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Abstract

The price elasticity of gasoline demand is a key parameter in evaluation of various policy options. However, most of the literature uses aggregate data to identify this elasticity. Temporal and spatial aggregation make elasticity estimates unreliable. We employ a unique dataset of all gasoline transactions in Iran during a four-month period around an unexpected exogenous price change to identify price elasticity. After controlling for date and individual fixed effects we estimate a robust significant price elasticity of -0.077. Aggregation of the same data by week, month, and city yields an estimate of -0.3 indicating a significant bias in earlier studies. We also identify a significant withholding behavior by consumers in response to anticipated price changes.

Keywords: Gasoline demand elasticity, Transaction-level data, Withholding behavior, Subsidy

JEL Classification Codes: C55, D12, Q31

Highlights:

- We use transaction-level data during four months around an exogenous price change to estimate gasoline demand elasticity.
- Based on regressions with date and individual fixed effects, a 10 percent increase in price leads to 0.77 percent reduction in gasoline consumption.
- We find significantly higher elasticities when we aggregate our transaction-level data.
- We control for withholding effects and find no change in our elasticities but the withholding effect itself is significant.

[1] This paper is based on the master thesis of Tavakoli which was carried out under the supervision of the other two authors.

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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 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 is 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 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 data challenges in the literature by using a unique administrative dataset that records all gasoline purchases in Iran. Our data contains all gasoline transactions between 20 February 2014 and 21 June 2014 allowing a direct measure of quantity and price for every transaction made by individuals over this period. Therefore, unlike (Levin et al. 2017) we do not need to infer quantity and price from observed purchases. We have also the ability to use transaction-level regressions and 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 elasticity after controlling for individual and time fixed effects.

Our transaction-level results indicate that a 1 percent increase in gasoline price results in 0.077 percent fall in gasoline quantity purchased. This result is fairly robust to controlling for an extensive set of fixed effects and possible demand fluctuations. To shed light on potential aggregation biases and to compare our results to other studies, we estimate demand 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 sources of this bias which 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 elasticity of gasoline demand.

However, we found an economically small but significant withholding effect. Furthermore, the estimates of gasoline demand 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 Section 3 we discuss the Iranian context and describe our unique data. Section 4 develops the estimation strategy. Section 5 provides the estimation results and Section 6 concludes.

2. Literature Review

Given the short span of our data, we focus on short-run consumption responses and rule out any changes in the available transportation technology. In their review, Anderson and Sallee (2016) conclude that estimates of the short-run price elasticity of gasoline demand are centered around -0.25. Furthermore, 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.

Using times series data, Hughes et al. (2006) estimate 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 U.S. per capita gasoline consumption and average retail price. They associate the reduction in price elasticity to “changing 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 demand 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 demand elasticity by including one lead and one lag of the change in gasoline price 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, an estimate of the elasticity based on state-level tax changes could have a smaller bias than estimates from non-tax price changes (Levin el al. 2017).

One noticeable exception that employs micro data is Levin et al. (2017). They use daily city-level gasoline price and expenditure 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 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 percent increase in gasoline price is associated with a 1 percent decline in miles travelled. Knittel and Sandler (2013) use a similar dataset to estimate driving elasticity. They find that average "two-year" elasticity of miles traveled is -0.15 across all vehicles, but the difference across vehicle types are substantial.

Very few papers study gasoline demand elasticity in Iran. Sohaili (2010) uses annual time series between 1959 and 2008 and finds 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 consumption of about 250 gasoline hubs over a ten-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 border provinces. We use a similar data source but at transaction-level allowing us to propose a precise estimate of gasoline demand 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[5], Iran has substantial energy subsidies. IMF (2015) reports that Iran spent 14 percent of GDP on petroleum products subsidies (namely gasoline, diesel and kerosene) in 2015 which is much higher than the world average of 2.5 percent.

