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What do one hundred million transactions tell us about demand elasticity of gasoline?

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Abstract

The price elasticity of gasoline demand is a key parameter in evaluation of various policies. However, most of the literature uses aggregate data to identify this elasticity. Temporal and spatial aggregation make such elasticity estimates biased. We employ a unique dataset of all gasoline transactions in Iran during a 4-month period around an unexpected exogenous price change to identify that price elasticity. We also identify a significant withholding behavior by consumers in response to anticipated price changes. The consumers reduce or postpone their purchases when they expect a decrease in prices. Controlling for date fixed effects would eliminate homogeneous withholding responses. However, heterogeneous responses to this anticipated price change would lead to an overestimation of price elasticity. After controlling for date, individual, and location fixed effects as well as the withholding behavior, we estimate a robust significant price elasticity of − 0.085. Aggregation of the same data by week, month, and city yields an estimate of − 0.3, indicating a significant bias in earlier studies.

Keywords Gasoline demand elasticity · Transaction-level data · Withholding behavior · Subsidy

JEL Classification C55 · D12 · Q31

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1 Introduction

The price elasticity of gasoline demand is a key parameter in evaluating various policies such as taxes (Bento et al. 2009), low carbon fuel standards (Holland et al. 2009), and even merger guidelines (Houde 2012). More importantly, policy makers are always interested in controlling gasoline consumption because of the negative externalities like CO2 emissions, pollution, and congestion. Therefore, knowing the impact of gasoline taxes and price changes on demand is a key issue (Brons et al. 2008).

While there are a plethora of papers that try to estimate price elasticity of gasoline demand, very few could provide reliable estimates. Most studies use household-reported gasoline consumption data or other imperfect measures over a month, a quarter or even a year to estimate the elasticity (Yatchew and No 2001; Hughes et al. 2006). In reality, consumers make gasoline purchase decisions on an ongoing basis, responding directly to the observed spot prices. Aggregating the data could lead to serious estimation biases because short-term responses would be masked (Levin et al. 2017).

We overcome these data challenges in the literature by using a unique administrative dataset that records all gasoline pumping transactions in Iran between 20 February 2014 and 21 June 2014. This allows direct measurement of quantity and price for every transaction made by the individuals. Therefore, unlike Levin et al. (2017), we do not need to infer quantity and price from observed purchases. Additionally, we have the ability to use transaction-level regressions to identify any potential short-term behavioral response.

In our context, individuals receive a set monthly gasoline quota for subsidized gasoline. Higher consumption is charged at a higher price. Therefore, the price of gasoline varies across individuals depending on their consumption and remaining quota. Moreover, in the middle of our sample, the price of gasoline exogenously and unexpectedly increased. Depending on their remaining quotas, consumers receive a heterogeneous price shock. Therefore, we are able to employ a difference-in-difference estimation strategy and identify demand price elasticity after controlling for individual, gas station, and time fixed effects.

Our preferred estimate from the transaction-level data indicates that a 1% increase in the gasoline price results in a 0.085% fall in the purchased quantity. This result is fairly robust to controlling for an extensive set of fixed effects and possible short-term demand fluctuations. To shed light on potential aggregation biases and to compare our results with other studies, we estimate the elasticity by aggregating transaction-level data along temporal and spatial dimensions. Using daily, weekly or monthly data and aggregating to city or province, we observe higher elasticities in the range of -0.30 and -0.6. We discuss the potential causes for this bias which also existed in prior studies like Levin et al. (2017).

Since individuals have the ability to stockpile small quantities of gasoline in fuel tanks, the inter-temporal substitution of gasoline might be significant. In our setting, the monthly recharging of the subsidized quota results in an anticipated price change at the beginning of each month. Therefore, individuals might withhold gasoline consumption toward the end of the month. Ignoring such withholding behavior, we would overestimate the price elasticity of gasoline demand. However, we found an economically small but significant withholding effect. Furthermore, the estimates of the price elasticity remain robust to controlling for withholding.

In the remaining of the paper, we first review the literature that tries to estimate gasoline demand price elasticity. In Sect. 3, we discuss the Iranian context and describe our unique data. Section 4 develops the estimation strategy. Section 5 provides the estimation results and Sect. 6 concludes.

2 Literature review

Given the short span of our data, we focus on the short-run consumption responses and rule out any changes in the available transportation technology. In their review, Anderson and Sallee (2016) conclude that the estimates of the short-run price elasticity of gasoline demand are centered around − 0.25. Furthermore, the short-run responses for miles traveled and fuel demand tend to align closely because on-road fuel economy is largely fixed in the short run. The papers reviewed, however, mainly rely on aggregate data and averages.

Hughes et al. (2006) estimate the gasoline short-run price elasticity to be between − 0.21 and − 0.34 for 1975 to 1980 and between 0.034 and − 0.077 for 2001 to 2006 using the U.S. per capita gasoline consumption and average retail price (time series). They associate the reduction in the price elasticity with the changes "in land-use patterns, implementation of the Corporate Average Fuel Economy program (CAFE), growth of multiple income households and per capita disposable income as well as a decrease in the availability of non-auto modes such as transit". Similarly, using annual gasoline consumption for 30 provinces in China from 1997 to 2008 and provincial gasoline prices, Lin and Zeng (2013) estimate the price elasticity of demand for gasoline to be between − 0.196 and − 0.497. They use regional diesel prices and international crude oil prices as instrumental variables to solve for the simultaneity of price and quantity. These estimates employ aggregate datasets and suffer from aggregation bias.

A branch of the literature uses gasoline tax changes to identify price elasticities. The idea is that forward-looking individuals take into account future tax changes when deciding on current gasoline consumption. Coglianese et al. (2017) estimate the demand elasticity by including one lead and one lag of the price change as controls. They find an elasticity of − 0.37 using monthly state consumption, price and gasoline taxes from January 1989 to March 2008. While this approach might have a better identification strategy, the estimated elasticity is larger because tax-related price changes are less likely to be correlated with unobserved demand fluctuations in other cities. Therefore, the elasticity estimates based on state-level tax changes could have a smaller bias than the estimates from non-tax price changes (Levin et al. 2017).

