Consumer Welfare and Misallocation in Panic Buying of Gasoline*

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Abstract

Panic buying describes a sudden, unanticipated surge in demand, triggered by a real or perceived disruption. In anticipation, consumers front-load purchases, thereby congesting the market and raising the risk of shortages. When prices are slow to adjust, non-price rationing emerges, with ambiguous effects on allocative efficiency across heterogeneous consumers. We study the welfare and allocative effects of panic buying in the context of a two-week episode of panic buying of gasoline in the UK. We combine novel data on station wait times and card transactions to study two sources of welfare loss: elevated shopping costs and misallocation. We develop a model in which heterogeneous consumers trade off the benefit from refueling, given their belief about future fuel availability, against endogenously determined shopping costs. Compared to the optimal allocation, we find substantial losses in status-quo consumer surplus driven by misallocation as front-loading consumers crowded out those with emptier gas tanks. We evaluate alternative allocation rules and their potential in mitigating these losses.

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1 Introduction

Panic buying describes a sudden, unanticipated surge in demand, triggered by a real or perceived disruption. In anticipation, consumers front-load purchases, congest the market, and raise the risk of shortages. Episodes of panic buying have surfaced repeatedly throughout modern history and frequently involve essential food items or inputs to household production.[1] Prices are often slow to adjust to the surge—a well-documented pattern in recent episodes[2]—and markets resort to non-price rationing, such as waiting in line or first-come-first-served. This raises efficiency concerns because markets no longer guarantee allocation to consumers with the highest marginal benefit. Instead, allocation may reflect heterogeneity in consumers' willingness to wait and search, or mere chance in the case of random rationing.

Despite growing policy interest in the consequences of panic buying,[3] empirical evidence on its efficiency and distributional impacts is limited. Such evidence is difficult to obtain, as it requires data that capture both the relevant dimensions of consumer heterogeneity and the dynamic nature of panic buying, such as changes in product availability and wait times.

This paper fills that gap by quantifying the welfare effects of panic buying in a real-world setting: a two-week episode of panic buying of gasoline in the UK in September 2021. This episode was sparked by news reports about potential delivery disruptions, triggering an immediate demand surge. Although prices remained stable, consumers faced increased non-pecuniary costs: long queues and widespread shortages that lasted for up to two weeks. Combining novel data on station wait times and card transactions, we focus on two sources of potential consumer welfare loss: elevated shopping costs and misallocation. To quantify these inefficiencies, we develop a model in which heterogeneous consumers decide whether to attempt refueling their cars after a news shock shifts their beliefs about the future availability of gasoline. The model incorporates two features of panic buying: (i) shopping costs rise endogenously as more consumers attempt to refill, and (ii) refill attempts can fail when stations are out of stock. We characterize the optimal fuel allocation for a planner who recognizes that consumers may overstate the likelihood of a supply disruption. Compared to the optimal allocation, we find that the surplus loss in equilibrium is driven by misallocation

[1] Prominent examples include bank runs in the Great Depression, gasoline shortages amid the US oil crises of the 1970s, and empty supermarket shelves for essential household goods and masks at the height of the COVID-19 pandemic. Episodes of panic buying tend to, but do not necessarily, occur during periods of economic uncertainty. Figure A1 shows that spikes in the quarterly number of *New York Times* articles that mention panic-buying related terms align closely with US recessions.

[2] See Neilson (2009), Cavallo, Cavallo, and Rigobon (2014), Gagnon and López-Salido (2020), Hansman, Hong, De Paula, and Singh (2020), Beatty, Lade, and Shimshack (2021), and Schmidt, Westbrock, and Hoegen (2023).

[3] See European Parliamentary Research Service (2020), House of Commons Environment, Food and Rural Affairs Committee (2021), and Government Office for Science (2023).

rather than shopping costs: consumers who would have refilled in normal times are crowded out by consumers who front-load their purchases. The size of this loss depends critically on whether consumers' beliefs are accurate or overly pessimistic. We conclude by evaluating the feasibility of mitigating these losses with alternative allocation rules.

The UK fuel crisis provides a unique opportunity to study the allocative effects of panic buying for several reasons. First, the episode cleanly isolates a belief-driven demand surge: the shock was triggered by news reports rather than fundamentals, and demand peaked well before any supply disruption would have materialized. We can therefore rule out anticipatory supply behavior and concurrent supply shocks. Second, we have granular demand-side data to measure how reliant individual consumers were on driving in the months before the panic—a key characteristic for understanding refueling during the panic. Third, we can point to a clear trigger event that shifted beliefs about fuel future availability: the leak of internal government meeting notes on September 23, 2021 and their rapid media circulation. This discrete shock lets us contrast refueling behavior before and after the leak. Finally, because gasoline is essential for daily activity and services, there is strong policy interest in its allocation and in interventions to curb panic buying at the point of sale (Government Office for Science 2023).

We begin by documenting several stylized facts about the panic buying episode, focusing on shortages, wait times, and distortions in fuel allocation in the short run. First, the severity of shortages varied substantially across locations, with especially high rates in the South East of England where the biggest population centers are. This variation largely reflects differences in gas station inventories before the panic. Second, shortages raised non-pecuniary shopping costs, with wait times reaching up to 30 minutes. At the same time, gas station retail prices were largely unchanged. Third, the news shock generated a large demand response: during the first five days, the number of consumers who refilled was up to 40% higher than in normal times. However, this surge was attenuated in markets with severe shortages and queues. Fourth, in severely affected markets, we find evidence consistent with crowding out: based on consumers' refueling frequency before the panic, we show that those who normally refuel at least every five days were *less* likely to do so during the first five days of the panic than in normal times. By contrast, those who typically would have refueled later were *more* likely to refill early.

Taken together, the demand response and the lack of price increases gave rise to queues and shortages, especially in markets where initial fuel inventories were low. These non-price constraints reduced observed refills both due to higher wait times and (more mechanically) due to shortages. In severely affected markets, consumers who front-loaded their purchases likely crowded out consumers who would have refueled in normal times.

To quantify the distortions to consumer welfare, we develop a model that maps observed refills and non-pecuniary costs to two model primitives: consumers' value of driving and value of time. The model studies the decision to attempt refueling after a news shock shifts consumers' beliefs about the future availability of gasoline. To keep the intertemporal trade-off tractable, we use a two-period setup: fuel supply is fixed in period 1 and resupply in period 2 is believed to be uncertain. In anticipation, some consumers front-load their purchases, creating queues and shortages that raise shopping costs for others. These congestion costs grow as more consumers attempt to refill. The benefit of refueling in period 1 depends on consumers' resupply belief, as well as their initial gas tank level and their value of driving, which reflects reliance on car use and the ease of short-run substitution. The cost of refueling depends on market-level shopping costs and consumers' value of time, which captures their willingness and ability to search and wait. Refill attempts can be unsuccessful due to shortages, which we model as random rationing among all consumers who attempt to refill. In equilibrium, the allocation of gasoline depends on consumers' beliefs, their initial gas tank levels, their values of driving and of time, as well as the initial fuel supply in the market.

Our model captures two sources of loss to consumer surplus: time-related shopping costs and allocative inefficiency. First, refill attempts are costly and queues impose waiting costs if stock is available. Second, consumers may be deterred from refueling due to shopping costs, or may not be able to obtain fuel due to shortage-induced rationing. To benchmark the equilibrium, we derive the optimal fuel allocation for a planner who evaluates the benefit of refueling at the true probability of resupply. If true resupply is unlikely, the planner allows targeted front-loading to ensure that high-value consumers can use their cars in both periods. However, if true resupply is likely, the planner seeks to prevent any front-loading.

We estimate the model to match consumers' refueling behavior in response to the panic shock.[4] Estimation leverages two sources of plausibly exogenous variation that separately shift the benefit and cost of refueling in the first period: consumers' initial gas tank levels, and cross-market variation in shopping costs. To that end, we predict consumers' tank levels based on their average frequency of refills before the panic and parametrize their value of driving and value of time as functions of observed and unobserved characteristics. The observed component includes rich proxies for consumers' reliance on driving, including their prior spending at gas stations, frequency of refills, and spending on other transportation modes. Under the assumptions that rationing happened at random and that the news shock changed beliefs uniformly across consumers and markets, we can link unobserved refill attempts to observed gas station transactions and use the variation in tank levels and

[4] We employ a hybrid estimator that combines likelihood score moments with simulated moments to match aggregate refill shares.

shopping costs to recover the joint distribution of the value of driving and the value of time. Consumers' belief about resupply is a free model parameter that we identify using a model-implied exclusion restriction: attempts by consumers who normally refill *every other* period depend on the resupply belief, whereas attempts by consumers who normally refill *every* period are independent of it.

Consistent with the notion that the value of driving captures reliance on car use, the estimated value of driving is increasing in prior gas station spending and the frequency of tank refills, and decreasing in spending on other transportation modes. Similarly, the estimated value of time is increasing in characteristics correlated with income like the prevalence of work-from-home. For both the values of driving and of time, unobserved heterogeneity is crucial and explains about 50% of the overall variation. Our model implies that consumers believed there was a 45% chance of resupply, implying that front-loading refills was beneficial. Translating these estimates into willingness to wait, we find that the median consumer in our sample would wait more than five hours to secure car use for five days—well beyond the wait times observed in the data.

With the model estimates in hand, we benchmark consumer surplus in equilibrium against the optimal allocation under two belief regimes: (i) consumers have accurate beliefs about resupply, and (ii) consumers have pessimistic beliefs, where the true resupply probability exceeds the belief. This distinction matters for the optimal allocation. With accurate beliefs, equilibrium surplus is 7.5% lower in markets with the most severe shortages, compared to the planner's allocation. The majority of this loss is due to misallocation, rather than shopping costs, because consumers who are expected to refuel in period 1 are rationed due to shortages. With pessimistic beliefs, the loss in consumer surplus is substantially higher because consumers forgo the option value of waiting by front-loading their refills. In particular, for a true resupply probability of 70%, we estimate a total surplus loss of 20–25% across markets. Thus, the market equilibrium does not achieve the optimal allocation under both belief regimes. In addition, if consumer behavior reflects overly pessimistic beliefs, excessive front-loading is another source of welfare loss from panic buying.

In counterfactual analyses, we evaluate alternative allocation rules to mitigate the losses to consumer surplus. We focus on demand-side interventions that can be enacted at the pump and contrast gas-gauge checks, an administrative rule with historical precedent, with mandatory wait times, an ordeal-based policy. We evaluate a simple "half-tank rule" that allows refueling only when a driver's gauge is below half full. We find that this blunt tool can restore allocative efficiency when consumers are overly pessimistic about resupply. By contrast, if beliefs are accurate and resupply is in fact unlikely, preventing high-value consumers with a half-full tank from refueling causes surplus loss; instead, mandatory wait times, set to clear the market, can efficiently target consumers with a high benefit from refueling. However, they impose substantial costs on inframarginal consumers, yielding modestly higher surplus compared to the status-quo equilibrium.

Our analysis demonstrates that misallocation is an economically important source of welfare loss from panic buying, and highlights a key channel: if beliefs deviate from the true likelihood of a disruption, consumers' precautionary behavior harms others and themselves. Policymakers should account for these inefficiencies when considering whether and how to intervene during belief-driven demand surges.

Related literature.—Our paper contributes to the literature on panic buying and stockpiling, which has grown markedly since the COVID-19 pandemic. Recent empirical work has documented how consumers' purchasing behavior responds to lockdown or natural disaster announcements (Hori and Iwamoto 2014; O'Connell, De Paula, and Smith 2021; Keane and Neal 2021; Prentice, Chen, and Stantic 2020; Wood 2024), to anticipated price increases or the lack thereof (Hansman, Hong, De Paula, and Singh 2020; Chakraborti and Roberts 2021), and to information diffusion via news outlets and social media (Iizuka, Toriumi, Nishiguchi, Takano, and Yoshida 2022; Nagy, Csóka, Gyimesi, Kehl, Németh, and Szűcs 2025). Focusing on the first COVID-19 lockdown in the UK, O'Connell, De Paula, and Smith (2021) show that all income groups increased spending on storable goods, but poorer households were relatively less likely to hoard, consistent with a higher prevalence of working away from home. They further document that the demand increase was driven by the extensive rather than the intensive margin, suggesting that per-transaction quotas are unlikely to prevent shortages. In our setting, lower-income consumers, as measured by their total spending, are more reliant on driving and face higher time-related frictions in obtaining gasoline. This pattern is consistent with evidence on the distributional impacts of tolling (Cook and Li 2025) and suggests that panic buying is regressive. Moreover, while the intensive-margin choice of how much to refuel is naturally constrained by tank size in our context, the findings of O'Connell, De Paula, and Smith (2021) indicate that the extensive margin is the key margin of adjustment more generally.

Theoretical work on panic buying has focused on explaining how such behavior can arise in equilibrium and which interventions can help mitigate it (Klumpp and Su 2021; Schmidt, Westbrock, and Hoegen 2023; Awaya and Krishna 2024; Noda and Teramoto 2024). With the exception of Awaya and Krishna (2024), these papers assume homogeneous consumers and model the transitional dynamics using multi-period inventory models in the style of Hendel and Nevo (2006a, 2006b). By compiling uniquely rich data on an illustrative panic buying episode, we present a novel perspective on this belief-driven phenomenon by investigating the role of heterogeneity in consumers' response to a panic-related shock.

Our perspective on the welfare effects of panic buying draws on the theoretical literature on rationing via ordeals (Nichols, Smolensky, and Tideman 1971; Nichols and Zeckhauser 1982; Besley and Coate 1992) and on the efficiency of non-price allocation mechanisms (Weitzman 1977; Hartline and Roughgarden 2008; Che, Gale, and Kim 2013; Condorelli 2012; Dworczak, Kominers, and Akbarpour 2021; Leshno 2022; Akbarpour, Dworczak, and Kominers 2024; Akbarpour, Budish, Dworczak, and Kominers 2024; Yang, Dworczak, and Akbarpour 2024). While ordeals, such as waiting, impose costs on inframarginal consumers, they can improve targeting efficiency if need is unobserved and correlated with willingness to bear the cost. While prior empirical work finds mixed results about the screening properties of ordeals,[5] we find that mandatory wait times improve allocative efficiency relative to the status quo, on average, but that the ordeal cost offsets part of the welfare gain. Conceptually, our paper is most closely related to Russo (2024), who studies the allocative and welfare effects of wait times in healthcare. Relative to her paper, we leverage a unique kind of shock—a shock to beliefs about fuel availability—that allows us to estimate consumers' benefit and compare the equilibrium outcome to the optimal allocation.

Lastly, our model of panic buying draws inspiration from the canonical bank-run model of Diamond and Dybvig (1983). In the classic bank-run model *without* deposit insurance, the productive technology makes the future availability of funds an equilibrium object, which leads to strong complementarities in consumer actions and equilibrium multiplicity. By contrast, in our setting—and in bank runs *with* deposit insurance—consumers anticipate supply disruptions (at banks or gas stations) in the short-run but expect liquidity to be restored eventually.[6] With plausibly exogenous resupply, strategic complementarities are weaker, ruling out multiplicity: if a consumer believes that the gas station will be restocked tomorrow, she need not run today regardless of what others do.[7]

Overview.—The rest of the paper proceeds as follows. Section 2 outlines the setting and Section 3 describes the data and measurement. Section 4 presents the stylized facts. Section 5 develops the model, while Section 6 discusses estimation and presents the results. Section 7 evaluates consumer welfare and counterfactual allocation rules. Section 8 concludes.

[5]Recent studies examine the screening properties of ordeals in the context of welfare programs (e.g., Finkelstein and Notowidigdo 2019; Deshpande and Li 2019; Rafkin, Solomon, and Soltas 2023) and healthcare (Zeckhauser 2021; Russo 2024; Shepard and Wagner 2025).

[6]Analogous to a "lender of last resort," countries typically hold strategic fuel reserves. Consumers face uncertainty about *when* these reserves will be made available.

[7]One could reintroduce richer coordination motives by allowing for higher-order uncertainty or belief updating (e.g., Goldstein and Pauzner 2005; Awaya and Krishna 2024). In our environment, however, a panic-buying episode only leads to congestion and shortages if a sufficiently large share of consumers comes to believe that a near-term market disruption is likely.

2 Setting

We study the UK fuel crisis of September 2021—a nationwide episode of panic buying sparked by media reports of possible fuel delivery disruptions due to a shortage of truck drivers.[8] While no immediate supply constraints existed, a sudden surge in demand led to long queues and widespread shortages that lasted up to two weeks. The crisis underscores the critical role of gasoline in sustaining daily life and essential services, raising concerns about scarce fuel allocation in the absence of a formal rationing mechanism.

Background.—This panic buying episode is a symptom of the supply chain vulnerabilities that emerged in the UK following the COVID-19 pandemic and Brexit. England had removed nearly all legal limits on social contact by the time this event occurred and the last closed sectors of the economy reopened on July 19, 2021. However, consumers had experienced repeated shortages of essential food items, and media reports had raised public awareness about supply chain fragility (O'Connell, De Paula, and Smith 2021; Coleman, Dhaif, and Oyebode 2022).[9]

In the months leading up to the fuel crisis, the UK faced a broad shortage of truck drivers as EU workers returned to their country of origin and vocational training was temporarily suspended (Government 2021). This did lead to a "handful" of gas stations owned by the British Petroleum Company (BP) to close temporarily in July 2021, but these disruptions were resolved within a day (Race 2021). Aggravating the situation at gas stations, the country introduced a new petrol fuel mixture—a switch from E5 to E10 with higher ethanol content—on September 1, 2021, which may have led to some stations drawing down their existing fuel stock (Muyldermans and MacCarthy 2021).[10]

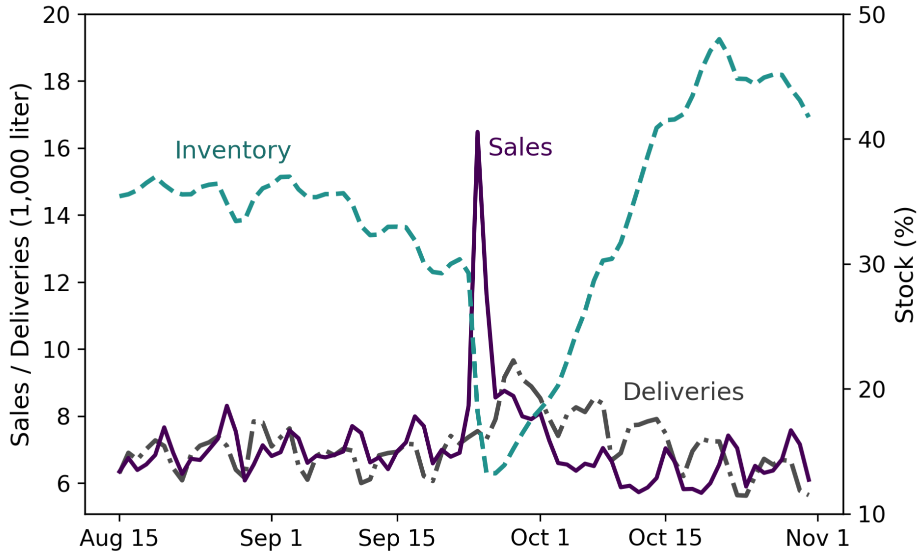
Trigger event.—A key feature of this setting is the clear trigger that shifted consumer beliefs about fuel availability. On September 16, 2021, government officials and industry representatives held a private task force meeting to discuss the impact of the driver shortage on fuel deliveries. During the meeting, a BP representative disclosed that their gas stations were operating at just two-thirds of the normal stock levels required for smooth functioning (The Economist 2021). One week later, on September 23, details from the meeting were leaked to the press and started to circulate widely through national news and social media.

[8] For more background on the 2021 UK fuel crisis, the corresponding Wikipedia entry. Last accessed Sep 18, 2025.

[9] The UK also has a history of fuel panic buying. In 2012, announcements of tank driver strikes triggered another fuel crisis.

[10] Notably, stock levels had already begun to decline in early September, which could reflect the E5/E10 switch or somewhat reduced deliveries due to the truck driver shortage (PRA 2021).

Figure 1: Daily average petrol sales, deliveries, and inventory level across stations in England



Note: Figure shows the average daily sales, deliveries, and inventory level for petrol across gas stations in England, from August 15 to October 31, 2021. Sales and deliveries are measured in thousands of liters; inventory levels are reported as the percent of tank capacity filled. Data are published by the UK Department for Energy Security and Net Zero (DESNZ). For more information, see Official statistics in development on average road fuel sales, deliveries and stock levels (monthly data). Last accessed Feb 11, 2024.

Sales spike, deliveries, and stock.—On the first day of the panic, Friday, September 24 (the day after the leak), national petrol sales surged to roughly 200% of the level observed the previous Friday. In response, stock levels fell sharply, from 29% of tank capacity on September 23 to just 13% four days later. Figure 1, based on official statistics from the UK Department for Energy Security and Net Zero, shows the evolution of average daily petrol sales, deliveries, and stock levels across gas stations in England. It took approximately two weeks for stock levels to return to their pre-panic levels, after which they stabilized around 10 percentage points higher than pre-panic stock levels.[11] Throughout this period, retail fuel prices remained stable (Office for National Statistics (ONS) 2022), consistent with the notion that the panic was driven by beliefs rather than fundamentals.

Shortages, queues, and concerns about misallocation.—As demand intensified, gas stations began running out of fuel, resulting in long queues forming at stations with remaining supplies, and forcing some consumers to wait "for hours" to refill (The Economist 2021).

While official figures on shortages and queue lengths are unavailable, industry and pro-

[11]Trends for diesel, illustrated in Figure A2, exhibit a similar, though slightly less pronounced, pattern. About 45% of all registered cars in the UK run on diesel.

fessional associations conducted surveys to evaluate the disruptions caused by the panic. On the retail side, BP estimated that 30% of its 1,200 UK gas stations had depleted their main fuel grades within two days of the demand surge (James 2021). The Petrol Retailers Association (PRA), representing roughly 5,500 independent fuel retailers, reported that 37% of its forecourts lacked fuel five days into the crisis. Retailers in London and the South East faced particularly severe shortages, with 13% of independent stations still empty ten days into the crisis (PRA 2021).