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[6], cards received a quota of subsidized gasoline. The amount of the quota is 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 new 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). For each fuel card, we know the exact time, place, quantity, value, and fuel grade of each pumping transaction. We restrict our study to privately-owned cars with a quota of 60 liters

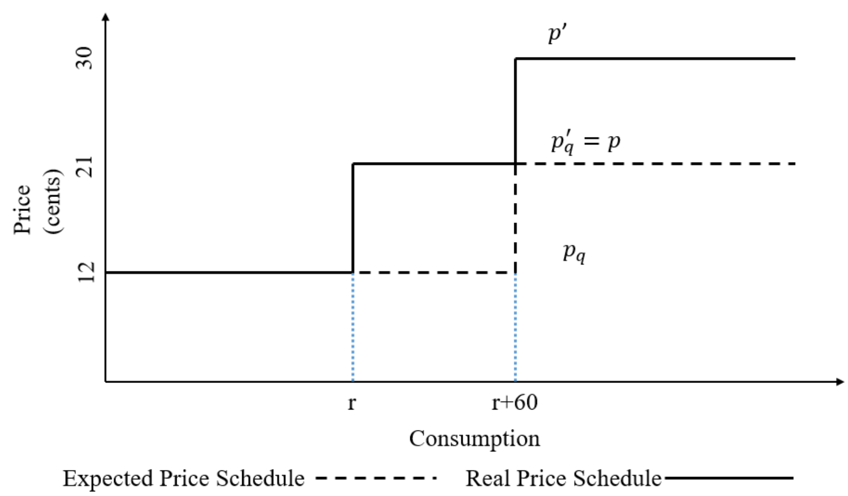
[5] Iran has 11 percent of world proven oil reserves (ranked 4th) and has 18 percent of gas reserves (ranked 1st).

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

per month during the study period. This constitutes 40 percent of total quantity and 43 percent of gasoline expenditure during our sample period [7].

During the four-month period preceding our sample and beyond it, gasoline price was fixed at about 12 cents per liter and 21 cents per liter, respectively for subsidized and less-subsidized gasoline[8]. 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 to become effective from 25 April 2014[9]. This had no impact on the remaining quota at p_q prices but the new quota (same amount as before) was priced at 21 cents per liter ($p'_q = p$). "Higher" gasoline price increased to 30 cents per liter (p') [10,11]. 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 subsidized gasoline expected to receive an addition of 60 liters on 22 April 2014. Thus, she was planning her consumption based on the dashed price schedule. However, the government instead 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 section 4.

Figure 1: Gasoline price schedules and their shares during sample period



[7] We drop the following card types (dropped cards in parenthesis): taxis (350 thousand cards), motor cycles (5.6 million cards), and cars with specific monthly quotas beyond 60 liters (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.

[8] 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.

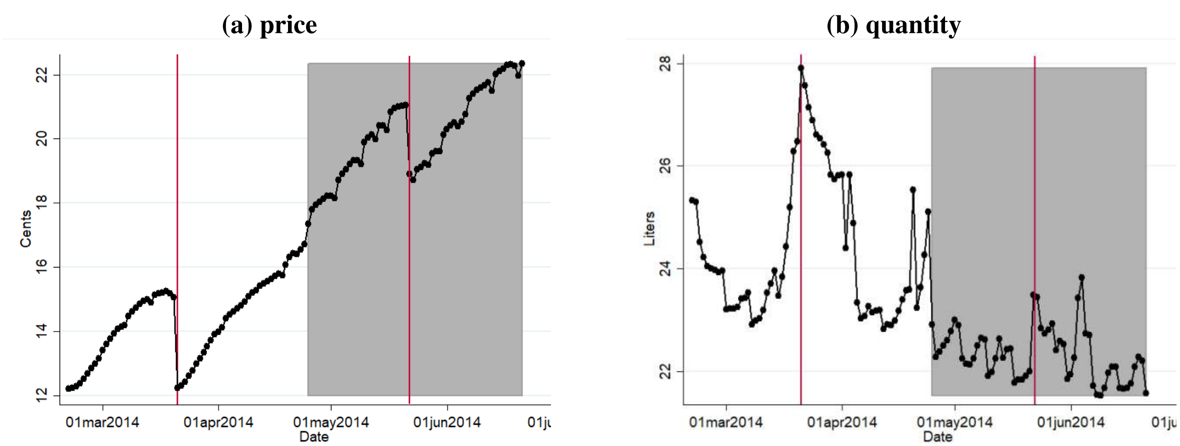
[9] This abrupt announcement resulted in some limited unrest and queuing at pump stations. But since the time between announcement and implementation was less than four hours there was limited leverage to hoard gasoline.