One noticeable exception that employs micro data is Levin et al. (2017). They use daily city-level gasoline prices and expenditures to estimate the price elasticity of gasoline demand in the United States. Using high-frequency data, they are able to include an extensive set of fixed effects and capture endogenous heterogeneity. They estimate gasoline demand elasticity to be in the range of − 0.27 and − 0.35. They show that aggregation produces smaller elasticities and emphasize the importance of using disaggregated data.

A few recent papers use individual-level data to estimate the driving elasticity with respect to fuel price. Gillingham et al. (2015) exploit detailed annual vehicle-level emission inspection test data from Pennsylvania and employ a fixed-effects estimation strategy (VIN fixed effects). They find that a 10% increase in the gasoline price is associated with a 1% decline in the miles traveled. Knittel and Sandler (2013) use a similar dataset to estimate the driving elasticity. They find that average "two-year" elasticity of miles traveled is − 0.15 across all vehicles, but the difference across vehicle types is substantial.

Very few papers study gasoline demand elasticity in Iran. Sohaili (2010) uses annual time series between 1959 and 2008 and finds the short-run and long-run gasoline demand elasticities to be, respectively, − 0.12 and − 0.23. Ghoddusi et al. (2018) use monthly administrative data on the consumption of about 250 gasoline hubs over a 10-year period to estimate smuggling as a function of distance to border. Their results indicate a high elasticity of smuggling demand in areas far from the border but within the border provinces. We use a similar data source but at transaction-level, allowing us to propose a precise estimate of gasoline demand price elasticity.

3 Context and data

Production, export, import and distribution of gasoline are under the control of government in Iran. The retail price of gasoline (and other fuels) is the same across the country and set by the government. Therefore, pumping stations are distribution agents with no control over price or quantity. This means gasoline supply is perfectly elastic. Like other resource-rich countries,[1] Iran has substantial energy subsidies. IMF (2015) reports that Iran spent 14% of GDP on subsidies for petroleum products (namely gasoline, diesel and kerosene) in 2015 which is much higher than the world average of 2.5%.

Due to rising demand and suspicions of fuel smuggling, the Iranian government embarked on an ambitious full monitoring system. From 27 June 2007, each gasoline-consuming vehicle was issued a smart fuel card as a rationing device. Fueling is only possible by these cards. Therefore, from this date, all fueling transactions are recorded and stored centrally by the government. With this system in place, the government implemented an individual pricing scheme. At the beginning of each month,[2] cards received a quota of subsidized gasoline. The amount of the quota is

[1] Iran has 11% of world proven oil reserves (ranked 4th) and has 18% of gas reserves (ranked 1st).

[2] Quotas are delivered on the first day of each Persian calendar month which corresponds to about 21st of each Gregorian calendar month.

based on the registered type of vehicles (22 types). Once the quota is finished, individuals pay a higher price (still subsidized compared to neighboring countries) with no further restriction on gasoline consumption. Unused quota is automatically transferred to the next month and has no effect on the allocation of the next month's quota.

In this paper, we use administrative gasoline purchase data from the fuel card database maintained by the National Iranian Oil Products Distribution Company (NIOPDC). Our data contains all gasoline transactions, nearly 500 million, between 20 February 2014 and 21 June 2014 (4 months). We know the exact time, place, quantity, value, and fuel grade of each pumping transaction of all cards. We restrict our study to privately-owned cars with a quota of 60 L per month during the study period. This constitutes 40% of the total quantity and 43% of the gasoline expenditure during our sample period.[3]

During the 4 months preceding our sample, the gasoline price was fixed at about 12 cents per liter and 21 cents per liter, respectively, for the subsidized and the less-subsidized gasoline.[4] We refer to the quota price as p_q and to the "higher" price as p. Nominal prices remained unchanged until 24 April 2014, when the government unexpectedly announced a price increase that became effective from 25 April 2014.[5] This had no impact on the remaining gasoline quota at p_q prices but the new quota (same amount as before) was priced at 21 cents per liter ($p_q^{'} = p$). The "higher" gasoline price increased to 30 cents per liter (p').[6,7] Therefore, after 25 April 2014, three prices were in place: $p_q < p_q^{'} = p < p'$. Figure 1 summarizes the price schedules before and after the change. A consumer with r liters of remaining subsidized gasoline is expected to receive an addition of 60 L on 22 April 2014. Thus, she was planning her consumption based on the dashed price schedule. However, the government unexpectedly increased the quota price and shifted the price schedule to the solid line. This abrupt price change shifts the supply curve and is our main source of identification discussed in more detail in Sect. 4.

It is worth noting that the fuel cards print the name of the number plate, vehicle type, and the name of the owner. To activate them in each pumping transaction, the holder must enter a password which is the last four digits of her national identification number. Hence the only possible method for formation of a resale market is to give the card and the password to another person for each transaction. Furthermore,

[3] We drop the following card types (dropped cards in parenthesis): taxis (350 thousand cards), motorcycles (5.6 million cards), and cars with specific monthly quotas beyond 60 L (3 million cards). Private cars with unusual quotas constitute many types including diplomatic and veteran-owned vehicles that might have different behavioral responses and hence are removed from our sample.

[4] This is equivalent to 45 cents per gallon. The same quality gasoline had an average price of 3.36 dollars per gallon in the US. We assume an exchange rate of 33,320 Rials per US dollar in this period.

[5] This abrupt announcement resulted in some limited unrest and queuing at pump stations. But since the time between announcement and implementation was less than four hours, there was limited leverage to hoard gasoline.

[6] During this period, the wholesale price of gasoline in the Persian Gulf was 75 cents per liter. Therefore, both prices were substantially subsidized, though the *high price* called as the unsubsidized price by consumers.

[7] Premium quality gasoline is priced at 10% higher than the corresponding regular quality gasoline.

