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Essays on Consumer Demand for Gasoline: Mexico and the United States

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Essays on Consumer Demand for Gasoline: Mexico and the United States

By

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DISSERTATION

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A mis padres, mis abuelos, mis tíos y mis primos. Este logro es el resultado de esfuerzos continuos a lo largo de generaciones. Muchas gracias a todos.

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Acronyms

CARB California Air Resources Board. 51, 52, 64, 65, 71

CARBOB California Reformulated Gasoline Blendstock for Oxygenate Blending. 64

CBOB Conventional Blendstock for Oxygenate Blending. 64

CDU crude distilling unit. 63

CONACYT Consejo Nacional de Ciencia y Tecnología. iv

CONAPO Consejo Nacional de Población. 9

CRE Comisión Reguladora de Energía. 5, 8

FCC fluid catalytic cracking unit. 63, 64, 71

HCU hydrocracking unit. 63, 64, 71

INEGI Instituto Nacional de Estadística y Geografía. iv, 5–7, 9

ITAM Instituto Tecnológico Autónomo de México. iv

LCFS Low Carbon Fuel Standard. 53, 72

MER Mexico's Energy Reform. vii, 3, 8, 17, 37, 38, 41

MoF Ministry of Finance. vii, ix, 1, 3–5, 20, 23, 36, 38, 41–45, 48

OSHA Occupational Safety and Health Administration. 60

PADD Petroleum Administration for Defense Districts. 61

PEMEX Petróleos Mexicanos. 2–5, 7

RBOB Reformulated Blendstock for Oxygenate Blending. 64

RVP Reid Vapor Pressure. 64, 65

SHCP Secreatría de Hacienda y Crédito Público. 9

UC University of California. iii, iv

USGC U.S. Gulf Coast. 55

0.1 Dissertation introduction

Energy markets are at the forefront of the conversation as policymakers worldwide experience a paradigm shift. Technological changes like the shale revolution and the efficiency gains in electricity generation through renewable resources have created abundant energy. In addition, the 2015 Paris Agreement has catalyzed a future where energy generation is less carbon intensive. Through these tectonic changes, policymakers slowly have abandoned the notion that market conditions will be dominated by a binding energy supply, commonly known as "peak oil" (Hubbert 1956). Instead, they are bracing for a world where climate policies and technology are pivotal in shaping demand. Yet, a past full of well-intentioned but perfectible policies is evidence that we are far from a good understanding of what drives consumer demand for energy. My dissertation expands our understanding of consumer demand for gasoline, the primary fuel source for transportation, and shows how public policies affect consumer welfare.

My research studies two distinct settings, but in both cases, I exploit regulatory constraints to causally identify fundamental parameters of consumer preferences. The first setting is the newly liberalized gasoline market in Mexico, where gas station operators can choose their pricing and branding strategies for the first time in more than 80 years. Mexico's regulatory environment before the liberalization allowed me to identify key preference parameters such as consumers' price sensitivity, willingness to drive, and the value for the convenience of product availability.

The market-level price elasticity of demand for Mexican consumers is between -0.42 and -0.64. Similarly, I estimate that, on average, consumers would need to save 13.8 MXNc/L (3.3 USDc/gal) at the pump to be indifferent to driving an extra kilometer to visit a gas station. However, considerable heterogeneity exists across households, driven chiefly by their income level. For example, low-income households are 55% more price sensitive than high-income households. Given my parameter estimates for heterogenous households, I estimate the welfare impact that consumers experienced between 2015 and 2019. During this period, retail prices were liberalized, and initially, there were substantial gas station openings. However, from late 2016 onwards, entry was constrained through regulatory backlogs. I find that for every peso gained in welfare from increased product availability, roughly two pesos are lost in welfare from increased prices.

I estimate an annual net loss of 7% of the markets' annual revenue or 1.43 billion MXN/year. However, this loss is not distributed evenly. Households in the top three income deciles consume 60% of the gasoline, while households in the bottom three deciles only consume 13% of the annual volume. Therefore, high-income households are affected the most by price increases, while low-income households benefit the most from the increased taxation by gas station openings. These policies have been regressive on a net basis, with low-income households being worse off by roughly 2.5% of their disposable income while high-income households are worse off by 1.5%.

In the second setting, I study California's gasoline market and consumers' price sensitivity. In this mature market, environmental regulations segment California from the rest of the contiguous U.S. I use this feature along with the rich data available for the state to control for current and persistent demand shifts. However, I purposely do not control for simultaneity bias which results in estimating a lower bound for the price elasticity of demand. This lower bound coincides with previous studies that have tried to estimate the price elasticity of demand, suggesting that their instruments may be weak or endogenous. I further propose refinery outages as a new set of instruments to estimate the price elasticity of demand. These instruments yield estimates that are statistically larger in magnitude than previous state-of-the-art instrumental variable estimates. The estimate of my preferred specification, -0.52, is 40% larger than what was reported in earlier research. Due to the segmented nature of California's gasoline market, refinery outages have a strong explanatory power. Due to their unexpected nature, these instruments are conditionally mean-independent of unobserved demand shocks. They satisfy the four main documented shortcomings of previously used instruments: a weak first stage, endogeneity with economic activity, endogeneity with consumers' anticipatory behavior, and they do not elicit long-term adaptative behavior.

The methods I use in this dissertation are varied, yet they are all grounded in causal inference. In the first essay, I use structural consumer behavior modeling through a random coefficients model to estimate fundamental preferences using cross-sectional market data. In the second essay, I use Monte Carlo simulations to build plausible counterfactual pricing scenarios had the markets not been liberalized. In the third essay, I use time series and local projection techniques to causally estimate consumers' price sensitivity.

The common focus of my research is to expand our understanding of demand by estimating fundamental consumer preferences. In the process, I find actionable insights that can be used by policymakers, businesspeople, and academics alike. For example, having estimated consumer preferences in the Mexico setting, I compute the welfare effects of the policies that followed the price liberalization. In the California setting, I propose a new set of instruments that can be used to inform policy design better and answer questions beyond fuel markets, including agricultural markets, cost passthrough and monetary policy, and even environmental policy.

Chapter 1

Mexico's gasoline markets: estimating the demand of spatially differentiated goods and heterogeneous agents.

1.1 Introduction

This is the first paper to estimate the price elasticity of demand for gasoline as a geographically differentiated good accounting for heterogeneous consumer preferences. I use a highly detailed data set in conjunction with a once-in-a-lifetime natural experiment of price controls for parameter identification. By estimating a structural model of consumer demand, I can estimate the consumers' price sensitivity, their willingness to drive, and how much they value ancillary services offered at the gas station.

I leverage a two-tiered fixed-fixed price regime in the cities of Mexicali and Tijuana. I find that the city-year elasticity of demand is between -0.42 and -0.64. However, I find substantial heterogeneity across consumers driven chiefly by their income level; households in the bottom income decile are 36% more price sensitive than households in the top decile.

My results are an order of magnitude larger than previous studies for Mexico (Díaz and Medlock 2021). This is consistent with the well-documented case that estimates of demand elasticity that control poorly for simultaneity tend to be biased towards zero (see Davis and Kilian 2011 and Coglianese et al. 2017). However, a fixed-price regime in Mexico and a pricing rule followed by the Ministry of Finance (MoF) provide plausible controls for simultaneity. In addition, my estimates are not statistically different from the ones reported by

Colina 2023b using an instrumental variable approach to estimate Californians' price-elasticity of demand.

In addition to estimating the price sensitivity of consumers, I estimate their willingness to drive to save money at the pump. Gas stations are geographically differentiated products that consumers need to reach to purchase the product. I find that the average consumer is willing to drive an additional kilometer to save $13^{MXN¢}/_{L}$ ($3\ ^{US¢}/_{gal.}$).[1] Consumers who are less price sensitive need larger price savings to merit searching; for example, consumers located in the top 25th percentile of the price-sensitivity distribution would require savings of $21^{MXN¢}/_{L}$ ($5\ ^{US¢}/_{gal.}$) to be indifferent to drive this extra distance.

Good estimates of how consumers trade off prices and quantities and prices for driving distance are essential for policy design and policy evaluation. For example, knowing the price elasticity of demand is essential for fiscal policy and has been a top priority for the Mexican government (Davis, McRae, and Seira Bejarano 2018, Contreras Astiazarán, Benjamín et al. 2020, Colina 2023a). Beyond the implications for Mexico's gasoline market, this heterogeneity has important implications for the provision of public transportation (disproportionately used by lower-income individuals) and electric vehicle (EV) charging stations (disproportionately used by high-income individuals).

Demand estimation has its challenges. In most markets, firms simultaneously choose their pricing and product attributes when introducing a product into a market (Borden 1965). This has long been recognized in economic models (Hotelling 1929) and empirical work that does not take this simultaneity into consideration risks of having biased estimates (Berry and Haile 2021). This paper relies on an unusual setting to identify structural parameters. During 2015, the industry had federally mandated price controls and lacked branding differentiation. Therefore, individually owned and operated retail stations were forced to charge the same price despite their location and local competitive pressures. Additionally, retailers operated under a franchise system in which the sole wholesaler was Petróleos Mexicanos (PEMEX), forcing every station to carry the same brand and sell the same quality of products.

I use a uniquely detailed data set of cross-sectional yearly gas station level sales, attributes, and locations for 2015 for the universe of gas stations as well as census data to estimate the structural demand parameters of the model. The random coefficients model is based on the work of Berry, Levinsohn, and Pakes 1995 but with a spatial component like Thomadsen 2005 and Davis 2006. This model allows for better substitution patterns across products as it recognizes consumer heterogeneity in their preferences as discussed in Gandhi and Nevo 2021 and in Berry and Haile 2021.

In section 1.2, I describe the institutional setting and the data I use. In section 1.3, I present the model and the structural parameters of interest. Section 1.4 talks about the identification strategy and section 1.5 shows the estimation results.

[1] This essay uses 2015 prices.

1.2 Institutional background and data

Despite being the world's sixth largest gasoline market, unlike similar markets, Mexico's retail gasoline market was characterized by heavy regulation that forced gas station operators to charge administered prices, sell the same fuels, and carry the same brand regardless of their location. However, after the implementation of Mexico's Energy Reform (MER), several restrictions were sequentially lifted, culminating in 2017 when gas station operators could carry their brands, sell different products, and determine their prices.

Figure 1.1: Recent regulatory developments in Mexico's retail gasoline industry

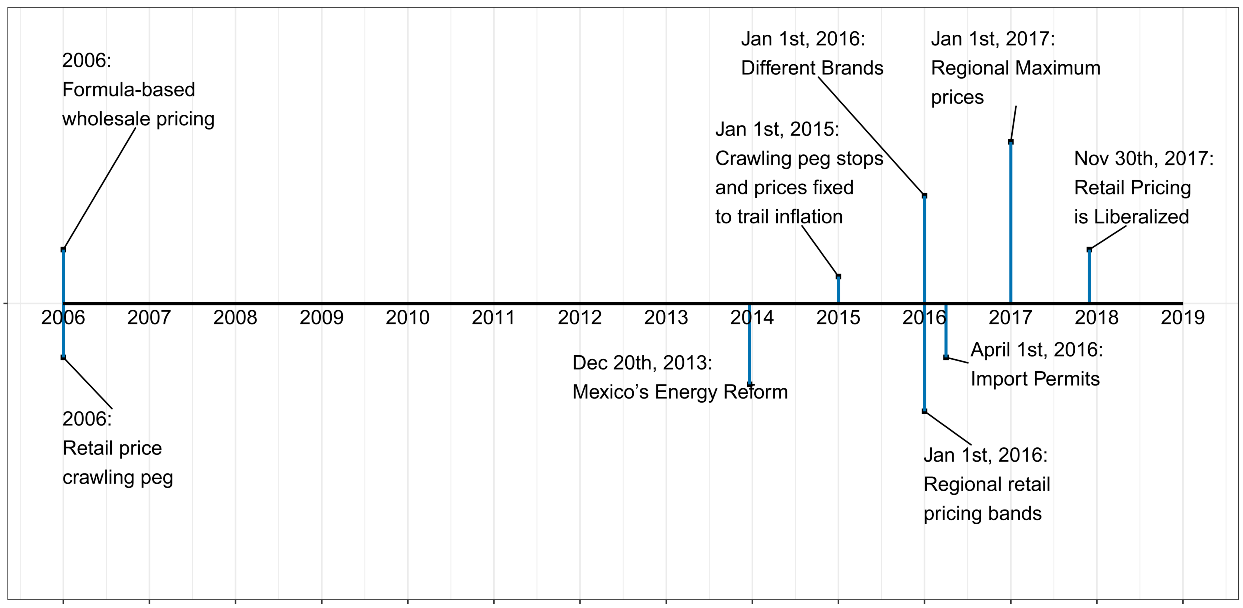


Figure 1.1 shows a timeline of regulatory changes in the industry's recent history. Gas stations in Mexico operate as franchises that are individually owned and operated. However, between 1938 and 2015, PEMEX, Mexico's national oil company, was enshrined by law as the only gasoline wholesaler, importer, and distributor of gasoline (Diario Oficial de la Federación 1938, Diario Oficial de la Federación 1940, and Diario Oficial de la Federación 1995). Consequently, all gas stations across the country carried the exact same fuels and had the same branding. Additionally, retail and wholesale price decisions were not left either to PEMEX nor to the gas station operators. Instead, the industry was under an administered-price regime where prices were determined at the federal level by the Ministry of Finance (MoF) (Secretaría de Hacienda y Crédito Público 2015). This setting contrasts with the setting in most other OECD-member countries in which retailers choose their branding, as well as different pricing and quality schemes (The Organisation for Economic Co-operation and Development- Secretariat 2013).

There were four distinct pricing regimes in the retail gasoline market from 1995 onward.

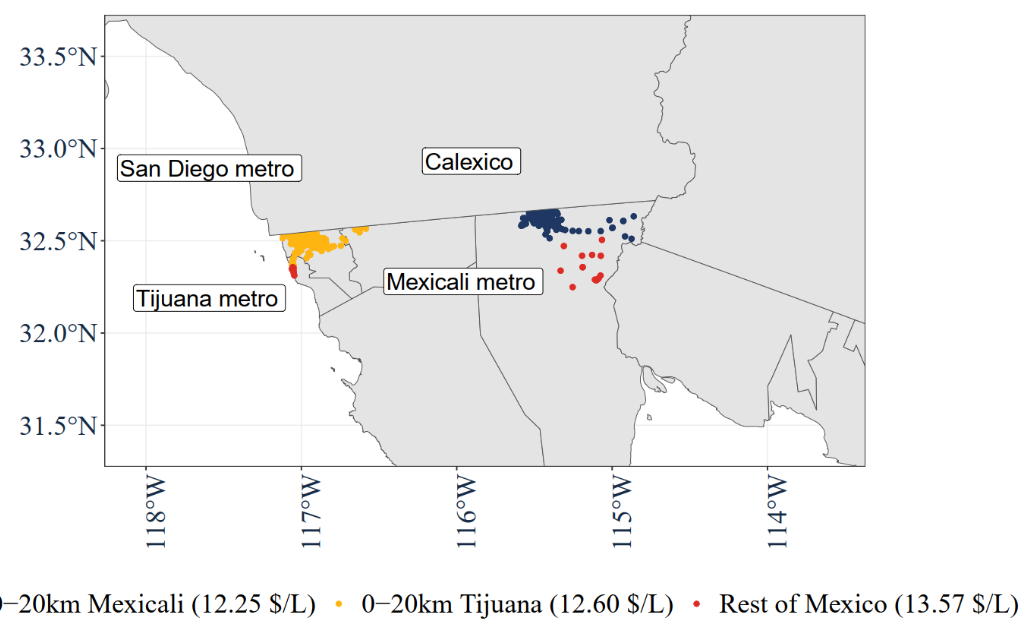
1. **One country - one price (1995 to Oct 2014)**. During this period, the MoF would present the fiscal budget to the Lower House of Congress (Cámara de Diputados); it would commit to a "one price"-national retail price policy for gasoline over the year. This price was held constant throughout the year, and in some years, it followed a steady rise (Diario Oficial de la Federación 1980).

   The difference between the regulated and international wholesale prices would be subsidized or taxed accordingly. By law, retailers had to buy from PEMEX at the national wholesale price (plus taxes/subsidies) and would have to sell at the retail price level targeted by the MoF.

2. **One country - two pricing zones (Sep 2014 to Dec 2015)**. After September 2014, the MoF established two pricing zones (Secretaría de Hacienda y Crédito Público 2015). The first zone consisted of gas stations located 20 km from the U.S.-Mexico border. They were assigned a price based on the prices of the relevant metropolitan area on the U.S. side of the border (see Figure 1.2). For example, the assigned price for gas stations in Tijuana was set to resemble prices in San Diego, prices in Mexicali were based on the prices in Calexico, and prices in Ciudad Juárez were based on prices in El Paso. Prices were adjusted for inflation throughout the year.

