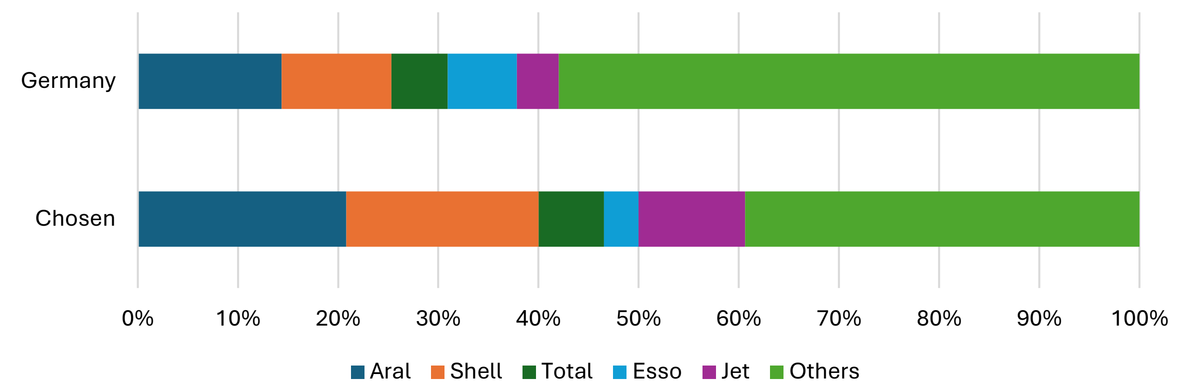

Figure 4: Distribution of the Number of Gas Stations by Brand in Germany and in our Sample

[10] We thank Anna Schütze (TU Dresden) for bringing this relevant point to our attention.

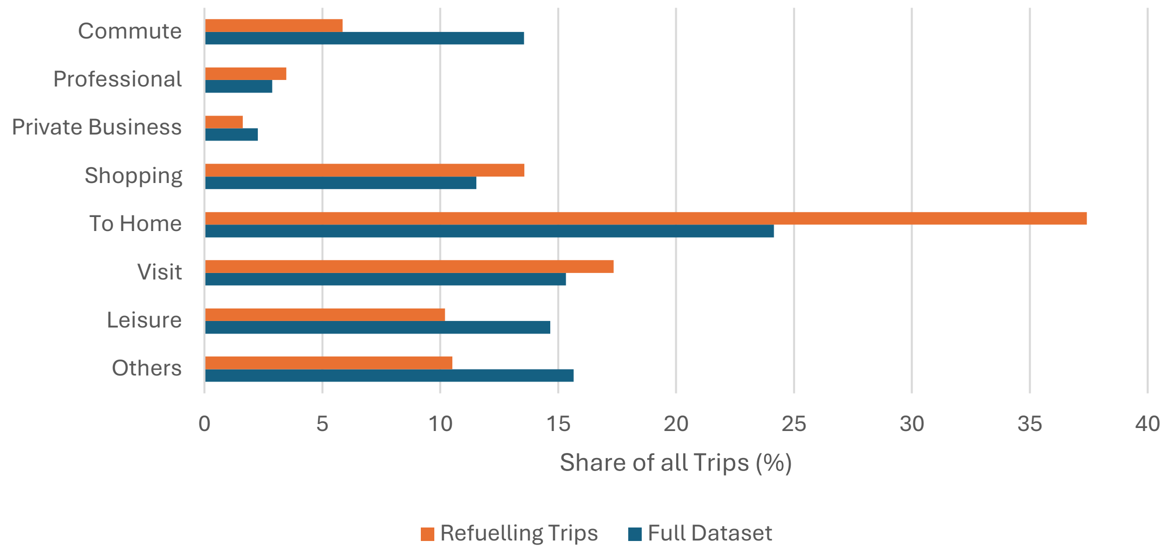

Figure 5: Shares of Final Purposes of Refuelling Trips and for all Trips

Germany's largest touring club ADAC, and Aral is part of the largest German brand-independent customer bonus program ("Payback"), which might further add to their market shares by increasing customer loyalty.