[10] 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.

[11] Premium quality gasoline priced at 10 percent higher than the corresponding regular quality gasoline.

Figure 2 shows average daily price and quantity of gasoline consumption during our sample. Average daily price increases during a month until the new quota is awarded which results in an abrupt price fall at the beginning of each Persian month (Figure 2-a). However, on 25 April the price increased which led to 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 2-b shows average daily quantity of gasoline consumption. The huge spike around the first vertical line is due to a two-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[12], but four days of delay in delivering the new month's quota signaled government's intentions to increases the price. Therefore, the graph shows relatively large spikes in the five days preceding the rise possibly due to stock piling behavior. Figure 2-b 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.

Figure 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.

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 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).

[12] The government announced the price increase just three hours before the implementation.

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*	58%	19.2	4,294,072	25.0	1.12	514.8

Notes: 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.
*W5 is from 28th day to the end of the month. To make W5 comparable to other weeks, it adjusts by day numbers.

Table 2 reports statistics for categories of fuel cards created by average monthly gasoline consumption. Median consumers purchase 75 liters per month, which is about 25 percent more than the monthly subsidized quota. Individuals on average deplete their subsidized quotas on the 24th day of each month and 78 percent of their consumption are by the lower rate. Despite various daily limits on usage, the distribution of gasoline consumption shows a fat tail pattern[13]. Top 1% of cars (84,510 cars) consume about 4% of total gasoline purchase, which is around 14 times 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 liters of monthly gasoline consumption will pay only the subsidized price. In contrast, only 56% of total gasoline purchase of consumers with more than 120 liters per month is from subsidized sources and their average gasoline price is about 17 cents. Finally, the last column shows the number of pumping per month for different cohorts of consumers. It shows that consumers with more than 120 liters of consumption pumping 5 times consumers with less than 30 liters of usage, and their average purchase per pump is about 16 and 26 liters, respectively.

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

Table 2: Summary Statistics of Monthly Gasoline Consumption

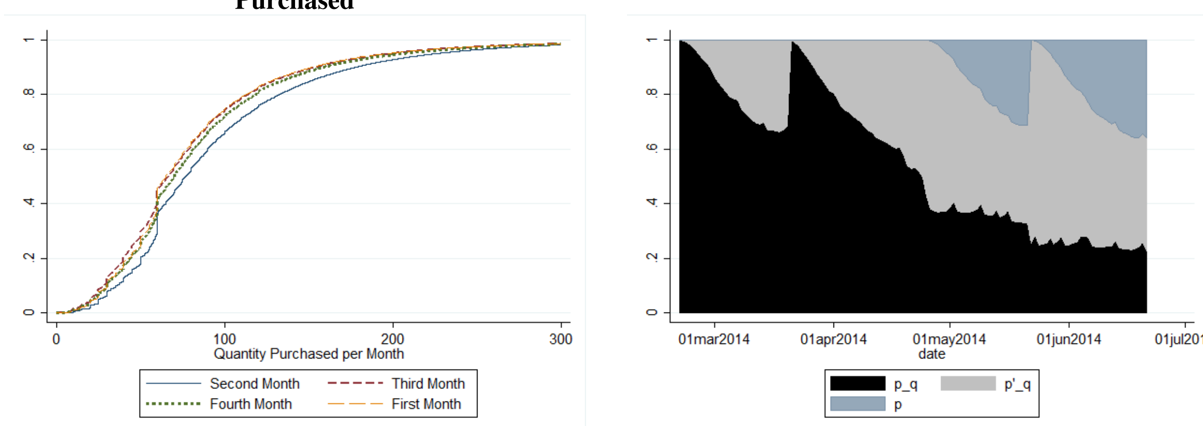
Average Monthly Consumption	# of VIN	Average Price (cents)	Share of Total Cons.	Share of Subsidized Pumping*	No. Pumping per Month
	(1)	(2)	(3)	(4)	(5)
$[0-30)$	99,131	12.2	0.3%	100%	1.6
$[30-59.5)$	2,094,559	13.4	13.9%	99%	2.6
$[59.5-60.5)$	240,391	14.6	2.0%	98%	2.8
$[60.5-90)$	3,222,237	14.7	32.1%	91%	3.5
$[90-120)$	1,403,738	15.6	19.5%	77%	4.4
$[120-+\infty)$	1,374,188	17.1	32.2%	56%	6.7
Total	8,434,244	14.9	100.0%	78%	3.9