   The second zone comprised the rest of the country below the 20 km line. Like the "One country-one price" price regime, the rest of the gas stations would have to charge the same price regardless of whether they were located downtown on a busy intersection or on the city's fringe.

Figure 1.2: Location of gas stations by pricing zone



3. **One country - several pricing zones (Jan 2016 to Nov 2017)**. Beginning in 2016 different pricing zones were established, and with them, a pricing band for maximum and minimum prices (Diario Oficial de la Federación 2014 and Comisión Reguladora de Energía 2016). During this period, retailers were allowed to carry non-PEMEX brands, and gasoline imports were liberalized.

4. **Localized competition (Nov 2017 - currently)**. Finally, from November 2017 to date, pricing bands were sequentially removed until retail prices were completely liberalized across Mexico. Currently, gas station operators can determine their pricing strategies (Comisión Reguladora de Energía 2017).

This paper studies retail gasoline demand in 2015 when all gas stations in Mexico carried the same brand, sold the same fuels, and prices were determined at the federal level by the MoF and not by local competitive pressures. However, the existence of different prices across the two pricing zones allows me to identify the price elasticity of demand given the data and the model.

1.2.1 Data

Gasoline is a relatively homogeneous product (Gary, Handwerk, and Kaiser 2007); however, for the end consumer, it is a spatially differentiated non-durable good since the consumer needs to travel to a given station on a regular basis to fill up their tank, usually on the way to work or shopping (Kitamura and Sperling 1987). To account for this feature in the retail gasoline market, I have the location of the universe of gas stations in Mexico.[2] Additionally, to account for the geographic distribution and demographic characteristics of the population, I use the 2000 and 2010 censuses that provide block-level data, see the bottom entries of Table 1.1. This data is provided by Instituto Nacional de Estadística y Geografía (INEGI), Mexico's statistics office. I also use the 2014 economic census to identify which gas stations are close to major businesses.

To model consumer heterogeneity, I use the city-level distribution of income and the number of children across households. I use INEGI's 2014 income and expenditure survey. Because income-expenditure surveys are carried out every two years, I use the 2014 survey to estimate data in my observation period. See table 1.2 for a summary of the distribution of income and children per household.

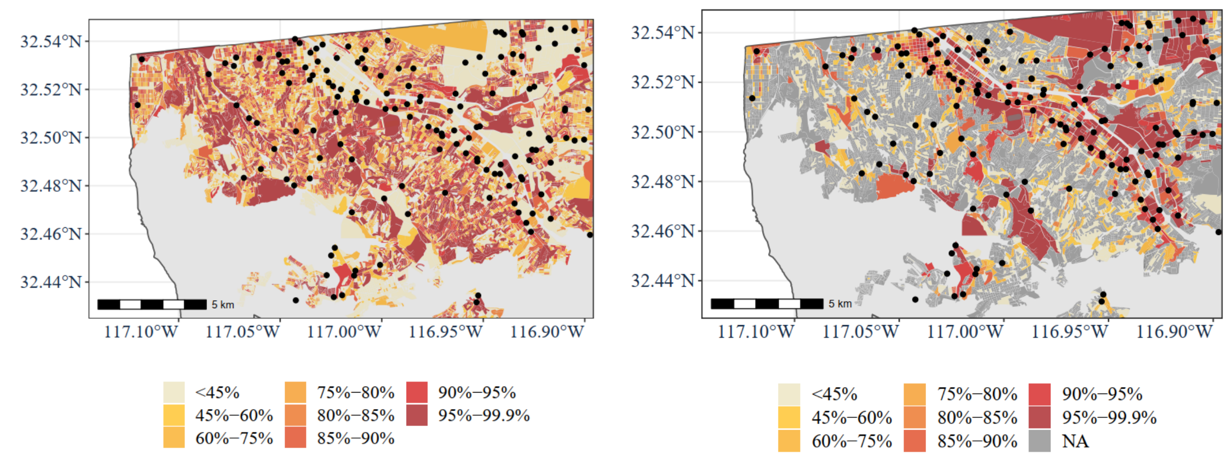
In 2015 gas stations were not allowed to carry different brands other than PEMEX. Despite this, each gas station offered its customers attributes beyond just gasoline. For example, gas stations could offer a convenience store, oil change services, ATMs on-site, online invoicing services, acceptance of gasoline vouchers, etc. These data were manually collected for every gas station in Mexico from "Guía Pemex", PEMEX's

[2] The data is provided by Comisión Reguladora de Energía (CRE), one of Mexico's energy regulators

Figure 1.3: Location of gas stations in comparison to household location and employment location

(a) Household density and station locations

(b) Employment density and gas station locations



official mobile app with the universe of gas stations in Mexico in 2015, their location, and attributes. See Table 1.1.

Table 1.1: Summary statistics of gas station characteristics

Variable	N	Mean	St. Dev	Min.	Max
Markets	2				
... Mexicali	224	45.6%			
... Tijuana	267	54.4%			
Sales (1,000 MXN/year)	467	37,062	25,443	1,512	199,641
Sales (1,000 L/year)	467	2,952	2,002	120	15,372
Market Shares (%)	467	0.372	0.231	0.011	1.5
Pricing band	491				
... 0-20km from U.S. border	455	92.7%			
... 20+km from U.S. border	36	7.3%			
Avg. distance from consum. (km)	491	3.012	0.646	0.584	4.827
Avg. distance sq. from consum. (km^2)	491	10.825	3.362	0.484	23.313
Convenience Store (Yes/No)	491				
... Yes	108	22%			
ATM on site (Yes/No)	491				
... Yes	6	1.2%			
Offers gas vouchers (Yes/No)	491				
... Yes	14	2.9%			
Close to big business (Yes/No)	491				
... Yes	208	42.4%			
Rack	467				
... TAD Mexicali	221	47.3%			
... TAD Rosarito	246	52.7%			

INEGI reports monthly retail gasoline prices for different cities; in conjunction with the pricing rules for 2015 and the location of gas stations, I can map the price each gas station was charging in 2015 (See Figure 1.2).

I have yearly sales for all gas stations in the North-Pacific region of Mexico in 2015. The data is

Table 1.2: Distribution of household characteristics according to income decile

Income decile group	Yearly income	Yearly expenditure		Household characteristics	
	Current income (MXN/year)	Public transport (MXN/year)	Fuel (MXN/year)	Cars owned by household (avg. cars/household)	Children in household (avg. child./household)
Mexicali					
.. *Decile 1*	59,522	2,206	2,014	0.21	0.59
	(6,362)	(3,877)	(3,354)	(0.43)	(1.09)
.. *Decile 5*	128,329	4,051	7,155	0.71	0.80
	(5,912)	(7,079)	(5,479)	(0.64)	(0.91)
.. *Decile 10*	331,649	1,833	20,228	1.73	0.30
	(39,233)	(4,702)	(9,175)	(1.13)	(0.48)
Tijuana					
.. *Decile 1*	50,644	2,578	1,436	0.18	0.63
	(9,906)	(4,049)	(3,054)	(0.39)	(0.86)
.. *Decile 5*	127,406	6,844	7,307	0.35	0.76
	(5,858)	(8,244)	(7,620)	(0.56)	(0.98)
.. *Decile 10*	327,369	2,985	15,629	0.90	0.73
	(31,558)	(6,283)	(11,824)	(0.79)	(1.00)

Note: I report the average value for the households in each income decile. The standard deviations are reported in parentheses.

provided by Next-level Consulting, a consulting firm that works alongside PEMEX on permits, regulation, and opening of new stations. Expenditure in public transportation comes from INEGI's 2014 Consumer Expenditure survey. The categories in the survey include expenditure on subway and light trains, buses, trolleybus, metro buses, vans, taxis, and intercity bus services, as well as fuels. See Table (1.2) for further details.

Table 1.3: Gasoline consumption across income deciles

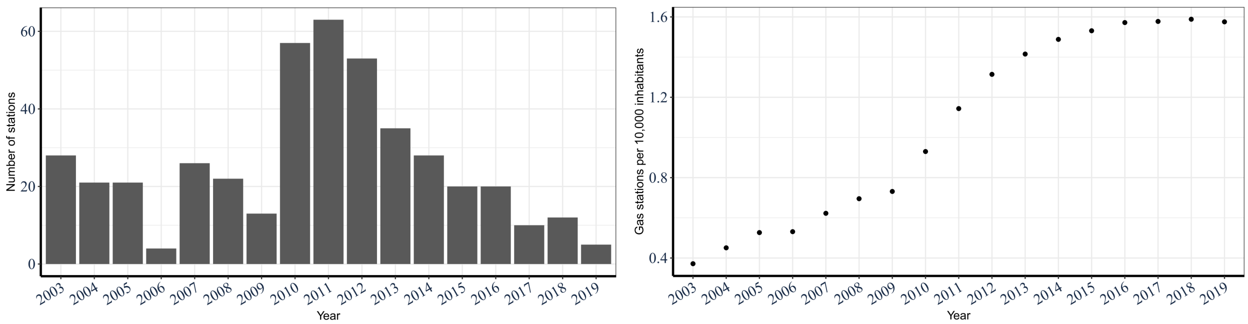
Liters of gasoline consumed per income decile in Mexicali and Tijuana		
Income decile	*Liters (million/year)*	*Percentage*
1	6.9	1.6%
2	20.4	4.8%
3	27.8	6.5%
4	22.4	5.3%
5	43.0	10.1%
6	41.6	9.8%
7	35.7	8.4%
8	57.0	13.4%
9	88.6	20.8%
10	81.6	19.2%

Another essential feature is how gasoline consumption is distributed across households of different income levels. In Mexico, the distribution of consumption is very uneven. For example, in Mexicali and Tijuana, households in the top three income deciles consume close to 60% of all the liters sold. In contrast, households in the bottom three deciles consume less than 13% of annual sales. See table 1.3 for additional information. In addition, within each income decile, several households do not consume gasoline at all. Nevertheless, these households benefit from the taxation of gasoline consumption as taxes are redistributed in the form of

Figure 1.4: Gas station availability in Mexicali and Tijuana

(a) Openings per year in Mexicali and Tijuana

(b) Gas stations per capita in Mexicali and Tijuana



government expenditure.

A major element of MER was that from 2013 to 2017, changes in regulation followed a pre-established timeline. One of the main changes was allowing Comisión Reguladora de Energía (CRE), one of the main energy regulators, to operate as an autonomous entity from the executive branch. However, in 2018, a new President was sworn in, and soon after, political pressure began for CRE to stop the approval of new gas station permits or even roll back some approvals (Wood 2018). In 2019 the new administration announced deep budgetary cuts to CRE for that fiscal year. The cuts translated into 30% less operational budget and downsizing of 60% of the workforce (Arena Pública 2019). This led to numerous articles in the specialized press pointing out the increase of regulatory backlogs, amongst them, the stall in the approval process of new gas station permits (S&P Global Platts 2020, Meana 2020, ONEXPO Nacional 2021).

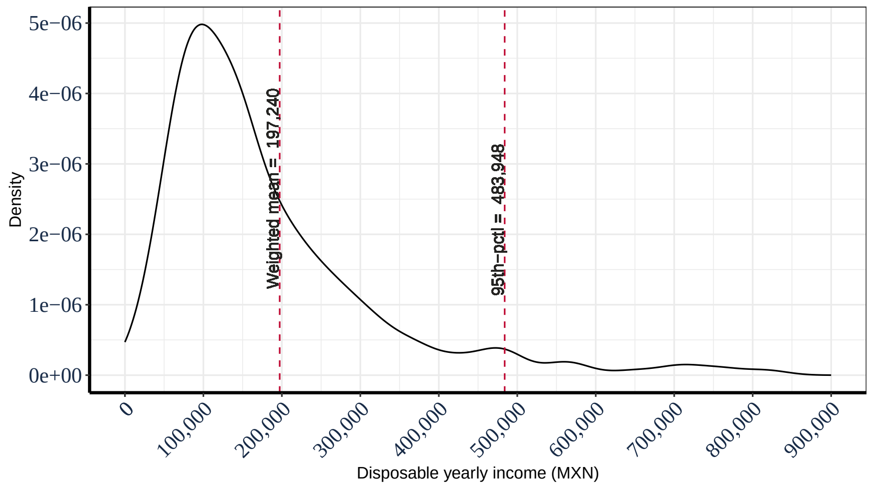
The Mexican fuel markets were left with an unusual mix of policies. Retail prices were liberalized, but entry was constrained due to regulatory backlogs. Before the passing of MER, there was an increase in the number of gas station openings. Then the number of openings declined due to regulatory backlogs. Figure 1.4a shows that the number of permits approved was substantially reduced in 2017, 2018, and 2019. For Mexicali and Tijuana, the number of stations per 10 thousand inhabitants plateaued at 1.58 in 2019, as shown in figure 1.4b. For comparison purposes, the number of gas stations per 10 thousand inhabitants in the U.S. is 4.6, in Canada is 3.1, and in Brazil is 2 (American Petroleum Institute 2023, Canadian Fuels Association 2023, Agência Nacional do Petróleo, Gás Natural e Biocombustíveis 2022).

1.3 The Model

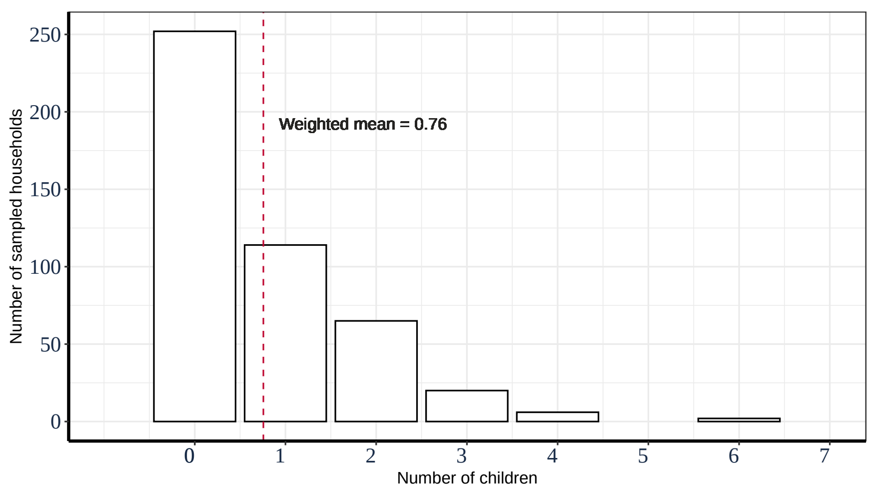
The model that I use to estimate demand is a random coefficients model following Berry, Levinsohn, and Pakes 1995, with a spatial differentiation component like Thomadsen 2005 and Davis 2006. It is a single-address model where consumers are located in their homes and choose a gas station to visit while having disutility for driving to get to a gas station. I do not impose the assumption that consumers are homogeneous; instead, their sensitivity to price and their idiosyncratic valuation of using a gas station depends on the level of the household income and the number of children in the household (See figure 1.5).

Figure 1.5: Marginal distribution of households' demographic characteristics

(a) Marginal distribution of disposable income



(b) Marginal distribution of children per household



I define a market as a metropolitan area-year unit.[3] Suppose that in each market $k = \{Tijuana,\ Mexicali\}$, there are $i = 1 \ldots I_k$ consumers facing a balanced choice set, where they choose among $j = 1 \ldots J_k$ gas stations. The indirect utility of each consumer is comprised of components that are both observed and unobserved to the econometrician. Then, I assume that the indirect utility is given by:

[3]Metropolitan areas are defined by Consejo Nacional de Población (CONAPO). CONAPO is a governmental agency in charge of data collection and analysis of demographic phenomena in Mexico. It comprises staff from INEGI, SHCP, Mexico's Ministry of Environment, amongst other agencies. CONAPO's analysis is based on commuting patterns and different measures of economic integration.

$$u_{ijk} = \gamma_i + \alpha_i(y_{ik} - p_{jk}) + x_{jk}\beta - \lambda_1 d_{ijk} - \lambda_2 d_{ijk}^2 + \xi_{jk} + \varepsilon_{ijk} \tag{1.1}$$

where γ_i and α_i are consumer-specific parameters and $\beta, \lambda_1, \lambda_2$ are parameters that are common to all consumers.