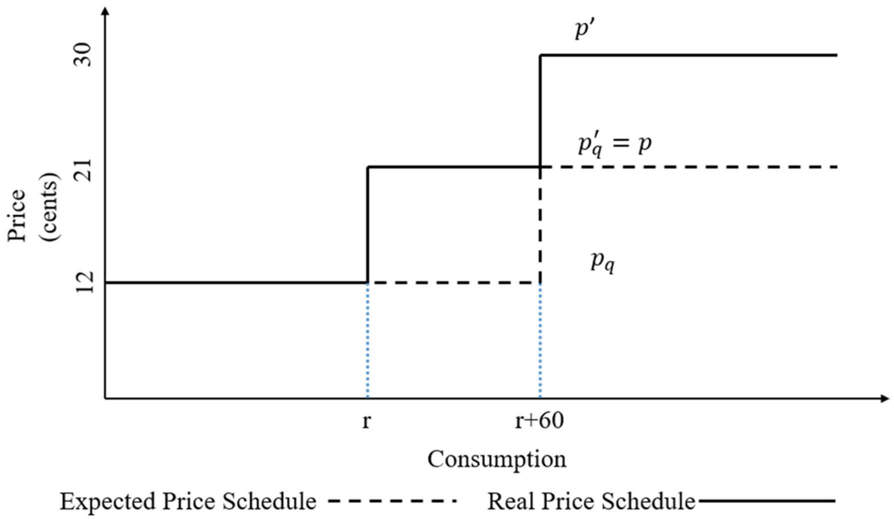

Fig. 1 Gasoline price schedules and their shares during sample period

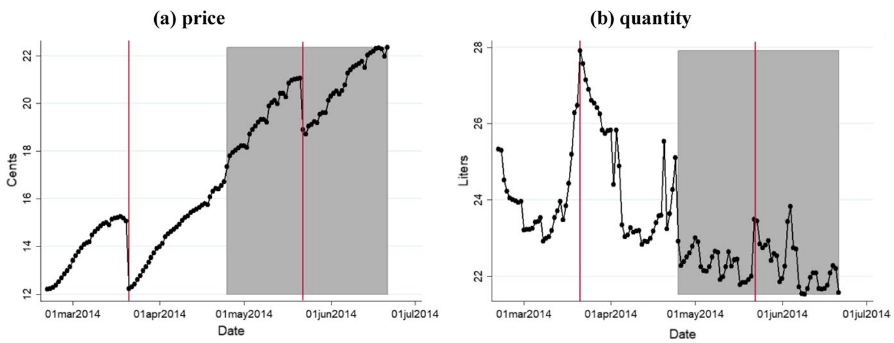

Fig. 2 Average daily price and quantity of gasoline. *Notes* The left panel shows average daily price defined as total gasoline expenditure over total consumption. The right panel shows average daily gasoline consumption conditional on pumping. Vertical lines demonstrate the first day of each month. The gray area indicates the period after 25 April 2014 when prices were increased

using someone else's card to fill the tank of another car is illegal and could result in penalties.[8] Therefore, we believe the high transaction cost of involvement in a resale market prevents equalization of prices for all consumers. Effectively, each consumer faces a government-determined individual price.

Figure 2 shows the average daily price and quantity of gasoline consumption during our sample. The average daily price increases during a month until the new

[8] Gas stations provide "station cards" for fueling of cars with no cards (stolen, malfunctioning, etc.). These station cards have an unlimited quota, but the supply is only at the higher price.

Table 1 Summary statistics by week of month

Week of month	% Subsidized gas (1)	Average price (cents/liter) (2)	# Unique fuel cards (3)	Average consumption (liter) (4)	Average # transactions by a fuel card (5)	Total consumption (million liters) (6)
W1	97	15.1	4,843,944	36.2	1.53	703.6
W2	85	16.1	4,857,050	34.5	1.51	672.2
W3	72	17.3	4,551,558	32.4	1.48	590.3
W4	63	18.2	4,538,621	33.0	1.50	600.9
W5[a]	58	19.2	4,294,072	25.0	1.12	514.8

Table shows average statistics by week in a month during our sample period. Column (1) reports percentage share of subsidized gasoline from total gasoline purchased. Column (2) reports average prices defined as total gasoline expenditure over total consumption. Column (3) reports the number of unique fuel cards used. Column (4) reports average consumption defined as total gasoline purchased over number of unique fuel cards used. Column (5) reports average number of fueling transaction by a card. Column (6) reports aggregate gasoline consumption.

[a]W5 is from 28th day to the end of the month. To make W5 comparable to other weeks, it adjusts by day numbers

quota is awarded, which results in an abrupt price fall at the beginning of each Persian month (Fig. 2a). However, on the 25 April 2014, the price increased unexpectedly. This resulted in the disappearance of the start of the month fall. From this date onward, the price gradually increases as people run down their remaining p_q quotas and start using the higher prices p'_q and p' quotas. Figure 2b shows the average daily quantity of gasoline consumption. The huge spike around the first vertical line is due to a 2-week holiday (Nowrouz). The overall declining trend is also reflecting the reversal of consumption to its non-holiday pattern. The price rise was implemented with very short notice,[9] but 4 days of delay in the delivery of the new month's quota signaled the government's intention to increases the price. Therefore, the graph shows relatively large spikes in the 5 days preceding the rise, possibly due to stockpiling behavior. Figure 2b also shows a jump in daily consumption on the first day of each month, possibly because of the arrival of subsidized quota and increased consumption due to withholding of consumption in the final week of the previous month.

To better illustrate the variability of fueling over the course of a month, Table 1 presents summary statistics by week of month. The first two columns confirm that over a month, consumers run down their gasoline quota and hence pay higher average prices. Column (3) shows the number of unique cars with a fueling transaction during each week. The declining pattern suggests that some consumers withhold further consumption as they finish their subsidized quota. In line with this hypothesis, column (4) indicates that average gasoline purchase per car in each week also declines. Column (5) again depicts this idea by documenting less frequent pumping

9 The government announced the price increase just three hours before the implementation.

Table 2 Summary statistics of monthly gasoline consumption

Average monthly consumption	# of VIN (1)	Average price (cents) (2)	Share of total cons (%) (3)	Share of subsidized pumping[a] (%) (4)	No. pumping per month (5)
[0–30)	99,131	12.2	0.3	100	1.6
[30–59.5)	2,094,559	13.4	13.9	99	2.6
[59.5–60.5)	240,391	14.6	2.0	98	2.8
[60.5–90)	3,222,237	14.7	32.1	91	3.5
[90–120)	1,403,738	15.6	19.5	77	4.4
[120– + ∞)	1,374,188	17.1	32.2	56	6.7
Total	8,434,244	14.9	100.0	78	3.9

Column (1) reports numbers of unique cards in each row. Column (2) reports average price defined as total expenditure over total consumption. Column (3) reports the share of each row in total consumption. Column (4) reports the share of total consumption with price p_q or p'_q. Column (5) reports the average frequency of pumping.

towards the end of the month. Extensive (less pumping) and intensive (smaller purchases) withholding effects result in a declining total gasoline consumption in column (6).