Notes: 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.

Figure 3 presents the cumulative distribution of monthly quantity purchased and share of different prices in daily consumption during the four months of our study. Figure 3-a shows that about 40 percent of consumers purchase less than 60 liters of gasoline in a month, and less than 30 percent of consumers purchase more than 100 liters. In Figure 3-b, the share of subsidized gasoline decreases in each month, and it is always decreasing after the price change. Moreover, the share of less-subsidized gasoline begins to increase as the new price is introduced.

Figure 3: Daily and Monthly Consumption

(a) Cumulative Distribution of Monthly Quantity Purchased **(b) Share of Different Prices in Daily Consumption**



Notes: In (a) top 1% of gasoline consumption (more than 300 liters) is dropped.

4. Estimation Strategy

There are two sources of price variation in our sample. First, based on past consumption, consumers arrive at different levels of remaining subsidized quota and hence face different prices. Second, the administrative price change on 25 April 2014 results in an exogenous variation in the price, which has heterogeneous implications for 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

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

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

Inclusion of individual fixed effects removes any cross consumer variation that is fixed over time. Hence, in Equation (1) identification is not coming from a comparison of high-use and low-use consumers. Presence of date fixed effects allows for a completely flexible trend in gasoline consumption and therefore controls for holiday effects and other potential temporal shifts in demand that affect consumers to the same extent. Use of individual fixed effects is an improvement over Levin et al. (2017)'s strategy of utilizing city fixed effects and to our knowledge no other paper has used individual fixed effects before. Moreover, we have access to all gasoline purchases in the country. Therefore, there are no sample selection.

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 subsidized 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 create 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 price elasticity. Date fixed effects in Equation (1) would control for global temporal patterns of gasoline consumption. Therefore, to the extent that deviations of individual consumers' temporal pattern from the global pattern is random, Equation (1) controls for intertemporal demand shifting.

We, however, estimate two alternative specifications that allow for heterogeneity of withholding responses. First, since consumers postpone or reduce their purchase towards 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 price in our specification. Hence, we have

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

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

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

Here ind_+ and ind_- are dummies indicating whether the price has increased or decreased compared to the last purchase, respectively. ind_{-ij} 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 estimation results based on aggregated data similar to Levin et al. (2017). This would later allow us to shed light on potential aggregation biases. Table 3Table 3 shows results for 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 quantities purchased divided by the total number of consumers. Similarly, average price is calculated by dividing the sum of gasoline expenditure by total quantity. Columns (1) and (2) are like the main specifications used in Levin el al. (2017) and report 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 percent decrease in 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 put it more concretely on why our aggregate price elasticity is more elastic than individual estimates, we consider the aggregation of Equation (1) as follows:

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

Where s denotes aggregation in either time or geographical horizon. λ_s are corresponding fixed effects of how we aggregate data and replace α_i and γ_t[14]. If we assume β^0 is the true elasticity from disaggregated data, we can compute the aggregate elasticity, by some abuse of algebraic notation, as:

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

$$= \beta^0 + (\bar{x}'\bar{x})^{-1}\bar{x}'(\lambda_s^0 - \widehat{\lambda_s}) + (\bar{x}'\bar{x})^{-1}\bar{x}'\overline{\varepsilon_s} \tag{6}$$

Equations (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

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

can approximate the gap between aggregate elasticity and individual elasticity by the association between error terms and prices (the third term in (6)) [15]. The sign of this channel is equal to the sign of $\sum_s(\sum_{i.t\in s} x_{it})\bar{\varepsilon_s}$. The presence of 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 aggregate data. However, in our setting, as consumers run down their subsidized quota towards the end of the month we observe a reduction in consumption and an increase in prices due to increasing block pricing. Hence, the correlation is negative and aggregate estimates are more elastic than elasticities from disaggregated data.

Table 3: Gasoline Demand Elasticity with Aggregate Data

	Dep. Variable = log(average quantity per capita)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cross-section	City	City	City	City	City	Province	Province
Time	Day	Day	Week	Month	Month*	Day	Month
log(average price)	-0.350***	-0.466***	-0.308**	-0.318***	-0.314**	-0.591***	-0.378**
	(0.128)	(0.090)	(0.121)	(0.105)	(0.133)	(0.138)	(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		

Notes: 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.

In our setting, there are two potential sources of endogeneity: withholding effect and consumer heterogeneity. We argued earlier that withholding can 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 higher price categories. Therefore, leaving individual heterogeneity uncontrolled would result in an upward bias. This concern could exist in a set up like Levin et al. (2017), because consumers can opt to

[15] 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 put 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.

use alternative ways of transportation and only purchase gasoline when prices are low. We rely on day and individual fixed effects to control for both sources of endogeneity.

Table 4 reports demand 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 0.24 percent 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 significantly reduce the elasticity in column (4). Here one percent increase in price is associated with 0.077 percent decline in consumption[16]. An alternative specification is to estimate a difference-in-difference specification when the dependent variable is change in consumption before and after the exogenous price shock and independent variable is the difference in individual prices. Noticeably, in this specification the individual fixed effects will cancel out. We find the price elasticity of demand to be 12.9 percent under this specification.

Table 4: Gasoline Demand Estimation with individual-level data

Dependent Variable:	log(quantity)				$\log\left(\frac{\text{quantity}_{i,t}}{\text{quantty}_{i,t-1}}\right)$
VARIABLES	(1)	(2)	(3)	(4)	(5)
$\log(\text{price}_{i,t})$	-0.243***	-0.187***	-0.229***	-0.077***	
	(0.0004)	(0.00057)	(0.0023)	(0.00033)	
$\log(\text{price}_{i,t}) - \log(\text{price}_{i,t-1})$					-0.129***
					(0.00080)
Constant	4.451***	4.100***	4.372***	3.532***	-0.143***
	(0.00248)	(0.00356)	(0.00144)	(0.00203)	(0.00095)
Observations	124,174,385	124,174,385	124,174,385	124,174,385	7,885,638
R-squared	0.0255	0.0333	0.4862	0.4934	0.0246
Fixed effects					
CAR (INDIVIDUAL)	NO	NO	YES	YES	NO
DATE	NO	YES	No	YES	YES

Note: 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. Column (5) reports the change in logarithm of gasoline consumption on change in logarithm of price controlling with day fixed effect.

To further control for heterogeneity in withholding, which might bias our estimates, we estimate equations (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 equation (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

[16] We also use other time fixed effects like day-of-month, day-of-week and month-of-sample fixed effects instead of day-of-sample fixed effects in individual level observations. The results are similar to the reported elasticity in Column (4) of Table 4. Also, multiple location fixed effect like city and province fixed effects do not change the elasticity of demand. These results are not shown for brevity.