Figure 5 displays the distribution of the final purposes of the observed refuelling trips (i.e., the purpose of the trip leg starting at the gas station) as well as of those of the total GPS-tracked dataset. In contrast to other studies and the overall distribution, we find only a small share of refuelling trips being related to commute (6%). This is a clear indication that people avoid delaying their workplace arrival by refuelling. In addition, the majority of commute trips takes place during the morning hours with fuel being relatively expensive. Returning home is the most important type of refuelling trip with a share of 37%, which is in line with 76% of the refuelling trips being home-related (i.e., starting or ending at home). While returning home is also the most common category in the overall dataset, the share is significantly lower with 24%, underlining that refuelling on the way home is common practice. In addition, 10% of all refuelling trips are exclusively for refuelling – starting at home and returning home after refuelling – and therefore also classified with the trip purpose "to home".[11] This corresponds well with findings from Kitamura & Sperling (1987), Dingemans et al. (1986), and Kuby et al. (2013). Further common trip purposes for refuelling stops are visits[12], shopping, and leisure. It is found that leisure trips are less frequent in the refuelling trips than in the overall sample. Similar to, but not as pronounced as for commute trips, people seem to prefer to reach their destination

[11] Another 1% is refuelling-exclusive but starting and ending somewhere else than home.
[12] "Visit" is identified as a trip purpose if a trip ends in a residential area with no other points of interest in the vicinity. The high share of "visit" trips could therefore also be partly due to misidentified home coordinates, which would shift some trips between "visit" and "to home".

without additional delays and refuel on the way back home or during other trips. This is also in line with the weekday distribution discussed before: As a considerable share of (especially longer-distance) leisure trips is done on weekends, the subsequent Monday is used for refuelling. Overall, Figure 5 outlines clear consumer preferences for refuelling during certain trip types with a low importance of arrival times or destination orientation.

5.2. Gas Station Choice

Table 4 provides insights into individuals' gas station choice by comparing the chosen gas station to available alternatives derived through the process outlined in section 3. As has been shown in Table 3, individuals choose from an average of 18 (median: 11) gas stations. Table 4 points out that the travel distance and time via the chosen gas stations is on average considerably shorter than via alternative gas stations. Note that this is not caused by our definition of the choice set, for which we assume that gas stations are distributed homogeneously in space and apply a buffer of double the observed diversion (cf. section 3). Instead, it is a clear indication that individuals choose gas stations that are close to the direct route from their origin to their destination. This holds for a comparison between all chosen and all non-chosen gas stations with relatively large differences (Columns "Chosen" vs. "Non-chosen" in Table 4) as well as for a direct comparison of each chosen gas station with its immediate alternatives, i.e. the non-chosen stations in the same choice set (Column "Difference"). Even though the differences in this context are smaller (due to the better comparability within choice sets), the route via the chosen alternative is on average 5km shorter than via alternative stations. Furthermore, all mean differences are statistically significant at the 1% confidence level according to respective t-tests.

Table 4: Comparison of Chosen Gas Stations with Alternatives

	Chosen[1]		Non-chosen[2]		Difference (Chosen vs. immediate alternatives)	
	Median	Average	Median	Average	Median	Average
Driving distance (km)	10.46	16.27	23.29	29.69	3.02	4.94
Driving time (mins)	25.15	20.40	32.83	34.72	1.34	-0.37
Detour distance (km)	0.67	1.88	3.68	8.16	-[3]	-[3]
Detour time (mins)	5.67	8.17	7.59	12.24	-[3]	-[3]
Price diesel (€/l)	1.68	1.68	1.69	1.69	0.00	0.00
Price E5 (€/l)	1.85	1.85	1.85	1.85	0.00	0.00
Price E10 (€/l)	1.79	1.79	1.79	1.79	0.00	0.00
Car wash (%)		15.73		16.81		0.02

[1] Observed driving distances and times.- [2] Calculated driving distances and times.- [3] The difference in detour distance and time is mathematically equivalent to the difference in absolute driving distance and time, respectively: $(D_{non-chosen} - D_{direct}) - (D_{chosen} - D_{direct}) = D_{non-chosen} - D_{chosen}$

On first sight, this appears to be primarily a distance difference, as the travel time difference is close to zero and even negative on average (caused by a few outliers). A potential explanation could be that driving distances are more predictable and more tangible for individuals than driving times, particularly when comparing (many) alternatives. However, a further analysis suggests that the explanation could be a data artifact: The "difference" column compares the observed journey of the chosen alternative with the calculated journey for the immediate available alternatives. While the correlation between calculated and observed travel distances is 0.97, pointing out that the routes coincide in the large majority of cases, the correlation in driving times is 0.76. It must thus be noted that real-world driving times differ from the calculated best-case travel times, potentially biasing a direct comparison. An alternative comparison between calculated travel times of the chosen gas station with the calculated alternative driving times shows a mean difference of 5.15 minutes (median: 3.66 minutes). This is in line with the previous finding that individuals choose gas stations that are close to their direct route.