The variable p_j is the price at the pump for regular gasoline and y_i is the level of income of individual i. The model nests the transport utility specifications by Hotelling 1929 and D'Aspremont, Jaskold Gabszewicz, and Thisse 1979 where $d_{ijk} \equiv d(L_{ik}, L_{jk})$ is the Euclidean distance from consumer i's location to the location of gas station j. Several studies like Phibbs and Luft 1995 and Boscoe, Henry, and Zdeb 2012 show that Euclidean distance is a very close approximation to the distance traveled through the road network, even on short distances (Buczkowska, Coulombel, and de Lapparent 2019).

Consumers do not always choose retail locations that are the closest to them because they derive utility from non-distance attributes (Rushton, Golledge, and Clark 1967, Eckert 2013, Ellickson and Grieco 2020). The vector of variables x_{jk} includes observed gas station on-site attributes like a convenience store or an ATM, services like oil changes, or payment facilities like the acceptance of gas vouchers.[4]

Table 1.4: Origin and destination survery when refueling

Activities before and after refueling						
	Activity at destination					
Activity at origin	Home	Work	Business	Shopping	Social	**Total**
Home	7.0%	8.1%	3.1%	12.5%	12.0%	**42.7%**
Work	10.5%	2.6%	1.6%	2.5%	0.9%	**18.1%**
Business	1.6%	0.9%	1.1%	0.5%	0.3%	**4.4%**
Shopping	12.1%	0.9%	0.7%	5.6%	2.1%	**21.4%**
Social	7.9%	0.6%	0.1%	1.8%	3.2%	**13.6%**
Total	**39.1%**	**13.1%**	**6.6%**	**22.9%**	**18.5%**	**100.0%**

Totals may not sum to 100% due to rounding, Table 2 from Kitamura and Sperling (1987).

Consumers are also known to refuel while commuting. For example, Houde 2012 uses origin/destination matrices to simulate, given the location of a consumer, the probability that they will travel through a specific route to each of the possible destinations. Additionally, Kitamura and Sperling 1987 document two salient features of refueling behavior: (1) the vast majority of consumers that refuel have home as an origin or destination, (2) yet other destinations may be visited during the trip (See table 1.4). To capture this feature, I include an additional variable to x_j, indicating if a gas station is close to a big business. I classify a business as a "big business" if it is among the top 10% of employers in a city. This dummy variable captures

[4] In Mexico, employers give gas vouchers as an employment benefit. For employers, it is easier to deduct this payment as a business expenditure.

the potential demand shock from increased traffic without imposing an *a priori* substitution structure as in a nested logit. That is $x_{jk} = \{big\_business_{jk}, convstore_{jk}, ATM_{jk}, vouchers_{jk}, oil\_change_{jk}\}$.

In the tradition of McFadden 1978, I assume that some attributes, ξ_{jk}, are unobserved by the econometrician, while the consumers and gas station operators can observe them all. Unobserved product attributes are captured by ξ_{jk} as described by Berry 1994. The variable ε_{ij} is a random utility shock with mean zero from a type-1 extreme value distribution whose draws are independent. For a given $\alpha_i, \beta_i, \xi_{jk}, \lambda_1, \lambda_2$, the probability that consumer i chooses gas station j for each market k is given by:

$$Pr(i, j|k) = \frac{exp(\gamma_i + x_{jk}\beta - \alpha_i p_{jk} - \lambda_1 d_{ijk} - \lambda_2 d_{ijk}^2 + \xi_{jk})}{1 + \sum_{g}^{J_k} exp(\gamma_i + x_{gk}\beta - \alpha_i p_{gk} - \lambda_1 d_{igk} - \lambda_2 d_{igk}^2 + \xi_{gk})} \tag{1.2}$$

$$\text{for } k = \{Mexicali, Tijuana\}$$

$$\begin{bmatrix} \alpha_i \\ \gamma_i \end{bmatrix} = \begin{bmatrix} \bar{\alpha} \\ \bar{\gamma} \end{bmatrix} + \Pi D_i + \Sigma \upsilon_i \tag{1.3}$$

$$E(\alpha_i) = \bar{\alpha}, \quad E(\gamma_i) = \bar{\gamma}$$

Similarly to Nevo 2001, the model captures the heterogeneity of tastes in consumers by letting structural taste parameters be distributed according to two main components: non-parametric demographic characteristics (D_i) in each market and a vector of random utility shocks independently drawn from a standard normal (υ_i). These random utility shocks are used to capture any additional unobserved consumer characteristics. The matrix of parameters Π relates demographic draws to individual taste parameters, while Σ is a matrix that relates additional structural shocks to individual taste parameters. I will estimate the elements of these matrices to obtain a distribution of the taste parameters.

The demand system is completed with the introduction of an "outside good" (McFadden 1978). For example, the consumer may decide not to visit any gas stations and instead use public transportation. Without an outside good, a homogeneous increase in price, as in the case of a tax, would not affect the quantities demanded in equilibrium. The indirect utility from the outside good is normalized to 0.

Let the mean utility for all consumers in market k from good j be expressed as

$$\delta_{jk} \equiv \bar{\gamma} - \bar{\alpha} p_{jk} + x_{jk}\beta - \lambda_1 \bar{d_{jk}} - \lambda_2 \bar{d_{jk}^2} + \xi_{jk} \tag{1.4}$$

where $\bar{d_{jk}} \equiv \int d(L_i, L_j) dP^\star(L_i)$ is the weighted average distance between gas station j and its clients, while $dP^\star(\cdot)$ is the non-parametric population distribution function of consumer locations in a 5 km radius around j.[5] This cutoff is chosen following reports that, on average, commuters in Mexico City do a 10km commute each day (Guerra 2017, Moovit insights 2022); unfortunately, there is limited information available about commuting patterns in Mexicali and Tijuana.

Let $\psi_{ijk} \equiv d_{ijk} - \bar{d_{jk}}$, and $\psi^2_{ij} \equiv d^2_{ijk} - \bar{d^2_{jk}}$. I can decompose the utility of consuming good j into its average level and an individual utility shock:

$$
\begin{aligned}
u_{ijk} &= \gamma_i - \alpha_i p_j + x_{jk}\beta - \lambda_1 d_{ijk} - \lambda_2 d^2_{ijk} + \xi_{jk} + \varepsilon_{ijk} \\
&= \overbrace{\bar{\gamma} - \bar{\alpha} p_j + x_{jk}\beta - \lambda_1 \bar{d_{jk}} - \lambda_2 \bar{d^2_{jk}} + \xi_{jk}}^{\delta_{jk} \equiv \text{Average utility}} + \\
&\qquad \underbrace{(\gamma_i - \bar{\gamma}) - p_{jk}(\alpha_i - \bar{\alpha}) - \lambda_1 \psi_{ijk} - \lambda_2 \psi^2_{ijk} + \varepsilon_{ijk}}_{\mu_{ijk} \equiv \text{Individual utility shock}} \\
&= \delta_{jk} + \mu_{ijk}
\end{aligned}
\tag{1.5}
$$

1.3.1 Aggregation

I can aggregate modeled individual choices to a market level such that they match with the observed market outcomes described in section 1.2. The market share of gas station j is the weighted probability that consumers in a market choose that gas station.

Let $A^k_j(x, p, \bar{d}, \bar{d^2}, \delta) \equiv \{(D_i, \upsilon_i, \varepsilon_i, \psi_i, \psi^2_i | u_{ij} \geq u_{ig} \; \forall \; g = 0, 1, \ldots, J_k\}$ be the set of individuals in market k who choose gas station j. The matrices $x, p, \bar{d}, \bar{d^2}$ include the attributes of all gas stations in each market. $dP(\cdot)$ denotes the marginal population distribution function and the third equality in equation (1.6) follows from an assumption of independence of D, υ and ψ, ψ^2.

Each gas station's market share can be characterized by

$$
\begin{aligned}
\tilde{s_{jk}} &= \int_{A^k_j} Pr(i, j|k) dP(\alpha_i, \beta_i) \\
&= \int_{A^k_j} \frac{exp(\delta_{jk} + \mu_{ijk})}{1 + \sum_g^{J_k} exp(\delta_{gk} + \mu_{ijk})} dP(\alpha_i, \beta_i) \\
&= \int_{A^k_j} \frac{exp(\delta_{jk} + \mu_{ijk})}{1 + \sum_g^{J_k} exp(\delta_{gk} + \mu_{ijk})} dP(\psi, \psi^2, D, \upsilon | \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma) \\
&= \int_{A^k_j} \frac{exp(\delta_{jk} + \mu_{ijk})}{1 + \sum_g^{J_k} exp(\delta_{gk} + \mu_{ijk})} dP(D, \upsilon | \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma) dP(\psi, \psi^2 | \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma) \\
&= s(\delta_{1k} \ldots \delta_{J_k}; \bar{\alpha}, \bar{\gamma}, \beta, \lambda_1, \lambda_2, \Pi, \Sigma)
\end{aligned}
\tag{1.6}
$$

For each market, k, the market share of station j derived from the model, denoted as $\tilde{s_j}$, holds for the J

[5] For the convenience of notation, I remove income from this equation since it will be differenced-out in the utility function when consumers are comparing among goods.

competitors and creates a system of J equations.

$$\begin{aligned} \tilde{s_{1k}} &= s(\delta_{1k} \dots \delta_{J_k}; \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma), \\ &\vdots \\ \tilde{s_{J_k}} &= s(\delta_{1k} \dots \delta_{J_k}; \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma). \end{aligned} \tag{1.7}$$

To be more precise, note that $\delta_{jk} = \delta(P_{jk}, x_{jk}, \bar{d_j}, \xi_{jk}; \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma)$. Then,

$$\begin{aligned} \tilde{s_{jk}} &= s(\delta_{1k} \dots \delta_{jk} \dots \delta_{J_k}; \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma), \\ &= s(\delta_{1k}(P_{1k}, x_{1k}, \bar{d_{1k}}, \xi_{1k}) \dots \delta_{jk}(P_{jk}, x_{jk}, \bar{d_{jk}}, \xi_{jk}) \dots \delta_{J_k}(P_{Jk}, x_{Jk}, \bar{d_{Jk}}, \xi_{Jk}); \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma), \\ &= s(P_{1k}, \dots, P_{Jk}, x_{1k}, \dots, x_{Jk}, \bar{d_{1k}} \dots, \bar{d_{Jk}}, \xi_{1k}, \dots, \xi_{Jk}; \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma) \;\; \forall j = 1 \dots J_k. \end{aligned} \tag{1.8}$$

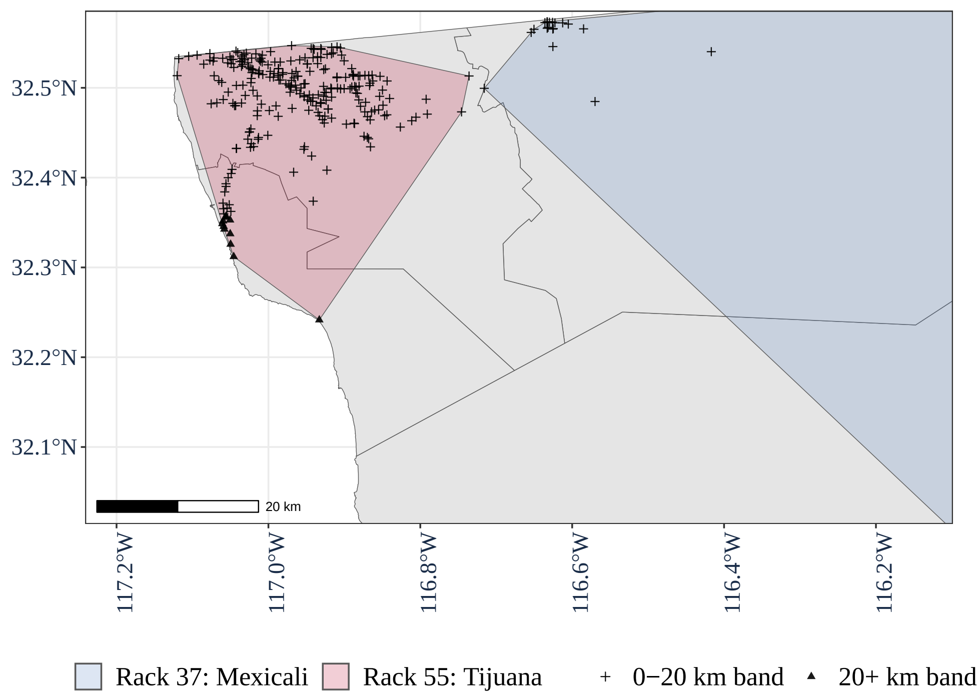
From equation (1.7), note that there are J unobserved mean utilities $(\delta_1, \dots, \delta_J)$ plus the unknown parameters of $\bar{\alpha}, \bar{\gamma}, \lambda_1, \lambda_2, \Pi, \Sigma$, which makes parameter estimation challenging. From equation (1.8), we observe that each share j depends on its own observed and unobserved attributes and also on the attributes of its competitors. This result is intuitive as we can think about gas stations being substitutes for one another. Therefore, the attributes of a competing gas station, g, will affect the residual demand that gas station j faces. See section 1.4 for further details about how I use instruments to identify demand.

The model has no closed-form solution. Therefore, I need to use initial values to start the algorithm that minimizes the objective function. I use 360 combinations of parameters as initial guesses and choose the value that yields the smallest value of the objective function. See the Appendix in section 1.A.1 for further details. As a robustness check to initial-value sensitivity, I present the results of a logit with a closed-form solution in section 1.B.

1.4 Identification Strategy

Given the highly regulated environment of Mexico's retail gasoline industry before 2015, many of the traditional concerns regarding endogeneity are ameliorated. For example, vertical differentiation in the form of different quality of inputs was nonexistent since every gas station offered the same fuel and all operated on a franchise system which made gas stations have a homogeneous look. Despite the tight regulation, gas station operators could choose their location. It is likely that gas station operators may choose a location L_j, which is in a high-traffic area. This would mean that they are closer, on average, to consumers, i.e., $E(\bar{d_j}\xi_j < 0)$. Figure 1.3a and 1.3b seem to indicate that is the case. To control for this, I use data from the economic census to identify which businesses are among the top 10% of the largest employers in Tijuana and Mexicali; then, I create a dummy variable indicating if a gas station is located within 300 meters from a large employer. Another concern is that the pricing tiers were assigned based on some unobserved factors at the regional level that are systematically driving demand or the cost of logistics from the rack. Racks are nodes where fuel transportation from ports and refineries shifts to distribution. The industry considers the rack price as the relevant regional wholesale price (Borenstein, Cameron, and Gilbert 1992 and Borenstein and Bushnell 2005). I either include rack-level fixed effects as a control, or I use the distance from each gas station to its corresponding rack as an instrument for unobserved logistics costs. Figure 1.6 shows a graphical representation of each rack's distribution area.

Figure 1.6: Distribution area for different racks and pricing bands



While all gas stations carried PEMEX's brand, color, and products, gas station operators were free to choose the size of the plot and the number of pumps in their business. It is possible, then, that some observed attributes are correlated with unobserved characteristics. For example, gas stations with a larger plot would be more likely to have an on-site convenience store (observed) and more pumps (unobserved). To address this issue, I use different instruments.

1.4.1 Instruments

The first challenge comes from the necessity to instrument for both prices and quantities. In a demand system of differentiated goods, the demand for one good depends on the demand for all other goods, see equation (1.6). Therefore, to identify the price response of demand for good j, it is essential to keep the demand for all other goods fixed.

This can be done by controlling for the observed product attributes of all other goods, yet ξ_{-jk} remains unaccounted for (see equation (1.4)). I need $J_k - 1$ instruments to account for the dependency of j's demand with the unobserved $\xi_{1,k}, \ldots, \xi_{j-1,k}, \xi_{j+1,k}, \ldots \xi_{J_k,k}$.

Despite dealing with a setting in which traditional differentiating attributes such as branding, advertising, and quality were closely regulated and homogenized, there might still be a concern for the endogeneity of some attributes with unobserved factors. For example, in this setting, it is likely that the presence of a convenience store or an ATM is not mean independent of other unobserved attributes. That is, I will need an additional $2 \times J_k$ instruments. I impose the common assumption that the rest of the elements of x_k are mean independent to ξ_k.

BLP instruments

The first set of instruments is obtained using a similar rationale to Berry, Levinsohn, and Pakes 1995: the demand of good j depends on the order of all related goods. If attribute a for good g is mean independent to the vector ξ_k, then a linear transformation of this attribute can create exogenous variation in demand for good j. That is, the assumption is that through pressures of oligopolistic competition, if the firm selling good g offers attribute a, the firm selling good j will react to that offering independently of its own unobserved attributes ξ_j.[6]

The closest competitors are determined by a procedure similar to Davis 2006 by considering gas stations that fall within a radius of 5km around gas station j. Then, I compute the average attributes they possess. For example, I compute the proportion of competing gas stations with an ATM on site or accepting gas vouchers.