From the consumer perspective, the Office for National Statistics (ONS) found that 37% of Britons experienced fuel shortages during late September and early October (Office for National Statistics (ONS) 2022). Additionally, a survey by the British Medical Association indicated that 45% of doctors reported staff delays due to refueling issues, and 29% noted staff absences, with disruptions again concentrated in London and the South East (BMA Media Team 2021). Consequently, various professional bodies, including teacher unions, and political figures advocated for prioritizing key workers during refueling (BBC 2021).[12]

Government response.—In an attempt to calm the situation, the government urged consumers to "not panic" and to "continue purchasing petrol as usual." In an official statement made jointly with industry stakeholders, the government reassured the public that the disruptions were due to "temporary spikes in customer demand, not a national shortage of fuel" (Department for Business, Energy & Industrial Strategy 2021b). Some news outlets suggested these reassurances inadvertently intensified the panic.[13]

Concurrently, the government enacted two measures from its *National Emergency Plan for Fuel* (Department for Business, Energy and Industrial Strategy 2020). On September 26, the government activated the *Downstream Oil Protocol*, temporarily exempting fuel firms from competition laws to allow coordinated delivery planning (Government 2021). Subsequently, on October 4—ten days after the initial sales surge—the government implemented *Operation Escalin*, deploying 200 military tanker personnel to support fuel deliveries (UK Government 2021; Department for Business, Energy & Industrial Strategy 2021a).[14] Following these measures and the stabilization of both fuel supply and consumer stockpiling behavior, fuel demand returned to normal levels (Office for National Statistics (ONS) 2022).

[12] Ambulances and school buses are typically refueled at operator depots with their own storage sites (*Operational Productivity and Performance in English NHS Ambulance Trusts: Unwarranted Variations* 2018; Confederation of Passenger Transport 2022).

[13] Iizuka, Toriumi, Nishiguchi, Takano, and Yoshida (2022) demonstrate, in the context of toilet paper shortages during COVID-19 in Japan, that corrective messaging intended to dispel shortage rumors increased demand and worsened shortages. The authors interpret this result as evidence of higher-order uncertainty where consumers, who are confident in product availability, remain uncertain about whether others share this belief.

[14] This operation was coordinated from Buncefield Oil Depot, approximately 40 km northwest of London.

Takeaways.—Overall, this panic buying episode constitutes an unanticipated demand shock, coupled with supply-side frictions. These frictions include, beyond a shortage of truck drivers, contractual rigidity of supply chains, multi-day lead times in fuel deliveries, and stickiness in retail prices.[15]

In response to this and other preceding crises in the UK, policymakers and researchers convened to examine factors driving panic buying and strategies to predict and mitigate such behaviors during crises. Their recommendations for future research include evaluating interventions aimed at reducing panic buying behavior at points of sale, such as supermarkets and petrol stations (Government Office for Science 2023).

3 Data and Measurement

A key feature of this setting is the availability of granular data on shopping costs and consumer spending at gas stations, before and during the panic. In the following, we describe the data, the sample construction, and the measurement of gas station shortages and wait times. We provide additional details in Appendix C.

3.1 Data

Transaction data.—Our primary data source is transaction data from a large payment card network. For our analysis, we focus on transactions made by UK-issued credit and debit cards at UK merchants between April 1–December 31, 2021. Accounting for the network's market share and the fact that about 80% of consumers prefer to use payment cards when purchasing gasoline, the data capture almost 60% of all transactions at gas stations in the UK (YouGov 2022). Each observation in the data represents a transaction between a cardholder and a merchant. The information captured is similar to what appears on a typical account statement: a unique card identifier, the merchant's name and geographic location (both postcode and latitude-longitude coordinates), the transaction amount (in £), and the date and time of transaction (in minutes). While we observe the retail category of the merchant, including a separate category for gas stations, we do not observe the specific goods purchased (e.g., petrol or diesel) or their prices. As we cannot link multiple cards held by the same individual, we treat each card as a separate consumer and use the terms consumer and card interchangeably.

[15] Retailers typically have exclusive supplier agreements that limit sourcing from alternative distributors. Retail prices typically reflect a weighted-average replacement cost and are adjusted when a new delivery arrives. Nonetheless, retailers are allowed to make short-term price adjustments in response to demand shocks.

Wait time data.—To measure wait times at gas stations, we obtain device-level dwell-time data from a location intelligence and foot traffic data company. These data are derived from software development kits (SDKs) embedded within mobile applications and track the location of devices conditional on user consent. For each gas station in the UK, we observe when a device was within 100 meters of the site and its total dwell time, capturing the sum of the time spent waiting and refueling the car. Station latitude–longitude coordinates come from *OpenStreetMaps* (OSM). To capture queues outside the 100-meter radius, we also observe device locations and dwell times for up to two hours prior to the visit. In total, these data span September 13 to October 12, 2021, and cover 1.1 million visits to about 8,250 gas stations.

Fuel price data.—We obtain station-level fuel price data from a fuel pricing and analytics company. Prices are derived from fleet-card transactions and reported by fuel grade (petrol or diesel) at a daily frequency. The dataset comprises a random subset of 1,402 gas stations spanning all major brands, observed from August 1 to October 31, 2021. The dataset also includes station latitude–longitude coordinates.

Aggregate station inventory data.—We obtain information on daily gas station inventories at the sub-regional level from the UK *Department for Energy Security and Net Zero* (DESNZ). These statistics are derived from a sample of 4,900 stations which capture about 80% of typical fuel sales in the UK. The data comprise daily grade-level sales (in liter), deliveries (in liter), and inventories (in percent of total capacity), averaged across stations in the same International Territory Level 3 (ITL-3) area, which corresponds to a county or local authority. We provide details about the different geographic units used in our analysis in Appendix C.1.

Supplementary data.—We combine several publicly available datasets to construct location-based proxies for consumers' reliance on driving. First, we obtain information about the prevalence of work from home from the *2021 UK Census*. Second, we gather information about the availability of public transportation from the *Urban Big Data Centre* at the University of Glasgow (Anejionu, Sun, Thakuriah, McHugh, and Mason 2019; *Public transport availability indicators (PTAI)* 2023). Third, we leverage door-to-door travel times by mode (car, public transport, biking, and walking) from Verduzco Torres and McArthur (2024). In our counterfactual exercise, we also use data on the market-level wage and income distribution from ONS. We describe these datasets in detail in Appendix C.2.

3.2 Consumer sample

Sample construction.—To accurately measure consumers' reliance on driving and spending behavior during the panic, we require that cards are actively used throughout the sample period and repeatedly transact at gas stations. In addition, a card must exhibit a spending pattern that allows us to impute their likely home location. To do so, we use transactions with merchants that consumers tend to visit close to their homes like grocery stores and post offices. Appendix C.3 describes the sample construction in detail.

In our analysis, a market corresponds to a travel-to-work area (TTWA), which approximates a self-contained labor market. To avoid inconsistencies in data availability and variable definition across countries, we restrict attention to TTWAs located in England and drop Northern Ireland, Scotland, and Wales.[16] A consumer's home location corresponds to a lower super output area (LSOA), which is a geographic area for census statistics and contains 400–1,200 households, similar to a US census tract. LSOAs, which map into TTWAs, are the geographic unit at which we observe location-based proxies of reliance in driving. Appendix C.1 describes the geographic units in detail.

Consumer characteristics.—We develop a rich set of characteristics based consumers' card transactions in the months before the panic (April 1–September 15, 2021) and their home locations. These characteristics inform the key dimensions of consumer heterogeneity in our model: the value of driving and the value of time. To that end, we develop variables that proxy consumers' reliance on driving and willingness to wait. We summarize the characteristics here and describe their construction in Appendix C.4.

First, we measure consumers' weekly spending at gas stations and the average number of days between refills.[17] Both variables are informative about consumers' regular gasoline consumption. Second, we measure consumers' total weekly spending, which is highly predictive of their income. Third, we compile four complementary measures of consumers' outside option to driving. Two of them indicate marginal car users: consumers' spending on other transportation modes (including public transportation, taxis, and ride shares), and the percent of home-LSOA residents who work from home. The other two variables capture the cost of substituting away from driving: consumers' time saved from conducting their shopping trips by car (relative to the next fastest transportation mode), and the availability of public transportation at the consumer's home location (*Public transport availability indicators (PTAI)* 2023).[18]

[16]England comprises 84% of UK population and and 78% of all gas stations.

[17]We define a refill as a gas station transaction of at least £10.

[18]The index measures "how public transport service provisions support basic activities of local residents" and reflects the number of trips passing through service stations, as well as the walking distance to these

Table 1: Consumer-level summary statistics

	Mean	SD	p10	p25	p50	p75	p90
(A) Gas station spending							
Gas station spending (£)	26.22	15.31	11.01	15.58	22.77	32.89	45.37
Average days between refills	11.02	6.05	4.71	6.62	9.62	14.00	19.38
(B) Broader spending							
Total spending (£)	364.70	163.91	198.79	248.59	325.03	437.31	587.75
Other transportation spending (£)	2.40	6.79	0.00	0.00	0.21	1.95	6.49
Relative time saved from driving (min)	163.71	167.76	29.98	58.18	109.76	203.16	367.86
(C) Home-LSOA characteristics							
Working from home (%)	34.81	13.46	17.86	24.29	33.83	44.27	53.12
Public transportation availability index	275.98	663.92	9.47	35.43	120.56	305.30	647.24
(D) Refill urgency							
Predicted days until next refill	5.46	5.38	0.00	0.92	4.33	8.10	12.64
Number of consumers	674,879						

Note: Table shows summary statistics for our consumer sample. Consumer characteristics are based on card transactions in the 24 weeks before the panic (April 1–September 15, 2021) and based on consumers' home locations (LSOAs). Panel (A) summarizes gas station spending, including average weekly spending at gas stations and average number of days between refills. A refill is defined as any gas station transaction exceeding £10. Panel (B) summarizes broader average weekly spending, including total spending, spending on other transportation (public transportation, taxi, and ride-share), and relative time saved from driving. Panel (C) summarizes characteristics of consumers' home locations including the percent of residents working from home, and the availability to public transportation. Table A1 shows rank correlations of the consumer characteristics. Panel (D) summarizes consumers' refueling urgency, i.e., the predicted number of days until their next refill, as of the evening of the day before the panic (September 23).

Gas tank level & refueling urgency.—The third dimension of consumer heterogeneity in the model is the initial gas tank level. We infer it from refueling behavior and measure it as the number of days since a consumer's last refill relative to the average number of days between refills. This yields a daily prediction of the consumer's next refill date. We define consumers predicted to refuel within the next five days as "high urgency," and consumers predicted to refuel in six or more days as "low urgency."

Summary statistics.—Our final sample includes 674,879 consumers, residing in 149 TTWAs and 30,357 LSOAs. Table 1 summarizes their characteristics and refueling urgency on the day before the panic. The average consumer spends £365 per week in total, including £26 at gas stations, and refills her car every 11 days. Average refill frequency varies widely across consumers, from every 4–5 days at the 10th percentile to every 19–20 days at the 90th per-

stops (Akbarpour, Dworczak, and Kominers 2024). A higher value reflects better availability of public transportation.

centile.[19] Weekly spending on other transportation is modest, averaging £2.40, reflecting that driving is the default transportation mode in the sample. The average consumer saves 164 minutes per week by traveling by car, with substantial heterogeneity from 30 minutes at the 10th percentile to about 6 hours and 8 minutes at the 90th percentile. There is also considerable variation in the prevalence of work from home: in the bottom decile, 18% of local residents work from home, compared to more than 53% in the top decile. Lastly, as of the end of day on September 23—the day before the sales spike—about 25% of consumers are predicted to refuel on the following day.

3.3 Gas station wait times and shortages

Wait times and shortages are the main sources of shopping costs that consumers faced during the panic. We describe their measurement below.

Gas station wait times.—We aim to capture the total time a consumer had to wait before a refill. To identify successful refills in the dwell time data, we restrict attention to visits where the device came within 35 meters of the gas station centroid. For these events, we sum up the total time spent within 500 meters of the gas station before the refill.

Wait times at individual gas stations are measured with substantial noise due to technological constraints and the limited sample size given our focus on a relatively short period of time.[20] Therefore, in our analysis, we pool gas station visits over the first five days of the panic and focus on the distribution of wait times at the market level.

Gas station shortages.—We infer gas station shortages from the transaction data. The underlying idea is that a shortage manifests as a pronounced dip in sales compared to normal levels. We measure a station's normal sales levels separately for each day of the week and time of the day using transactions from April 1–September 15, 2021. In particular, we sum up the amounts of all transactions at station j on day t between 12–3pm and 3–6pm, and take the median over the pre-panic period. We say that station j on day t experiences a *partial* shortage if sales fall below 55% of median sales in both 3-hour intervals. Similarly, a *full* shortage occurs if sales fall below 20% of median sales in both intervals. We allow for some buffer in sales to accommodate potential non-fuel sales, while the two-interval condition helps avoid flagging temporary variation.[21]

[19] Conditional on refilling, the average consumer spends £32 and buys 24 liters of gasoline (assuming she buys petrol).

[20] SDKs typically only record the location of a mobile device when an app is actively used, and sampling frequency varies across apps and devices.

[21] On average, shop sales account for approximately 11% of gas station revenue, with substantial variation across brands (PRA 2021).

To align measurement, we aggregate the shortage indicators to get the percent of station-days with a partial or full shortage in market m during the first five days of the panic. While the two shortage measures are highly correlated, we primarily use partial shortages because it captures the shortage of one of the two main fuel grades.[22]

4 Stylized Facts

We develop four stylized facts from the UK fuel crisis that speak to two sources of inefficiency from panic buying: non-pecuniary shopping costs and misallocation. We begin by documenting the severity of shortages and wait times across markets, and then illustrate the change in consumers' refueling behavior compared to normal times.

To develop these facts, we focus on short-run distortions during the first five days of the panic, from Friday, September 24–Tuesday, September 28. We choose this five-day period for three practical reasons. First, about half of consumers typically refill during the this period, implying we observe both routine refills and deviations from usual behavior. Second, the period is short enough that repeated refills are rare, letting us treat the choice to refill as a one-off decision. Third, the period aligns with the typical interval for grade-specific deliveries, meaning that most stations receive at least one delivery during this period.

Fact 1: Markets with lower initial inventories experienced more severe shortages.

We begin by documenting substantial heterogeneity in the severity of shortages across markets. Panel (A) of Figure 2 shows a map of TTWAs in England, with each market shaded according to the percent of station-days with a partial shortage during the first five days of the panic. While the average market saw 32% of station-days with shortage, markets in the South East experienced partial shortages up to 60%.

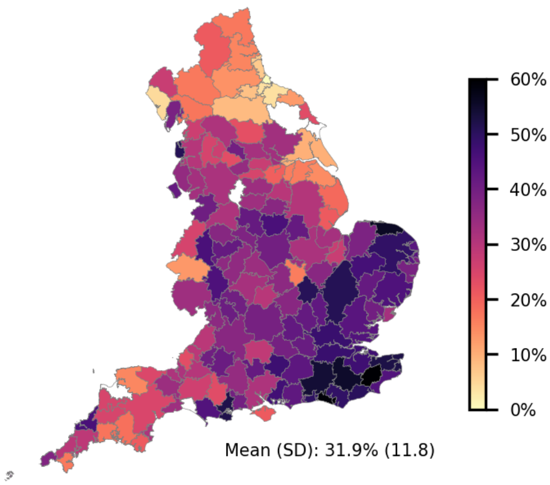
A key driver of this cross-market variation are differences in initial gas station inventory levels. Panel (B) of Figure 2 shades markets according to their average inventory of petrol two days before the panic. Inventories varied widely across markets, with particularly low levels in the South East.The link to shortages is striking and differences in inventory levels explain about 42% of the variation in partial shortages.[23] In Figure A5, we extend the analysis and

[22] A linear fit between the two shortage measures yields a slope coefficient of 0.63 (SE: 0.03), with an R^2 of 0.78. At the end of 2021-Q3, 43.1% of licensed vehicles in England were diesel-powered; among privately owned vehicles, the share was 38.9% (Department for Transport 2024).

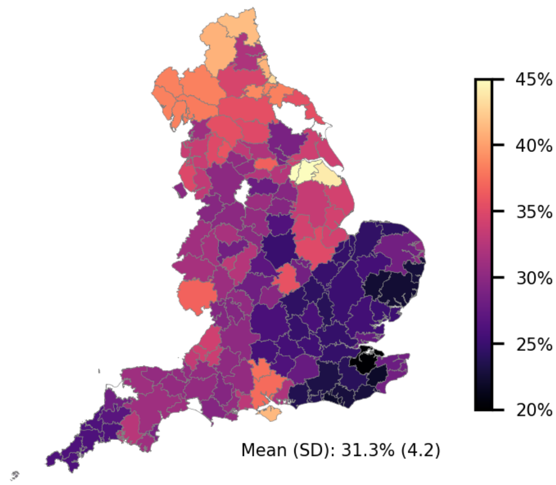
[23] Figure A3 illustrates the correlation between initial inventory levels and the severity of partial and full shortages during the first five days of the panic. Figure A4 shows the spatial distribution of full shortages and of initial diesel inventory levels.

Figure 2: Shortage severity and initial petrol inventory at market level

(A) Station-days with partial shortage



(B) Initial petrol inventory levels



Note: Figure shows severity of shortages and initial petrol inventory level at the market level. Panel (A) shows a map of TTWAs in England, colored according to the percent of station-days with a partial shortage during the first five days of the panic, ranging from low (yellow) to high (black). Panel (B) shows the same map with markets colored according to the average station inventory level for petrol on September 22, 2021, on a scale from high (yellow) to low (black). Inventory levels are reported in percent of tank capacity filled. We omit 5 markets due to insufficient data (white).

relate various market characteristics to the initial sales shock and to our shortage measures. While no characteristic meaningfully predicts the size of the sales shock, initial inventory levels are the strongest correlate of shortages.

This stylized fact yields three takeaways. First, the strong correlation with initial fuel inventories validates our measures of shortage severity. Second, the cross-market variation in shortages likely stems from plausibly exogenous variation in pre-panic inventory levels—a feature we revisit when discussing identification of our model.[24] Third, we view the fact that no market characteristic predicts the size of the sales shock as indicative of a homogeneous shift in consumers' beliefs following the news shock.

Fact 2: Shortages increased wait times at gas stations without affecting prices.

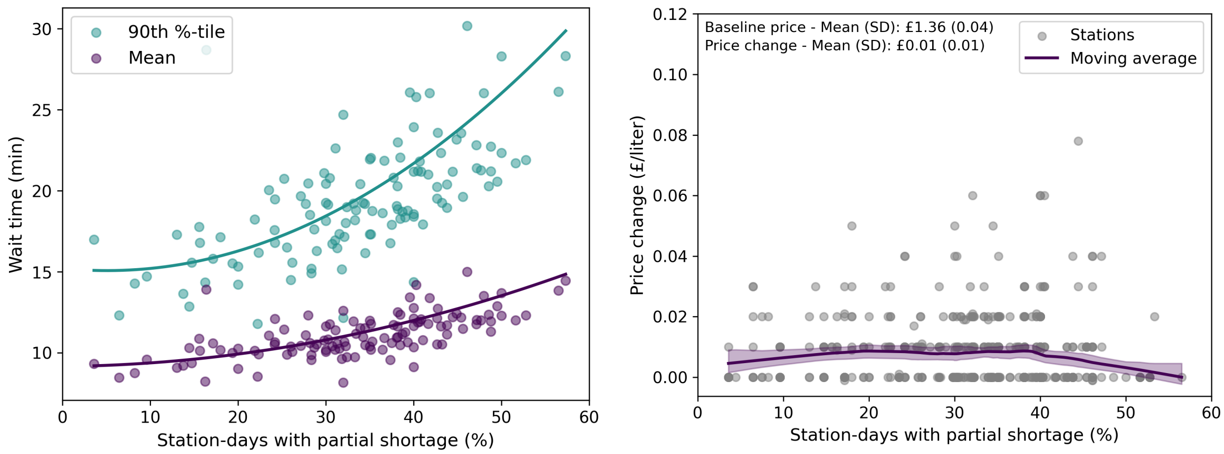
Next, we document how the monetary and time-related costs of refueling changed during

[24]Markets with lower inventories held thinner buffer stocks, i.e., less inventory relative to typical demand, and likely relied on just-in-time deliveries. While we treat the subsequent supply response (e.g., increased deliveries after the initial sales spike) as given, our estimation approach accounts for the fact that our shortage measures likely overstates the true extent of rationing.

Figure 3: Gas station wait times and price changes, by station-days with partial shortage

(A) Market-level wait times

(B) Station-level changes in petrol prices



Note: Figure shows market-level wait times at gas stations and station-level price changes by percent of station-days with a partial shortage. Panel (A) shows the market-level average and 90-th percentile of wait times (in minutes) during the first five days of the panic by shortage severity. We omit markets with less than 200 refill events in the wait times data during this period. Panel (B) shows changes in gas station petrol prices (in £/liter) from two days before to five days after the start of the panic by shortage severity. Each dot represents one gas station. We limit the sample to stations without a partial shortage on the days of price measurement. The line illustrates the local moving average with a 95% confidence interval. Two days before the panic, the average price per liter of petrol was £1.36, corresponding to \$7.05 per gallon. Figure A7 shows market-level wait times and station-level price changes by percent of station-days with a full shortage.

the first five days of the panic.

Panel (A) of Figure 3 shows the relationship between shortage severity and market-level wait times. Markets with more severe shortages experienced higher wait times, especially in the right tail of the distribution.[25] Average wait times increase only modestly under shortages, from 8 to 14 minutes. This corresponds roughly to about a two- to three-fold increase relative to average dwell time before the panic.[26] Thus, while we do find evidence consistent with long queues at gas stations, average wait times did not rise enough to clear the market, as reflected by the severity of shortages.

At the same time, fuel prices at gas stations remained largely unchanged. Panel (B) of Figure 3 shows short-run changes in station-level petrol prices by market-level shortage severity. Five days into the panic, prices were on average £0.01 (0.74%) higher than two days before the panic. This price change is small in absolute and relative terms, and we

[25]The relationship between shortages and wait times is best understood in the context of a queuing model. Each market is a queuing system and each gas station is a server. A shortage corresponds to a server failure and reduces the capacity available in the market. Subsequently, arrival rates at remaining stations increase, causing queues to form more rapidly.