In addition, Table 4 points out a non-existent price difference for all three fuel types between chosen and non-chosen gas stations: Consumers do not seem to choose gas stations that are particular cheap. The existence of a car wash (based on the data discussed in section 3) does also not seem to have an influence on individuals' gas station choice – non-chosen alternatives even have car wash facilities slightly more often than chosen gas stations.

Figure 6 visualises how often the chosen gas station was the best option by driving distance, time, and price. It underlines the previous findings, pointing out that the chosen gas station was along the shortest or fastest route in 248 and 256 cases compared to offering the cheapest prices in 225, 233, and 218 cases for E5, E10, and diesel, respectively. This includes around

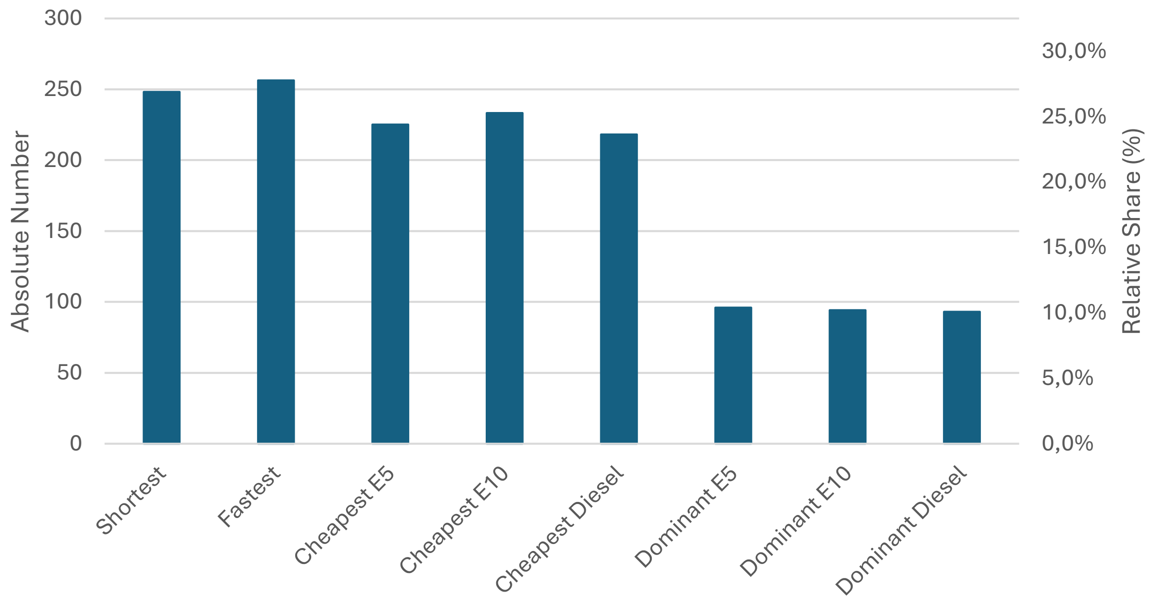

Figure 6: Superiority of Chosen Gas Stations

90 observations in each case that are identified as "dominant" alternatives, providing the shortest route (with almost identical numbers using fastest routes) and the cheapest price at the same time. This provides further evidence that the required detour plays a major role in consumers' gas station choice and outweighs price differences in the majority of cases. A heterogeneity analysis finds that the pattern is constant across groups: For refuelling trips in urban and rural areas as well as for regular and less frequent drivers, the observed shares of superior characteristics of the chosen gas stations closely follow the ones presented in Figure 6.

Overall, the comparison between chosen and non-chosen gas stations provides a consistent picture that consumers choose gas stations based on the necessary detour. Stations that are close to the direct route from the origin to the final destination are preferred, while we find no evidence for a measurable role of the fuel price. From a competition policy perspective, this finding suggests that gas stations compete within an area that is considerably smaller than often assumed. We find no evidence that consumers are willing to drive up to 30 (in urban areas) or even 60 minutes (in rural areas) for a lower fuel price, as implied by the model previously used by the BKartA. As for the new definition of 20 to 30 minutes driving time around gas stations (cf. BKartA, 2022), our findings point at the low end of this range. The large majority of refuelling stops is done during relatively short trips at a station close to the direct route from the origin to the destination. Nevertheless, the high density of gas stations in Germany provides consumers with a considerable choice set and gas stations with a competitive environment even in small geographic areas.