Waldfogel-Fan instruments

Another set of instruments is obtained using a similar rationale as Waldfogel 2003 and Fan 2013. Consider two distinct but adjacent neighborhoods in a city: a high-income neighborhood and a low-income neighborhood.

[6] While this assumption might be largely unavoidable, in this setting is less troublesome than in previous research. First, gas station operators do not determine pricing, which generally can be adjusted more freely. Second, most attributes are fixed assets which are more challenging to adjust to own-demand shocks. Third, advertisement was almost nonexistent due to a lack of branding differentiation.

Suppose there are two gas stations, each mainly serving one of these neighborhoods but with partially overlapping service areas. Each gas station will offer attributes that cater to the preferences of most of its customers. However, to attract customers from a competitor, gas stations will also provide attributes their competitors offer.

I use a set of instruments that consider the demographic characteristics of the clients around gas station j's competitors. I consider the same 5km radius as before to determine who the competitors are. I measure the average school years of people living around each gas station and the number of people earning at least five times the minimum wage as a proxy for the number of high-earners in the area.

1.4.2 Price variation

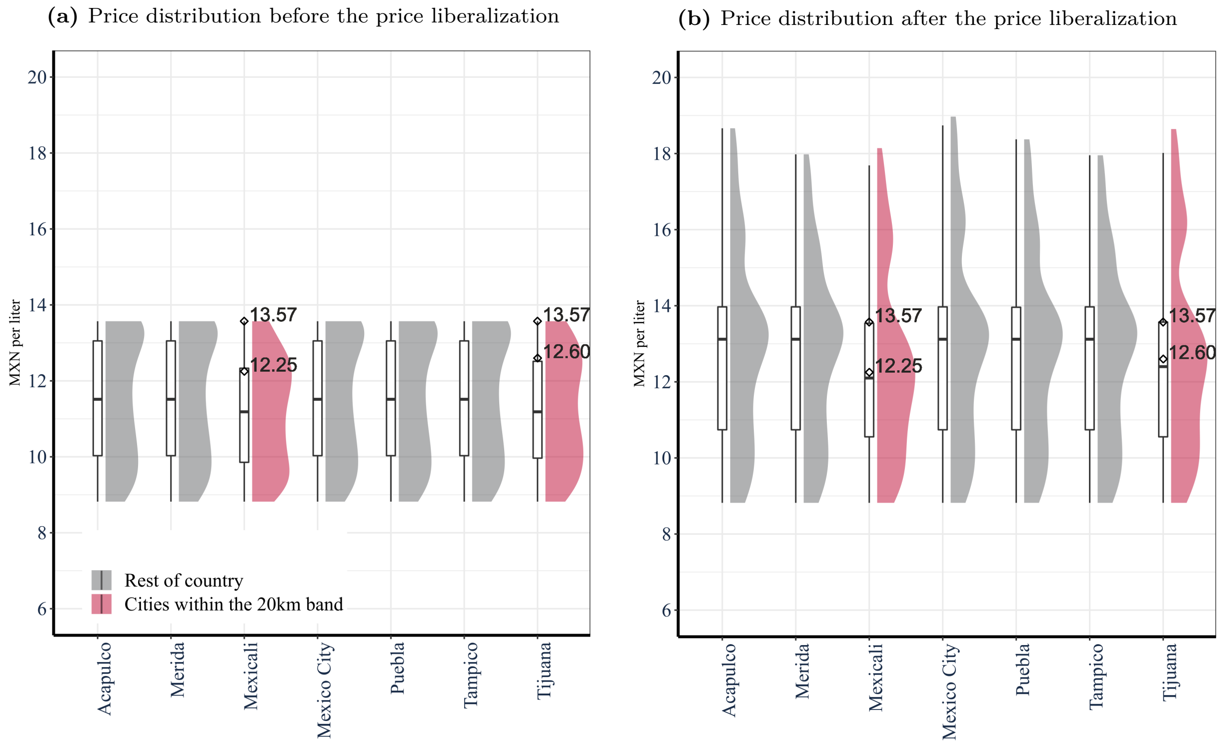
Having a fixed price regime has substantial advantages since it eliminates the simultaneity in pricing and attributes decisions. However, this setting has its downsides. For parameter estimation purposes, the main downside of a fixed-price regime is that there is less variety of prices than in a conventional setting. In this case, there are three distinct prices: 12.25,12.60, and 13.57 pesos per liter.

Despite less variety, the price variability is enough to identify the $\bar{\alpha}$ parameter. For example, a common instrument used to identify price sensitivity is the change in taxes. Li, Linn, and Muehlegger 2014 explain that most tax changes are around $10^{US¢}/_{gal}$. In this setting, the price difference within each market is $1.32^{MXN}/_{L}$ and $0.97^{MXN}/_{L}$, for Mexicali and Tijuana, respectively. This translates to $31.5^{US¢}/_{gal}$ and $23.1^{US¢}/_{gal}$, respectively.[7]

Additionally, these prices are representative of the prices that Mexican consumers had been facing. That is, they do not correspond to a time when prices were unusually low or elevated. For example, the left panel of figure 1.7a shows the distribution of historical retail prices across different cities from January 2011 to the right before prices were liberalized on January 2016. Notice that the "low" administered prices, both for Tijuana and Mexicali, are located close to the 75th percentile. The "high" price is located at the edge of the distribution, but there is a considerable mass in that section. That is, these prices were a common occurrence in both the Mexicali and Tijuana markets. This becomes even starker when we consider the market prices observed after the price regulation was lifted.The price distribution in figure 1.7b) includes prices from January 2011 up to July 2018; the "low" prices are located near the median of the distribution, whereas the "high" price is located near the 75th percentile.

[7]Using an exchange rate of $15.86^{MXN}/_{USD}$, the average rate for 2015.

Figure 1.7: Distribution of historical retail prices before and after MER across cities



1.5 Model estimation results

The estimations of the model parameters can be seen in table 1.5. The first rows of the table show the parameter estimates and standard errors for the "mean" parameters and then estimates for the parameters for the matrix Π and Σ. Further down the tables, I report the market-level elasticity of demand, savings needed to drive an additional kilometer, and how much being close to a big business increases sales, on average.

RC Model 1 and 3 include rack-level fixed effects, RC Model 2 is identical to RC Model 3 but does not have rack-level fixed effects. The coefficients in RC Model 2 and 3 and the estimates of market-level elasticity seem relatively stable. This could indicate that controlling for local fixed effects is unnecessary once the demographic data is included in the model.

My preferred model is RC Model 2. The model estimation confirms that consumers within a city have heterogeneous price sensitivity. This model's estimates show that consumers with higher disposable income are less price sensitive. This can be seen in the estimate in the row called "Price-Disp. Income" in the section in table 1.5 for estimates of the Π matrix. Figure 1.8 shows the marginal distribution of the α parameter for the city of Tijuana. The mean estimate, $\bar{\alpha}$, is -3.96 with a 95% confidence interval between -4.06 and -3.85,

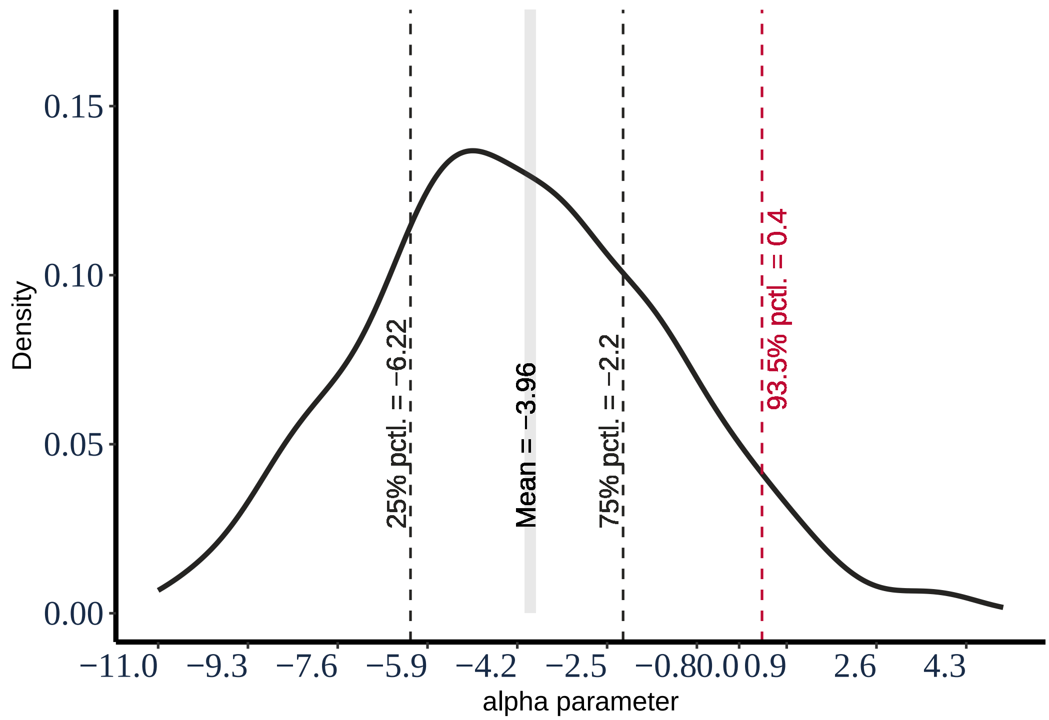
Table 1.5: Estimation results of Random Coefficient models

	RC Model 1		**RC Model 2**		**RC Model 3**	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Parameter Name	*Estimate*	*s.e.*	*Estimate*	*s.e.*	*Estimate*	*s.e.*
Means						
.. Intercept			74.4 ***	0.002		
.. Prices	-3.6 ***	0.051	-3.96 ***	0.053	-3.73 ***	0.188
.. Avg. dist	1.18 ***	0.384	0.88 ***	0.329	1.02 ***	0.427
.. Avg dist sq.	-0.21 ***	0.075	-0.15 ***	0.064	-0.19 **	0.084
.. Big business	0.13	0.077	0.12 *	0.069	0.12	0.076
.. Conv. Store	-0.07	0.068	-0.07	0.069	-0.06	0.070
.. ATM			0.3 ***	0.084	0.3 ***	0.105
.. Accepts vouchers			0.19	0.257	0.19	0.259
.. Sells oil			-0.13	0.163	-0.12	0.169
Σ (cov. Struc.)						
.. Intercept	2.0 ***	0.019	1.984 ***	0.0004	1.98 ***	0.000
.. Intercept & prices	1.83 ***	0.373	1.708 ***	0.046	1.71 ***	0.046
.. Prices	2.4 ***	0.187	2.535 ***	0.059	2.54 ***	0.059
Π (cov demog.)						
.. Intercept-Dist. Shock	0.98 ***	0.034	0.96 ***	0.005	0.99 ***	0.064
.. Intercept-Dist. Sq Shock	0.95 ***	0.037	0.88 ***	0.009	0.94 ***	0.137
.. Interc.-Disp. Income	0.97 ***	0.014	0.98 ***	0.004	0.96 ***	0.021
.. Interc.-Num kids	0.91 ***	0.005	0.9 ***	0.007	0.89 ***	0.032
.. Price-Dist. Shock	0.14	0.155	0.27 *	0.142	0.12	0.547
.. Price-Dist. Shock sq	-0.24	0.181	-0.48 ***	0.040	-0.28 ***	0.091
.. Price-Disp. Income	0.82 ***	0.043	0.9 ***	0.036	0.73 ***	0.031
.. Price-Num children	-0.06	0.157	-0.13	0.105	-0.33	0.472
Rack-level F.E.	Yes		No		Yes	
Post-estimation calc.						
.. ΔP to drike add. 1km	-0.35		-0.24		-0.40	
	Mexicali	*Tijuana*	*Mexicali*	*Tijuana*	*Mexicali*	*Tijuana*
.. Mkt. price elast.	-0.36	-0.7	-0.42	-0.64	-0.36	-0.71
.. Avg. Market share (s)	0.36%	0.43%	0.36%	0.43%	0.36%	0.43%
.. Δs/Δd	-0.004%	-0.005%	-0.022%	-0.027%	-0.004%	-0.005%
.... Change in sales	-1.2%	-1.2%	-6.3%	-6.3%	-1.2%	-1.2%
.. Δs/Δbig business	0.045%	0.055%	0.044%	0.053%	0.046%	0.055%
.... Change in sales	12.6%	12.6%	12.3%	12.2%	12.7%	12.7%

Notes: Since the model is not linear, post estimation calculations are evaluated at the mean.
(***) indicate significance at the 2.5% level, (**) at the 5% level, and (*) at the 10% level.

as shown in the gray shaded area. The bottom quartile has a parameter value of -6.22 or less, while the top quartile has a value of -2.2 or greater. Similarly, consumers have heterogeneous valuations of refueling at a gas station versus public transport. For example, households with more children are more likely to refuel and use their car instead of taking a public transportation mode (See row “Interc.-Num. kids”).

Figure 1.8: Marginal distribution of α for consumers in Tijuana



Note: The gray shaded region represents the 95% confidence interval around the mean estimate

These model specifications do not have a closed-form solution. Similar to Ito and Zhang 2020, I try 360 different initial values to start the numerical solution algorithm. Out of these initial values, I report the parameters that yield the smallest value for the objective function that is being minimized. Further details are reported in the Appendix in section 1.A.1.

As a robustness check to the model's sensitivity to initial values, I estimate a similar model to equation (1.1) using a logit model with a closed-form solution. To do so, I impose the assumption that consumers are homogeneous but still derive utility from all the same attributes as in equation 1.1. The model described is in the Appendix in section 1.B and written explicitly in equation 1.14.

The estimates of the logit model are reported in table 1.B.1 and are similar to the estimates found by numerical methods in the random coefficients model. In Logit Model 2, the price sensitivity parameter, α is estimated to be -3.06 and is statistically significant. This compares to an estimate of -3.96 for $\bar{\alpha}$ for RC

Model 2. Similarly, the estimates Logit Model 2 show an elasticity of demand of -0.56 and -0.73 for Mexicali and Tijuana, respectively. Meanwhile, RC Model 2 estimates elasticities to be -0.42 and -0.64.

These results are an order of magnitude larger than previous estimates for the elasticity of demand in Mexico (Díaz and Medlock 2021). A well-documented case is that estimations that fail to control for supply and demand simultaneity will be biased towards zero (Davis and Kilian 2011 and Coglianese et al. 2017). My estimates account for simultaneity given the nature of the pricing policy followed by the MoF and use BLP and Waldfogel-Fan instruments to instrument for price and product characteristics. In addition, I show the robustness of the estimates to model misspecification by reporting the results of the random coefficients model and logit model in tables 1.5 and 1.B.1, respectively. My estimates are slightly higher than the ones reported by Colina 2023b who estimates the price elasticity of gasoline demand in California. However, the results are not statistically different despite Colina 2023b using local projection and state-of-the-art I.V. estimation procedures, techniques that are considerably different than the ones used in this paper.

1.6 Post estimation calculations

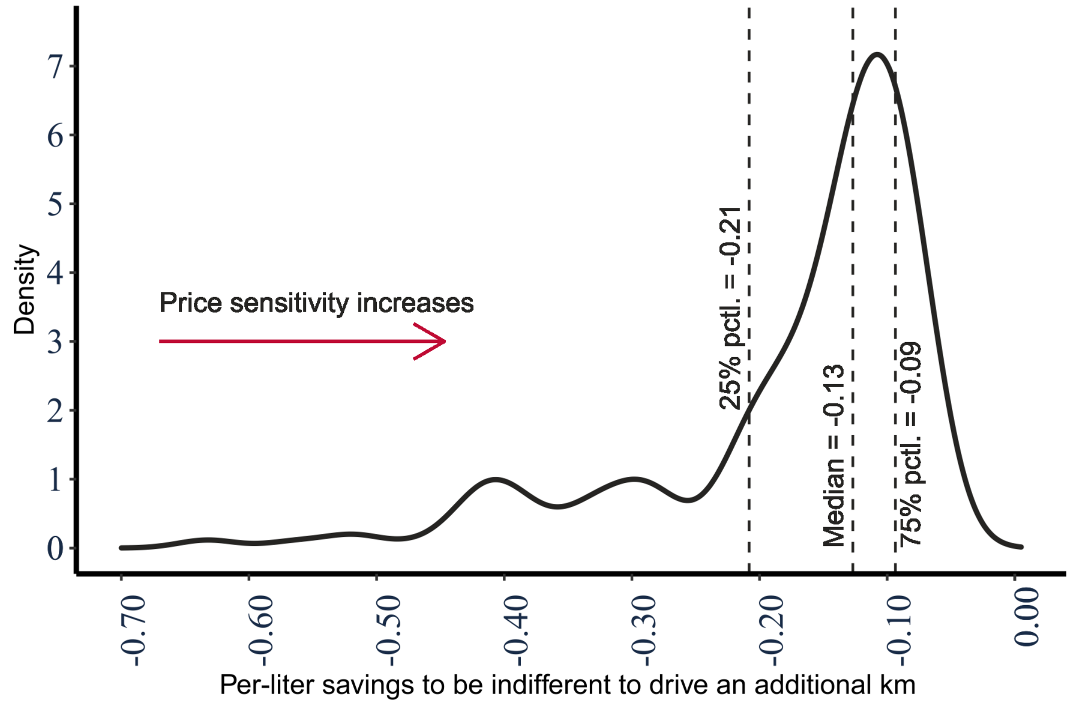
Given the estimates of RC Model 2, I can do some post-estimation calculations to learn about the empirical distribution of taste parameters and consumers' willingness to drive. The model estimates a market-level price elasticity of -0.42 and -0.64 for Mexicali and Tijuana, respectively. The estimates vary due to the level of income and number of children in the household; see figure 1.5. This feature of the model allows for localized estimates and to estimate heterogeneous impacts of price liberalization at the market level.