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 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 equation (3). If consumers experience a 10 percent price increase they reduce consumption by around -0.86 percent. Therefore, while we find significant and heterogeneous withholding effects, controlling for it does not change our benchmark estimates of price elasticity. Finally, consumers may change their purchase behavior after the price reform and postpone their pumping. This is a further withholding due to the reform. To address this concern, we include dummies for days a driver delays pumping. However, part of the variation that identifies the demand elasticity is captured by these dummy, so we expect the estimate of this specification to be a lower bound for the elasticity. We find estimate of the elasticity to be around 4% in this specification.

Table 5: Alternative Specification of Controlling for Withholding

	Dependent Variable = log(quantity)			
VARIABLES	(1)	(2)	(3)	(4)
$\log(\text{price}_{ij})$	-0.077***	-0.084***	-0.086***	-0.039***
	(0.00033)	(0.00034)	(0.00039)	(0.00036)
$\text{ind}_{+ij} \times \log(p_{ij})$			-0.148***	
			(0.00057)	
$\text{ind}_{-ij} \times \log(p_{ij})$			0.038***	
			(0.00070)	
$\text{nf}_{ij} \times \log(p_{ij})$		0.109***		
		(0.00044)		
Constant	3.532***	3.529***	3.491***	3.222***
	(0.00203)	(0.00210)	(0.00267)	(0.00251)
Observations	124,174,388	124,174,385	115,740,327	115,740,327
R-squared	0.4934	0.4947	0.4971	0.4957
Fixed effects				
CAR (INDIVIDUAL)	YES	YES	YES	YES
DATE	YES	YES	YES	YES
DAYS TO PUMP	NO	NO	NO	YES

Note: 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 higher ($\mathbf{ind}_{+ij} = \mathbf{1}$) or lower ($\mathbf{ind}_{-ij} = \mathbf{1}$) than the last transaction and their interactions with the logarithm of the current transaction price. In column (4), we include dummies for days between consecutive purchases.

5.2. Robustness checks

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

Table 6: Robustness Checks on Various Samples

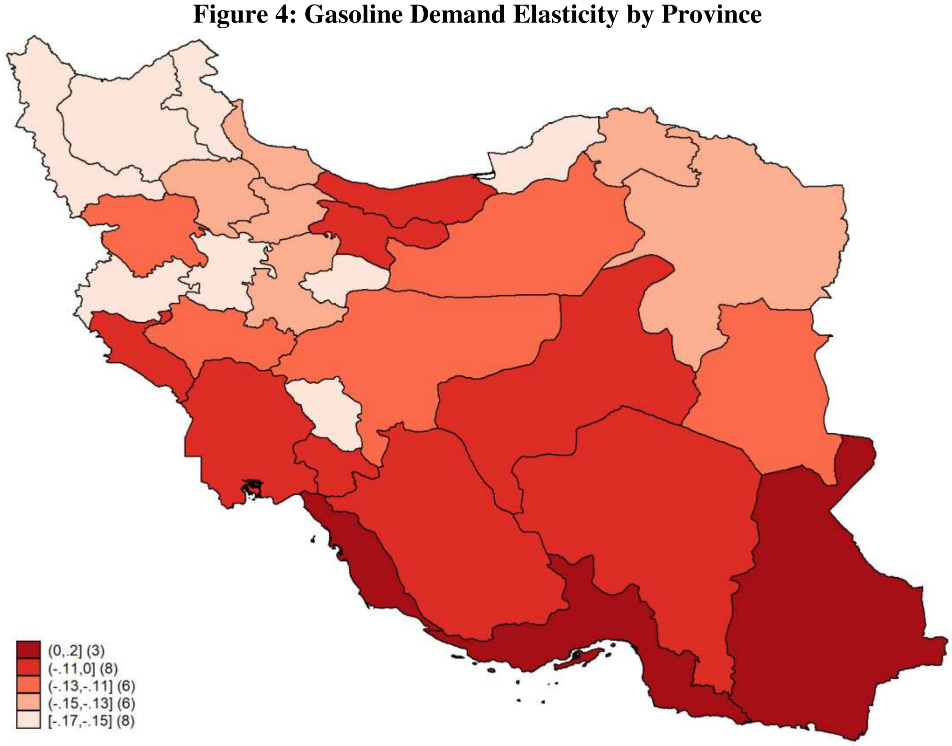
	$n_{it} < 3$	$q_{it} \leq 60$	$\#_{per\ month} > 2$	$21\ March \leq date \leq 21 May$	$20\ April \nleq date \nleq 30\ April$
	(1)	(2)	(3)	(4)	(5)
$ln(price_{i,t})$	-0.069***	-0.073***	-0.032***	-0.063***	-0.086***
	(0.00033)	(0.00032)	(0.00049)	(0.00047)	(0.00034)
Constant	3.493***	3.451***	3.136***	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