[26]Before the panic, the average gas station visit took 4.2 minutes, primarily reflecting the time spent refueling. We do not expect the average pump time to increase by more than 30 seconds because pumps have an average flow rate of at least 15 liters per minute and consumers bought 5–9 liters more, on average.

find no evidence of a correlation with shortage severity. Also ten and 28 days after the sales spike, we find only small price changes and no heterogeneity by initial shortage severity (see Figure A6).[27]

Because we find no evidence of an endogenous price response in either the short- or medium-run, we omit prices and price expectations from the model. The lack of such a response is consistent with well-documented price rigidities (e.g., Nakamura and Steinsson 2008; Kehoe and Midrigan 2015), including around large demand shocks and natural disasters (Cavallo, Cavallo, and Rigobon 2014; Gagnon and López-Salido 2020; Hansman, Hong, De Paula, and Singh 2020). Stable prices despite shortages are also common in US retail fuel (e.g., Neilson 2009; Beatty, Lade, and Shimshack 2021). In our setting, the most plausible explanation is that retailers feared reputation costs: Consumers strongly dislike price hikes in emergency situations (Holz, Jiménez-Durán, and Laguna-Müggenburg 2024), and the market is concentrated with a handful of brands dominating the retail sector. While the UK has no legal constraints on price hikes, such as anti-price-gouging laws, the UK Competition and Markets Authority monitored practices and issued fines for price gouging during the COVID-19 pandemic (Competition and Markets Authority 2025).

Fact 3: In markets with severe shortages and wait times, relatively fewer consumers refueled their cars.

Next, we document the change in consumers' refill behavior during the panic and the differential impact of shortages and wait times. We focus on the extensive margin and compare the share of consumers who refuel their cars during the first five days of the panic to the same five-day period two weeks prior (September 10–September 14).

Figure 4 shows binscatter plots of the percent of consumers refueling in either period by shortage severity (Panel (A)) and average wait time (Panel (B)). Consistently across markets, about 51% of consumers refuel within the five-day period in normal times. During the panic, markets with minimal shortages and wait times saw refill rates increase to 65–70%. However, only about 55% of consumers refueled in the most severely impacted markets.[28]

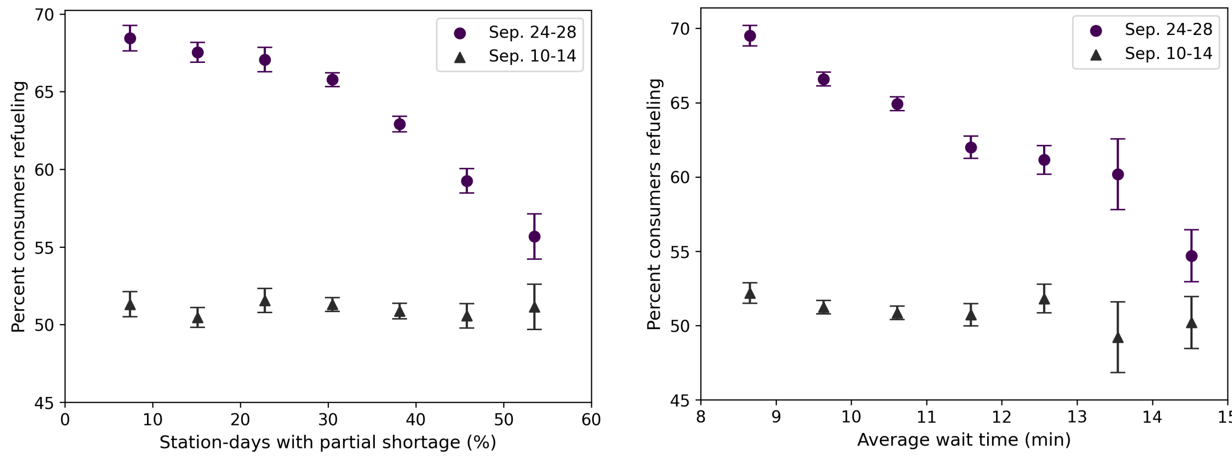
These patterns suggest two takeaways. First, a significant share of consumers responded to the news shock and rushed to gas stations to refuel their cars. Second, shortages and wait times prevented some consumers from refilling, either because they could not find stock

[27] The modest increase in fuel prices 14–28 days after the panic start likely reflects a rise in the crude oil price. This trend is supported by a statement of the PRA Chairman, Brian Madderson in the Guardian: "Expect anything from one, two or even 3p a litre increases at the pump. This is not profiteering. This is genuine wholesale price increases caused by global factors." (Clinton 2021).

[28] We compare the distribution of consumers' refueling urgency in Figure A8 and find no noticeable difference between the two periods, indicating that the news shock was unanticipated.

Figure 4: Market-level refill rates by shortage severity and average wait time

(A) Refill rates by shortage severity (B) Refill rates by wait time



Note: Figure shows binscatter plots of market-level refill rates by shortage severity and average wait time. Both panels show the percent of consumers refueling their cars during the first five days of the panic (Sep. 24-28; purple) and the same five-day period two weeks earlier (Sep. 10-14; gray). Panel (A) plots the refill rates against market-level shortage severity. Panel (B) plots the refill rates against the average wait time. Figure A9, Panel (A) shows market-level refill rates by percent of station-days with a full shortage.

or because they did not attempt a refill due to heightened time-related costs. If not for these constraints, a homogeneous change in consumers' beliefs would predict a more uniform upward shift in refill rates.

Fact 4: In markets with severe shortages, consumers with low refueling urgency crowded out high-urgency consumers.

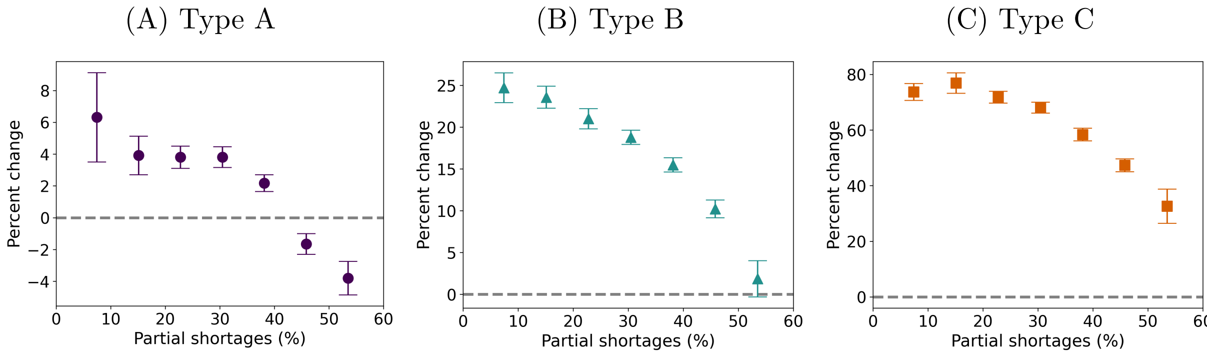
Next, we present evidence consistent with misallocation: in markets with severe shortages, consumers with low urgency to refuel crowded out high-urgency consumers.

In Figure 5, we show the percent change in refill rates relative to normal times for three consumer types. Type-A consumers refill every five days, on average, and thus face high urgency to refuel. Type-B consumers typically refill less frequently, but they experience the news shock when they are predicted to refuel during the first five days of the panic. Type-C consumers are predicted to refill in six or more days, facing low urgency.[29]

In the most affected markets, type-A consumers are significantly *less* likely to refill during the first five days of the panic compared to two weeks prior. At the same time, type-C consumers are still 40% more likely to refill in these markets. This pattern is consistent with a crowding-out effect: by front-loading refills, consumers raised wait times and depleted

[29]Table A2 compares consumer characteristics across the three urgency types.

Figure 5: Change in refill rates, by shortage severity and urgency type



Note: Figure shows binscatter plots of the percent change in market-level refill rates by shortage severity for three urgency types. Type-A consumers refill every five days (high refueling urgency). Type-B consumers refill less frequently but are predicted to refill within the next five days (high refueling urgency). Type-C consumers are predicted to refill in six or more days (low refueling urgency). For each type, we show the percent change in refill rates during the first five days of the panic and the same five-day period two weeks prior. We predict each consumer's refueling urgency as of the end of day on September 23 (panic period) and September 9 (normal times). The horizontal line at zero indicates no change in refill rates between the two periods. Figure A9, Panels (B)–(C) show the percent change in refill rates by percent of station-days with a full shortage.

inventories, preventing some consumers with high urgency from refueling.[30] Our model of panic buying, which we introduce in the following section, allows us to quantify how large this inefficiency is and whether alternative allocation rules can mitigate it.

5 Model

We build a model of panic buying that captures the stylized facts of the UK fuel crisis: (i) non-pecuniary shopping costs, which depend on the initial inventory level in the market, (ii) front-loading of consumers who would not have refilled in normal times, and (iii) potential crowding out of others.

Formally, we develop a model of consumers' refill attempts. Motivated by our setting, consumers experience a news shock which changes their belief about the future availability of fuel. Queues and shortages, which jointly determine how costly a refill attempt is, are determined in equilibrium. To that end, each consumer who attempts a refill exerts a negative externality by raising wait times and reducing inventory available to others. We assume that consumers are atomistic and exert the same, infinitesimal externality.[31]

[30] Figure A10 measures the extent of front-loading by normalizing the change in market-level refill rates by the maximum feasible shift, showing how close behavior came to a full pull-forward. Type-C consumers exhibit consistent front-loading across markets. By contrast, type-A consumers shows substantial heterogeneity, with clear back-loading in some markets.

[31] In Appendix D, we investigate the intensive margin of consumers' refueling behavior and find a similar response across urgency types. Conditional on refueling, consumers bought 29–32 liters of fuel, on average, during the first five days of the panic, corresponding to a 22-36% increase compared to normal times.

5.1 Setup

The model has two periods, $t \in 1, 2$. There is a unit mass of risk-neutral consumers, who decide whether to attempt a refill in period 1 or wait until period 2.[32] In period 1, fuel supply is fixed at $Q \in [\lambda, 1)$, where λ denotes the share of consumers who typically refill in one period.[33] Thus, we measure supply in terms of the share of people who can fill and assume that there is enough supply to satisfy the normal demand level. In contrast, resupply in period 2 is believed to be uncertain. Specifically, consumers experience a news shock at the start of period 1 and form a belief about the likelihood of fuel deliveries in period 2. For simplicity, we assume that all consumers hold the same ex-ante belief that resupply happens with probability $\tilde{s} \in (0, 1)$. We allow consumers' belief to differ from the true probability of resupply, which denote by s.[34]

Wait times and shortages.—We model wait times and shortages as functions of the share of consumers who attempt a refill in period 1. We denote this share by n.

Following the queuing literature, we specify the average wait time as an increasing and convex function of n (Shortle, Thompson, Gross, and Harris 2018, p.90).[35] Because consumers face minimal waits in normal times, we say that queues start to form once $n > \lambda$. In particular,

$$\phi'(n) > 0 \quad \text{and} \quad \phi''(n) > 0 \quad \text{for} \quad n > \lambda \tag{1}$$

with $\phi(n) = 0$ for $n \leq \lambda$.

In the model, shortages lead to random rationing. That is, if $n > Q$, fuel is as-good-as randomly allocated among all consumers who attempt a refill. We can write the probability of a successful refill conditional on attempting as

$$q(n) = \min\{1, Q/n\} \ . \tag{2}$$

This specification assumes that consumers who attempt a refill arrive at gas stations in an order that is uncorrelated with their preferences and urgency to refuel.

[32]We assume that consumers refill their entire tank and that tank capacity is binding.

[33]As illustrated in Figure 4, about 51% of consumers in our sample refill their cars over the five-day period in normal times, implying that $\lambda \approx 0.51$.

[34]In our setting, this wedge may reflect incomplete information about the true extent of the truck driver shortage.

[35]In standard queuing models, such as the M/M/c model, customers arrive according to a Poisson process. The average wait time in such models is increasing and convex in the arrival rate, and increases faster if relatively fewer servers are available. In our context, an increase in n corresponds to an increase in the arrival rate. A shortage corresponds to a decrease in the number of servers.

5.2 Refill attempts

Consumers attempt to refuel in period 1 if the expected utility of an attempt exceeds that of waiting and refueling in period 2. Next to the resupply belief and the prevailing market-level wait times and shortages, this decision depends on three consumer characteristics: their *per-period* value of driving, v_i, their value of time, τ_i, and their urgency type, g_i.

Because consumers experience the news shock at different fuel levels, they differ in how urgently they need to refuel to continue using their cars. To keep with the two-period setup, we define three, discrete urgency types based on consumers' refill frequency before the panic and their refueling urgency (or initial gas tank level) at the start of period 1. We describe the urgency types and their decisions below. Details are provided in Appendix E.

Type-A consumers.—A type-A consumer typically refills every period and therefore starts period 1 with an empty tank. To use her car in period 1, she must refill. Because she depletes a full tank within one period, her decision is statistic and does not depend on the resupply belief.[36] For a given share of consumers who attempt a refill, n, the consumer attempts herself iff:

$$U_{iA}(n\,;\,v_i,\tau_i) \;=\; q(n)\Big(v_i \;-\; \tau_i\,\phi(n)\Big) \;-\; \tau_i\,c \;+\; \varepsilon_i \;\geq\; 0\;. \tag{3}$$

The consumer can successfully refill with probability $q(n)$. In this case, she obtains her value of driving, v_i, but has to queue and pay the waiting cost, $\tau_i\,\phi(n)$. In any case, she has to pay the time-related fixed cost, c, making an attempt costly even if unsuccessful. As more consumers attempt a refill, $q(n)$ decreases and $\phi(n)$ increases, making an attempt relatively less attractive. ε_i denotes a logit error assumed to be T1EV. We normalize the non-driving outside option utility to zero plus a utility shock.

The value of driving, v_i, represents the consumer's value of using her car relative to the next-best available transportation option, which may include no transportation at all. It can be viewed as her reliance on car use or sensitivity to running out of fuel, and reflects her private costs of substituting away from driving in the short-run. The value of time, τ_i, captures her opportunity costs of time and reflects her willingness and ability to search for stock and wait in line. If consumers differ in their value of time, queues and shortages impose different effective prices on different consumers.[37] We treat (v_i,τ_i) as latent variables and

[36] Conditional on refilling, gasoline consumption over the period is fixed in the short run. The choice margin is whether to refill, not how much to consume.

[37] Akbarpour, Dworczak, and Kominers (2024) make a similar argument that differences in consumers' willingness to pay may reflect idiosyncratic preferences and the ability to pay. Especially in the short-run, consumers may face frictions such as scheduling constraints.

later parametrize them as functions of observed and unobserved consumer characteristics.[38]

Type-B consumers.—A type-B consumer typically refills every other period and enters period 1 with an *empty* gas tank. Like type A, she must refill in period 1 to use her car. Since her gas tank lasts two periods, her attempt decision is dynamic and depends on the resupply belief $\tilde{s}$. In particular, she attempts a refill iff:

$$U_{iB}(n, \tilde{s}\,;\, v_i, \tau_i) \;=\; q(n)\Big(\underbrace{(1+\delta)(1-\tilde{s}\delta)}_{\equiv L_B(\tilde{s})}\, v_i \;-\; \tau_i\, \phi(n)\Big) \;-\; \tau_i\, c \;+\; \varepsilon_i \;\geq\; 0\;. \tag{4}$$

We refer to $L_B(\tilde{s})$ as the urgency loading for type B. This term captures that a successful refill guarantees her value of driving in period 1 *and* protects her against the case of no resupply in period 2. She discounts future periods at $\delta < 1$ and accounts for the continuation value of any gas on hand at the end of period 2 if she were to refill in period 2. For simplicity, we abstract from the supply-side inventory problem and assume that fuel availability in period 2 is independent of the equilibrium realization in period 1.[39]

Type-C consumers.—A type-C consumer also refills every other period, but enters period 1 with a *half-full* tank. She could wait until period 2, but might prefer to front-load her refill to avoid the case of no resupply. She attempts to refill iff:

$$U_{iC}(n, \tilde{s}\,;\, v_i, \tau_i) \;=\; q(n)\Big(\underbrace{\delta(1-(1+\delta)\tilde{s})}_{\equiv L_C(\tilde{s})}\, v_i \;-\; \tau_i\, \phi(n)\Big) \;-\; \tau_i\, c \;+\; \varepsilon_i \;\geq\; 0\;. \tag{5}$$

Because she is guaranteed to use her car in period 1, the only gain from refilling early is her value of driving in period 2 in the case of no resupply. Attempting an early refill is only beneficial if she believes that resupply is unlikely, namely $\tilde{s} \leq 1/(1+\delta)$. If instead $\tilde{s}$ is high, she prefers to wait due to the continuation value of gas on hand.

Altogether, we can summarize consumers' refill attempts across urgency types g as:

$$U_{ig}(n, \tilde{s}\,;\, v_i, \tau_i) \;=\; q(n)\Big(\underbrace{L_g(\tilde{s})\, v_i}_{\equiv \mathcal{V}_i(\tilde{s})} - \tau_i\, \phi(n)\Big) \;-\; \tau_i\, c \;+\; \varepsilon_i \;\geq\; 0\;, \tag{6}$$

[38] We assume consumers know their (v_i, τ_i) and that they remain constant across periods. (v_i, τ_i) may be correlated, but we do not force them to co-vary in any particular way.

[39] If resupply does not happen, no consumer will attempt to refill in period 2. If resupply happens, there is no risk of shortages and refills happen as part of longer shopping trips. Therefore, consumers hold no expectations over wait times and shortages in period 2, and face no wait times, shortages, or the fixed attempt cost in period 2.

with type-specific loading $L_A = 1$, $L_B = (1+\delta)(1-\tilde{s}\delta)$, and $L_C = L_B - 1$, that shift the benefit a refill as a function of $\tilde{s}$. We refer to $\mathcal{V}_i(\tilde{s}) = L_g(\tilde{s})\, v_i$ as the refill benefit of consumer i of type g, given the resupply belief $\tilde{s}$.

Given n, consumer i attempts a refill with probability

$$\pi_{ig}(n, \tilde{s}\,;\, v_i, \tau_i) = \Pr(U_{ig}(n, \tilde{s}) \;\geq\; 0)\ . \tag{7}$$

5.3 Market equilibrium and planner solution

We next derive the market equilibrium and planner solution to our model. The planner may deviate from the market allocation for two reasons: he seeks to allocate fuel based on the refill benefit, independent of consumers' value of time, and he evaluates the refill benefit at the true resupply probability, s.

Market equilibrium.—In our model, the market equilibrium is a fixed point in the share of consumers who attempt to refill in period 1. To ensure uniqueness, we assume that (v_i, τ_i) are i.i.d. draws from a bivariate distribution F that is continuous, strictly increasing, and has unbounded support on $(0, \infty)$ across the population of drivers.[40]

Let λ_A denote the share of type-A consumers in the market, λ_B the share of type-B consumers, and $\lambda_c = 1 - \lambda_A - \lambda_B$ the share of type-C consumers. Given n, the aggregate attempt probability is

$$\begin{aligned}\Psi(n) \;=\; \lambda_A \int \pi_{iA}(n)\, dF(v_i, \tau_i \,|\, g_i = A) \;+\; \lambda_B \int \pi_{iB}(n)\, dF(v_i, \tau_i \,|\, g_i = B) \\ +\; \lambda_C \int \pi_{iC}(n)\, dF(v_i, \tau_i \,|\, g_i = C)\ . \end{aligned} \tag{8}$$

Since Ψ maps from $[0, 1]$ to itself and is weakly decreasing in n, it follows (by Brouwer's fixed-point theorem) that the function has a fixed point. In addition, with the regularity conditions on F and assuming that $\tilde{s} < 1/(1+\delta)$, the fixed point is unique and satisfies $n^* > \lambda$, meaning that more consumers attempt to refill than in normal times.[41]

Consumer welfare.—Our model captures two sources of loss to consumer welfare, reflecting the shopping costs and allocative inefficiency. First, consumers who attempt a refill pay

[40] These regularity conditions ensure that there is a unique ranking of consumers in order of v_i/τ_i. In addition, the assumption of a homogeneous externality ensures that order of arrival at gas stations does not matter, thus avoiding the equilibrium indeterminacy of finite-player games as in Berry (1992).

[41] Note that $n \leq \lambda$ cannot constitute an equilibrium because $\phi(\lambda) = 0$ and $q(\lambda) = 1$. For $n > \lambda$, $\phi(n)$ is strictly increasing and $q(n)$ is weakly decreasing, implying that Ψ is strictly decreasing. Consequently, $\Psi(n)$ is a contraction mapping, and by a simple single-crossing argument, $\Psi(n)$ intersects the 45-degree line exactly once, establishing the unique equilibrium share of consumers attempting to refill.

the fixed cost of an attempt and, conditional on finding stock, also pay the waiting cost. Second, consumers may be deterred from attempting due to time-related costs, or may be rationed by shortages. We can write the ex-ante expected consumer welfare as

$$\mathcal{W}^{EQ}(\tilde{s}) \;=\; \int \pi_i(n^*, \tilde{s}\,;\, v_i, \tau_i)\; \mathrm{E}\left[\, U_i(n^*, \tilde{s}\,;\, v_i, \tau_i) \,\right]\, dF(v_i, \tau_i)\ , \tag{9}$$

where $\pi_i(n^*, s)$ is the equilibrium attempt probability and $\mathrm{E}\left[U_i(n^*, s)\right]$ is the ex-ante expected utility of a refill attempt.

Planner solution.—Our planner differs from the market equilibrium in two ways. First, we assume that the planner can assign state-contingent refill rights, which guarantee refills in period 2 regardless of resupply. This feature ensures that assigned consumers do not have to queue and pay no attempt cost. Consequently, the planner seeks to maximize the total refill benefit independently of consumers' values of time.[42] Second, the planner evaluates the refill benefit at the true resupply probability, affecting the relative ranking of consumers. In particular, if consumers are too pessimistic about resupply ($\tilde{s} < s$), the planner will prioritize consumers with high refill urgency, i.e., type-A and type-C consumers, even if they have a low value of driving, v_i.