In Mexico, the average commuting distance is 5 km on a one-way trip. The median consumer would be indifferent to drive an additional kilometer if it meant refueling at a price that is $13^{MXN¢}/_{L}$ ($3.1^{US¢}/_{gal}$) lower. I compute willingness to drive as $\Delta P_i = \frac{-(\lambda_1+2\lambda_2 d_{ijk})}{\alpha_i}$, the ratio of the disutility of driving another kilometer over the disutility of a peso increase in the retail price. Given the heterogeneity in price sensitivity, the willingness to drive varies across consumers. More price-sensitive consumers will require fewer savings at the pump to be willing to drive an additional kilometer.

Figure 1.9 shows the marginal distribution of the consumers' willingness to drive. The horizontal axis shows the savings that would be needed for a consumer to be indifferent to drive an additional kilometer. The median consumer needs savings of $13^{MXN¢}/_{L}$ ($3.1^{US¢}/_{gal}$), whereas the least sensitive consumers need savings of $21^{MXN¢}/_{L}$ ($5^{US¢}/_{gal}$) and while the top 25% more price-sensitive consumers require savings of $9^{¢}/_{L}$ or less.

My results show that price sensitivity depends on the level of disposable income. There is a negative correlation between the level of income and the magnitude of the price sensitivity. Higher-income households

Figure 1.9: Marginal distribution of consumers' willingness to drive



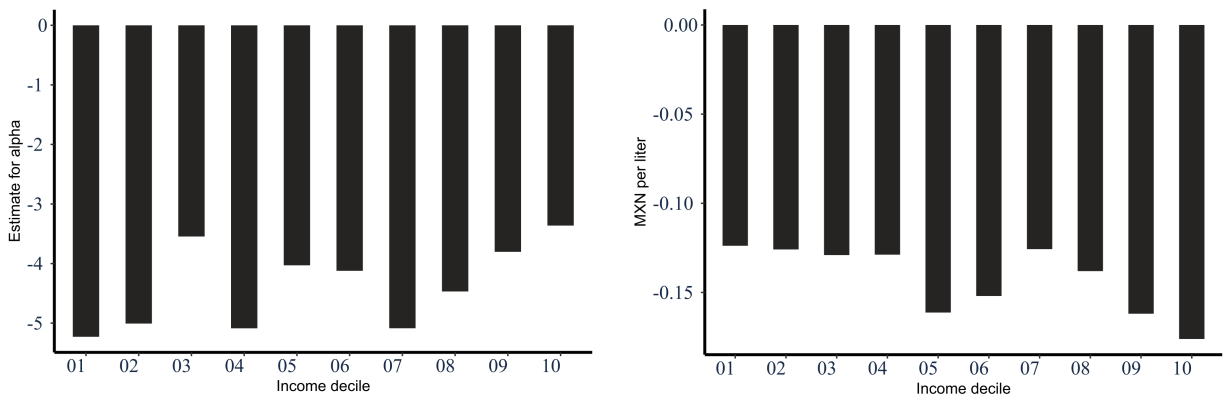
tend to be less price sensitive than lower-income ones. Therefore, high-income households tend to need higher discounts at the pump to be incentivized to travel an additional kilometer.

The level of income and the magnitude of the price sensitivity are negatively correlated; however my results do not show a homothetic relationship. For example, table 1.6 shows that the median household in income decile 3 has a lower magnitude of price sensitivity than the median household in decile 4. This estimation result matches the distribution of household consumption of fuel as depicted in table 1.3. Despite lower income levels, households in income decile 3 consume more liters per year than their counterparts in decile 4.

Similarly to Seim and Waldfogel 2013, the lack of data on individual purchase decisions prevents me from separating the decision to visit a gas station and the purchase decision. Therefore, I make some assumptions. It would take, on average, two minutes to drive one kilometer in downtown Tijuana. Considering this and assuming that in each visit, a consumer will fill up half their tank of gas (25 L approx.), I can compute how much consumers in different households value an hour of driving. Unsurprisingly, as income grows, the implied value of an hour-driven increases as well. However, when compared to high-income households, low-income households value an hour of driving proportionately much more than their median hourly earnings. The top decile of households, who have incomes comparable to the median U.S. household, value their driving time as 65% of their hourly earnings, which is consistent with Dorsey, Langer, and McRae 2022 who estimate

Figure 1.10: Consumer preferences across income deciles

(a) Price sensitivity: α (b) Savings needed to drive an additional kilometer



that customers from the U.S. value their driving time at 89% of their wage. See table 1.6 for further details.

Table 1.6: Summary of estimation results by income decile

Income decile	Earnings (MXN/hr.)	Parameter: α	Savings to drive (MXN/km)	Implied value of driving (MXN/hr.)
1	21.3	-5.23	-0.124	92.9
2	32.3	-5.01	-0.126	94.4
3	39.3	-3.55	-0.129	96.8
4	46.7	-5.09	-0.129	96.6
5	55.9	-4.03	-0.161	121
6	64.6	-4.12	-0.152	114
7	77.5	-5.09	-0.126	94.3
8	96.1	-4.47	-0.138	104
9	128	-3.8	-0.162	121
10	204	-3.36	-0.176	132
Corr. with hourly earnings		0.615	-0.786	0.784

1.7 Conclusion

This is the first paper to estimate the retail elasticity of demand for gasoline as a spatially differentiated product allowing for heterogeneous consumers. I find that market-level price elasticity is between -0.42 and -0.64. Additionally, I find that a consumer's price sensitivity depends on their income level and that low-income households are up to 55% more price sensitive than high-income households. I also find that consumers dislike driving and that the median household would need 13 MXN¢/L in savings at the pump to be indifferent to driving an additional kilometer.

The results of this paper contrast with previous studies for Mexico, such as Díaz and Medlock 2021 by finding elasticity estimates that are one order of magnitude larger. A well-documented case is that estimations that fail to control for supply and demand simultaneity will be biased towards zero (Davis and Kilian 2011 and Coglianese et al. 2017). My estimates account for simultaneity given the nature of the pricing policy followed by the MoF and are an order of magnitude larger than previous studies. I perform several tests to show the robustness of the estimation procedure. I show that the results are robust to model specification and the evaluation nodes of the numerical method. In addition, the results are not statistically different from Colina 2023b, which uses a state-of-the-art estimation procedure for instrumental variables for the California context (See Essay 3 for further details).

The results of this essay are essential to answer policy evaluation questions; while most of these questions focus on estimating the average effect across consumers, there are several valuable insights that can be gained from knowing the distributional consequences of a program, e.g. Vivalt 2015 and Colina 2023a. I use a rich data set that allows me to avoid imposing the assumption that consumers are heterogeneous. My estimates confirm that consumers are widely different. These results should serve as a cornerstone in studying policy impacts in such an unequal society like Mexico's. See Colina 2023a for further details.

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Appendix

1.A Estimation procedure

Modeling demand for gasoline as a differentiated product that is part of a demand system poses several estimation challenges as described in Section 1.3.1. Let $\hat{\theta} \equiv \{\bar{\alpha}, \bar{\gamma}, \beta, \lambda_1, \lambda_2, \Pi, \Sigma\}$, from equation (1.6) it is evident that demand for gas station j depends on the characteristics of all other gas stations $(\delta_1(x_1, \xi_1; \hat{\theta}) \ldots \delta_J(x_{jk}, \xi_{jk}; \hat{\theta})$. Additionally, I am not imposing the assumption of a single representative agent. Instead, I am assuming heterogeneous agents whose mean level of utility is determined by the parameters $\bar{\alpha}, \bar{\gamma}, \beta, \lambda_1, \lambda_2$ interacted with the product's characteristics. Parameters $\bar{\alpha}, \bar{\gamma}, \lambda_1, \lambda_2$ are scalars while β is a vector of length 6. In this model, what makes agents heterogeneous are deviations from the mean level of utility, these taste parameters are present in the matrices Π, Σ where $dim(\Pi) = 2 \times 4$ and $dim(\Sigma) = 2 \times 2$. The matrix Σ is symmetric, therefore has only 3 unknown parameters. Overall, there are J_k equations per market and $J_k + 10 + 8 + 3 = J_k + 21$ unknowns.

Suppose there are $m = 1 \ldots \mathcal{M}_k$ instruments, Z_m ,for each of the j products in market t such that

$$E(Z_{mk}\xi_k) = 0 \quad m = 1 \ldots \mathcal{M}_k \;\; for \; k = \{Mexicali, Tijuana\} \tag{1.9}$$

The sample moment condition is

$$\begin{aligned} m_{m,J_k}(\bar{\alpha}, \bar{\gamma}, \beta, \lambda_1, \lambda_2) &\equiv \frac{1}{J_k} \sum_{j=1}^{J_k} \xi_{jk} Z_{mjk} \\ &= \frac{1}{J_k} \sum_{j=1}^{J_k} (\hat{\delta}_{jk} - \bar{\gamma} - x_{jk}\beta + \bar{\alpha} P_{jk} + \lambda_1 \bar{d_{jk}} + \lambda_2 \bar{d_{jk}^2}) Z_{mjk} \end{aligned} \tag{1.10}$$

To estimate the model, I follow the estimating procedure of Conlon and Gortmaker 2020. Broadly speaking, it is a three-step procedure:

- **Step 1**: Take some values of $\hat{\theta} = \hat{\theta}_0$ as given and solve for estimates $\tilde{\delta}_1 \ldots \tilde{\delta}_J$ using the system of J

equations generated by equation (1.6).

$$
\begin{aligned}
\tilde{s_1} &= s(\tilde{\delta}_1 \ldots \tilde{\delta}_J; \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma) \\
&\vdots \\
\tilde{s_J} &= s(\tilde{\delta}_1 \ldots \tilde{\delta}_J; \bar{\alpha}, \bar{\gamma}, \beta, \Pi, \Sigma)
\end{aligned}
\tag{1.11}
$$

- **Step 2**: Given the estimates of the mean utilities from Step 1, use a set of instruments Z_{mk} to compute $Q(\hat{\theta})$:

$$
Q(\theta) \equiv \left[G_{J_k}(\bar{\alpha}, \bar{\beta}, \lambda_1, \lambda_2)\right]' W_{J_k} \left[G_{J_k}(\bar{\gamma}, \beta, \bar{\alpha}, \lambda_1, \lambda_2)\right] \tag{1.12}
$$

where

$$
G_{J_k}(\theta; \tilde{\delta}, x_k, P_k, \bar{d}_k, \bar{d}_k^2) = \begin{bmatrix} \frac{1}{J_k} \sum_{j=1}^{J_k} (\tilde{\delta}_{jk}(\hat{\theta}_0) - \bar{\gamma} - x_{jk}\beta + \bar{\alpha} P_{jk} + \lambda_1 \bar{d_{jk}} + \lambda_2 \bar{d}_{jk}^2) \times Z_{1jk} \\ \vdots \\ \frac{1}{J_k} \sum_{j=1}^{J_k} (\tilde{\delta}_{jk}(\hat{\theta}_0) - \bar{\gamma} - x_{jk}\beta + \bar{\alpha} P_{jk} + \lambda_1 \bar{d_{jk}} + \lambda_2 \bar{d}_{jk}^2) \times Z_{\mathcal{M}jk} \end{bmatrix} \tag{1.13}
$$

and where W_j is a weighting matrix with $dim(W_j) = \mathcal{M} \times \mathcal{M}$.

- **Step 3**: In the next estimation round, r, choose $\hat{\theta}(r)$ and repeat Step 1 and Step 2. Find $\hat{\theta(\cdot)}$ that minimizes equation (1.13).

More details on the estimation procedure are discussed at length in Conlon and Gortmaker 2020, Nevo 2000 and Berry, Levinsohn, and Pakes 1995.

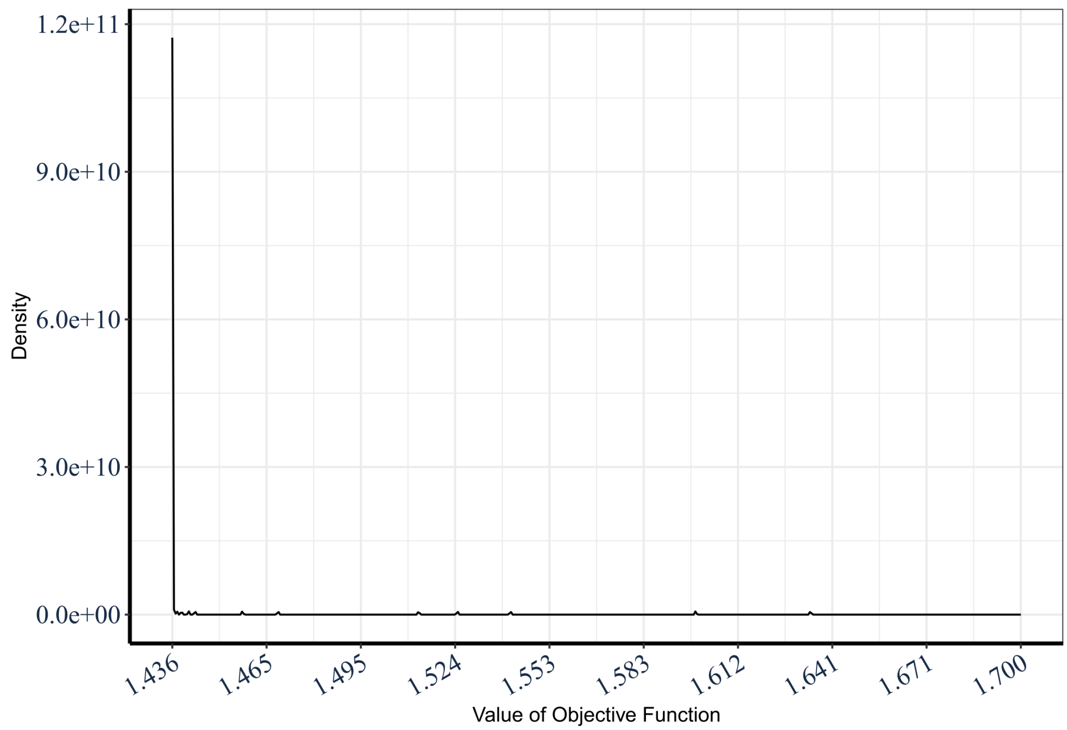
A particular challenging point in the estimation procedure arises because each consumer faces a different distance to a gas station j. That is, even if two customers were to visit the same gas station and be exposed to the same prices or services, $d(L_i, L_j) \neq d(L_{i'}, L_j)$ $i \neq i'$, where $d(L_i, L_j) \equiv d_{ij}$ be the Euclidean distance between consumer i's home and gas station j. Following Davis 2006 As described in section 1.3, specifically in equation (1.5).

1.A.1 Initial values

As discussed in section 1.3, the model does not have a closed-form solution. To solve the model, an initial guess is required to start the algorithm that looks for the minimum of the objective function.

Similar to Ito and Zhang 2020, I use 360 different combinations of initial values. I follow Conlon and Gortmaker 2020 and use a Broyden, Fletcher, Goldfarb, and Shanno method (L-BFGS) to search over the "new" initial values, (Virtanen et al. 2020). After finding different solutions, I choose the initial value that provides the minimum objective function value.

Figure 1.A.1: Values of the objective function for different starting points in the solution algorithm



1.B Alternative model specifications: standard Logit.