Note: 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 pumping in any day. In column (2), we exclude the entire transactions of a consumer who has purchased more than 60 liters 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 one month before and after the reform. In column (5), we drop observations within a week before and after the reform.

Column (1) reports estimates of our benchmark specification when cars that have fueled more than two pumping in a day are removed entirely from the sample. We conjecture any smuggling behavior causes frequent pumping in at least one day in our sample. Interestingly, 15 million observations are removed in this robustness, but the estimate of demand elasticity is equal to our benchmark model. Column (2) reports elasticity estimates for consumers who pump less than 60 liters in a day, which results in the same coefficients. In column (3) we drop consumers that pump infrequently. Here, we remove cars that pump less than two times within a month and find consistent estimates. The estimate is reduced since people with few gasoline purchase are less sensitive to price changes. Next, we focus on 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 of our benchmark estimates.

Finally, we estimate our benchmark model using observations in each province. Figure 4 shows that estimates of gasoline demand elasticity in 20 out of 31 provinces falls between -0.17 and -0.11. All the estimates are statistically significant at 1 percent. Only three estimates are positive which has the lowest t-statistics among all estimates. Interestingly, near-border provinces that are notorious for smuggling, show strange gasoline demand elasticity. Northwestern and northeastern provinces, subject to smuggling to Turkey and Afghanistan, respectively, show elastic demand to price changes. However, we find that in south provinces that are the source of smuggling gasoline to Persian Gulf countries, gasoline demand elasticity is inelastic. Since we have limited our study to privately-owned cars, we interfere that the difference in elasticity is due to difficulty of personal smuggling in south provinces through maritime borders.

Figure 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.

6. Conclusion

Our benchmark gasoline price elasticity estimate of -0.077 is less than recent studies like Levin et al. (2017) and Coglianese et al. (2017). However, once we aggregate our data to levels similar to previous studies we observe higher elasticities. Therefore, it seems that aggregation bias exists even in studies that used finer but not individual level data. We discuss reasons of similarities and dissimilarities between our results and other studies. Our discussion amplifies the importance of institutional framework in estimation of elasticity.

Our main source of identification is the unanticipated price change, which induces the change in gasoline demand. Using individual-level data, concerns about the endogeneity of prices is mitigated; however, another potential source of endogeneity arises. The intertemporal deterministic price change between months that is known to all consumers, changes gasoline demand. The consumers reduce or postpone their purchase, when they expect a decrease in prices. If homogenous, controlling for date fixed effects, would eliminate responses to anticipated price changes. However, heterogeneous responses to this anticipated price change, would lead to overestimation of demand elasticity. We use various individual-level specifications to control for heterogeneous withholding behavior, and find slight changes in demand elasticity.

In the period of this study, the price of gasoline increased by 61%. Our elasticity estimate of -0.077 suggests that consumption declined by just around 5% due to the price increase. This finding is consistent with 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.

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