Given the true resupply probability $s \in \{0, 1\}$, the planner assigns at most Q refills to the consumers with the highest refill benefit, $\mathcal{V}_i(s)$, conditional on $\mathcal{V}_i(s) \geq 0$. Let ζ^* be the cutoff that solves

$$\int \mathbf{1}\left\{\mathcal{V}_i(s) \geq \zeta^*\right\}\, dF_v(v) \;=\; Q\ .$$

Then, consumer welfare under the planner's allocation equals

$$\mathcal{W}^{SP}(s) \;=\; \int \left[\mathcal{V}_i(s)\right]_+ \mathbf{1}\left\{\mathcal{V}_i(s) \geq \zeta^*\right\}\, dF_v(v)\ . \tag{10}$$

6 Estimation and Identification

Estimation leverages the observed equilibrium realizations of shortages, wait times, and refill decisions. Identification comes from variation in refill urgency across consumers and shopping costs across markets that independently shift the benefit and cost of a refill attempt. To link observed refills to model primitives, we rely on several assumptions outlined below.

[42] Suppose the planner seeks to allocate $q > \lambda$. Doing so in period 1 would create queues and reduce realized benefits. With state-contingent rights, the planner can postpone type-C consumers to period 2, avoiding queues.

6.1 Parametrization

Consistent with the stylized facts, we define period 1 as the first five days of the panic. A type-A consumer typically refuels every five days. Type B refuels less frequently but is predicted to refuel during the first five days of the panic. Type C is predicted to refill in six or more days. Table A2 reports consumer characteristics by urgency type. On average, type-A consumers spend more at gas stations and overall, and they realize greater time savings from car travel. By contrast, the types look similar in prior spending on other transportation, the prevalence of working from home, and the availability of public transportation in their home-LSOA.

We model the value of driving, v_i, and value of time, τ_i, as functions of observed and unobserved consumer characteristics. Specifically, we assume that (v_i, τ_i) follow a bivariate lognormal distribution:

$$\ln v_i \;=\; \bar{v} \;+\; X_i' \boldsymbol{\beta} \;+\; \eta_i \tag{11}$$

$$\ln \tau_i \;=\; \bar{\tau} \;+\; X_i' \boldsymbol{\gamma} \;+\; \kappa_i \;, \tag{12}$$

where X_i is the vector of consumer characteristics described in Table 1 and

$$\begin{pmatrix} \eta_i \\ \kappa_i \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_v^2 & \rho\sigma_v\sigma_\tau \\ \rho\sigma_v\sigma_\tau & \sigma_\tau^2 \end{bmatrix} \right) \;. \tag{13}$$

We assume that, conditional on X_i, the distribution of (v_i, τ_i) is common across markets. Hence, any cross-market heterogeneity is attributed to differences in observed characteristics alone. As neither v_i nor τ_i is directly observed, we treat both as latent variables. In the estimation, they can be thought of as random effects.[43]

Following the assumption of random rationing, we model the conditional refill probability as a Bernoulli draw with the success rate determined by the observed severity of shortages in a market. In particular, we assume the following parametric relationship between equilibrium shortages and rationing,

$$q_m = \Pr(\text{refill}_i \,|\, \text{attempt}_i = 1) = \exp(\alpha W_m) \;, \tag{14}$$

where W_m denotes the share of station-days with a partial shortage in market m, and α is a parameter to be estimated. This specification ensures that the conditional probability equals 1 in markets without shortages ($W_m = 0$) and that it decreases in shortage severity

[43] For estimation, we measure all covariates in X_i in deviations from the sample mean. Thus, the constant in each equation is the mean of the dependent variable.

for $\alpha < 0$.

We can now write the net expected utility from refilling in period 1 as a function of covariates and parameters:

$$U_{igm}(\theta\,;\, X_i, W_m, \phi_m) = \\ \underbrace{\exp(\alpha W_m)\Big(L_g(\tilde{s})\, v(X_i,\eta_i) - \tau(X_i,\kappa_i)\,\phi_m\Big) \,-\, \tau(X_i,\kappa_i)\, c}_{\equiv \bar{U}_{ig}} + \varepsilon_{im}\ . \quad (15)$$

The type-specific loading, $L_g(\tilde{s})$, is a function of the resupply belief, $\tilde{s}$, which is a free parameter in the model. ϕ_m is the market-average wait time during the first five days. We assume that all consumers face the same fixed cost of a refill attempt equal to $c = 6$ minutes, reflecting the average driving time from a consumer's home-LSOA to the closest gas station. We set $\delta = 0.9993$, corresponding to an annual discount rate of 5%. With seven consumer characteristics in X_i, the parameter vector θ contains 21 coefficients and is given by $\theta = \{\bar{v}, \boldsymbol{\beta}, \bar{\tau}, \boldsymbol{\gamma}, \sigma_v, \sigma_\tau, \rho, \tilde{s}, \alpha\}$.

We can then write the attempt probability in its standard logit form:

$$\pi_{igm} = \Pr(\text{attempt}_i = 1) = \exp(\bar{U}_{igm}) \,/\, \big(1 + \exp(\bar{U}_{igm})\big)\ , \quad (16)$$

and account for random rationing to get the probability of a refill, $p_{igm} = \pi_{igm} \cdot q_m$.

6.2 Identification

We aim to recover the model parameters from consumers' behavior in response to the panic shock using a single cross-section of choices. In the following, we discuss what variation in consumers' refill rates identifies their value of driving and value of time, (v_i, τ_i), the resupply belief, $\tilde{s}$, and the random rationing parameter, α. We provide an intuitive argument for identification here and refer to Appendix F for a formal derivation.

Values of driving and time.—To build intuition, suppose we observed the decision to *attempt* a refill for the same consumer at different levels of refueling urgency and across markets with different time-related shopping costs. Identification of the values of driving and of time, (v_i, τ_i), comes from two orthogonal shifts: urgency shifts the benefit of attempting, while shopping costs shift the cost of attempting. Intuitively, conditional on shopping costs, an attempt at *low* urgency indicates a high v_i, whereas no attempt at *high* urgency indicates a low v_i. Within urgency type, comparing a low-cost to a high-cost market identifies the value of time (conditional on v_i): the refill benefit is fixed across markets, so differences in attempts are driven by τ_i through time-related shopping costs.

These comparisons require that the news shock was unanticipated, meaning consumers experienced it at random points in their refill cycle, and changed beliefs uniformly for all consumers and markets. In addition, markets must be identical except for initial fuel inventories, giving rise to plausibly exogenous variation in shortages and wait times in equilibrium.

Resupply belief.—In the model, consumers hold an ex-ante belief about resupply following the news shock.[44] We include this belief as a free parameter to rationalize observed refill rates. Identification leverages an exclusion restriction implied by our model: refill attempts of type-A consumers are independent of $\tilde{s}$. Thus, how much more likely a type-B consumer is to attempt a refill, compared to a type-A consumer with the same (v_i, τ_i), is informative about $\tilde{s}$: a larger gap indicates a more pessimistic belief about resupply.

In practice, we do not observe the *same* consumer as an urgency type A and B: by definition, a type-A consumer must refill more frequently, on average. Therefore, we rely on extrapolating the value of driving across urgency types in characteristics space, at least along the dimension of average days between refills.

Random rationing.—To recover attempt probabilities from observed refill rates, we assume that rationing happens at random. Thus, observed refills are a representative subset of all attempts. In addition, we rely on the parametric mapping of market-level shortage severity, W_m, to the conditional success probability, q_m. Intuitively, α governs how quickly the expected utility of an attempt decays as we move the same consumer to markets with more severe shortages. While within-market differences in refill rates across urgency levels pins down v_i, the ratio of these differences across markets with different W_m pins down α. See Appendix F for more details.

Identifying assumption.—In practice, identification relies on comparing refill decisions of observably similar consumers (i) within markets across types $g \in \{\text{A,B,C}\}$ and (ii) across markets at different time-related shopping costs (W_m, ϕ_m). To that end, we rely on the following four assumptions.

(A1) **News shock & beliefs.** The news shock was unanticipated and shifted resupply beliefs uniformly across consumers and markets.

(A2) **Shopping costs & rationing.** Consumers form correct expectations about equilibrium wait times and shortages; among those who attempt a refill, rationing is random.

[44] It is plausible that consumers overstated the true probability of delivery disruptions relative to how industry experts or the government assessed the situation. This is, however, not inconsistent with rational expectations given that consumers probably had much less information available.

(A3) **Exogeneity.** Unobserved heterogeneity is independent of market and type, meaning $(W_m, \phi_m, g_i) \perp (\eta_i, \kappa_i)$.

(A4) **Support & mapping.** There is sufficient overlap in observables X_i across urgency types and markets. Primitives follow the mappings $v_i = v(X_i, \eta_i)$ and $\tau_i = \tau(X_i, \kappa_i)$ that are invariant across types and markets.

We allow (v_i, τ_i) to vary with observed consumer characteristics X_i, but assume that unobserved tastes, (η_i, κ_i), are i.i.d. and that their distribution is invariant to X_i. Thus, cross-market comparisons are valid because market shocks (W_m, ϕ_m) are as-good-as random relative to unobserved tastes, and within-market cross-type comparisons are valid because type does not shift v_i or τ_i beyond its effect on X_i. We discuss our assumptions about consumers' beliefs in detail in Section 6.5.

6.3 Estimation

We estimate the model using a hybrid procedure that combines likelihood score moments, in the style of a generalized method of moments (GMM) estimator, with simulated moments of aggregate refill shares, as a simulated method of moments (SMM) estimator. By stacking these moments, we ensure that the model fits observed refill rates while preserving the likelihood-implied curvature that stabilizes estimation.

Specifically, for each candidate parameter vector $\hat{\theta}$, we simulate refill probabilities $p_{igm}(\hat{\theta})$ and form two sets of moments. First, we include score-type moments based on the average prediction error, $y_{igm} - p_{igm}(\hat{\theta})$. Second, we form aggregate moments that match refill shares by market and urgency type. The estimator then minimizes the mean squared distance between empirical and model-implied moments. We describe the moment conditions in detail in Appendix G.

6.4 Results

Table 2 presents the estimation results. For the value of driving, we estimate marginal effects consistent with the notion that v_i reflects consumers' reliance on driving: it is increasing in prior gas station spending, average refill frequency, and time saved from driving. In addition, v_i is decreasing in total spending and spending on other transportation modes, consistent with lower costs of substituting away from driving. The value of time is increasing in the prevalence of work from home, potentially reflecting the preferences of more affluent consumers. In addition, we find that consumers who refill *less* frequently face a higher cost to waiting, conditional on gas station spending. Overall, our results suggest that panic buying

Table 2: Estimation results

	$\ln v_i$ equation		$\ln \tau_i$ equation	
Constant	1.2515	(0.1757)*	–1.3538	(0.1365)*
Gas station spending	0.6968	(0.0862)*	0.1356	(0.1025)
Average days between refills	–0.9088	(0.0873)*	0.7176	(0.0739)*
Total spending	–0.5214	(0.0765)*	–0.6160	(0.1076)*
Other transportation spending	–0.7132	(0.3725)	–0.3886	(0.3590)
Relative time saved from driving	0.3304	(0.1105)*	0.2121	(0.1237)
Home-LSOA working from home	0.5064	(0.3556)	1.6863	(0.2251)*
Public transportation availability	–0.0314	(0.1674)	–0.1195	(0.2404)
Unobserved heterogeneity, SD	3.7907	(0.1370)	3.7679	(0.1235)
Unobserved heterogeneity, correlation	0.3988	(0.0352)		
Resupply belief, $\tilde{s}$	0.4521	(0.0035)		
Random rationing, α	–0.1206	(0.0374)		

Note: Table reports point estimates and standard errors of the model parameter. All covariates are measured in deviations from their sample mean. Standard errors from 100 bootstrap samples clustered at the market level. * Significant at the 5% significance level.

is regressive because lower-income consumers, as measured by total card spending, are more reliant on driving *and* face higher time-related frictions in obtaining gasoline. This finding is consistent with existing evidence on the distributional impacts of highway tolling, which shows that lower-income drivers benefit most from priced toll lanes because they drive longer distances and can achieve higher time savings (Cook and Li 2025).

Furthermore, we find that unobserved heterogeneity is substantial and equally important for both the value of driving and the value of time. This is true in absolute terms ($\hat{\sigma}_v = 3.79$ and $\hat{\sigma}_\tau = 3.77$) and relative to the (absolute) mean (3.03 and 2.79, respectively). Similarly, observables account for 42% of the variation in $\ln v_i$ and for 46% of the variation in $\ln \tau_i$. We also estimate a positive correlation of $\hat{\rho} = 0.4$ between the unobserved components of the value of driving and the value of time. This implies that consumers with a higher unobserved reliance on driving also face higher frictions of refueling during the panic, potentially exacerbating misallocation.

We estimate a resupply belief of 0.45, implying that consumers assigned a 55% chance to resupply disruptions following the news shock. With this belief, front-loading is beneficial for type-C consumers. Across markets, we find modest random rationing in equilibrium. Figure A11 illustrates the estimated relationship between shortage severity (W_m) and the conditional refill probability (q_m). In the most affected markets, consumers had a 93% success probability conditional on attempting a refill.

Table A3 summarizes key moments of the distribution of the value of driving and value of time. To provide intuition for their magnitudes, we translate the estimates into a measure of consumers' willingness to wait. That is, for each consumer i, we solve for the wait time, ϕ_i, that sets their expected utility of refueling to zero, i.e., $L_g(\hat{\bar{s}})\,\hat{v}_i - \hat{\tau}_i\,\phi_i = 0$. Overall, consumers' predicted values of driving and of time are positively correlated, with a rank correlation of 0.33. The median consumer in our sample is willing to wait 5 hours and 13 minutes to ensure five days of car use. However, willingness to wait is highly correlated with urgency: The median type-C consumer is only willing to wait 32 minutes.

6.5 Discussion

In our setup, panic buying results from a change in beliefs about future fuel availability. Because we do not observe beliefs, we rely on two key assumptions which we discuss below.

First, we assume that consumers correctly anticipate equilibrium wait times and shortages in their market, while holding a possibly pessimistic belief about the likelihood of resupply. Empirically, consumers appear to have assigned a lower probability to resupply than did the government or industry experts. This is not at odds with rational expectations: beliefs are formed ex ante over a stochastic event, and observing a single, more favorable ex post realization does not render those ex ante probabilities inconsistent with rational expectations. One explanation for a wedge in beliefs is that consumers have incomplete information about the upstream fuel market and the severity of the truck driver shortage.

Second, we assume that the news shock shifted beliefs uniformly across consumers and markets. This arguably strong assumption can bias our results in two ways. First, if belief heterogeneity reflects information differences about resupply, then we would (incorrectly) load this heterogeneity onto unobserved preferences (η_i, κ_i) and treat it as welfare-relevant. However, some of that unobserved heterogeneity may also reflect risk attitudes or fueling preferences, which are features a planner would care about. Consequently, we cannot cleanly separate informational heterogeneity from unobserved tastes. Second, if beliefs vary systematically with shortage severity (e.g., more pessimism where disruptions are worse), then part of the observed decline in refill attempts in these markets reflects beliefs rather than shopping costs. Extrapolating from less-affected markets would understate refill attempts and overstate the value of time.[45] The biggest concern would be if beliefs were market- and type-specific and the relative decline in refill rates were to reflect optimism rather than crowding out.

Given the lack of data on consumer beliefs, we adopt the uniform-belief assumption and

[45] Markets with severe shortages also feature longer waits, making them especially informative about τ_i. This covariance can tilt estimates upward if not accounted for.

recover $\tilde{s}$ that rationalizes observed outcomes. We view the resulting preference estimates as stylized bounds suited to our goal of measuring misallocation rather than a full welfare ranking under heterogeneous, belief-driven behavior. In ongoing work, we are relaxing the uniformity assumption.

7 Consumer Welfare and Counterfactuals

7.1 Consumer welfare

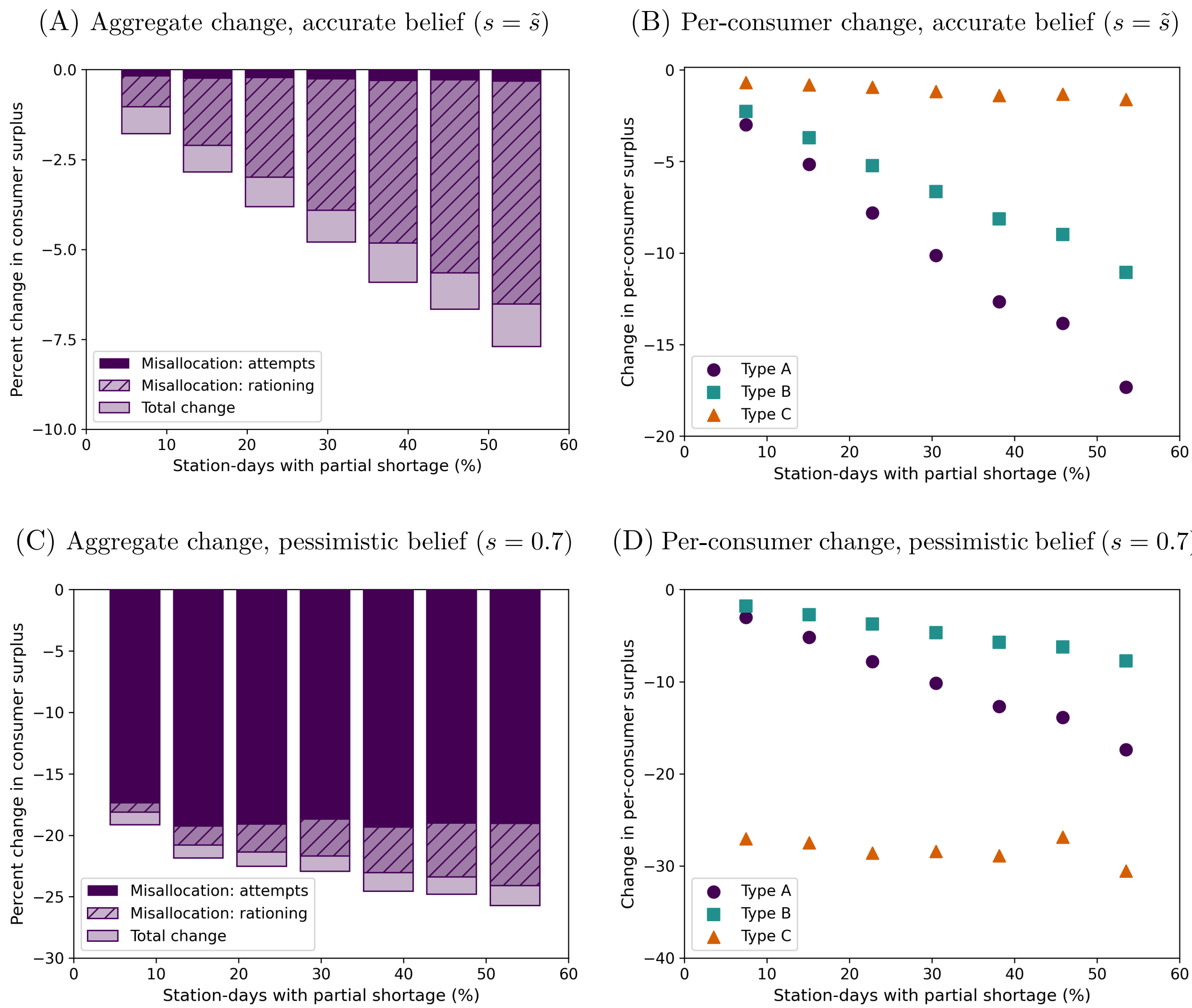
We benchmark consumer welfare in equilibrium against the optimal fuel allocation. The planner seeks to allocate fuel to the Q_m consumers with the highest, positive refill benefit, $L_g(s)v_i$, given the true resupply probability s. Because we observe at least some shortages in all markets, we measure Q_m by the share of consumers with a refill in period 1.

The loss in consumer surplus from misallocation is simply the difference in the aggregate refill benefit in equilibrium and the optimal allocation. To separate misallocation due to wait times versus random rationing, we compute this difference twice: first weighting refill benefits by attempt probabilities, which captures forgone refills due to queues, and then by refill probabilities, which also captures failed attempts due to shortages. The total surplus loss, which corresponds to the difference in consumer welfare in Equations (9) and (10), additionally accounts for the fixed cost of refill attempts and the waiting cost of successful attempts. We compute the change in consumer welfare both for the case that consumers' belief is accurate ($s = \tilde{s}$) and for the case that they are too pessimistic about resupply ($s = 0.7$).

Figure 6 shows the relative change in consumer surplus across markets by shortage severity. Panels (A) and (B) report the aggregate and per-consumer surplus loss, respectively, for the case that consumers' resupply belief is accurate. Compared to the optimal allocation, equilibrium surplus is steadily decreasing with shortage severity and up to 7.5% lower in the most affected markets. This decline is driven by misallocation and is due to shortages in particular. That is, consumers attempted to refill despite higher wait times but were ultimately rationed because stations were out of stock. Losses in total surplus are concentrated among consumers with high refill urgency, especially type-A consumers.

Panels (C) and (D) consider the case that consumers' are too pessimistic about resupply. We evaluate consumers' refill benefit at the true probability, set to $s = 0.7$, while weighting by equilibrium attempt and refill probabilities. Since the likelihood of resupply is high, the planner will not allocate any fuel to type-C consumers as they are better off waiting until period 2. Consequently, we find sizable welfare losses across markets, driven by consumers

Figure 6: Loss in consumer welfare, equilibrium vs optimal allocation



Note: Figure shows the difference in aggregate and per-consumer surplus in equilibrium relative to the optimal allocation, by market-level shortage severity (percent of station-days with a partial shortage). We group markets into seven bins by shortage severity and report bin averages. Panels (A) and (B) assume consumers' resupply belief is accurate ($s = \tilde{s}$). Panels (C) and (D) assume the true resupply probability is $s = 0.7$. Panels (A) and (C) show the percent loss in aggregate surplus (total loss), as well as the loss from misallocation from attempts and random rationing. Panels (B) and (D) report the type-specific, per-consumer losses in total surplus in levels.

who front-load their refills. This case highlights a key welfare channel of panic buying: when beliefs deviate from reality, consumers' precautionary behavior can harm others and themselves.