Table 2 reports the statistics for the categories of fuel cards created by average monthly gasoline consumption. Median consumers purchase 75 L per month, which is about 25% more than the monthly subsidized quota. Individuals on average, deplete their subsidized quotas on the 24th day of each month and 78% of their consumption are by the lower rate. Despite various daily limits on usage, the distribution of gasoline consumption shows a fat tail pattern.[10] Top 1% of cars (84,510 cars) consume about 4% of the total gasoline purchases, which is around 14 times the mean consumption. Expectedly, consumers with high levels of consumption benefit less from subsidies as a share of their total consumption. In particular, cars with less than 60 L of monthly gasoline consumption will pay only the subsidized price. In contrast, only 56% of the total gasoline purchases of consumers with more than 120 L per month are from subsidized sources, and their average gasoline price is about 17 cents. Finally, the last column shows the number of pumping transactions per month for different categories. It shows that the consumers with more than 120 L of consumption have 4.2 times more pumping transactions than the consumers with less than 30 L of usage, and their average purchase per pump is about 16 and 26 L, respectively.

Figure 3 presents the cumulative distribution of the purchases monthly quantity and the share of different prices in daily consumption during the 4 months of our study. Figure 3a shows that about 40% of consumers purchase less than 60 L of gasoline in a month, and less than 30% of consumers purchase more than 100 L. In Fig. 3b, the share of subsidized gasoline decreases in each month, and it is always

[10] On a given day a cardholder can only engage in three fueling transactions with a daily limit of 180 L.

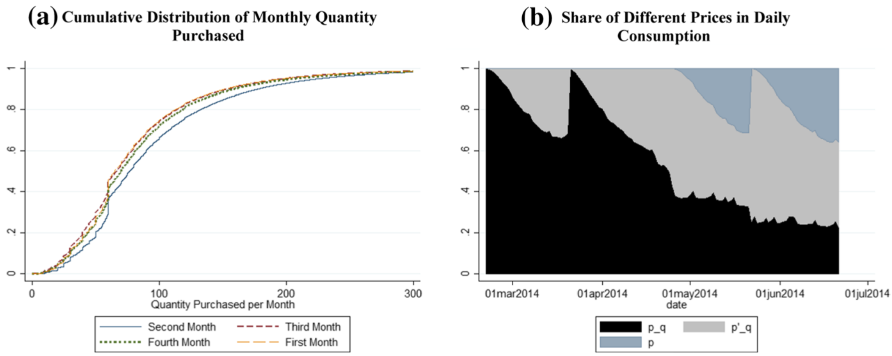

Fig. 3 Daily and monthly consumption. *Notes* In (a) top 1% of gasoline consumption (more than 300 L) is dropped

decreasing after the price change. Moreover, the share of less-subsidized gasoline begins to increase as the new price is introduced.

4 Estimation strategy

There are two sources of price variation in our sample. First, the consumers have different amounts of remaining subsidized quota and hence face different prices in each transaction based on their past consumption. Second, the administrative price change on 25 April 2014 results in an exogenous variation in the price, which has heterogeneous effects for the consumers based on their remaining quota on 24 April 2014. In this paper, we need to control for the first source of variation, because past demand shocks might be correlated with current demand shocks. The second type of variation is, however, our main source of identification.

We estimate our main specification using transaction-level data as follows

$$\ln q_{ijst} = \alpha_i + \gamma_t + \psi_s + \delta g_{ijst} + \beta \ln p_{ijst} + \varepsilon_{ijst} \tag{1}$$

where $\ln q_{ijst}$ is the natural logarithm of quantity of gasoline purchased by consumer i in transaction j on date t at gas station s. α_i, γ_t, ψ_s are, respectively, individual, date, and gas station fixed effects. g_{ijst} captures the share of premium-grade gasoline purchased. $\ln p_{ijst}$ is the natural logarithm of the price, β is the price elasticity of demand and ε_{ijst} is the error term.

The inclusion of individual fixed effects removes any cross-consumer variation that is fixed over time. Hence, in Eq. (1), identification is not coming from a comparison of high-use and low-use consumers. The presence of date fixed effects allows for a completely flexible trend in gasoline consumption and therefore controls for the holiday effects and other potential temporal shifts in demand that affect consumers similarly. The station fixed effects could control for potential location-specific characteristics such as holiday destinations. The use of individual fixed effects is an improvement over Levin et al. (2017)'s strategy of utilizing city fixed effects and to the best of our knowledge no other paper has used individual fixed effects before.

The presence of the quota system without a resale market creates individual-level variation in prices which is essential for this strategy. Moreover, we have access to all gasoline purchases in the country. Therefore, there are no sample selection or measurement errors.

Our context features a known price change at the beginning of each month, which creates an inter-temporal shift of gasoline consumption. More precisely, the presence of quotas has two effects. The increase in average (expected) price reduces demand. At the same time, the prospect of receiving subsidized quota at the beginning of each month creates incentives to shift consumption from the end of month to the beginning of the next month. The latter is what we call "withholding effect" and should be controlled for. The former is, however, a genuine demand response and should be measured in the estimation of the price elasticity. The date fixed effects in Eq. (1) would control for any global time patterns in gasoline consumption. Therefore, to the extent that deviations of individual consumers' timing of their gasoline consumption from the global pattern are random, Eq. (1) controls for inter-temporal demand shifting.