In table 1.B.1, I report the estimates of three different model specifications. One of the advantages of the standard logit model is that it has a closed-form solution, but the implicit assumption is that consumers are homogeneous.

In the simplest model, Logit Model 1, consumers only have utility over prices and distance:

$$u_{jk} = \gamma + \alpha y - \alpha p_{jk} - \lambda_1 d_{jk} - \lambda_2 d_{jk}^2 + \varepsilon_{jk}$$

Columns 1 and 2 in table 1.B.1 show the model's estimates and its standard errors. The estimates show intuitive results, consumers dislike driving to a gas station and dislike paying for gasoline. However, there is a concern for omitted-variable bias since the model is not accounting for demand shifters as amenities offered on-site. Abnormally high estimates for the elasticity of demand at -4.66 for Tijuana and -4.15 for Mexicali could indicate this is the case.

Table 1.B.1: Estimation results of Logit models

	Logit Model 1		Logit Model 2		Logit Model 3	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Parameter Name	*Estimate*	*s.e.*	*Estimate*	*s.e.*	*Estimate*	*s.e.*
Param. Estim.						
.. Intercept	17.93 ***	2.478	-0.24 ***	0.009		
.. Prices	-1.62 ***	0.181	-3.06 ***	0.116	0.23	0.164
.. Avg. dist	-0.54 ***	0.162	0.00	0.000	0.00	0.000
.. Avg dist sq.			0.00	0.099	0.00	0.011
.. Big business			0.04 ***	0.005	0.12	0.080
.. Conv. Store			-0.02 ***	0.001	-0.07	0.068
.. ATM			-0.01	0.000	0.01	0.050
.. Accepts vouchers			0.00	0.000	0.02	0.010
.. Sells oil			-0.01	0.001	0.03	0.094
Rack-level F.E.	No		No		Yes	
Post-estimation calc.						
.. ΔP to drike add. 1km	-0.33		-0.32		0.14	
	Mexicali	*Tijuana*	*Mexicali*	*Tijuana*	*Mexicali*	*Tijuana*
.. Mkt. price elast.	-4.15	-4.66	-0.56	-0.73	0.34	0.46
.. Avg. Market share (s)	0.36%	0.44%	0.36%	0.43%	0.36%	0.43%
.. Δs/Δd	-0.004%	-0.005%	-0.003%	-0.004%	0.000%	0.000%
.... Change in sales	-1.1%	-1.1%	-0.9%	-0.9%	0.0%	0.0%
.. Δs/Δbig business			-0.1%	-0.1%	0.054%	0.066%
.... Change in sales			-20.8%	-20.8%	15.2%	15.2%

Since the model is not linear, post-estimation calculations are evaluated at the mean.
(***) indicate significance at the 2.5% level, (**) at the 5% level, and (*) at the 10% level

Columns 3 and 4 in table 1.B.1 show the estimates for Logit Model 2. This specification controls for gas-station-level attributes.

$$u_{jk} = \gamma + \alpha y + x_{jk}\beta - \alpha p_{jk} - \lambda_1 d_{jk} - \lambda_2 d_{jk}^2 + \varepsilon_{jk} \tag{1.14}$$

The estimated parameters are statistically different from zero, considerably reducing the elasticity estimates. This supports the intuition that consumers value gas station amenities, not just price. However, a potential source of endogeneity could come from self-selection, where gas stations in affluent regions offer different attributes. To control for this, Logit Model 3 includes rack-level fixed effects; however, as is common with these types of controls, the fixed effects absorb all price variation (Berry and Haile 2021).

Chapter 2

The liberalization of Mexico's gasoline markets: entry, price controls, and consumer welfare

2.1 Introduction

This essay measures the consumer welfare effects of the regulatory changes in Mexico's retail gasoline market from 2016 to 2019. The regulatory changes started with the liberalization of retail gasoline prices in 2016 after almost eight decades of a federally mandated retail price policy. Now, gasoline retailers are allowed to choose their pricing strategies. The policy change led to some gas station openings anticipating price liberalization. However, retail prices increased much more than changes in wholesale prices for the 2016 to 2019 period as entry was curtailed from regulatory backlogs. Higher product availability coupled with higher prices makes the consumer welfare impact ambiguous.

To compute the welfare effects, I use the estimates of the demand for gasoline as a spatially differentiated good as reported in chapter 1. By leveraging a natural experiment with a unique and detailed data set, I control for supply and demand simultaneity while avoiding the assumption that consumers are homogeneous.

I find that for every peso gained in welfare from additional product availability, roughly two pesos are lost due to increased retail prices. Overall, there is an aggregate welfare loss of 7.1% of the annual market revenue or 1,400 million $^{\text{MXN}}/_{\text{year}}$ (88.2 million $^{\text{USD}}/_{\text{year}}$).[1]

A wide disparity in gasoline consumption characterizes Mexico; the top three income deciles consume

[1] I define the distinct markets as the metropolitan areas of Mexicali and Tijuana

roughly 60% of gasoline while the bottom three consume 13%. Despite the disparity, low-income households benefit the most from new gas station openings as it increases overall tax transfers. High-income households are the most affected by price increases as they overwhelmingly consume more gasoline.

Given the large disparity in consumption, the brunt of this set of policies is carried by high-income households. For example, the median household in the bottom income decile is worse off by roughly 1,500$^{\text{MXN}}/_{\text{year}}$ (94.5$^{\text{USD}}/_{\text{year}}$). In comparison, the median household in the top income decile is worse off by almost 4,000$^{\text{MXN}}/_{\text{year}}$ (252$^{\text{USD}}/_{\text{year}}$). However, this set of policies has been regressive. As a proportion of income, low-income households are worse off by 3% of their annual disposable income, while high-income households are affected by just 1.5% of their income.

Aside from the demand estimation, determining the correct policy counterfactual is a major challenge. I leverage the strict regulatory environment in Mexico's fuels market and the pricing rule the Ministry of Finance (MoF) followed when setting retail prices to construct plausible counterfactual scenarios. I simulate how the MoF would have set retail prices in response to changes in international prices of wholesale gasoline. I then compare the welfare outcomes of the observed 2019 prices to the simulated prices located in the 25th, 50th, and 75th percentile of the distribution of counterfactual prices.

2.2 Predicting counterfactual market shares

To estimate demand for retail gasoline, I use a highly detailed data set of the universe of gas stations in Mexicali and Tijuana in 2015, which includes their location, sales volume, attributes, and average price charged throughout that year. For the following years, I can observe the location, attributes, and pricing of the universe of gas stations, incumbents, and entrants alike. For further details, see essay 1.

In a social program context, a key challenge for policy evaluation is determining the correct counterfactual outcomes had the policy not been implemented (Heckman and Vytlacil 2007). Models like logit or probit have a well-documented history of producing bad counterfactual predictions due to the independence of irrelevant alternatives issue (Ray 1973). Other models, such as a nested logit, impose an a priori substitution pattern. For further discussion, see section 1.B.

A random coefficient model would be the best choice to predict changes in the choice set as it doesn't impose a priori substitution patterns Berry and Compiani 2021. I follow a three-step procedure to test how well the model performs: first, I estimate the model's parameters. The estimates are shown in section 1.5. Second, I compute the values of ξ for all gas stations in Mexicali and Tijuana (see figure 2.2.2). Third, I simulate the consumer choices by taking the parameter estimates and ξ as given, and then I input the different product and demographic characteristics into the model. The prediction errors are displayed in

Figure 2.2.1: Modeled and observed market shares

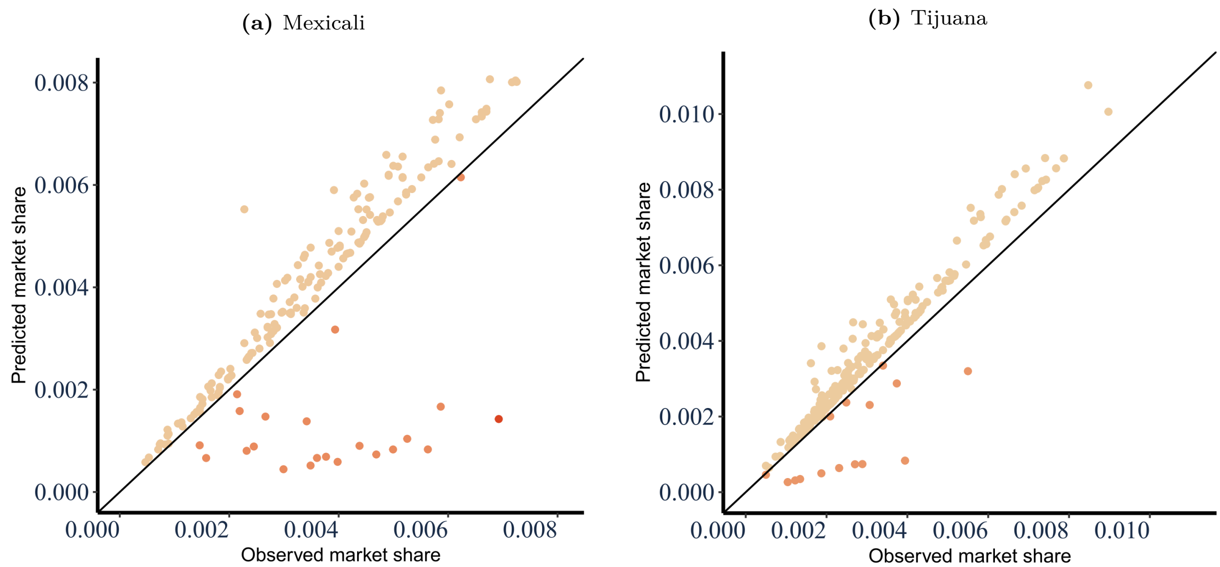
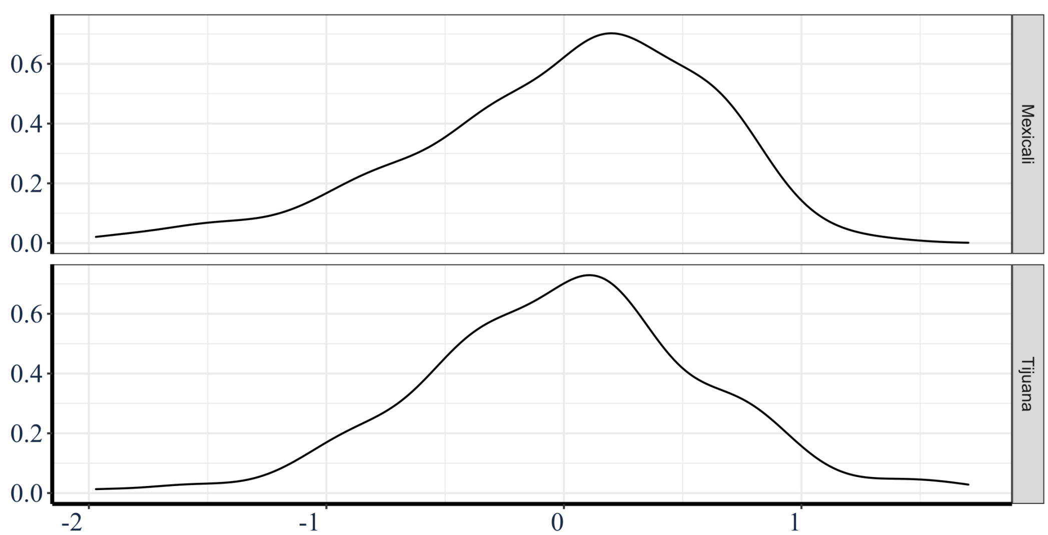


Figure 2.2.1.

Overall, the model seems to be performing relatively well at predicting market shares, given the observable attributes of the gas stations.

Figure 2.2.2: Non parametric distribution of unobserved attributes ξ_k across markets



2.3 Consumer welfare impacts

Price liberalization brought substantial gas station openings, initially, yet it also led to an increase in prices. However, the entirety of the price change cannot be attributed to MER since international wholesale gasoline prices increased during the 2016-2019 period and the MoF would have adjusted taxes accordingly. Therefore, the main challenge is to define the correct counterfactual scenario to compare the observed outcomes to. Fortunately, the MoF followed a pricing formula for the retail prices as described in equation (2.1).

While the ultimate objective is to compute the welfare change from enacting MER, I start by computing, separately, the welfare change that households experienced from 2015 to 2019 from increased product availability and from price changes. In each setting, given the prices and product availability, I compute the taxes collected from the sales of fuel. Given that there is no explicit information about the use of these taxes, I assume that what is collected is redistributed evenly across households. This is an arbitrary yet necessary assumption. While ENIGH provides data on the amount of government transfers received, the vast majority of government expenditure goes to other services like education and healthcare (Castelletti 2013). Estimating how households consume public services, conditional on their income level, requires additional assumptions. Future work will test different distribution assumptions. In the same vein as Petrin 2002, I use compensating variation to compute the consumer welfare gains.

2.3.1 Scenario (1): Consumer welfare change from additional product availability

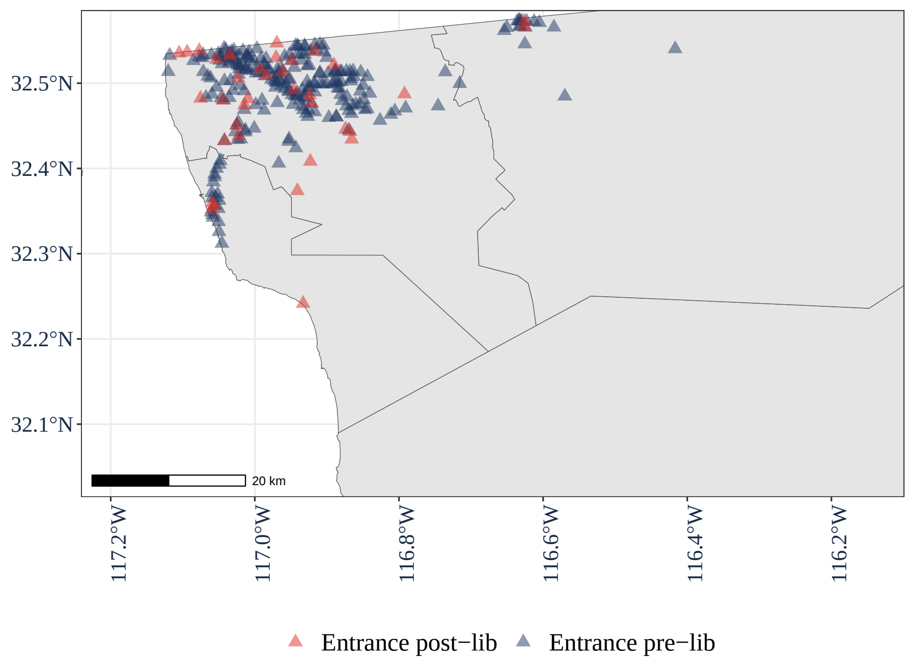
While it is generally agreed upon that consumers benefit from additional products, Dixit and Stiglitz 1977 and Mankiw and Whinston 1986 show that, in theory, consumers might not benefit much if the new products are not sufficiently differentiated. I measured how much consumers benefited from additional gas stations.

Few empirical papers have tested if consumers benefit from more product availability. Some notable exceptions include Berry and Waldfogel 1999, Petrin 2002, Seim and Waldfogel 2013, and Berry, Eizenberg, and Waldfogel 2016, who examined radio stations, minivans, and liquor stores. No one has studied the benefits of increased availability in retail gasoline markets.

To isolate the benefit of additional gas stations, I keep prices constant at the 2015 levels and simulate consumer choices in a counterfactual market with the gas stations that opened between 2016 and 2019. I refer to these stations as entrants. I can observe the attributes and location of entrant gas stations. Depending on their location relative to the U.S. border, I assign the price they would have been charging, given the administered price regime in 2015.

In this setting, the first challenge comes from data limitations. Since I cannot observe gas-station-level sales post-liberalization, I cannot estimate ξ for entrants. However, I have the non-parametric distribution of ξ for incumbent gas stations. See figure 2.2.2 for the distribution in Mexicali and Tijuana. Depending on its market location, I take random draws with no replacement from the corresponding non-parametric

Figure 2.3.1: Location of incumbent and entrant gas stations in Tijuana



distribution and assign them to each entrant gas station.

Given the new choice set, I then compute the individual choice probabilities of each gas station for all consumers in each market. Figure 2.3.1 shows the location of entrant and incumbent gas stations in the metropolitan area of Tijuana. Table 2.3.1 summarises the number and types of gas stations in the new choice set.