We next turn to alternative allocation mechanisms to evaluate their potential in mitigating these surplus losses.

Table 3: Consumer surplus under counterfactual allocation mechanisms

	Accurate belief ($s = \tilde{s}$)			Pessimistic belief ($s = 0.7$)		
Shortage severity bin	1	2	3	1	2	3
(A) Aggregate change in surplus (%)						
Status quo: misallocation	–1.9	–4.0	–5.6	–20.7	–21.7	–23.8
Status quo: total change	–2.7	–5.0	–6.7	–21.7	–23.0	–25.3
Gas gauge check	–4.5	–4.4	–4.6	0	0	0
Mandatory wait: misallocation	–0.5	–0.7	–1.5	–19.0	–18.2	–18.5
Mandatory wait: total change	–1.8	–2.5	–4.7	–20.9	–20.7	–22.9
(B) Per-consumer change in surplus						
Status quo: type A	–4.7	–10.7	–13.9	–4.7	–10.7	–13.9
Status quo: type B	–3.5	–6.9	–9.0	–2.6	–4.9	–6.3
Status quo: type C	–0.3	–0.4	–0.4	–26.9	–28.8	–28.0
Gas gauge check: type A	0.00	0.01	0.03	0	0	0
Gas gauge check: type B	0.01	0.02	0.05	0	0	0
Gas gauge check: type C	–8.9	–9.7	–9.6	0	0	0
Mandatory wait: type A	–1.9	–2.9	–6.3	–1.9	–2.9	–6.3
Mandatory wait: type B	–2.2	–3.3	–6.0	–2.0	–3.0	–5.4
Mandatory wait: type C	–1.0	–1.5	–2.3	–27.0	–29.1	–27.4

Note: Table summarizes the difference in aggregate and per-consumer surplus in the status-quo equilibrium and under counterfactual allocation rules, relative to the optimal allocation, by market-level shortage severity (percent of station-days with a partial shortage). We group markets into three bins by shortage severity and report bin averages. We separately consider the case of an accurate consumer belief ($s = \tilde{s}$) and a pessimistic belief ($s = 0.7$).

7.2 Counterfactual allocation mechanisms

Our counterfactual analysis examines demand-side interventions that can be enacted at the pump immediately after the news shock. We contrast an administrative rule with historical precedent with an ordeal-based policy. We evaluate their surplus effects relative to the planner and the status-quo equilibrium.

Gas gauge checks.

Our first counterfactual allocation rule is inspired by past panic-buying episodes of gasoline. During the 1970s energy crisis, several states in the US adopted rationing programs which included gas gauge checks or minimum sales requirements. These rules aimed to reduces queues and prevent high-tank level consumers from topping off their tanks unnecessarily (U.S. Department of Transportation 1981).

We implement the so-called "half-tank rule," which imposes that only consumers with less than a half-full tank are allowed to refill. In the context of our model, this implies that type-C consumers are excluded from refilling in period 1. We assume that the rule is announced immediately after the news shock, implying that high-urgency consumers (type A and type B) can refill, facing no queues, shortages, or the fixed cost of an attempt.

Table 3 summarizes the aggregate and per-consumer surplus change relative to the optimal allocation. For comparison, we also report the surplus loss in the status-quo equilibrium.

The implication of this rationing rule highly depends on the resupply probability. If consumers are pessimistic and resupply is likely, then gas gauge checks can achieve the optimal allocation. For $s = 0.7$, the rationing rule does what the planner seeks to achieve: prevent type-C consumers from refilling. However, if consumers' belief is accurate, gas gauge checks create a surplus loss. Now, the planner would prefer to allocate fuel to type-C consumers with a high value of driving to ensure they can use their cars in both periods. In this case, gas gauge checks are a blunt tool that fails to allocate fuel to some high-value consumers.

This rule hinges on a unique feature of setting: because consumers arrive with their cars, gas stations can observe fuel-on-hand and effectively screen on urgency. In many other settings, inventories are not observable, making such checks infeasible. Motivated by this limitation, we next consider a market-based allocation mechanism.

Mandatory wait times.

As shortages rather than wait times drive misallocation, we consider a policy that raises the ordeal cost by imposing a mandatory wait at the pump.

Formally, we increase the wait time ϕ_m in each market until the predicted share of consumers with a refill equals supply Q_m, holding the attempt cost and random rationing at zero. Figure A12 illustrates the distribution of mandatory wait times across markets. The average market must impose a wait of 1 hour and 4 minutes to clear the market, with substantial variation across markets. The heterogeneity in wait times across markets reflects differences in initial stocks and in the distribution of consumers' willingness to wait.

In the case of accurate beliefs, we find that mandatory wait times can substantially improve allocative efficiency by effectively targeting consumers with a high refill benefit. For example, in the most affected markets, mandatory waits reduce the surplus loss from misallocation by 73% compared to the market equilibrium. Type-A consumers, in particular, benefit because of their higher willingness to wait. However, wait times do create additional costs for inframarginal consumers. Accounting for the ordeal cost, wait times only yield a

27% improvement in consumer surplus over the status-quo equilibrium.

In the case of pessimistic beliefs, increasing wait times provides minor improvements over the status-quo because there is still a substantial mass of type-C consumers who are willing to wait beyond the market-clearing wait time.

In Appendix I, we translate the mandatory wait time into a market-clearing fixed cost per refill using the market wage distribution. While switching to a fixed cost has minimal effect on aggregate and type-specific surplus, it reduces the likelihood of refueling among low-wage consumers, implying regressive effects along the wage distribution.

8 Conclusion

This paper studies the welfare and allocative effects of panic buying during the 2021 UK fuel crisis. We establish two main results. First, relative to the optimal allocation, welfare losses in equilibrium are driven by misallocation rather than elevated shopping costs. In particular, high-value consumers who would have normally refilled are crowded out due to shortages. Second, the effectiveness of counterfactual policies hinges on the accuracy of consumers' beliefs. When disruptions are unlikely, blunt rules that defer low-urgency purchases can restore efficiency. Yet, such rules can be infeasible or at odds with beliefs. Ordeal-based policies can improve targeting, but they do so by imposing additional costs on inframarginal consumers.

In this paper, we develop a framework to recover consumers' values of driving from their response to the panic shock, reflecting their preferences for not running out of fuel. Our planner allocates fuel based on these private values, in addition to tank levels and the resupply probability. A *social* planner might deviate from this allocation and assign weights based on the *social* value of gas on hand. Recovering social welfare weights is beyond the scope of the study and left to future research.

As we study consumers' decision to attempt a refill immediately after the news shock, we are limited to counterfactual policies that operate on the extensive margin. Therefore, several interventions discussed or deployed in previous panic buying episodes fall outside the model. This includes maximum-sales limits which would require modeling repeat purchases and endogenous fuel consumption. Due to the lack of a price response, we cannot estimate consumers' sensitivity to prices in the panic environment nor evaluate the effect of mandatory price hikes. Existing demand elasticities likely overstate consumers' short-run price sensitivity in our setting.

The mechanisms and findings we document extend beyond fuel to markets where supply falls short of demand and resupply is uncertain. This includes panic buying of other consumer products, such as toilet paper, over-the-counter medication, or baby formula, as well as the allocation of COVID vaccines and temporary shortages of semiconductors or generic prescription drugs.

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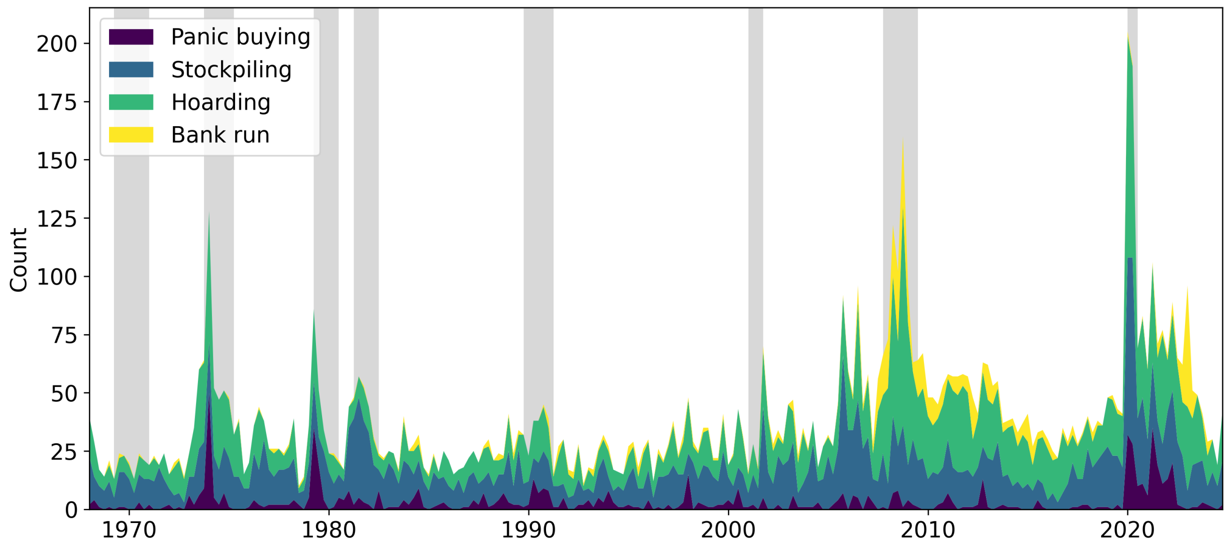
Appendix

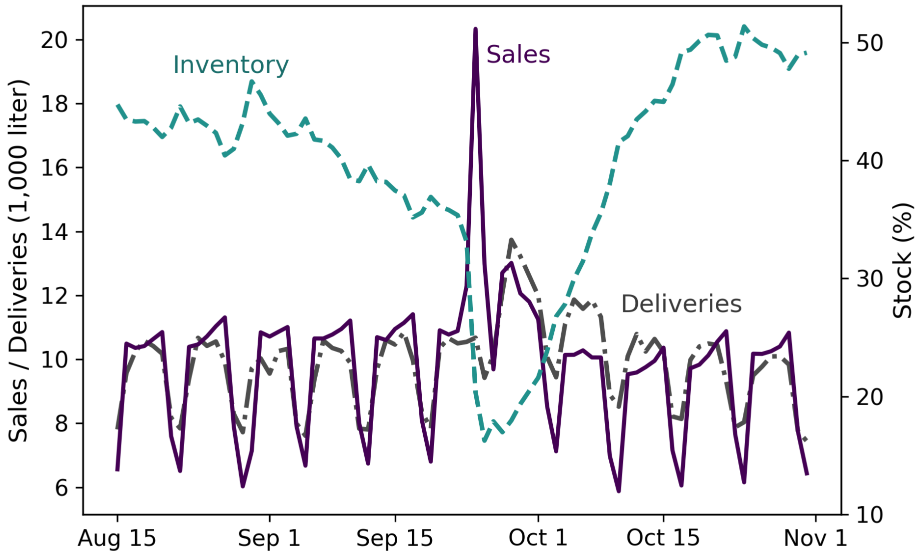
A Additional figures

Appendix Figure A1: Quarterly number of NY Times articles with panic buying related term, 1968Q1-2024Q4



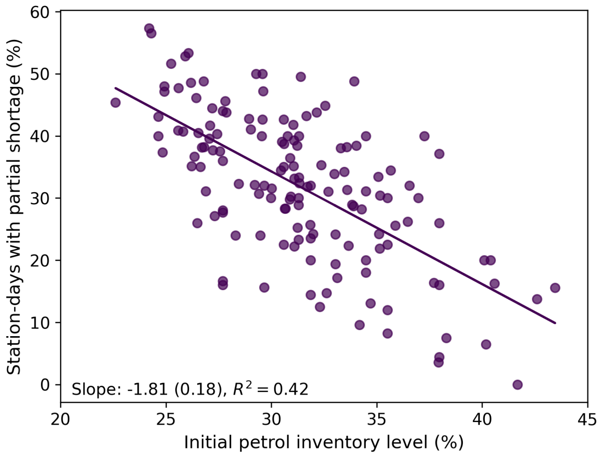
Note: Figure shows the quarterly number of New York Times articles mentioning a term related to panic buying, together with periods of U.S. recessions (gray areas), for 1968Q1-2024Q4. Panic buying related terms include "panic buying," "stockpiling," "hoarding," and "bank run." Quarterly article counts are from the The New York Times Developer Network using the Article Search API. Dates of U.S. recessions as inferred by GDP-based recession indicator. Source https://fred.stlouisfed.org/series/JHDUSRGDPBR. Last accessed May 26, 2025.

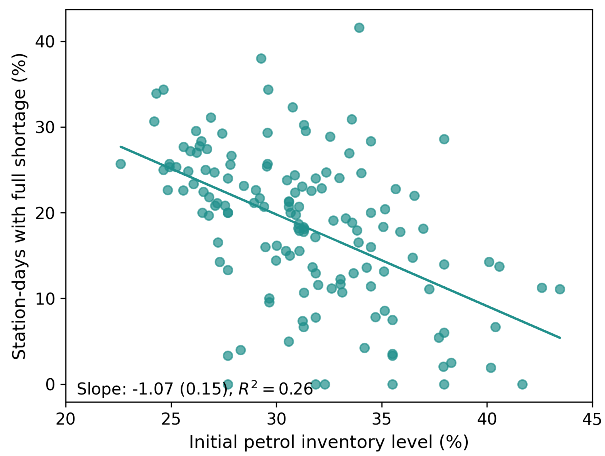
Appendix Figure A2: Daily average diesel sales, deliveries, and stock level across stations in England



Note: Figure shows the average daily sales, deliveries, and inventory level for diesel across gas stations in England, from August 15 to October 31, 2021. Sales and deliveries are measured in thousands of liters; inventory levels are reported as the percent of tank capacity filled. Data are published by the UK Department for Energy Security and Net Zero (DESNZ). For more information, see Official statistics in development on average road fuel sales, deliveries and stock levels (monthly data). Last accessed: Feb 11, 2024.

Appendix Figure A3: Relationship between market-level shortage severity and initial petrol inventory level

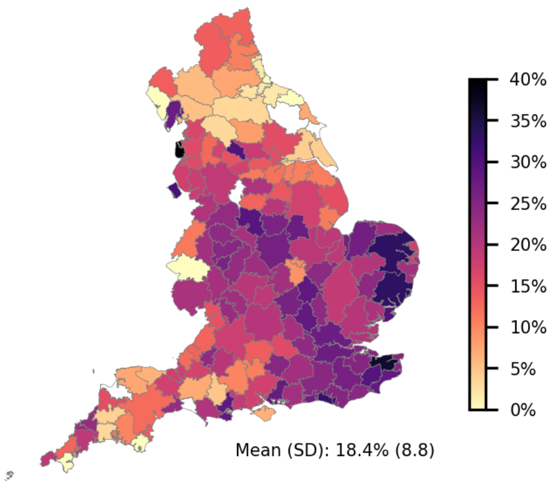




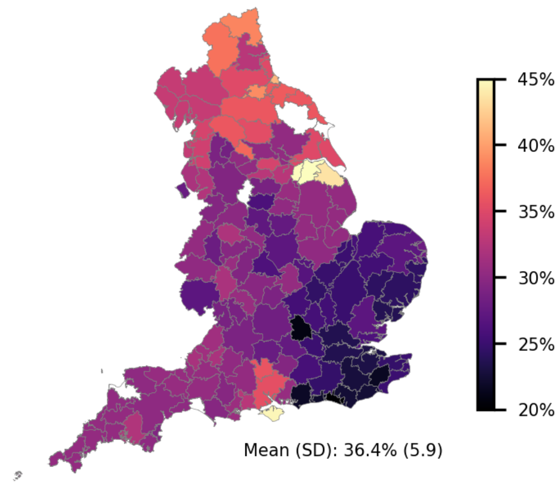
Note: Figure shows the bi-variate relationship between market-level shortage severity (y-axis) and initial petrol inventory level (x-axis). Panel (A) shows the relationship for our partial shortage severity measure. Here, each dot represents one travel-to-work area. Panel (B) plots the market-level percent of station-days with a *full* shortage during the first five days of the panic against the market-average initial petrol inventory level. Each dot represents one travel-to-work area. Figures list the slope coefficient, standard error, and R^2 of bi-variate OLS regressions. We omit 5 markets due to insufficient data.

Appendix Figure A4: Shortage severity and initial diesel inventory at market level

(A) Station-days with full shortage



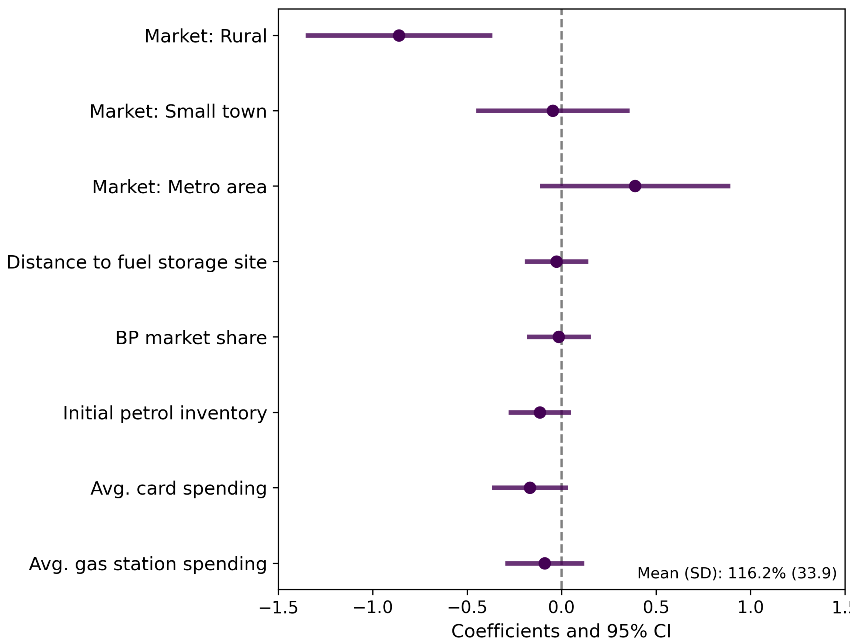
(B) Initial diesel inventory levels



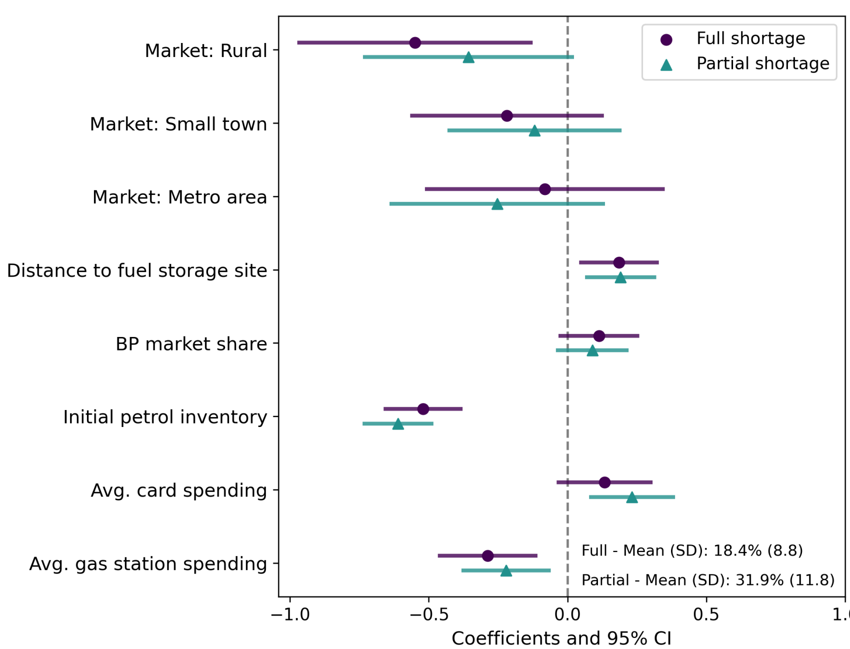
Note: Figure shows severity of shortages and initial diesel inventory level at the market level. Panel (A) shows a map of TTWAs in England, colored according to the percent of station-days with a full shortage during the first five days of the panic, ranging from low (yellow) to high (black). Panel (B) shows the same map with markets colored according to the average station inventory level for diesel on September 22, 2021, on a scale from high (yellow) to low (black). Inventory levels are reported in percent of tank capacity filled. We omit 5 markets due to insufficient data (white).

Appendix Figure A5: Partial correlations of market characteristics with sales shock and shortages

(A) Median sales shock on first day of panic



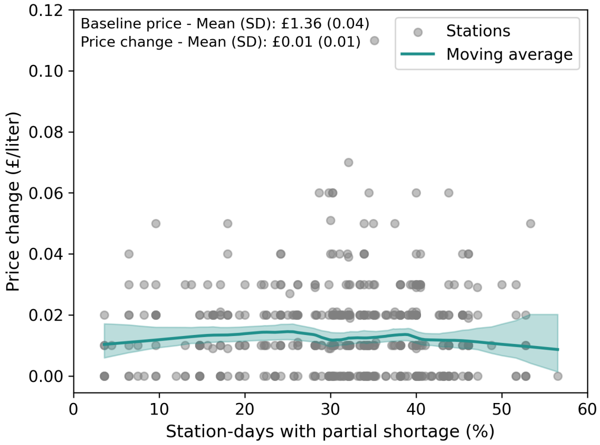
(B) Station-days with shortage during first five days of panic



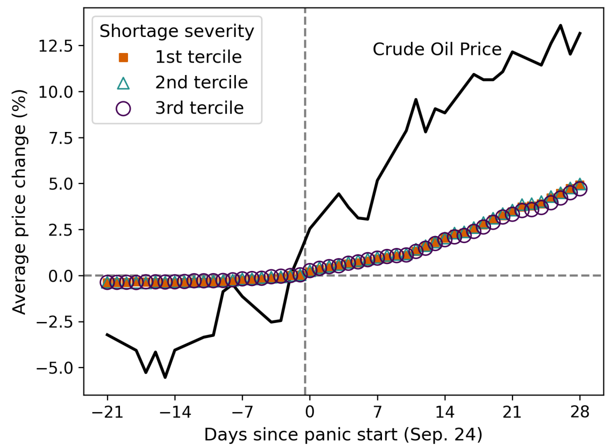
Note: Figure shows partial correlations of market characteristics with market-level sales shock (Panel (A)) and shortage severity (Panel (B)). Each panel shows the coefficients and 95% confidence intervals of a linear regression of the market-level outcome on a series of market characteristics. In Panel (A), the dependent variable is the median gas station sales shock in a market on the first day of the panic. In Panel (B), the dependent variable is the share of station-days with a full (purple) or partial (teal) shortage during the first five days of the panic. Market characteristics include indicators for rural/urban classification (omitted category: large town), distance to the closest fuel storage cite from the population-weighted market centroid, share of BP stations, initial petrol inventory level, average consumer spending in pre-period, and average gas station spending in per-period. Outcomes and continuous characteristics are standardized before estimation such that coefficients represent the effect of a one standard deviation increase. We omit 5 markets due to insufficient data.