We, however, estimate two alternative specifications that allow for heterogeneity in withholding responses. First, since consumers postpone or reduce their purchases toward the end of each month, we expect to see higher consumption on their first pumping in a new month. We define a dummy variable for the first pumping in a new month (nf_{ijt}), and include this dummy and its interaction with the price in our specification:

$$\ln q_{ijt} = \alpha_i + \gamma_t + \delta g_{ijt} + \beta_1 nf_{ijt} + \beta_2 \ln p_{ijt} + \beta_3 nf_{ijt} \times \ln p_{ijt} + \varepsilon_{ijt} \tag{2}$$

A second way to address withholding is to examine whether a drop or a rise in prices compared to the previous purchase, causes an inter-temporal change in consumption behavior and in particular, the price elasticity. Equation (3) tries to achieve this:

$$\begin{aligned} \ln q_{ijt} = \alpha_i + \gamma_t + \delta g_{ijt} + \beta_1 ind_{+ijt} + \beta_2 ind_{-ijt} + \beta_3 \ln p_{ijt} \\ + \beta_4 ind_{+ijt} \times \ln p_{ijt} + \beta_5 ind_{-ijt} \times \ln p_{ijt} + \varepsilon_{ijt} \end{aligned} \tag{3}$$

Here ind_+ and ind_- are dummies indicating whether the price has increased or decreased compared to the last purchase, respectively. ind_{-ijt} takes the value of one only if the individual has consumed her limit in the last month and it is her first purchase in the new month. This individual is subject to withholding in the last month, so β_5 would control for the withholding effect.

5 Results

5.1 Main results

We start by presenting the estimation results for the aggregated data similar to Levin et al. (2017). This would later allow us to shed light on the potential

Table 3 Gasoline demand elasticity with aggregate data

Cross-section Time	Dep. variable = log (average quantity per capita)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	City	City	City	City	City	Province	Province
	Day	Day	Week	Month	Month[a]	Day	Month
log (average price)	−0.350*** (0.128)	−0.466*** (0.090)	−0.308** (0.121)	−0.318*** (0.105)	−0.314** (0.133)	−0.591*** (0.138)	−0.378** (0.150)
Observations	26,948	26,948	3,757	884	663	3,782	124
R-squared	0.8372	0.7949	0.9445	0.9777	0.9814	0.8527	0.9787
Fixed effects							
Date	Yes						
Day of week		Yes				Yes	
Month		Yes		Yes	Yes	Yes	Yes
Day of month		Yes				Yes	
Week			Yes				
Province						Yes	Yes
City	Yes	Yes	Yes	Yes	Yes		

Standard errors are robust and clustered at the cross-sectional unit to allow for arbitrary serial correlation. The dependent variable is the logarithm of average per-capita quantity defined as the sum of quantities purchased divided by the total number of consumers. Moreover, the average price defined as the total expenditure per total quantity purchased at the appropriate level of spatial and temporal aggregation. Columns (1) and (2) report city-day level elasticity estimates with two different sets of fixed effects. Column (4) and (5) show estimates for aggregation by Persian and Georgian month, respectively.

Standard errors in parentheses

** and *** indicates statistical significance at the 95 and 99 percent level, respectively

aggregation biases. Table 3 shows the results for the datasets collapsed to city-day, city-week, city-month, province-day, and province-month observations. In all columns, the dependent variable is the logarithm of average per-capita quantity, which is equal to the sum of purchased quantities divided by the total number of consumers. Similarly, the average price is calculated by dividing the sum of gasoline expenditure by the total quantity. Columns (1) and (2) are like the main specifications used in Levin et al. (2017) and report the city-day level elasticity estimates with two different sets of fixed effects. The estimate in column (1) is like what Levin et al. (2017) find, but column (2) estimate is larger than their estimate. Averaging the data over a longer time span (week and month) in columns (3) to (5) slightly reduces the magnitude of the elasticity. A one percent increase in price is associated with 0.31% decrease in the monthly consumption. Columns (6) and (7), respectively, collapse the data to province-day and province-month observations. In summary, and unlike Levin et al. (2017), we do not see a decrease in the elasticity estimates after aggregation.

To discuss why our aggregate price elasticity is higher than the individual estimates, we consider the aggregation of Eq. (1) as follows:

$$\ln \overline{q_s} = \hat{\lambda}_s + \hat{\beta} \underbrace{\ln \overline{p_s}}_{\bar{x}} + \overline{\varepsilon_s} \tag{4}$$

where s denotes aggregation in either the time or geographical domains. λ_s is the corresponding fixed effects based on how we aggregate the data and replace α_i and γ_t.[11] If we assume β^0 is the true elasticity from the disaggregated data, we can compute the aggregate elasticity, by some abuse of algebraic notation, as:

$$\hat{\beta} = \left(\bar{x}'\bar{x}\right)^{-1}\bar{x}'\left(\sum_{(i,t)\in s}\left(\alpha_i + \gamma_t\right) + \bar{x}\beta^0 + \sum_{(i,t)\in s}\varepsilon_{it}\right) \tag{5}$$

$$= \beta^0 + \left(\bar{x}'\bar{x}\right)^{-1}\bar{x}'\left(\lambda_s^0 - \hat{\lambda}_s\right) + \left(\bar{x}'\bar{x}\right)^{-1}\bar{x}'\overline{\varepsilon_s} \tag{6}$$

(5) and (6) are valid under the assumption that individual fixed effects or their aggregate counterparts are uncorrelated with log prices. Furthermore, under this assumption, we can approximate the gap between the aggregate and individual elasticities by the association between the error terms and prices (the third term in (6)).[12] The sign of this channel is identical to the sign of $\sum_s \left(\sum_{i,t\in s} x_{it}\right)\overline{\varepsilon_s}$. The presence of the increasing block pricing in our context is the main factor that explains why aggregation creates an opposite effect. In Levin et al. (2017) aggregate demand shocks would be positively correlated with average prices which imposes an upward bias on the elasticity in the aggregate data. However, in our setting, as consumers run down their subsidized quota toward the end of the month we observe a reduction in consumption and an increase in prices due to the increasing block pricing. Hence, the correlation is negative and the aggregate elasticities are higher than the elasticities from disaggregated data.