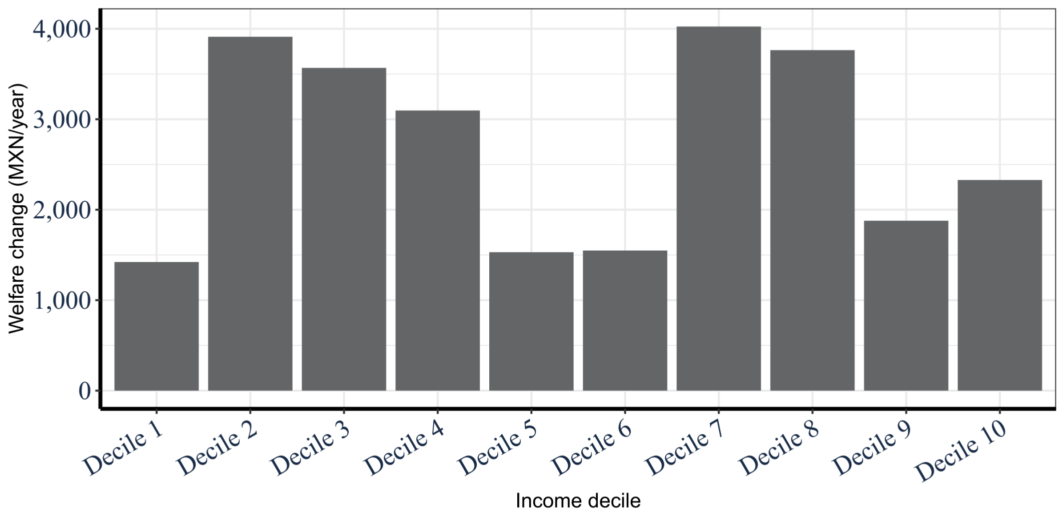
Table 2.3.1: Gas station types by market

Market	**Station type**	**Number**
Metro Mexicali	Incumbent	214
	Entrant	10
Metro Tijuana	Incumbent	235
	Entrant	32

Higher product availability increases overall consumption as transportation costs are reduced for some households. The increase in consumption translates into an increase in the taxable base of roughly 8.6%, increasing the transfers to all households. High-income households, who are less price sensitive and consequently less willing to drive to refuel, benefit from the increased convenience. While the gasoline consumption by low-income households is relatively small, they benefit from increased transfers.

The gain from increased product availability results in an aggregate increase in consumer welfare of 1,459,453,575 MXN/year (91,963,048USD/year). The gasoline industry in Mexicali and Tijuana has a yearly

Figure 2.3.2: Welfare changes from gas station openings



revenue of 20,225,820,000 MXN (approx. 1.27 billion USD). Then, the entry of 42 gas stations increased household welfare by roughly 7.2% of the annual revenue.

However, the benefits of new gas stations are not spread evenly. The median household in the first decile benefits in 1,422$^{MXN}/_{year}$, mostly derived from increased tax transfers. The median household in the tenth decile benefits in 2,328$^{MXN}/_{year}$, mostly from the convenience of increased station availability.

2.3.2 Consumer welfare change from price changes

Between 2016 and 2019, we observe an increase in retail prices. However, the entirety of the retail price change cannot be attributed to the price liberalization since international wholesale prices also increased during this time period, and Mexico imports the vast majority of the gasoline it consumes. Then, there is the challenge of determining the right benchmark that would have been observed in 2019 had the policy not been removed.

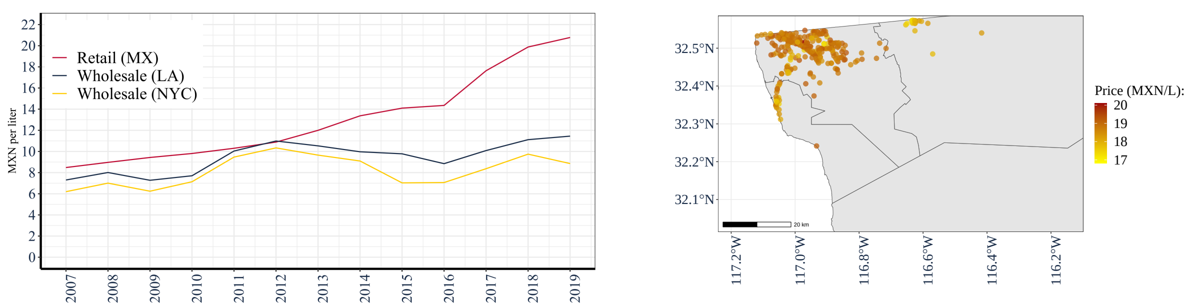
In figure 2.3.3a we can observe that wholesale prices in New York City and Los Angeles follow a similar trajectory with an increase of 1.82$^{MXN}/_{L}$ and 1.67$^{MXN}/_{L}$ throughout the 2016-2019 period, respectively.[2] Mexican retail prices are also increasing during this period but disproportionately more at 6.67$^{MXN}/_{L}$ on average. Figure 2.3.3b shows a cross-section of average observed retail prices at every gas station in Tijuana throughout 2019.

[2]New York City prices are taken from the prices of futures contracts with delivery in New York Harbor. Los Angeles prices are taken from CARBOB spot prices measured in Los Angeles.

Figure 2.3.3: Price evolution in Tijuana

(a) Retail and wholesale gasoline price trajectories

(b) Cross-section of 2019 retail prices in Tijuana



Retail pricing rule

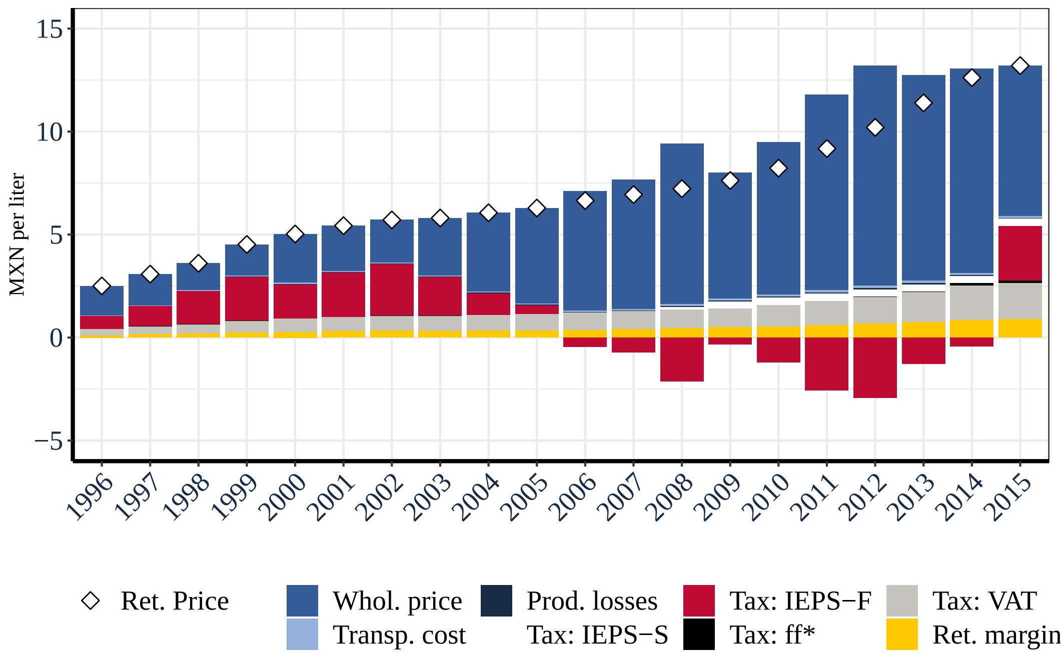
Prior to MER, the MoF would follow a pricing formula as depicted in equation (2.1) (Clavellina Miller 2015 and Secretaría de Energía 2017). The variable $P_{ret,t}$ is the objective retail price for time period t; $P_{whol,t}$ is a reference price for wholesale gasoline; $TranspC_t$ are estimated transport costs from the rack to the gas station; $RetMargin_t$ is the "profit margin" left to the retailer; $ProdLoss_t$ are the estimated losses from product transportation and handling; Tax_t^{fossil} are taxes on fossil fuels; $Tax_t^{IEPS-Fed}$ is a federal variable tax. IEPS stands for *Impuesto Especial sobre Producción y Servicios* and it is a family of taxes applied to gasoline, tobacco, alcohol, and sodas. VAT_t is a value-added tax of 16%, and $Tax_t^{IEPS-State}$ is a state-level tax similar to the federal tax, $Tax_t^{IEPS-Fed}$.

$$\begin{aligned} P_{ret,t} = & (P_{whol,t} + TranspC_t + RetMargin_t + ProdLoss_t + \\ & Tax_t^{fossil} + Tax_t^{IEPS-Fed}) \times VAT_t + Tax_t^{IEPS-State} \end{aligned} \tag{2.1}$$

Through this formula, the MoF would target a retail price, $P_{ret,t}$, for a period t and would adjust $Tax_t^{IEPS-Fed}$ to partially compensate for changes in $P_{whol,t}$. In Figure 2.3.4, we can observe the different prices and components in the years from 2006 to 2014. During this period, $Tax_t^{IEPS-Fed}$ even becomes a subsidy in years of increased wholesale prices.

In the following section, I will compute welfare changes based on different benchmark scenarios of retail pricing policies. I'll begin with the observed price change between 2015 and 2019 to gauge the size of the impact prices have on consumer welfare and then compare it to the welfare gains from gas station entry. Then, I'll simulate possible pricing policies that the MoF could have followed had it kept its price-control policy and adjusted Federal IEPS taxes to the changes observed on international wholesale prices.

Figure 2.3.4: Components of the MoF's pricing formula



*Note: ff stands for fossil fuel; IEPS−F for Federal IEPS, and IEPS−S for State IEPS

2.3.3 Scenario (2): Consumer welfare change from price changes and a passive Ministry of Finance

The purpose of this scenario is to gauge the magnitude that price increases have on consumer welfare. This counterfactual scenario assumes that the price control policy had been kept in place and that the MoF let a complete pass-through of the change in international wholesale prices onto retail prices. The change for wholesale L.A. gasoline, the relevant benchmark for Mexicali and Tijuana, was of 1.67 MXN/L from 2015 to 2019.

To isolate the effect of price on welfare, I keep the choice set as the one consumers faced in 2015; that is, I assume there were no entrants. I also keep the number of households constant to isolate the effect of price on the quantity consumed. I call this scenario the "Passive MoF" as the MoF would not have lowered taxes in response to a price increase.

The increase in retail prices translates into a welfare loss of 1,354,021,316 MXN/year (6.7% of the industry's annual revenue). The brunt of the loss is mostly evenly distributed. High-income households are affected by higher prices at the pump, which reduces the taxable base by 11.15%, resulting in lower transfers to lower-income households. All consumers are negatively affected by the increase in prices. The median household in the first decile is worse off by 4,623 MXN/year, while the median household in the tenth decile is worse off

Figure 2.3.5: Welfare change from a simulated complete wholesale price pass through into retail prices

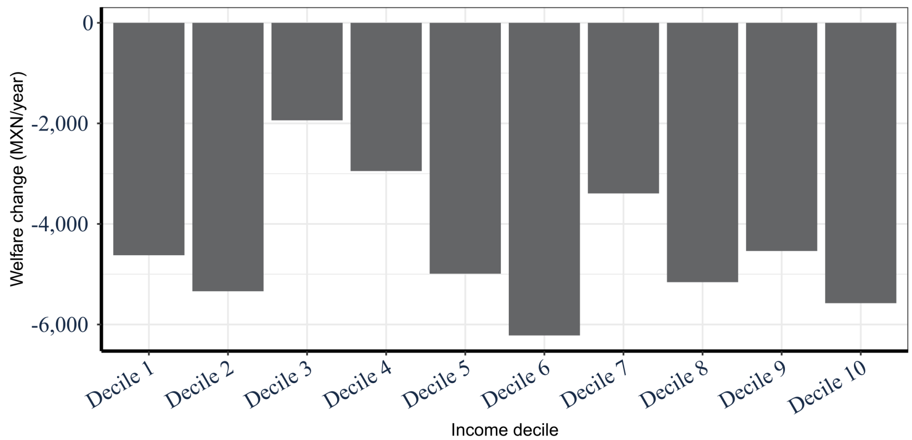


Table 2.3.2: Variance-covariance matrix of contemporaneous changes in the retail pricing formula

Variance-Covariance Matrix from 1995-2016 (Changes)			
	Wholesale price	**Federal Tx (IEPS)**	**Ret. Margin**
Wholesale price	0.2110	-0.2062	0.00032
Federal Tx (IEPS)	-0.2062	0.2040	-0.0003
Ret. Margin	0.0003	-0.0003	0.0001

by 5,576$^{\text{MXN}}/_{\text{year}}$. See figure 2.3.5 for the impact distribution across households.

2.3.4 Scenario (3): Consumer welfare change from price changes and a proactive Ministry of Finance

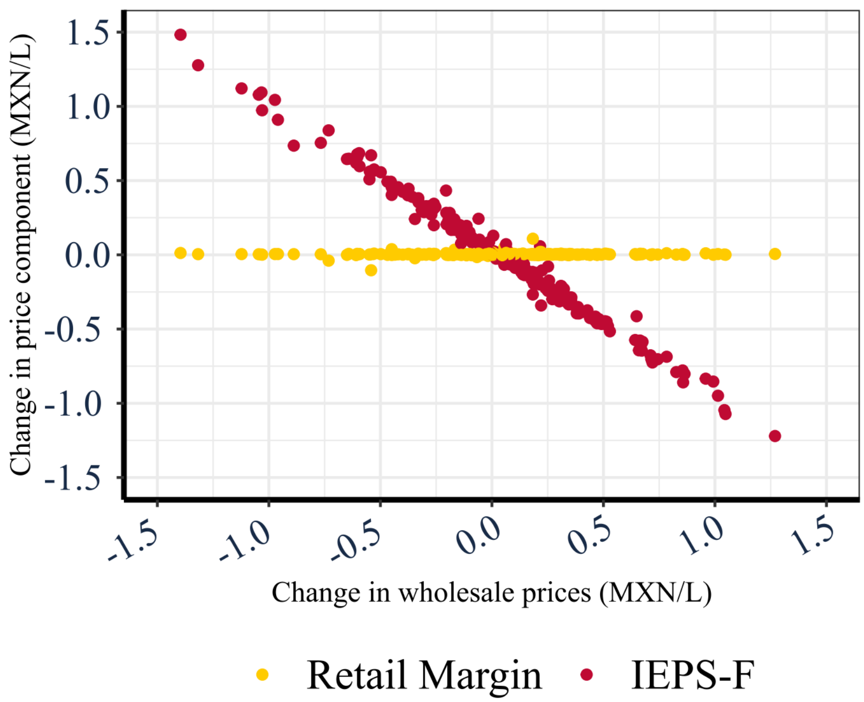
Figure 2.3.4 shows how the MoF adjusted the level of the Federal IEPS in response to international wholesale prices before retail price liberalization. The level of Federal IEPS was the main adjustment lever; for example, figure 2.3.6 shows that retail margin levels would not be adjusted to changes in international wholesale prices.

The MoF would reduce (increase) the Federal IEPS tax in response to increases (reductions) in wholesale price, but it wasn't always a one-to-one change. The relevant counterfactual scenario involves continuing this policy; however, it is uncertain how aggressively the MoF would have adjusted taxes in the presence of the observed changes in wholesale prices throughout 2016 and 2019.

I perform simulations of possible pricing paths the MoF could have followed using Montecarlo simulations. These counterfactual pricing paths will serve as the prices in the benchmark scenarios. I use the variance-covariance matrix in table 2.3.2 to make random draws from a multivariate normal.

The results of the simulation exercise are presented in figure 2.3.7. Interestingly, as time has passed

Figure 2.3.6: Rolling correlation between international wholesale prices and administered components of the MoF's pricing formula from 1995 to 2015



from when prices were liberalized, the observed average yearly price lies further away in the distribution of simulated prices. For example: had the administered price regime been kept, the median simulated price would have been 13.78$^{MXN}/_{L}$ for 2017, while the average observed price is 17.63$^{MXN}/_{L}$. This is beyond 17$^{MXN}/_{L}$, the average simulated price that is two standard deviations away from the mean.

Had the price-control policy remained in place, the MoF could have followed different tax policies. For ease of exposition, I will focus on three scenarios. These three outcomes are characterized by retail prices in the 25^{th}, 50^{th}, and 75^{th} percentile of the distribution of simulated prices. Retail prices in the 25^{th} percentile result in a "low tax" scenario, while retail prices in the 75^{th} percentile result in a "high tax" scenario. I refer to the scenario with prices in the 50^{th} percentile as the "base case" scenario.