Appendix Figure A6: Gas station price changes and shortage severity

(A) Station-level price changes after 10 days



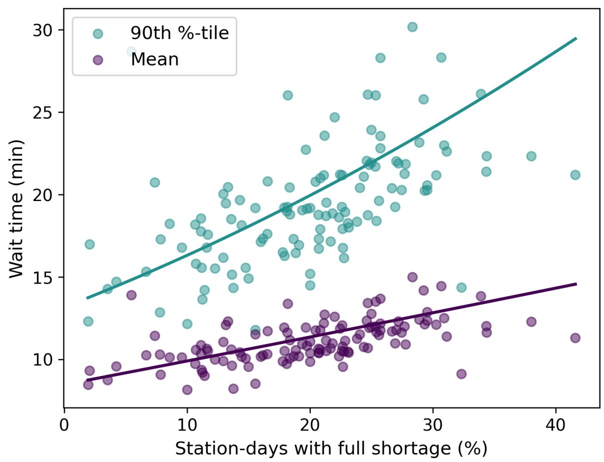
(B) Average price changes and crude oil price



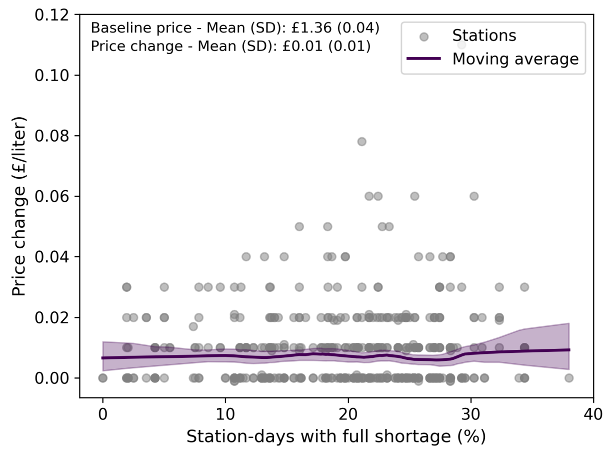
Note: Figure illustrates station- and market-level price changes by shortage severity. Panel (A) plots changes in gas station petrol prices (in £/liter) from 2 days before to 10 days after the start of the panic, against the market-level percent of station-days with a partial shortage. Each dot represents on gas station. We limit the sample to stations without a partial shortage on the days of price measurement. The line illustrates the local moving average with a 95% confidence interval. Panel (B) shows time series of the percent change in average petrol prices (relative to 2 days before the panic) from 3 weeks before to 4 weeks after the start of the panic. Stations are grouped into terciles based on the market-level percent of station-days with a partial shortage during the first five days of the panic. The black line shows the percent change in the daily Europe Brent Spot Price FOB (relative to 2 days before the panic) reported by the U.S. Energy Information Administration. Source: Europe Brent Spot Price FOB (Dollars per Barrel); US EIA. Last accessed Sep 15, 2025.

Appendix Figure A7: Gas station wait times and price changes, by station-days with full shortage

(A) Market-level wait times

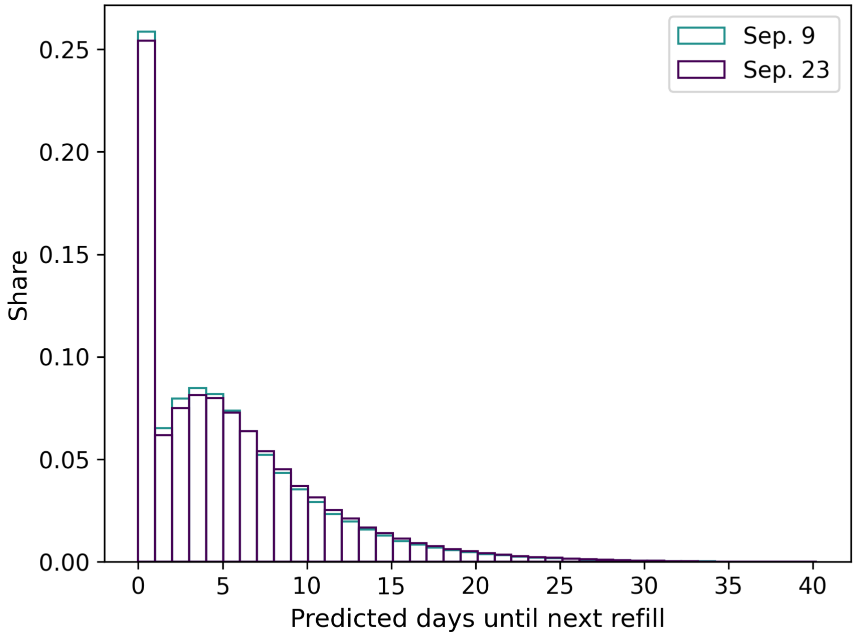


(B) Station-level changes in petrol prices



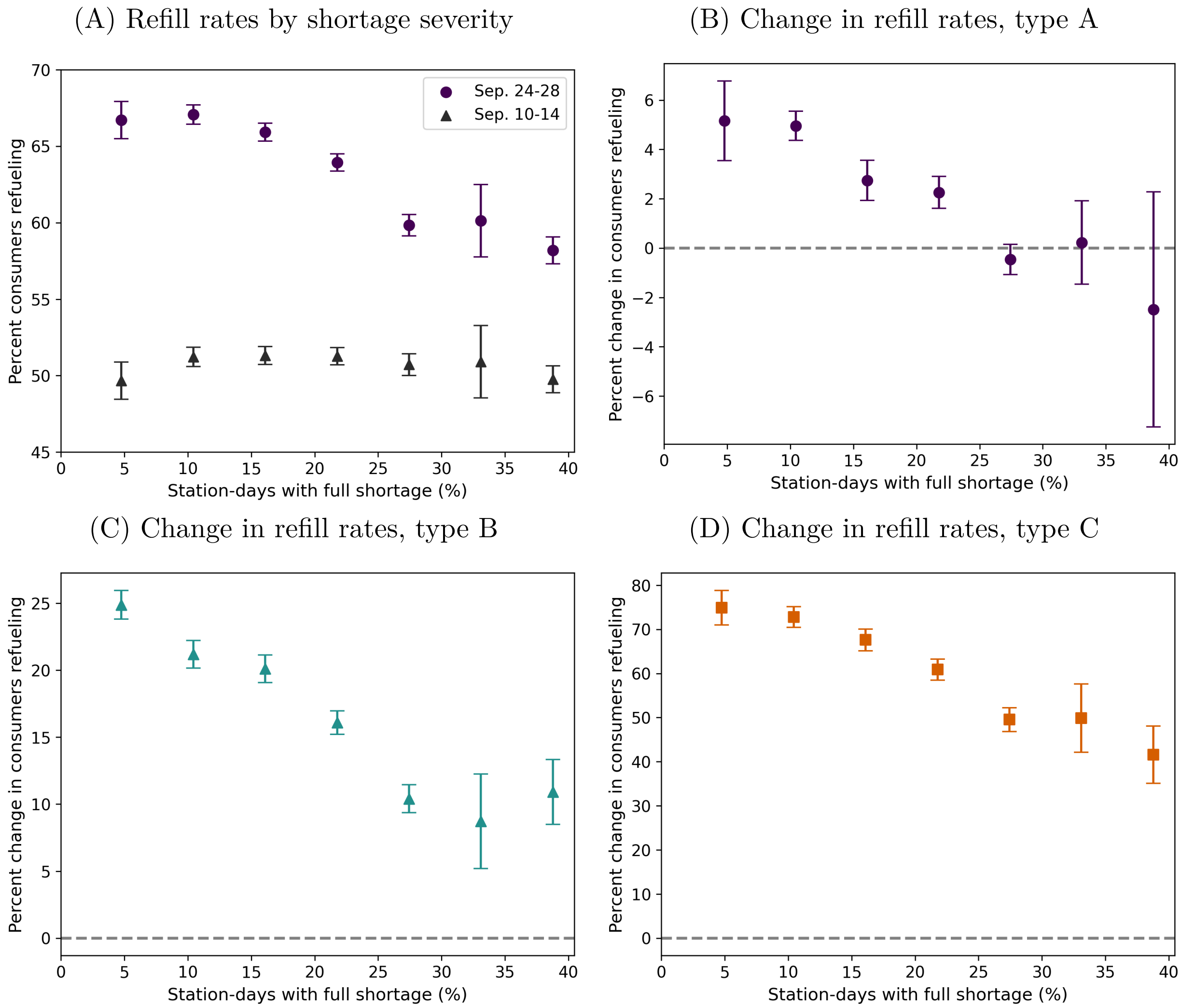
Note: Note: Figure shows market-level wait times and station-level price changes by the percent of station-days with a *full* shortage. Panel (A) shows the market-level average and 90-th percentile of wait times (in minutes) during the first five days of the panic by shortage severity. We omit markets with less than 200 refill events in the wait times data during this period. Panel (B) shows changes in gas station petrol prices (in £/liter) from two days before to five days after the start of the panic by shortage severity. Each dot represents one gas station. We limit the sample to stations without a full shortage on the days of price measurement. The line illustrates the local moving average with a 95% confidence interval. Two days before the panic, the average price per liter of petrol was £1.36, corresponding to $7.05 per gallon.

Appendix Figure A8: Predicted days until next refill, September 9 & September 23



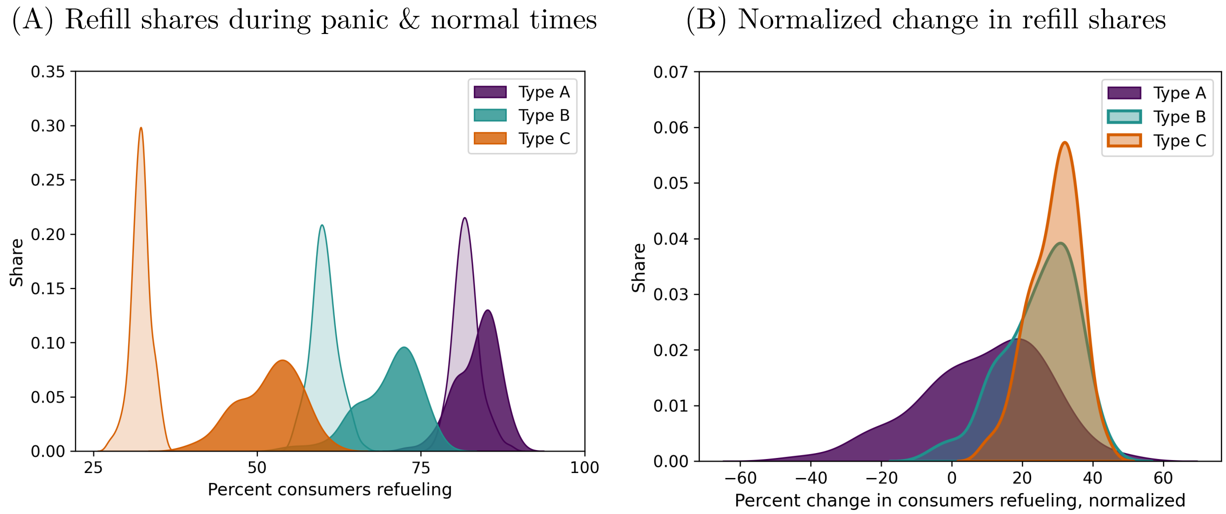
Note: Figure shows the distribution of the predicted number of days until consumers' next refill, as of the evening of September 23, one day before the panic, and September 9, two weeks before the panic.

Appendix Figure A9: Market-level refill rates and relative changes, by station-days with full shortage



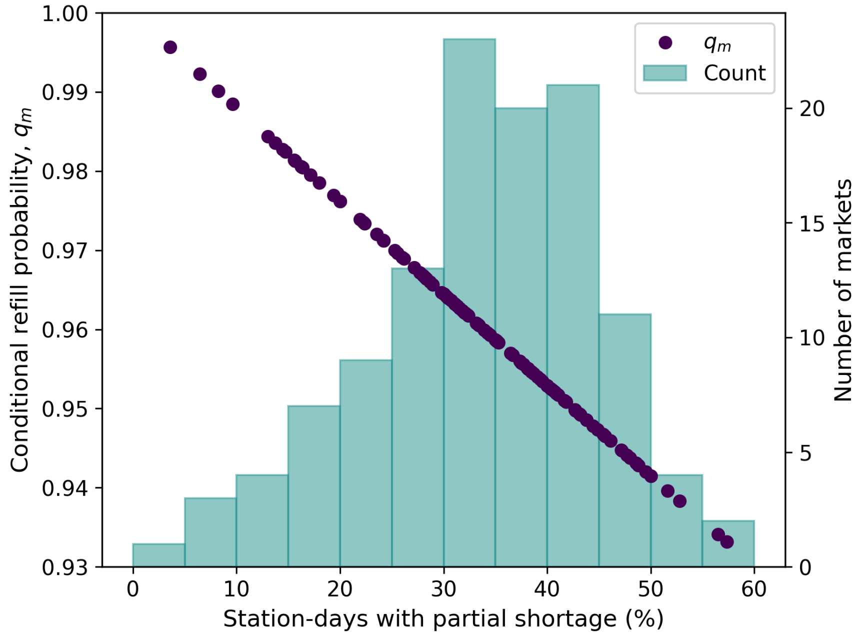
Note: Figure shows binscatter plots of market-level refill rates and type-specific changes in refill rates, by percent of station-days with a full shortage. Panel (A) shows the percent of consumers refueling their cars during the first five days of the panic (Sep. 24-28; purple) and the same five-day period two weeks earlier (Sep. 10-14; gray). Panels (B)–(D) show the percent change in refill rates between the two periods for three urgency types. Type-A consumers refill every five days (high refueling urgency). Type-B consumers refill less frequently but are predicted to refill within the next five days (high refueling urgency). Type-C consumers also refill less frequently and are predicted to refill in six or more days (low refueling urgency).

Appendix Figure A10: Market-level refill rates of high- and low-urgency consumers



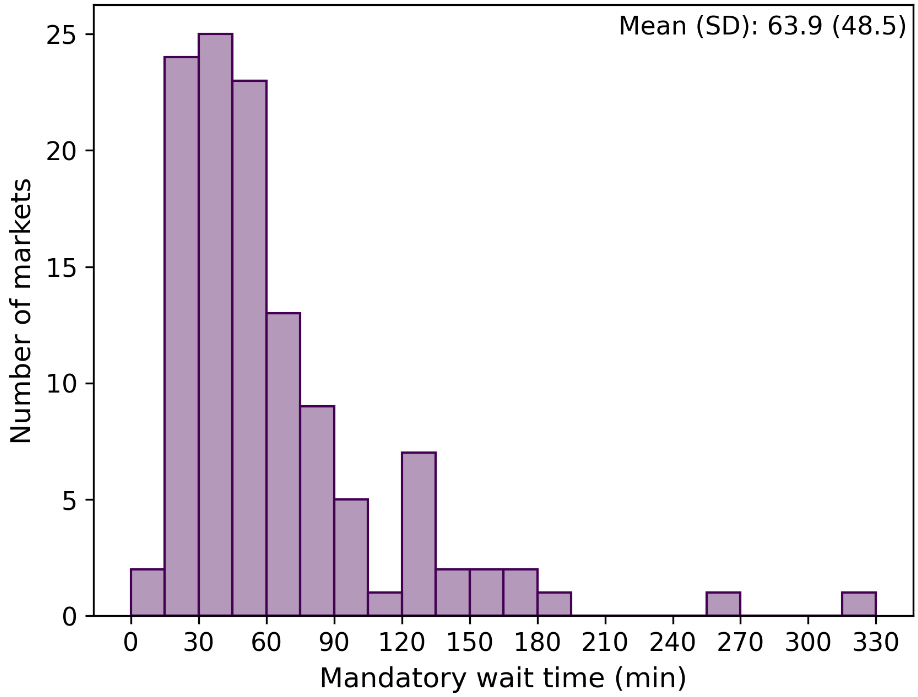
Note: Figure shows distributions of market-level refill rates by urgency type and normalized changes therein. Panel (A) shows the distribution of type-specific market refill rates (in %) in normal times (September 10–14) and during the first five days of the panic (September 24–28). Panel (B) shows the normalized change in market-level refill rates between the two periods. That is, for each market and type, we compute the percent change in the refill rate and divide it by the maximum possible change.

Appendix Figure A11: Equilibrium relationship between shortage severity and conditional refill probability



Note: Figure shows the equilibrium relationship between market-level shortage severity (W_m) and the conditional refill probability ($\hat{q}_m$), as well as the distribution of shortage severity across markets.

Appendix Figure A12: Distribution of market-clearing wait times



Note: Figure shows a histogram of model-predicted, market-clearing wait times. We obtain these wait times by increasing ϕ in Equation (6) until the predicted share of consumers with a refill equals the available supply Q. We measure Q by the share of observed refills during the first five days of the panic.

B Additional tables

Appendix Table A1: Consumer-level summary statistics, rank correlations

	Gas station spending	Average days between refills	Total spending	Other transportation spending	Relative time saved from driving	Work from home	Public transportation availability
Gas station spending (£)	1.00	-0.74	0.34	0.05	0.30	0.07	-0.00
Average days between refills		1.00	-0.18	-0.01	-0.23	0.02	0.00
Total spending (£)			1.00	0.18	0.14	0.10	0.00
Other transportation spending (£)				1.00	0.00	0.18	0.01
Relative time saved from driving (min)					1.00	0.13	0.01
Work from home (%)						1.00	0.02
Public transportation availability							1.00

Note: Table shows rank correlations of consumer characteristics measured in the pre-period. These characteristics include a consumer's average weekly spending at gas stations, average number of days between refills, total card spending, spending on other transportation (public transportation, taxi, and ride-share), relative time saved from driving, percent of home-LSOA residents working from home, and the public transportation accessibility index. See Table 1 for summary statistics.

Appendix Table A2: Consumer-level summary statistics, by urgency type

	Type A		Type B		Type C	
	Mean	SD	Mean	SD	Mean	SD
(A) Gas station spending						
Gas station spending (£)	49.05	19.98	25.62	11.94	20.61	10.32
Average days between refills	3.91	0.79	10.17	4.64	13.78	6.25
(B) Broader spending						
Total spending (£)	429.19	177.79	363.14	162.03	348.74	157.48
Other transportation spending (£)	2.37	7.08	2.49	6.92	2.31	6.58
Relative time saved from driving (min)	223.30	206.03	163.71	165.50	147.56	154.20
(C) Home-LSOA characteristics						
Working from home (%)	34.76	13.31	34.84	13.52	34.79	13.43
Public transportation availability index	276.13	661.39	276.41	670.73	275.52	657.87
(D) Refill urgency						
Predicted days until next refill	2.00	1.59	1.67	1.76	10.11	4.74
Number of consumers	81,283		293,705		299,891	

Note: Table shows summary statistics for our consumer sample, by urgency type. We report the type-specific mean and standard deviation of each consumer characteristic. We assign consumers to urgency types based on the average refill frequency in the months before the panic and their predicted refill date as of the end of day on September 23. Type-A consumers refill every five days (high refueling urgency). Type-B consumers refill less frequently but are predicted to refill within the next five days (high refueling urgency). Type-C consumers also refill less frequently and are predicted to refill in six or more days (low refueling urgency).

Appendix Table A3: Summary statistics, predicted model primitives

	$\hat{v}_i$		$\hat{\tau}_i$	$\hat{WTW}_i$
(A) All consumers				
p25	0.22		0.01	0.16
p50	3.58		0.26	5.22
p75	58.13		4.50	163.13
Rank correlation		0.33		
(B) Type A consumers				
p25	1.83		0.01	11.84
p50	27.29		0.11	230.34
p75	404.37		1.95	4389.19
Rank correlation		0.41		
(C) Type B consumers				
p25	0.25		0.01	0.81
p50	3.90		0.23	18.45
p75	58.97		4.00	402.65
Rank correlation		0.37		
(D) Type C consumers				
p25	0.12		0.02	0.02
p50	1.90		0.35	0.53
p75	30.23		6.13	12.43
Rank correlation		0.34		

Note: Table shows key moments of the predicted value of driving, v_i, value of time, τ_i, and the implied willingness to wait, WTW$_i$, in hours. We compute a consumer's willingness to wait by solving for the wait time that sets $L_g(\tilde{s})v_i - \tau_i\phi$ to zero.

C Data and measurement

C.1 Geographic units and crosswalks

Travel to work areas.—We define a market as a *Travel to Work Area* (TTWA), which approximates a self-contained labor market area and is defined by the UK Office for National Statistics (ONS) based on commuting patterns. We use the 2011 definition of TTWAs, which stipulates that at least 75% of the area's resident workforce works within the area, and at least 75% of jobs in the area are filled by local residents. TTWAs cross administrative boundaries and aim to reflect functional economic geographies. For more information, see the official ONS user guide for the 2011 TTWAs.

Lower Super Output Areas.—We assign each consumer to a *Lower Super Output Area* (LSOA), which is small geographic unit developed by the ONS to report consistent and stable local area statistics over time. A LSOA typically contains 400–1,200 households and 1,000–3,000 residents, and is comparable in size to a US census tract. We use the 2011 LSOA definition, which map into 2011 TTWAs. For more information, see the ONS user guide for the 2011 Census geographies.