In our setting, there are two potential sources of endogeneity: withholding effect and consumer heterogeneity. We argued earlier that withholding could potentially cause overestimation of demand elasticity. Consumer heterogeneity is also an important source of bias in our setting. A price-inelastic driver, who consumes more, often pumps more than her limit and falls into the higher price category. Therefore, leaving individual heterogeneity uncontrolled would result in an upward bias. This concern could exist in a setup like Levin et al. (2017) because consumers can opt to use alternative ways of transportation and only purchase gasoline when prices are low. We rely on day, individual, and location fixed effects to control for both sources of endogeneity.

[11] For simplicity we exclude g_{ijt}, but one can simply add this covariate to the aggregate specification.

[12] This equation corresponds to Equation 20 in Levin et al. (2017). They identified three sources of gap between aggregate elasticity and city-day elasticity. In our setup, we assume the aggregation does not change the weights to each observation. If aggregation puts different weights to each observation compared with the dis-aggregated estimates, then the difference in weights times the actual elasticity estimate is another source of deviations. Their exercise to measure the source of bias reveals that this channel as well as the second source is insignificant and economically small.

Table 4 Gasoline demand estimation with individual-level data

Variables	Dependent variable = log (quantity)				
	(1)	(2)	(3)	(4)	(5)
$\log\left(\text{price}_{\text{i,t}}\right)$	−0.243*** (0.0004)	−0.187*** (0.00057)	−0.229*** (0.0023)	−0.077*** (0.00033)	−0.0849*** (0.000319)
Observations	124,174,385	124,174,385	124,174,385	124,174,385	124,173,771
R-squared	0.0255	0.0333	0.4862	0.4934	0.498
Fixed effects					
Car (Individual)	No	No	Yes	Yes	Yes
Date	No	Yes	No	Yes	Yes
Gas station	No	No	No	No	Yes

The dependent variable is the logarithm of daily gasoline consumption. The price is the transaction expenditure per transaction purchase. Standard errors are robust and clustered at individual level to allow serial correlation for each customer. In all specifications, we control for share of premium-grade gasoline purchased. Column (1) has neither car nor day fixed effect. Column (2) and (3) report estimates of elasticity with, respectively, day of sample and individual fixed effects. In column (4) both individual and day of sample fixed effects are included. In column (5) all individual, day of sample and gas station fixed effects are included.

Standard errors in parentheses

** and *** indicates statistical significance at the 95 and 99 percent level, respectively

Table 4 reports the price elasticity estimates using individual-level data. Column (1) does not include any fixed effects and finds one percent increase in gasoline price is associated with a 0.24% reduction in gasoline consumption. Columns (2) and (3) add day and individual fixed effects one at a time and find slight changes. But, controlling for both fixed effects as well as gas station fixed effects significantly reduces the elasticity in column (5). Here one percent increase in price is associated with a 0.085% decline in consumption.[13] Quantile estimates using the same specification show that the elasticity increases from 0.059 for the 25th percentile to 0.097 for the 75th percentile of consumption.

To further control for the heterogeneity in withholding, which might bias our estimates, we estimate Eqs. (2) to (3). Column (1) in Table 5 repeats the estimates from column (4) of Table 4 for comparison. Column (2) presents results of a regression based on Eq. (2). Consumers' response to price changes is very inelastic in the first pumping of a month, since they had postponed their consumption. We can identify this coefficient separately because in the first pumping after the change, the price increases. This estimation works similar to a difference-in-difference-in-difference regression, comparing the change in consumption between two pumping

[13] We also use other time-fixed effects like day of month (30 dummy), day of week (7 dummy) and month of sample (4 dummy) fixed effects instead of day of sample fixed effects in individual-level observations. The results are similar to the reported elasticity in Column (5) of Table 4. Also, multiple location fixed effects like city and province fixed effects do not change the elasticity of demand. To capture regional trends, we also include month by province fixed effect that do not change the results. These results are not shown for brevity.

Table 5 Alternative specification of controlling for withholding

Variables	Dependent variable = log (quantity)		
	(1)	(2)	(3)
$\log\left(\text{price}_{\text{ij}}\right)$	−0.077*** (0.00033)	−0.084*** (0.00034)	−0.086*** (0.00039)
$ind_{+ij} \times \log\left(p_{ij}\right)$			−0.148*** (0.00057)
$ind_{-ij} \times \log\left(p_{ij}\right)$			0.038*** (0.00070)
$nf_{ij} \times \log\left(p_{ij}\right)$		0.109*** (0.00044)	
Constant	3.532*** (0.00203)	3.529*** (0.00210)	3.491*** (0.00267)
Observations	124,174,388	124,174,385	115,740,327
R-squared	0.4934	0.4947	0.4971
Fixed effects			
Car (Individual)	Yes	Yes	Yes
Date	Yes	Yes	Yes

The dependent variable is the logarithm of the transaction gasoline purchased. The price is the transaction expenditure divided by the transaction purchase. Standard errors are robust and clustered at an individual level to allow serial correlation for each customer. In all specifications, we control for share of premium-grade gasoline purchased. In all regressions, we control for individual and day of sample fixed effects. Column (1) reports the base specification estimates. In column (2), we include a dummy whether the purchase is the first pumping of a month and its interaction with the logarithm of current price. In column (3), we include dummies whether the current transaction price is higher ($\mathbf{ind}_{+\mathbf{ij}} = 1$) or lower ($\mathbf{ind}_{-\mathbf{ij}} = 1$) than the last transaction and their interactions with the logarithm of the current transaction price.

Standard errors in parentheses

** and *** indicates statistical significance at the 95 and 99 percent level, respectively

transactions before and after a new month in two consecutive months. Still, the effect of withholding is small. Finally, column (3) reports the results of a regression based on Eq. (3). If consumers experience a 10% price increase, they reduce consumption by around − 0.86%. Therefore, while we find significant and heterogeneous withholding effects, controlling for it does not change our benchmark estimates of the price elasticity.[14]

[14] We also execute an exercise when average daily prices of gas station are used as IV's for the individual prices. This specification will remove individual variation and keep station-level variation in prices. In a specification similar to Column (5) of Table (4), we find an elasticity of − 1.7% that is smaller than our benchmark. We interpret this result due to the weak IV and the removal of useful exogenous individual-level variation created by the unexpected price increase in 24 April 2014.