Despite the consistent findings of our analysis, the situational context of the covered time period is important. Fuel prices were relatively stable between April and December 2023 and generally decreasing after the price hike caused by Russia's war in Ukraine in 2022. Nevertheless, our data suggest an average price range of 0.09€/l (median: 0.07€/l) between the cheapest and the most expensive available gas station. While price differences between gas stations were not as large as in the previous year (cf. ADAC, 2026), consumers could still save considerably with a price-conscious gas station choice. Even though the participants in this study did not exploit this saving potential and instead preferred shorter routes over lower prices, this finding should not be generalised into situations of higher overall prices (and higher price awareness) or stronger price fluctuations (and higher saving potential).

6. Conclusions

Local gasoline markets and the competition situation of gas stations are a constant subject of discussion for policy makers and antitrust authorities. While existing research on the topic focuses mostly on the price effects of specific policy measures (e.g., fuel tax changes) or on the price elasticity of demand, policies commonly rely on rather arbitrary market definitions. Few studies discuss the market situation of gas stations from the perspective of consumers refuelling their vehicles. This paper addresses this gap, analysing the gas station choice of individuals based on a sample of 922 GPS-tracked refuelling trips, survey information, and gas price data.

The results point out consistently that consumers minimise detours by choosing gas stations that are close to the direct route from their origin to their destination. While the median detour is only 670m, we cannot confirm a price difference between chosen and non-chosen gas stations, suggesting that drivers do not choose particularly cheap gas stations if they require a longer detour. Nevertheless, the majority of drivers avoids times that are known for high fuel prices (such as Sundays), indicating at least some price sensitivity. In a policy-context, this implies that commonly used area thresholds are too large, as customers are usually not willing to accept a 15- or 30-minute detour even for considerably lower prices.

The largest share of refuelling stops is done during trips home, while stops on the way to work or leisure destinations are avoided. Special-purpose refuelling trips are rare – this should be considered by policymakers when discussing the market definition of gas stations, as it contradicts commonly used approaches. Specific to the German fuel market are the observed brand differences. In particular, Aral and Shell attract a significantly higher customer share than their market presence suggests, potentially due to their established customer loyalty programs and additional services such as shops, cafés, and toilets. Market definitions should account for this, for example by giving gas stations with additional services are larger attraction area. A problem in this context is the lack of data, as information on the additional services gas stations offer are generally not available.

Two main directions for further analyses remain to strengthen the understanding of consumers' gas station choice. On the one hand, a discrete choice model is to be applied to the dataset analysed descriptively in this paper. The random utility theory-foundation of these models provides a systematic approach to the analysis of individuals' preferences (Ortúzar & Willumsen, 2024). The estimation of the impact of driving time and fuel price allows identifying a value of time and thereby quantifying the trade-off drivers face when refuelling. The descriptive findings presented in this paper suggest a high value of time, which should be confirmed by an econometric model. The strongly unbalanced panel structure can be accounted for in a mixed logit model by incorporating respective error components, while interaction effects can identify heterogeneity for example between income groups.

On the other hand, the results should be confirmed in a variety of contexts. As mentioned, the dataset analysed in this paper covers a period of reasonably stable fuel prices and little public and political debate about policy measures. A detailed understanding of consumers' refuelling behaviour requires to also analyse how individuals behave in less stable fuel market situations. The sudden and sharp fuel price increases caused by Russia's war in Ukraine in 2022 and the 2026 war in Iran could provide interesting settings for such analyses, if data are available. Additional studies on fuel market-related policy measures such as fuel tax reductions or increases, fuel price caps, or price setting-regimes (such as the "Austrian" model) could provide further insights into the interaction between gas station operators and car drivers.

Overall, the findings of this paper point out that further research is necessary to gain a better understanding of consumers' gas station choice and refuelling behaviour. Heuristic approaches such as "Individuals choose the cheapest gas station within 30 minutes driving time" fall short and cannot cover the heterogeneous requirements and limitations individuals face in real-world scenarios.

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