Middle Super Output Areas.—We obtain income estimates at the level of a *Middle Super Output Area* (MSOA). MSOAs usually comprise four or five LSOAs, with 2,000–6,000 households and 5,000–15,000 persons. We use the 2011 LSOA definition, which map into 2011 TTWAs. For more information, see the ONS user guide for the 2011 Census geographies.

International Territorial Level 3.—The UK *Department for Energy Security and Net Zero* publishes daily average fuel sales, deliveries, and inventory levels at sampled gas stations at the *International Territorial Level 3* (ITL-3). This geographic classification, developed by ONS, splits the UK into 179 regions, corresponding to counties, unitary authorities, or grouped districts. Because there is no one-to-one mapping of ITL-3 to TTWA, we use the lat-lon coordinates of gas stations in the OSM data to construct the average station inventories at the TTWA level. In particular, we assign the average inventory level to all gas stations in an ITL-3 and take the average across all stations in a TTWA.

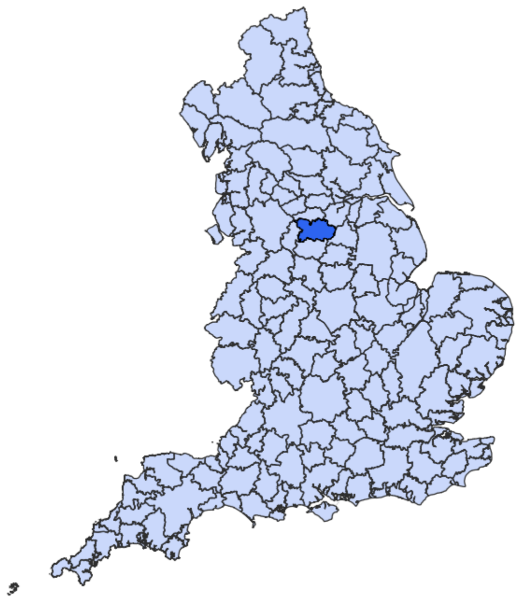
ONS Postcode Directory.—To link the different geographic units, we use the August 2022 version of the ONS Postcode Directory. This directory links ZIP Codes (or postal codes), to LSOAs (both 2011 and 2021 versions), and to TTWAs. For more information, see the ONS Postcode Directory (August 2022).

Appendix Figure A13: United Kingdom

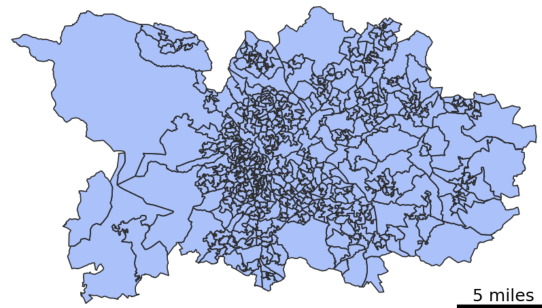
Note: Figure shows a map of the United Kingdom, comprising the countries England, Northern Ireland, Scotland, and Wales. England is colored in dark-blue because our analysis focuses on markets in this country. The red circle represents London.

Appendix Figure A14: Travel-to-work areas and lower super output areas

(A) TTWAs in England



(B) LSOAs in TTWA Sheffield



Note: Figure shows a map of travel-to-work areas (TTWAs) in England, with TTWA Sheffield in dark-blue, (Panel (A)) and a map of all lower super output areas (LSOAs) in TTWA Sheffield.

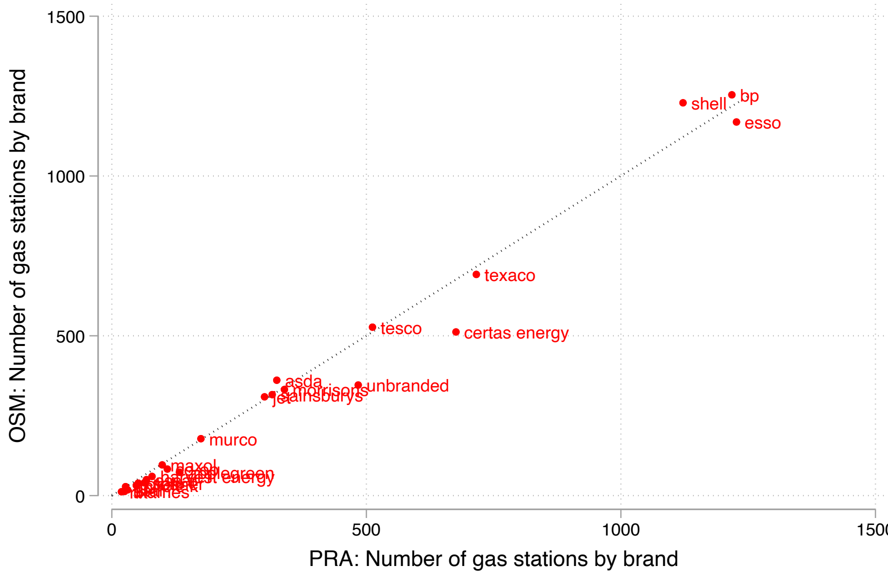
C.2 Supplementary data

OpenStreetMaps.—We obtain the latitude-longitude coordinates and brand information of gas stations in the UK from *OpenStreetMaps* (OSM). The data scrape was done in May 2024. In total, we identify 8,258 gas stations—6,474 in England, 809 in Scotland, 501 in Wales, and 474 in Northern Ireland. We assessed the accuracy of the location information by manually searching for about 1,700 gas stations with missing brand information.

Figure A15 compares the number of gas stations by brand identified in the OSM data to the number of gas stations by brand reported in the 2022 Market Review by the Petrol Retailers Association (PRA) (PRA 2021). According to PRA, there is a total of 8,378 open site, including sites under development, in the UK as of November 2021. For nationwide brands, we identify roughly the same number of stations in the OSM as reported by PRA.[46]

[46]Certas energy is an independent fuel distributor and comprises a range of smaller brands.

Appendix Figure A15: Number of gas stations by brand, Open Street Maps (OSM) versus Petrol Retailers Association (PRA)



Note: Figure shows the number of UK gas stations by brand identified in the Open Street Maps data against the number of UK gas stations by brand as reported in the 2022 Market Review by the Petrol Retailers Association (PRA 2021). Numbers reported by PRA rely on data from the Experian Catalist UK, released November 2021. Dashed line shows the 45 degree line. Figure omits 489 stations in OSM not matched to a brand in the PRA records, and 216 stations in the PRA records not matched to a brand in the OSM data.

2021 UK Census.—We obtain LSOA-level characteristics from the UK Census, which was conducted in March 2021. These data include information about the percent of employed residents that "work mainly at or from home." We use this variable as one consumer characteristic in the values of driving and of time. For more information, see the official ONS variable documentation.

Public transportation availability index.—We obtain LSOA-level data on public transportation availability from the Urban Big Data Centre at the University of Glasgow. The construction of the availability index is described in Anejionu, Sun, Thakuriah, McHugh, and Mason (2019). Broadly, the authors use service schedules from 2016 and the hourly distribution of trips to measure the hourly number of trips passing a stop or station. To aggregate this index to the LSOA level, the authors also account for the service areas of stations/stops.

Travel time data.—We obtain mode-specific travel time data at the LSOA level from Verduzco Torres and McArthur (2024). For each origin LSOA, the data contain the estimated travel time to all destination LSOAs that can be reached within 150 minutes by car, public transportation, biking or walking. Travel times assume free traffic flow. Thus, total trip duration is right-censored.

Market-level wage distribution.—We obtain key moments of the 2021 wage distribution for each TTWA from the UK *Annual Survey of Hours and Earnings* (ASHE). This dataset reports the average hourly wage, the three quartiles, and the nine deciles of the wage distribution. We use the gross hourly pay for all (full-time) employees residing in a TTWA. For more information, see the ONS data documentation.

Income estimates for small areas.—We obtain income estimates at the MSOA level, based on the financial year ending 2020. For more information, see the ONS data documentation.

C.3 Sample construction

In this section, we describe the construction of our consumer card sample. The goal is to identify payment cards that are actively used throughout the sample period (April 1–December 31, 2021), frequently transact at gas stations, and exhibit a spending pattern that allows us to impute their likely home location. As we cannot link multiple cards held by the same individual, we treat each card as a separate consumer and use the terms "card" and "consumer" interchangeably.

We impose three primary selection criteria. First, a card must record at least £50 of spending every week, ensuring active usage throughout the sample period. Second, a card must have at least five refills between April 1–September 15, 2021, and at least two refills between November 1–December 31, 2021. We define a refill as a gas station transaction of at least £10. This requirement ensures that a card is actively used at gas stations. In addition, it allows us to measure how frequently the consumer refills their car, on average, in the months leading up to the panic. Lastly, a card must register at least 10 transactions with at least three distinct "at-home" merchants during off-work hours in each quarter. Merchants in the "at-home" category include grocery stores and supermarkets, butcher and cheese shops, bakeries, drug stores and pharmacies, post offices, banks, and ATMs. Off-work hours are defined as any time before 9am or after 5pm on a weekday, or any time on a weekend. Based on this information, we impute a card's home location as the centroid of the latitude-longitude coordinates of the three most frequently visited "at-home" merchants in a quarter. We only keep cards for which the implied home locations each quarter are within 5 kilometers of each other. This allows us to assign each card to a lower super output area (LSOA), which we refer to as the card's home location.

C.4 Consumer characteristics and refill urgency

In this section, we describe the construction of our consumer characteristics and refill urgency.

We develop a set of characteristics to proxy for consumer's value of driving and value of time—the two key dimensions of consumer heterogeneity in our model. These variables are derived from consumers' card transactions in the 24 weeks before the panic, from April 1–September 15, 2021, as well as their home locations.

Gas station spending (£).—We sum up the amount of all transactions of consumer i with UK gas stations. Gas stations include both "full-service stations," which may provide amenities like a convenience store or car wash, or as "automated fuel dispensers," which are pay-at-pump stations.

Average days between refills.—We count the number of days between two refills. We define a refill as a gas station transaction exceeding £10. For each consumer i, we take the average number of days between refills.

Total spending (£).—We sum up the amount of all transactions of consumer i with UK merchants.

Other transportation spending (£).—We sum up the amount of all transactions with UK merchants in retail categories public transportation, taxis, and ride shares.

Time saved from car travel (min).—We combine consumers' card transactions with mode-specific travel times to measure how much time they save from traveling by car. For each consumer, we observe when and where they transacted on a given day, allowing us to reconstruct their shopping trips. In particular, we allow each consumer to make one shopping trip a day, beginning and ending at her home location. For each trip, we measure the total travel time from home → merchant #1 merchant #2 → ...→ home for travel by car, public transportation, bike, and walking. As travel times are right-censored, we assign a time of two hours to every unobserved link on a trip. We then compute the time saved from using a car relative to the next fastest mode. On days without a transaction, we assume the consumer makes no shopping trip and, thus, records zero time saved from car travel. For each consumer, we compute the average weekly time saved from car travel, in minutes. Both the likelihood of making a trip and the length of each trip contribute to this measure. It thus captures the cost of substituting transportation modes while maintaining the consumer's observed spending pattern.

Working from home (%).—We obtain this variable from the *2021 UK Census*. It reports, for each LSOA, the percent of residents in employment who work from home on a regular basis.

Public transportation availability index.—We obtain this index from *Public transport availability indicators (PTAI)* (2023), and its construction is detailed in Anejionu, Sun, Thakuriah, McHugh, and Mason (2019). The index measures "how public transport service provisions support basic activities of local residents" and reflects the number of trips passing through service stations, as well as the walking distance to these stops. A higher value reflects better availability of public transportation.

Gas tank level & refueling urgency.—For each consumer i and day t, we measure refueling urgency based on the number of days since their last refill relative to their average refill frequency. Suppose consumer i refuels her car every seven days, on average, and that her last refill was on September 22. Extrapolating her average refueling behavior, the next refill is predicted to be on September 29. Thus, at the end of day on September 22, she predicted to refuel in seven days. On September 23, she is predicted to refuel in six days, and so on.

D Additional stylized facts

Fact 5: Conditional on refueling, consumers purchased more gasoline, even those with low urgency.

Conditional on refueling, consumers purchased more gasoline during the panic, even those with low refueling urgency. Table A4 presents summary statistics of market-average gas station spending and refill volumes (in liters) for the three urgency types. Consistent with refueling urgency, we find the largest relative increase in spending and quantity during the first five days of the panic for type-A and type-B consumers. Yet, even type-C consumers spent 26% more and bought 22% more gasoline compared to the same period two weeks before.

The intensive-margin response yields two takeaways. First, in normal times, consumers do not always fill their tanks completely but leave unused capacity.[47] Second, during the panic, consumers likely fill their entire gas tank once at the pump.[48] Given the comparable intensive-margin response across urgency types, we adopt the simplifying assumption that all consumers, regardless of when they are predicted to refill next, exert the same externality by reducing the remaining stock for subsequent consumers.[49]

Appendix Table A4: Market-level average gas station spending and quantity purchased, by refill urgency

	Type A		Type B		Type C	
	Mean	SD	Mean	SD	Mean	SD
Gas station spending (£)	57.08	3.63	48.87	2.69	43.75	2.55
Percent change in spending (%)	39.80	6.64	29.85	4.69	25.86	4.69
Quantity purchased (liter)	31.98	3.76	31.86	2.04	28.82	2.23
Percent change in quantity (%)	36.16	18.12	25.15	9.34	22.34	12.64
Number of markets	65					

Note: Table shows summary statistics of average gas station spending (£) and quantity purchased (liter) during the panic, across 65 markets. We compare consumers' purchasing behavior during the first five days of the panic (Sep. 24-28) to the same five-day period two weeks prior. For each market and type, we compute the average gas station spending and quantity purchased, conditional on refilling, in either period. Table shows the type-specific average (change) across markets. We focus on 65 (out of 149) markets where we observe total quantity purchased for at least 10 consumers per group. This restriction is necessary as we observe fuel prices, needed to impute quantity, only for a subset of stations.

[47] This behavioral pattern has also been documented by Hastings and Shapiro (2013) and Dorsey, Langer, and McRae (2025).

[48] At most gas stations during the panic, consumers were to purchase as much gasoline as they wished. Only 367 stations, owned by the EG Group and operating under the BP, Esso, or Texaco brands, imposed a £30 per fill cap to ensure customers "have a fair chance to refuel" (Munbodh 2021).

[49] Changes in the third decision margin—the station choice—are left to future work.

E Model details

Below, we outline consumers' attempt decisions by comparing the expected utility of attempting a refill to that of waiting.

For a consumer of type A, the attempt decision is static. She decides to attempt if the expected utility exceeds that of waiting,

$$q(n)\,(v_i - \tau_i\,\phi(n)) \;-\; \tau_i\,c \;+\; \varepsilon_{1i} \;\geq\; \varepsilon_{0i}$$

A refill attempt is successful with probability $q(n)$, in which case she gains her value of driving but has to pay the waiting cost. In any case, she pays the fixed cost of an attempt, c. We normalize the utility from no attempt to zero and assume ε_{ij} follows an $EV(0,1)$ distribution. Rearranging yields equation (3).

For a type-B consumer, the refill decision is dynamic because the gas tank lasts two periods. The attempt decision is given by

$$q(n)\,((1+\delta)\,v_i - \tau_i\,\phi(n)) - \tau_i c + (1-q(n))\,\tilde{s}\delta(1+\delta)\,v_i + \varepsilon_{1i} \;\geq\; \tilde{s}\delta(1+\delta)\,v_i + \varepsilon_{0i}$$

In case of a successful attempt, she receives twice the value of driving (discounted across periods) and pays the waiting cost. In case of a failed attempt, she loses out on using her car in period 1, but can refill in period 2 with probability s. In that case, she receives her value of driving in period 2 as well as the continuation value of gas on hand, $\delta\,v_i$. This also describes her expected utility of waiting.

For a type-C consumer, the attempt decision is given by

$$\begin{aligned} q(n)\,((1+\delta)\,v_i - \tau_i\,\phi(n)) - \tau_i c + (1-q(n))\,(v_i + s\delta(1+\delta)\,v_i) + \varepsilon_{1i} \\ \geq\; v_i + s\delta(1+\delta)\,v_i + \varepsilon_{0i} \end{aligned}$$

The attempt decision looks similar to type-B, except that a failed attempt or waiting yields the additional value of driving in period 1.

F Model identification

This section outlines the formal identification argument in the ideal thought experiment. In this exercise, we assume that we can observe the attempt or refill probability of the same consumer—same (v_i, τ_i)—across urgency types, $g \in \{\text{A,B,C}\}$, and across markets with different levels of shopping costs, (ϕ_m, q_m). We further assume that the news shock is unanticipated shifts beliefs uniformly to $\tilde{s}$.

With i.i.d. T1EV errors, the attempt probability is

$$\pi_{igm} = \exp(\bar{U}_{igm}) / \left(1 + \exp(\bar{U}_{igm})\right), \qquad \bar{U}_{igm} = q_m\Big(L_g(\tilde{s})\,v_i - \tau_i\,\phi_m\Big) - \tau_i c\ ,$$

and the *attempt log-odds* equals

$$\ell_{g,m}(i) \;\equiv\; \log \frac{\pi_{igm}}{1-\pi_{igm}} = \bar{U}_{igm} \ .$$

Case 1: Attempts and conditional success probabilities are observed.

Identifying v_i.—With $\ell_{g,m}(i)$ and q_m observed, we can solve for the value of driving, v_i, by comparing the attempt log-odds of the Type B and Type C. In the same market, the time cost $\tau_i\phi_m$ is identical across urgency types. Thus, by taking the B-C difference, we get

$$\ell_{B,m}(i) - \ell_{C,m}(i) = q_m\big(L_B - L_C\big)v_i = q_m\, v_i \quad \Rightarrow \quad v_i = \frac{\ell_{B,m}(i) - \ell_{C,m}(i)}{q_m} \ ,$$

leveraging the fact that $L_B(\tilde{s}) - L_C(\tilde{s}) = 1 \ \forall \tilde{s}$.

Identifying τ_i.—To identify τ_i, we can use the attempt log-odds of Type A. In the same market m,

$$\ell_{A,m}(i) = q_m\big(v_i - \tau_i\phi_m\big) - \tau_i c \quad \Rightarrow \quad \tau_i = \frac{q_m\, v_i - \ell_{A,m}(i)}{q_m\phi_m + c} \ .$$

Thus, (v_i, τ_i) are point-identified from (A,B,C) within a single market.

Identifying $\tilde{s}$.—Identification of the resupply belief $\tilde{s}$ relies on the "exclusion restriction" that Type A's attempt decision is independent of $\tilde{s}$ and on the functional relationship $L_C = L_B - 1$. In particular, we can form the following ratio of differences in attempt log-odds,

$$\begin{aligned}
&\ell_{B,m}(i) - \ell_{A,m}(i) = q_m\big(L_B(\tilde{s}) - 1\big)\, v_i = q_m\, L_C(\tilde{s})\, v_i, \\
&\frac{\ell_{B,m}(i) - \ell_{A,m}(i)}{\ell_{B,m}(i) - \ell_{C,m}(i)} = L_C(\tilde{s}) \ = \ \delta\big(1 - (1+\delta)\tilde{s}\big),
\end{aligned}$$

and solve for $\tilde{s}$,

$$\tilde{s} = \frac{1}{(1+\delta)} \cdot \left(1 - \frac{1}{\delta} \cdot \frac{\ell_{B,m} - \ell_{A,m}}{\ell_{B,m} - \ell_{C,m}}\right) \ .$$

Intuitively, the B-A gap captures the "insurance component" of refilling early; normalizing by the B-C gap removes $q_m v_i$ and maps one-for-one into $\tilde{s}$. Notably, recovering the resupply belief does not rely on knowing q_m or (v_i, τ_i).

Case 2: Attempts are not observed; conditional success probabilities are not observed.

In the data we do not observe refill attempts. Instead, under the assumption of random rationing, we observe successful refills, which happen with probability $p_{igm} = \pi_{igm}\, q_m$.

If q_m were known, we can define the q-adjusted logit

$$\tilde{\ell}_{g,m}(i) \;\equiv\; \log \frac{p_{igm}}{q_m - p_{igm}} = \log \frac{\pi_{igm}}{1-\pi_{igm}} = \bar{U}_{igm}$$

and all identification steps above hold with ℓ replaced by $\tilde{\ell}$.

However, because q_m is not observed, we rely on the parametric mapping between shortage severity, W_m, and the conditional success probability. In particular, we assume a functional relationship $q_m = q(W_m; \alpha)$, with $q(0) = 1$ and $q'_\alpha < 0$. Then, we can define the q-adjusted logit as a function of α,

$$\tilde{\ell}_{igm}(i;\alpha) \;\equiv\; \log \frac{p_{igm}}{q(W_m;\alpha) - p_{igm}} \; .$$

To recover the parameter α, we need three markets $m \in \{1, 2, 3\}$ with distinct values for W_m. For each candidate parameter value α and consumer i, define

$$D_{12}^{B\text{–}C}(i) \;\equiv\; \big(\tilde{\ell}_{B,1}(i,\alpha) - \tilde{\ell}_{B,2}(i,\alpha)\big) - \big(\tilde{\ell}_{C,1}(i,\alpha) - \tilde{\ell}_{C,2}(i,\alpha)\big)$$

and the ratio

$$R_{12,13}(i;\alpha) \;\equiv\; \frac{D_{12}^{B\text{–}C}(i;\alpha)}{D_{13}^{B\text{–}C}(i;\alpha)} \; .$$

At the true value α^*, the ratio $R_{12,13}(i;\alpha^*)$ does not depend on consumer i. Thus, α can be recovered by minimizing the cross-consumer dispersion in $R_{12,13}(i;\cdot)$. Because q_m is unobserved, the logical order of identification starts with recover α following the previous step with $\tilde{\ell}$.