Table 6 Robustness checks on various samples

	$n_{it} < 3$	$q_{it} \leq 60$	$\#_{permonth} > 2$	$21\,March \leq date \leq 21\,May$	$20\,April \nleq date \nleq 30\,April$
	(1)	(2)	(3)	(4)	(5)
$\ln\left(price_{i,t}\right)$	−0.069***	−0.073***	−0.032***	−0.063***	−0.086***
	(0.00033)	(0.00032)	(0.00049)	(0.00047)	(0.00034)
Constant	3.493***	3.451***	3.136***	3.568***	3.589***
	(0.00201)	(0.00120)	(0.00299)	(0.00280)	(0.00210)
Observations	105,468,473	105,884,312	64,362,219	62,216,604	113,624,132
R-squared	0.5015	0.4873	0.4740	0.5384	0.4973
Fixed effects					
Car (Individual)	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes

The dependent variable is the natural logarithm transaction consumption. The price is the transaction expenditure divided by the transaction purchase. Standard errors are robust and clustered at individual level to allow serial correlation for each customer. In all columns, we control for car fixed effects, day of sample fixed effects. Moreover, in all specifications, we control for share of premium-grade gasoline purchased. In column (1), we exclude all transactions of a consumer who has fueled more than two pumpings in any day. In column (2), we exclude the entire transactions of a consumer who has purchased more than 60 L in any day. In column (3), we exclude the entire transactions of a consumer who has pumped less than two times within a month. Column (4) reports the elasticity estimate when using observations for 1 month before and after the reform. In column (5), we drop observations within a week before and after the reform.

Standard errors in parentheses

** and *** indicates statistical significance at the 95 and 99 percent level, respectively

5.2 Robustness checks

One might argue that each individual has the option of using other people's quotas. We think this challenge would not cause a serious bias in our estimates. First, subsidized gasoline incentivizes the consumers to use their own cards for fueling. Second, even if they are short on subsidized gasoline, they would have to bear some costs to find a card with suitable amount of subsidized gasoline to benefit from lower prices, since, as discussed, consumers, on average, deplete their subsidized quota on 24th day of each month. So, using their own card to fuel or postponing the purchase seems to be more viable. Finally, according to rumors, continuation of receiving subsidized gasoline was subject to a frequent usage of fuel card. Hence, because we have detailed information on fuel consumption per card, we can try to exclude outliers in terms of gasoline use in our robustness.

However, our main concern is that identification may stem from outlier consumers and particular demands like traveling and smuggling. This concern is motivated by the findings reported in Ghoddusi et al. (2018). They find that gasoline elasticity varies with distance from the border. This result highlights the importance of smuggling that might have been substantially affected by the price change on 24 April. Therefore, our robustness checks are to remove consumers with frequent pumping,

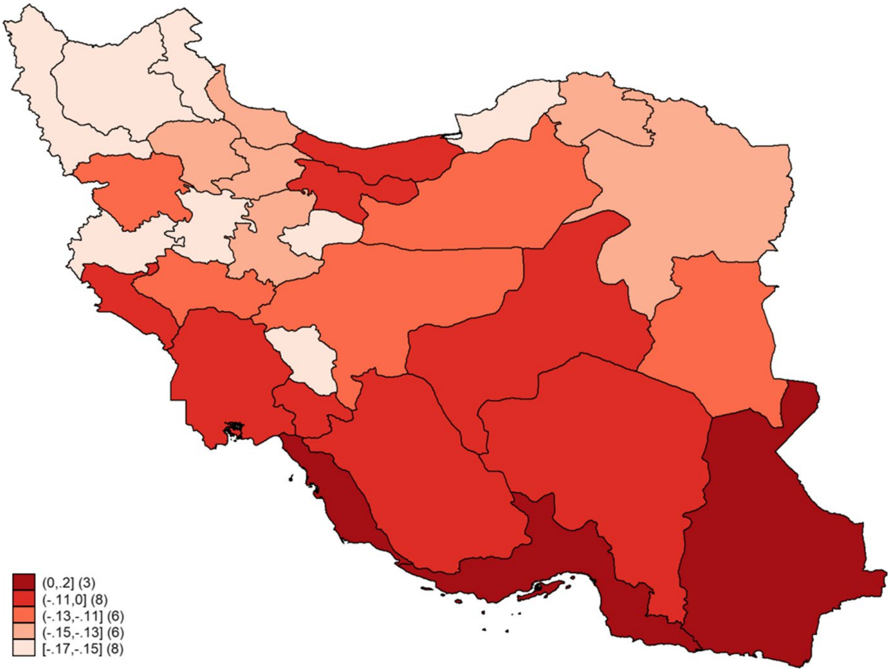

Fig. 4 Gasoline demand elasticity by province. *Notes* Legend shows the intervals and number of provinces, in parentheses. For each province, we run our main specification, column 4 of Table 4, the transaction level estimate by day and individual fixed effects. Lighter color represents higher elasticities

high demands and estimate elasticity in different time horizons. Table 6 reports our robustness estimates on various samples of data.

Column (1) reports the estimates of our benchmark specification when we remove cars that have more than two pumping transactions on any day. We conjecture any smuggling or resale behavior causes frequent pumping in at least 1 day in our sample. Interestingly, 15 million observations are removed in this robustness, but the estimate of the elasticity is unchanged. Column (2) reports the elasticity estimates for the consumers who pump less than 60 L in a day, which results in the same coefficients. We also entirely exclude any consumer with at least 1 day of more than 60-L pumping and find the same results. In column (3), we drop the consumers that pump infrequently. Here, we remove cars that pump less than two times within a month and find a smaller elasticity. The estimate is reduced since people with few gasoline purchases are an important source of variation. When the price is increased on 24 April, these consumers are more likely to hold large remaining quota and hence enjoy a lower price. Furthermore, consumers with more frequent pumping transactions are high usage and less sensitive to price changes. Next, we focus on the robustness checks using various subsamples of days. Column (4) uses observations within one month before and one month after the reform and column (5) removes observations within a week before and after the reform. Again, we find very consistent results to our benchmark estimates.