G Moment conditions

In this appendix, we describe our hybrid estimation approach in detail. We combine likelihood-based score moments, in the style of a generalized method of moments (GMM) estimator, with matching simulated and empirical moments, in the style of simulated method of moments (SMM). We stack these moments and weight them to ensure roughly equal contribution to the overall objective. Below, we outline the GMM and SMM moments in detail. Our goal is to estimate the following vector of model parameters,

$$\theta = \{\bar{v}, \boldsymbol{\beta}, \bar{\tau}, \boldsymbol{\gamma}, \sigma_v, \sigma_\tau, \rho, \tilde{s}, \alpha\} \; .$$

G.1 GMM-style moments

We use GMM-style moment conditions based on the orthogonality between prediction errors and exogenous covariates. Let Z_i denote the set of instruments/covariates. The population restrictions are

$$\mathbb{E}\big[(y_{igm} - p_{igm}(\theta))\, Z_i\big] \;=\; 0.$$

For each candidate $\hat{\theta}$, we form the empirical analogs using the following Z_i components: indicators for urgency types $g \in \{A, B, C\}$, market-level shortages W_m, wait time ϕ_m, and consumer characteristics X_i.

G.2 SMM-style moments

Our estimator targets moments derived from type- and market-specific refill shares. Below, we describe their construction and outline their link to the model parameters.

The reason for targeting aggregate moments of type- and market-specific refill shares is two-fold. First, the type-specific loading, $L_g(\tilde{s})$, creates variation across urgency types in the value of driving (and value of time) of the *marginal consumer with a refill*. That is, the marginal type-C consumer must have a higher value of driving (or lower value of time) than the marginal type-A or type-B consumer because of the lower urgency loading. Second, markets with low non-pecuniary costs are disproportionately informative about the value of driving, whereas markets with severe shortages and high wait times are informative about the value of time. Thus, we construct moments targeted to distinct margins of the model. We illustrate the influence of each model parameter on the predicted refill shares in Appendix H.

Let $\bar{y}_{gm} = 1/N_{gm} \sum_{i\in(g,m)} y_i$ denote the share of consumers with a refill during the first five days of the panic for urgency type $g \in \{A, B, C\}$ in market m. Further, we assign markets into quartiles based on shortage severity, W_m. We denote these quartiles by r_W.

1. For each type g and shortage quartile r_W, we target the average $\bar{y}_{gm}$ across markets in the quartile. These moments are informative about $\bar{v}$ and $\tilde{\tau}$. Differences in $\bar{y}_{gm}$ are informative about $\tilde{s}$.

2. For each shortage quartile r_W, we target the variance in $\bar{y}_{gm}$ across types in market m, averaged across markets in r_W. These moments are informative about σ_v and σ_τ, which govern the dispersion in v_i and τ_i. For instance, an increase in σ_v dilutes the influence of the urgency loading and moves type-specific refill rates closer together.

3. We target the covariances

$$\begin{aligned}&\mathrm{Cov}\left(W_m, \bar{y}_{Am} - \bar{y}_{Cm}\right)\\ &\mathrm{Cov}\left(W_m, \bar{y}_{Bm} - \bar{y}_{Cm}\right)\;,\end{aligned}$$

   which are informative about the correlation of unobserved heterogeneity, ρ. This parameter governs whether a negative shock to a consumer's value of driving is compensated by a negative shock ($\rho > 0$), or amplified by a positive shock ($\rho < 0$) to the value of time. The effect of this correlation on refill shares is disproportionately important for type-A and type-B consumers. Thus, we target the covariance of W_m with the difference in refill rates of type-A and type-B consumers relative to type-C consumers.

4. For each type g and consumer characteristic x_i, we target the covariance between the refill indicator y_{ig} and the characteristic x_i. We do so separately for markets with below/above median shortage severity (W_m), and for markets with below/above median wait times (ϕ_m). These moments are separately informative about $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$. In particular, cross-type differences in characteristics of observed refills load onto $\boldsymbol{\beta}$. Similarly, under the assumption of random rationing, cross-market differences in X_i of observed refills load onto $\boldsymbol{\gamma}$.

5. We target the slope of $\bar{y}_{gm}$ with respect to shortage severity (W_m) and wait times (ϕ_m), separately for markets with below/above median shortage severity. That is, for each type g and below/above median split, we implement the following regression,

$$\bar{y}_{gm} = \alpha_g + \beta_{1g} \, W_m + \beta_{2g} \, \phi_m + \varepsilon_{gm} \ ,$$

and target the coefficients $\hat{\beta}_{1g}$ and β_{2g}. The change in refill rates with respect to W_m is particularly informative about α as it governs how quickly shortages translate into random rationing.

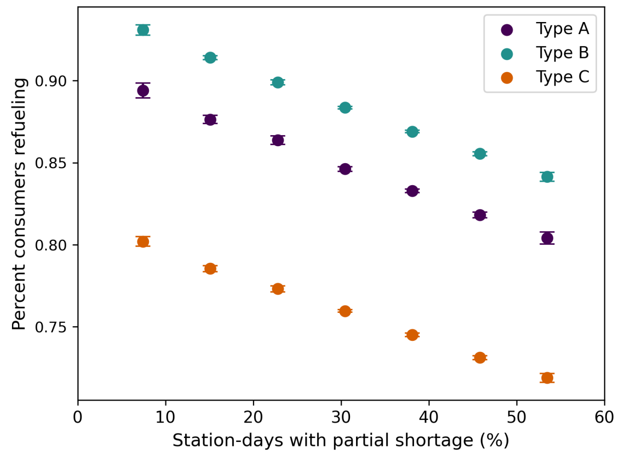
H Model simulation

This section illustrates how each model parameter affects the location and shape of predicted refill rates across markets and urgency types. This exercise motivates the moment conditions used in estimation. We use observed wait times, ϕ_m, and shortage severity, W_m, and simulate refill probabilities for

$$\{\bar{v} = 1.25, \bar{\tau} = -0.75, \sigma_v = 1.00, \sigma_\tau = 1.00, \rho = 0.8, \tilde{s} = 0.25, \alpha = 0.2\}$$

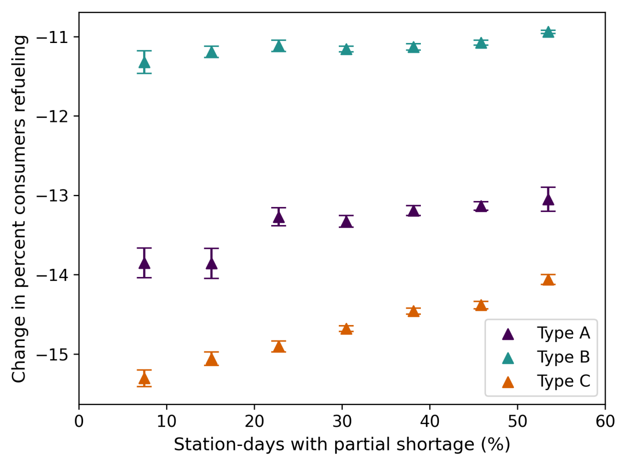
Figure A16 shows a binscatter plot of the market-by-type refill rates. Because we abstract from observed consumer characteristics, the underlying distribution of (v_i, τ_i) is identical across urgency types and markets. Thus, differences in type-specific refill rates across markets arise from variation in (ϕ_m, q_m) only. Differences in market-specific refill rates across urgency types only reflects the urgency loadings, $L_g(\tilde{s})$. With $\tilde{s} = 0.25$, we have $L_B(\tilde{s}) > L_A = 1 > L_C(\tilde{s})$. Consequently, the marginal type-C consumer who attempts a refill must have a higher value of driving, or lower value of time, than the marginal type-A or type-B consumer.

Appendix Figure A16: Market-by-type refill rates, benchmark



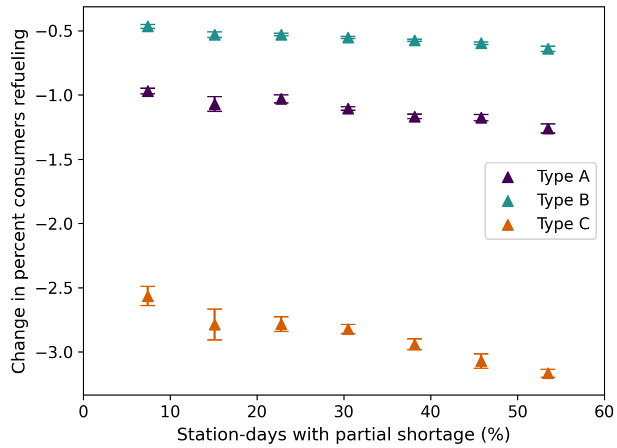
Average value of driving, $\bar{v}$. Figure A17 illustrates the level change in the refill rates (in %) for $\bar{v} - 1$. Decreasing the average value of driving lowers refill rates for all urgency types, especially so for type-C consumers who have a lower urgency loading. Conditional on type, refill rates decrease more in low-shortage markets.

Appendix Figure A17: Change in percent consumers refueling, $\bar{v} - 1$



Average value of time, $\bar{\tau}$. Figure A18 illustrates the change in refill rates for $\bar{\tau}+1$. Refill rates decrease for all types. Conditional on type, refill rates decrease more in high-shortage markets.

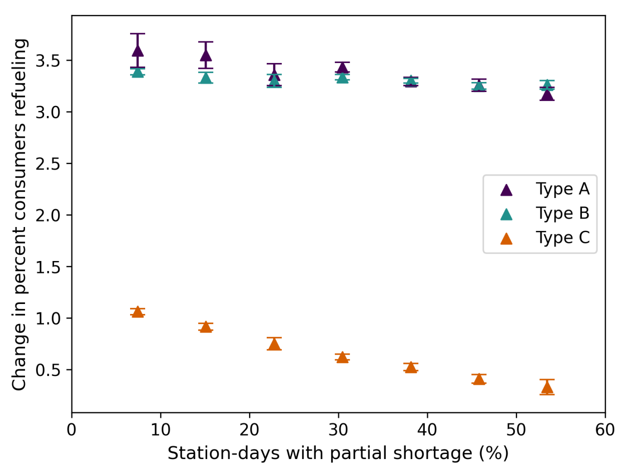
Appendix Figure A18: Market-by-type average refill rates, $\bar{\tau} + 1$



Unobserved heterogeneity in value of driving, σ_v. The standard deviation of the value of driving manipulates the relative positioning of refill rates across urgency types, especially of type-C consumers relative to types A and B. Figure A19 shows the change in refill rates for $\sigma_v/2$. Decreasing σ_v moves type-specific refill rates further apart from one another.

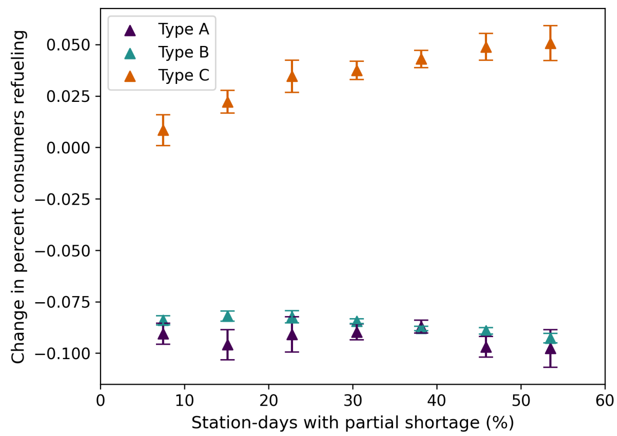
A lower σ_v reduces the mass in the tails of the v_i-distribution. For type-A and type-B consumers, the decrease in the left tail dominates because the higher urgency loading can compensate for the loss in the right tail. For type-C consumers, the loss is more uniform.

Appendix Figure A19: Market-by-type average refill rates, $\sigma_v/2$



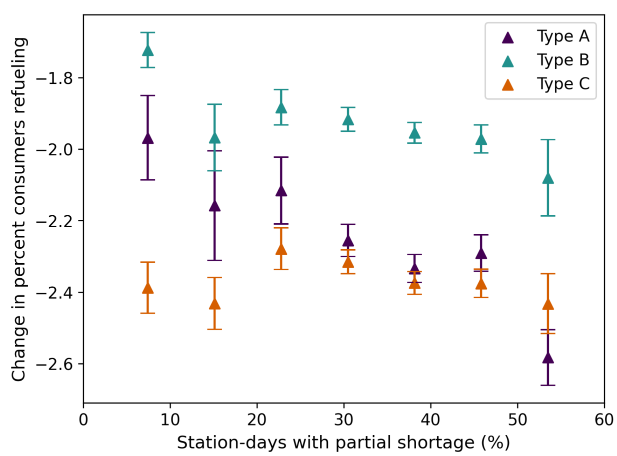
Unobserved heterogeneity in value of time, σ_τ. Figure A20 illustrates the change in refill rates for $\sigma_\tau/2$. Here, decreasing σ_τ moves type-specific refill rates closer together as it increases refill rates of type-C consumers and lowers those of type-A and type-B consumers.

Appendix Figure A20: Market-by-type average refill rates, $\sigma_\tau/2$



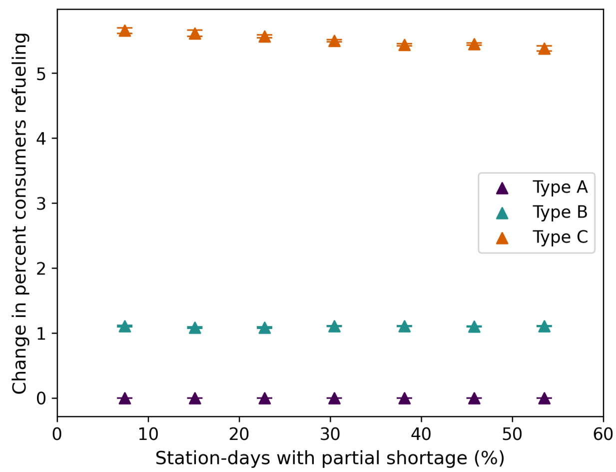
Correlation in unobserved heterogeneity, ρ. Figure A21 illustrates the change in refill rates when changing ρ from 0.8 to -0.8. The parameter ρ governs the correlation of the unobserved heterogeneity in the value of driving and of time. With $\rho = 0.8$, a low v_i is compensated by a low τ_i. With $\rho = -0.8$, the effect of a low v_i is amplified by a high τ_i, reducing the expected utility of an attempt.

Appendix Figure A21: Market-by-type average refill rates, $(-1)\rho$



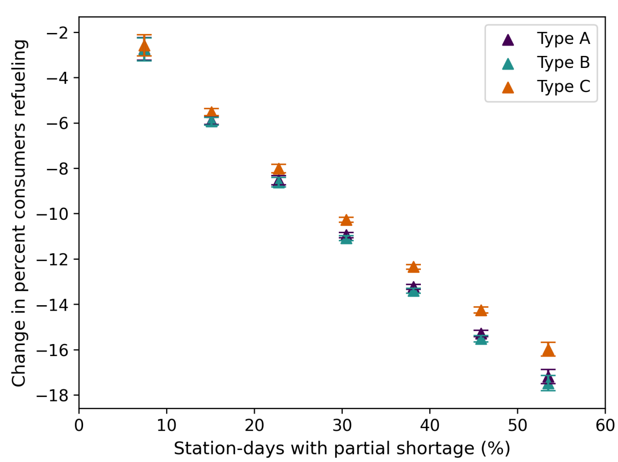
Resupply belief, $\tilde{s}$. The resupply belief governs the gap in average refill rates of type-B and type-C consumers relative to type-A consumers. In particular, as $\tilde{s}$ changes, refill rates of type-A consumers remain unchanged because their decision is independent of $\tilde{s}$. In addition, how $\tilde{s}$ changes the relative location is constrained by the relationship $L_C(\tilde{s}) = L_B(\tilde{s}) - 1$. Figure A22 shows the change of a decrease in $\tilde{s}$: refill rates of *both* type-C and -B consumers increase.

Appendix Figure A22: Market-by-type average refill rates, $\tilde{s}/2$



Shortage parameter, α This parameter governs the relationship between observed shortages and the conditional success probability of refilling. It governs how quickly the expected utility of a refill attempt decreases as shortage severity increases. Since the conditional probability is 1 for $W_m = 0$, a decrease in α corresponds to a rotation of average refill probabilities around the intercept.

Appendix Figure A23: Market-by-type average refill rates, 3α



I Additional counterfactual: Fixed cost of refueling

In this section, we translate the market-clearing wait time into a fixed monetary cost per refill based on the market-level wage distribution. We find that the average market clears at a fee of £15.40. Yet, several markets require a fee of more than £30. In addition, switching from wait times to fixed costs has distributional implications and harms low-wage consumers.

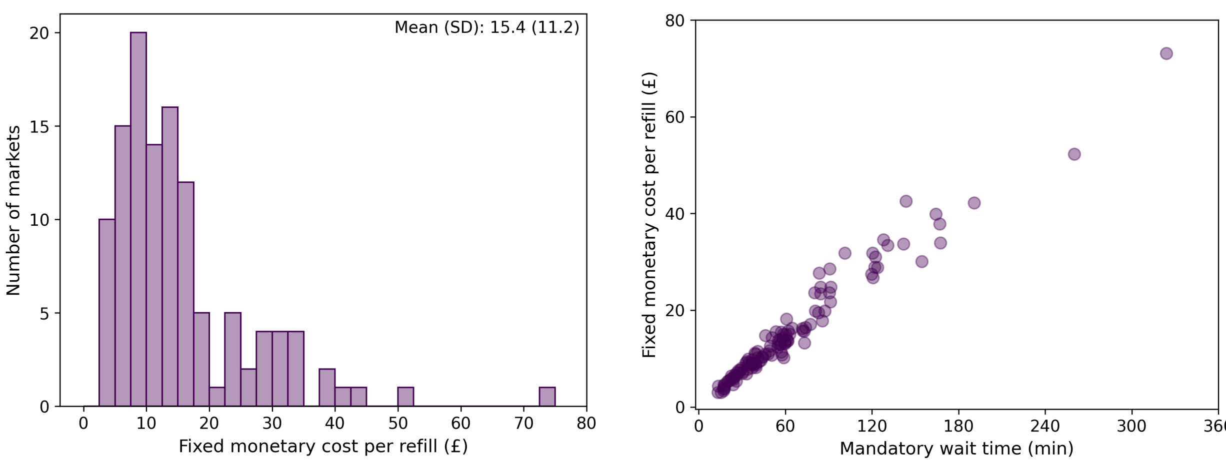
To recover the market-level wage distribution, we leverage data from the 2021 Annual Survey of Hours and Earnings (ASHE), which reports key moments of the wage distribution of each TTWA. We focus on the hourly gross pay across all working residents and assume that wages follow a log-normal distribution (Mincer 1974; Neal and Rosen 1999). We recover the parameters by matching the market-specific data moments.

To assign wages to consumers, we rely on the distribution of annual household incomes across Middle Super Output Areas (MSOAs). In particular, we observe the 2020 annual household income and the 2021 household count at the MSOA level. We assign each household in an MSOA the average annual income. We then assign each MSOA to a decile in the market-specific income distribution, accounting for the number of households in each MSOA. Consumers are then assigned to the income decile of their home-MSOA, which is a cluster of LSOAs. A consumer in income decile d gets a random draw from the d-th decile of her home-market wage distribution. To obtain consumers' willingness to pay to be able to refill, we multiply their willingness to wait by their hourly wage. We then search for the fixed cost that equates market-level demand with supply Q_m.

Figure A24 illustrates the distribution of market-clearing fixed costs and their relationship with market-clearing wait times. Overall, the aggregate and type-specific loss in consumer surplus under a fixed per-refill cost is similar to that of mandatory wait times (see Table A5). However, we do find that by switching from mandatory wait times to a fixed cost, refill shares of low-wage consumer decrease while those of high-wage consumers increase (see Figure A25).

Appendix Figure A24: Market-clearing fixed costs

(A) Distribution of market-clearing fixed costs   (B) Wait times vs fixed costs



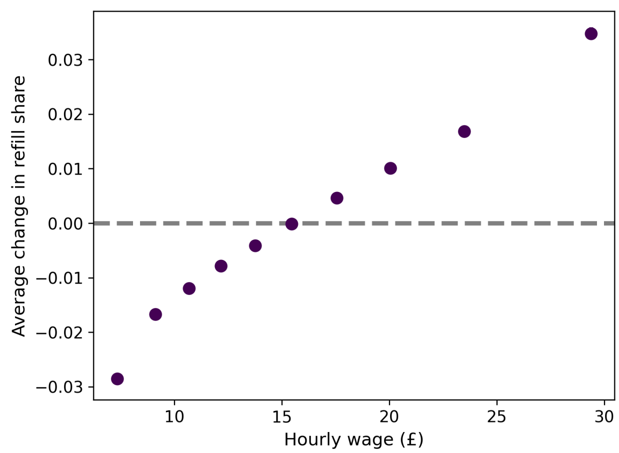
Note: Figure shows the distribution of market-clearing fixed costs (Panel (A)) and the relationship with market-clearing wait times (Panel (B)).

Appendix Table A5: Consumer surplus under market-clearing fixed costs

	Accurate belief ($s = \tilde{s}$)			Pessimistic belief ($s = 0.7$)		
Shortage severity bin	1	2	3	1	2	3
(A) Aggregate change in surplus (%)						
Fixed cost: misallocation	–0.5	–0.7	–1.4	–19.0	–18.2	–18.6
Fixed cost: total change	–1.8	–2.4	–4.6	–20.9	–20.7	–23.0
(B) Per-consumer change in surplus						
Fixed cost: type A	–1.9	–2.8	–6.1	–2.0	–2.8	–6.1
Fixed cost: type B	–2.2	–3.2	–6.0	–2.0	–3.0	–5.4
Fixed cost: type C	–1.0	–1.5	–2.2	–27.0	–29.1	–27.5

Note: Table summarizes the difference in aggregate and per-consumer surplus under a fixed cost per refill, relative to the optimal allocation, by market-level shortage severity (percent of station-days with a partial shortage). We group markets into three bins by shortage severity and report bin averages. We separately consider the case of an accurate consumer belief ($s = \tilde{s}$) and a pessimistic belief ($s = 0.7$).

Appendix Figure A25: Change in refill share under fixed cost vs wait time, by consumer wage



Note: Figure shows the average change in refill shares between a market-clearing fixed cost vs wait time, by consumer wage.