Finally, we estimate our benchmark model separately for each province. Figure 4 shows that the estimates of the gasoline demand price elasticity in 20 out of 31 provinces fall between − 0.17 and − 0.11. All the estimates are statistically significant at 1%. Only three estimates are positive which has the lowest t-statistics among all estimates. Interestingly, near-border provinces that are notorious for smuggling show strangely positive gasoline demand elasticities. Northwestern and northeastern provinces, subject to smuggling to Turkey and Afghanistan, respectively, show elastic demand to price changes. However, we find that the southern provinces that are the source of smuggling gasoline to the Persian Gulf countries have an inelastic gasoline demand. Since we have confined our study to the privately-owned cars, we interpret the difference between elasticities based on the difficulty of personal smuggling in the southern provinces through maritime borders.

6 Conclusion

Our benchmark gasoline price elasticity estimate of − 0.085 is less than the recent studies like Levin et al. (2017) and Coglianese et al. (2017). However, once we aggregate our data to levels similar to the previous studies, we observe higher elasticities. Therefore, it seems that aggregation bias exists even in the studies that used finer but not individual-level data. We discuss reasons for similarities and dissimilarities between our results and other studies. Our discussion amplifies the importance of the institutional framework in the estimation of elasticity.

Our main source of identification is the unanticipated price change that affects individuals heterogeneously based on their remaining gasoline quota. Using individual-level data mitigates concerns about the endogeneity of prices. However, another potential source of endogeneity arises. The rationing system involves an expected price decline at the beginning of each month when the subsidized quotas are allocated. Therefore, the consumers might reduce or postpone their purchase when they expect a future decrease in prices. If this withholding is homogenous, the date-fixed effects would eliminate them. However, heterogeneous responses to this anticipated price change would lead to an overestimation of demand elasticity. We use various individual-level specifications to control for the heterogeneity of the withholding behavior. We find a small significant withholding effect that is orthogonal to our unexpected price variation, meaning the estimated price elasticity does not change.

In the period of this study, the price of gasoline increased by 61%. Our elasticity estimate of − 0.085 suggests that consumption declined by just around 5% due to the price increase. This finding is consistent with the annual growth in fuel consumption in Iran. The annual growth in gasoline consumption in the year following the reform was 1.7% compared to 7.7% in the year earlier. The results show that gasoline demand is responsive to prices in the short run. Therefore, an effective policy to reduce gasoline consumption and the resulting emissions is to impose taxes or increase prices. Our approach is built on the unique rationing system of Iran which allows use of individual-level fixed effects. This increases the validity of our estimates but is not feasible in the usual context of regional prices (gas station prices). However, we believe that our estimates have wider applicability for developing countries with similar contexts. An important feature of the Iranian context is that most cities do not have a well-extended reliable public transport network and private car commuting is the main mode of transport for within and between city destinations. The existence of cheap and reliable transport alternatives could result in a more elastic demand as consumers have better outside options.

There are three important avenues for extending this research. First, our focus was on the short-run elasticity. There are theoretical reasons to believe in larger long-run elasticities as consumers adapt to prices by choosing their work location, investing in fuel-efficient vehicles, and similar strategies. The estimation of long-run elasticities is more difficult as it is harder to identify an exogenous source of long-run price variation. Second, the heavy subsidies even for the higher price charge outside the ration system, result in significant smuggling opportunities across the borders. Since we focus on private cars we do not have the main chunk of smuggling in our data. But it would be very interesting to separately identify the price elasticity of smuggling similar to Ghoddusi, et al. (2018). Finally, the two-tier pricing system creates discontinuous jumps in marginal prices for consumers reaching the quota limit. Bunching methods could be used to identify the price elasticity of demand. This strategy would use a more structural approach and rely on the inter-temporal shifting behavior to identify the elasticity. Therefore, the nature of the variation used would be different, and separation of withholding and average responses rely on structural assumptions.

Declaration

Conflict of interest All authors declare that they have no conflict of interest.

References

Anderson ST, Sallee JM (2016) Designing policies to make cars greener. Annu Rev Resour Econ 8:157–180

Bento AM, Goulder LH, Jacobsen MR, von Haefen RH (2009) Distributional and efficiency impacts of increased US gasoline taxes. Am Econ Rev 99(3):667–699

Brons M, Nijkamp P, Pels E, Rietveld P (2008) A meta-analysis of the price elasticity of gasoline demand. A SUR Approach Energy Econ 30(5):2105–2122

Coglianese J, Davis LW, Kilian L, Stock JH (2017) Anticipation, tax avoidance, and the price elasticity of gasoline demand. J Appl Econom 32(1):1–15

Gillingham K, Jenn A, Azevedo IML (2015) Heterogeneity in the response to gasoline prices: evidence from Pennsylvania and implications for the rebound effect. Energy Econ 52(1):41–52

Ghoddusi H, Rafizadeh N, Rahmati MH (2018) Price elasticity of gasoline smuggling: a semi-structural estimation approach. Energy Econ 71:171–185

Holland SP, Hughes JE, Knittel CR (2009) Greenhouse gas reductions under low carbon fuel standards? Am Econ J Econ Pol 1(1):106–146

Houde J-F (2012) Spatial differentiation and vertical mergers in retail markets for gasoline. Am Econ Rev 102(5):2147–2182

Hughes JE, Knittel CR, Sperling D (2006) Evidence of a shift in the short-run price elasticity of gasoline demand. No. w12530. National Bureau of Economic Research

Knittel CR, Sandler R (2013) The welfare impact of indirect pigouvian taxation: evidence from transportation. NBER, working paper

Levin L, Lewis MS, Wolak FA (2017) High frequency evidence on the demand for gasoline. Am Econ J Econ Pol 9(3):314–347
Lin C-YC, Zeng JJ (2013) The elasticity of demand for gasoline in China. Energy Policy 59:189–197
Sohaili K (2010) The effect of determining gasoline price according to market mechanism on environment pollution (case study of Iran). Procedia Environ Sci 2:270–273
Yatchew A, No JA (2001) Household gasoline demand in Canada. Econometrica 69(6):1697–1709