Based on these three main outcomes, the policy implementation had an adverse effect on consumer welfare. However, the magnitude of the impact varies. Table 2.3.3 summarises the welfare outcomes that use these three counterfactual scenarios as a starting point to compare to the 2019 outcome. In the 2019 outcome, retail prices are the highest at 20.78$^{\text{MXN}}/_{\text{L}}$. This is due, in some part, to an average per-liter tax of 4.6$^{\text{MXN}}/_{\text{L}}$; however, most of the difference with respect to wholesale prices cannot be explained by high taxes alone. High retail prices result in 1,001.35 million liters sold annually and a tax collection of 4,646 million MXN annually.

Figure 2.3.7: Welfare change under counterfactual simulated scenarios following the MoF's pricing rule

(a) Welfare change for the median household in each income decile

(b) Aggregate welfare change at the income decile level

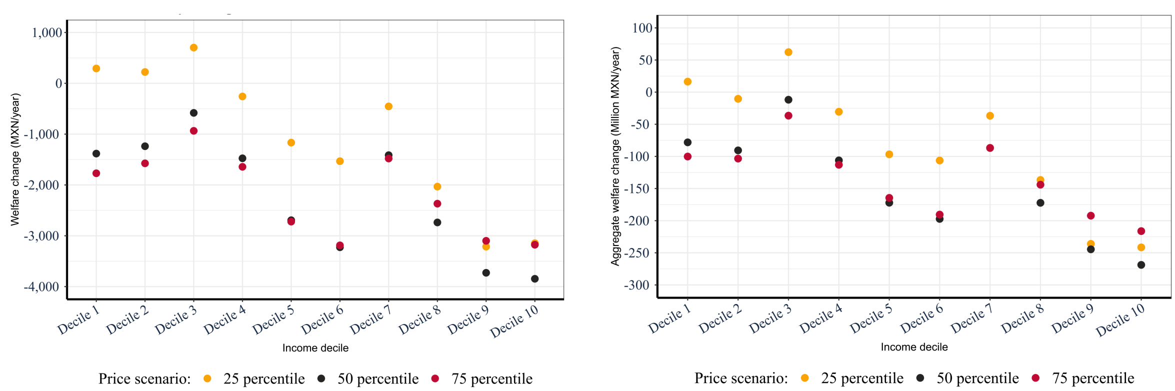


Figure 2.3.7b shows the welfare change for all the households within one decile. There are two things that stand out: in all the scenarios, there is an aggregate welfare loss for most of the income deciles. Second, generally speaking, the higher the income, the higher the loss. As households become more wealthy, they consume more liters of gasoline, and the brunt of higher prices overshadows the benefits of transfers.

In a "low tax" counterfactual scenario, retail prices would have been relatively low at 12.27MXN/L and, despite having the largest amount of liters sold, tax collection would have been relatively low at 4,327.48 million MXN/year given a low average per-liter tax of 2.8MXN/L. The retail price change between this scenario and the 2019 observed outcome is the largest. The brunt of this effect is carried by high-income households (Deciles 9 and 10) who consume the most gasoline. Low-income households are affected much less as they consume much less gasoline and benefit from marginally higher tax transfers. See the yellow dots in figures 2.3.7a and 2.3.7b.

Table 2.3.3: Consumption, taxation, and welfare under different simulated scenarios following the MoFs pricing rule

Outcomes of simulated tax policy given the retail pricing rule						
Scenarios	**Percentile**	**Prices**	**Liters sold** (mill./year)	**Taxes** (mill. MXN/year)	**Aggr. welfare change** (mill. MXN/year)	**Share of revenue (annual)**
Counterfactual	25th	12.27	1,501.22	4,327.48	-816.36	4.0%
	50th	13.71	1,363.48	5,062.45	-1,428.47	7.1%
	75th	15.23	1,286.76	5,274.66	-1,347.43	6.7%
2019		20.78	1,001.35	4,646.12	-	-

In a "high tax" scenario, the converse is true. Counterfactual retail prices would have been high, to begin with, at 15.23MXN/L, so high-income households would have been affected much less due to a lower price increase. In this case, however, low-income households bear the brunt of the policy as the change in collected taxes would have been the highest going from 5,274 million $^{\text{MXN}}/_{\text{year}}$ to 4,646.12 million $^{\text{MXN}}/_{\text{year}}$.

The "base case" scenario has the highest level of consumer welfare among the three analyzed scenarios. Therefore, the change from this scenario to the 2019 outcome is the largest. See the blue dots in figures 2.3.7a and 2.3.7b. In the "base case" scenario, there is somewhat of a balance between the amounts of taxes redistributed and the prices paid at the pump; see table 2.3.4 for further details. For example, for deciles 8, 9, and 10, the median household experiences lower levels of utility from consumption. At the same time, these households receive a higher level of utility from the tax transfers in Pricing Scenario 50% than in Pricing Scenario 25%.

Starting from the "base case" scenario, every income decile is worse off in aggregate. Going from this scenario to the 2019 outcome results in going to a high-price setting with relatively low taxes. The top three deciles are the most affected in this scenario since they overwhelmingly consume more gasoline. Increasing taxes can benefit some income deciles as the increase in transfers more than compensates for the loss of paying more at the pump. For example, increasing taxes and going from Pricing scenario 25% to Pricing scenario 50% increases the level of utility for the median household in Decile 1. However, increasing taxes too much will eventually affect households. See the median household in Decile 10 going from Scenario 50% to 75%.

In the last column of table 2.3.3, we observe that, on aggregate, the price liberalization policy has led consumers to a worse outcome. The main culprit is that retail prices have increased much more than the increase in taxes and wholesale prices combined. This has had two adverse effects on welfare: first, higher-income households, who are the customers who derive the most utility out of the consumption of gasoline in this market, end up paying higher prices. Second, due to higher prices, aggregate consumption falls, and overall tax collection decreases. Even though I assumed that tax collection is distributed evenly, it is lower-income households that benefit the most since they tend to be more price sensitive and more sensitive to income levels due to a higher magnitude of α_i, see table 1.6.

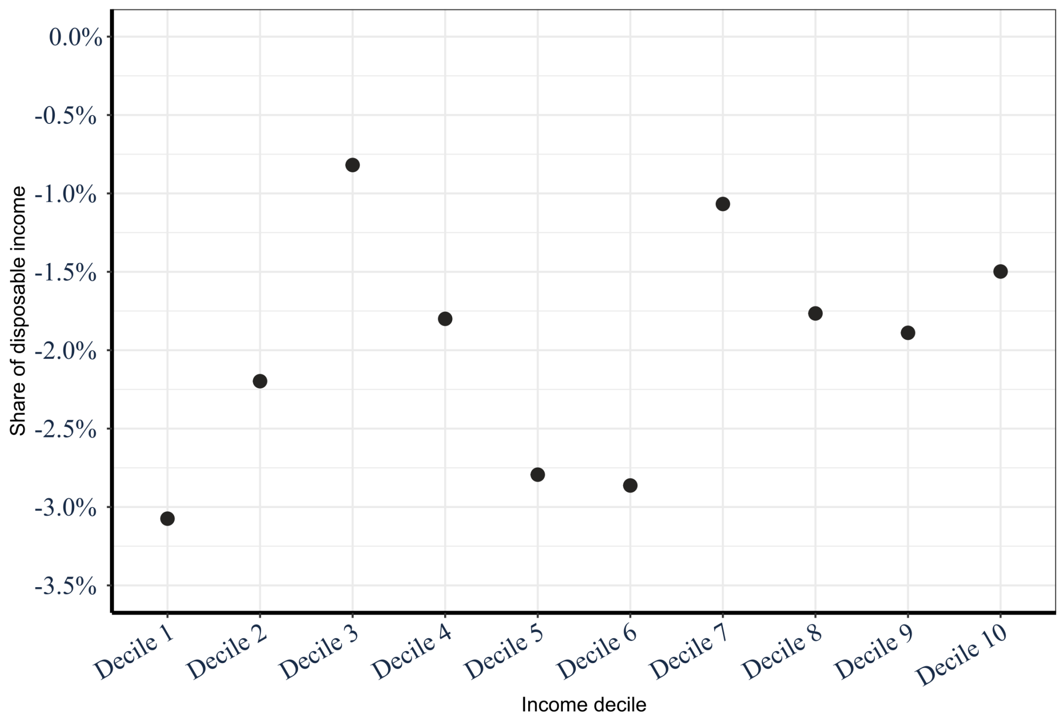
Table 2.3.4: Sources of utility under counterfactual pricing scenarios

Utility level for the median household within each decile according to source												
Income decile	**Pricing Scenario 25%**			**Pricing Scenario 50%**			**Pricing Scenario 75%**			**2019 Outcome**		
	Consumption	*Transfers*	***Total***	*Consumption*	*Transfers*	***Total***	*Consumption*	*Transfers*	***Total***	*Consumption*	*Transfers*	***Total***
1	3,583	50,248	**53,831**	3,174	58,781	**61,955**	2,782	61,245	**64,027**	2,185	57,048	**59,233**
2	16,351	49,943	**66,294**	15,627	58,425	**74,052**	15,082	60,874	**75,956**	14,403	51,958	**66,361**
3	15,121	35,606	**50,727**	14,771	41,653	**56,424**	14,359	43,399	**57,758**	14,343	45,746	**60,089**
4	17,292	39,194	**56,486**	16,526	45,850	**62,376**	15,725	47,772	**63,497**	14,623	41,681	**56,304**
5	21,544	56,511	**78,055**	19,986	66,109	**86,095**	18,398	68,880	**87,278**	16,093	59,119	**75,212**
6	18,763	49,737	**68,500**	16,480	58,184	**74,664**	14,212	60,623	**74,835**	11,244	46,524	**57,768**
7	22,435	40,870	**63,305**	20,656	47,812	**68,468**	19,052	49,816	**68,868**	16,835	34,803	**51,638**
8	20,933	54,756	**75,689**	17,188	64,056	**81,244**	14,030	66,741	**80,771**	11,047	46,470	**57,517**
9	45,408	43,426	**88,834**	42,303	50,801	**93,104**	39,527	52,931	**92,458**	36,179	40,208	**76,387**
10	42,503	46,117	**88,620**	38,190	53,950	**92,140**	34,102	56,211	**90,313**	30,488	37,563	**68,051**

My preferred choice for a counterfactual scenario is Pricing Scenario 50%. In this scenario, taxes collected are higher than in the 2019 outcome; therefore, consumers still experience a decrease in transfers jointly with increased prices. In this scenario, consumers are worse off by 1,428.47 million MXN per year in aggregate.

Almost every decile is worse off, yet the ones more affected by the policy, in absolute levels, are households in the eighth, ninth, and tenth income deciles who overwhelmingly consume more gasoline. Households in deciles 1 and 2 are affected by a decrease in transfers.

Figure 2.3.8: Welfare change as a proportion of income



However, as a percentage of income, welfare loss is the highest for low and middle-income households. Figure 2.3.8 shows that the welfare loss is 3.07% and 2.2% for the median household in deciles 1 and 2, respectively. Households in deciles 5 and 6 lose 2.8% and 2.88% of their annual income. Finally, the median household in the 10th decile is worse off by 1.5% of their annual income. These results suggest this policy has had regressive effects on welfare.

2.4 Conclusion

After over eighty years of price control policies, the Federal Government allowed gas stations to choose their pricing strategy. However, due to regulatory backlogs, the number of gas stations that entered the market was constrained. This led gas station operators to increase their prices more than wholesale prices during that period.

Building on the work presented in essay 1, I use the demand estimates obtained by Colina 2023 to estimate consumer demand. I then define a counterfactual scenario of how prices would have looked like had the price control policy remained in place. I first leverage the MoF's formulaic pricing rule to estimate the variance-covariance matrix between taxes and wholesale prices. Then, given the observed wholesale monthly price changes, I simulated 1,000 possible price paths across four years, yielding a total of 48,000 simulated prices. From 2017 onward, the observed retail price is higher than the 99th percentile of simulated prices.

My preferred counterfactual is the scenario of taxes that yields retail prices in the 50th percentile of the distribution of simulated prices. I compare the welfare change from this scenario to the observed 2019 outcome. I find that, in the aggregate, households are worse off from this policy by 1,428 million $^{\text{MXN}}/_{\text{year}}$ (7.1%of the markets' annual revenue).

In absolute levels, households in the eighth and ninth income deciles are affected the most as they overwhelmingly consume more gasoline than lower-income households. However, lower-income households are adversely affected as well. The increase in retail prices leads to a decrease in liters sold and a reduction in taxes collected. This, in turn, turns into lower government spending, which households benefit from.

Overall, this policy has had a regressive impact on household welfare. The median household in the bottom decile is worse off by 3.07% of their annual income, while the median household in the top income decile is worse off by 1.5%.

The observed increase in retail prices cannot be explained only by the increase in wholesale prices and the change in taxes. It is plausible that regulatory backlogs resulting in a lower number of gas station openings and the ability of gas stations to choose their own pricing have given station operators the ability to exercise local market power.

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Chapter 3

Accidents Happen: using capacity outages as instruments to estimate gasoline price elasticity

3.1 Introduction

The long-term price elasticity of demand for gasoline is a key parameter used in economic research, policy design, and business decisions. Yet, causally estimating it using observational data has proven to be challenging. For effective estimation, researchers need to control the level of demand and have price variation that is exogenous to unobserved demand components (Berry and Haile 2021). Economists use an instrumental variable (I.V.) estimation approach to achieve the latter. If instruments are weak or controls for demand are incomplete, the resulting estimates will likely be biased toward zero (Coglianese et al. 2017).

One difficulty when measuring demand shocks has been that detailed data is not generally available for the very large U.S. market. Measures of supply shocks have been even more difficult to identify and weakly correlated with prices resulting in weak instruments. In short, effectively measuring both lower-frequency demand shocks as well as higher-frequency supply shocks has been elusive. In this paper, I use the California gasoline market's specific features to identify the short and long-term price elasticities of demand.

The California gasoline market is unique in the U.S., given its large size and strict environmental regulations. This allows me controlling for demand shocks first and then use supply shocks that have strong associations with retail prices. To achieve the environmental standards set by the California Air Resources

Board (CARB), refiners in California must build special and costly units that produce specific blending components that are not required in the rest of the country. As a result, CARB-grade gasoline is only consumed in California and is almost exclusively produced there. California is, consequently, close to a segmented gasoline market. Therefore, reductions in refining capacity cannot easily be compensated by importing gasoline and can greatly impact prices.

I start by using detailed controls for demand shocks. To the extent that demand is persistent, I can (at least partially) control for demand shocks by including lagged sales. The rich data in California allow me to also control for inventories, imports, and capacity utilization. For example, if a persistent demand shock hits, the refiners will adjust their inventories and refinery utilization in anticipation of this prolonged shock. Including such lagged variables as controls, I estimate demand elasticities to be between -0.31 and -0.27, in line with previous estimates, e.g. Levin, Lewis, and Wolak 2017 and Coglianese et al. 2017. These estimates cannot perfectly control for all demand shocks. Therefore, there is still some attenuation bias from supply and demand simultaneity. Therefore, these estimates should be seen as a lower bound on the absolute size of the demand elasticity.

In the second step, I introduce refinery outages as instruments for supply shocks to address supply and demand simultaneity. Over the sample period, California has seen large refinery outages. For example, due to an explosion at the Torrance refinery in 2015, seven percent of the refining capacity was unavailable for over a year. But there have been many other refinery outages that are smaller and more frequent. These outages are the result of power outages, operational accidents, or the need to replace parts, and they are plausibly exogenous. Therefore they can be used as instruments for supply shocks. Specifically, the instruments are relevant since they directly impact supply, consumers do not anticipate it, and it is conditionally uncorrelated to gasoline demand.

However, not all outages are the same. Outages rarely happen at a refinery-wide level. Instead, there are specific refining units within the refinery that stop working. Each of these units has a different production capacity, and their outputs are important inputs to other refining processes. Therefore, losing a small refining unit that creates a critical component can have an outsized effect on the whole refining process. I use detailed data set with information on which refining units stopped working, the dates, and how much capacity has been lost.

Based on these instruments, I am able to calculate two sets of price elasticity estimates for the California gasoline retail market. I estimate the one-month price elasticity of demand to be -0.36 and the long-term elasticity to be -0.52 . The estimate of the latter is substantially more precise than previous state-of-the-art I.V. estimates from recent studies (Coglianese et al. 2017 and Levin, Lewis, and Wolak 2017). My standard errors are less than half of the earlier estimates (0.11 vs 0.239 for the preferred specifications). Additionally, I find that my estimates are 40% higher and statistically different at a 5% level.

Most of the previous research uses instruments that either take information from the crude oil market or from changes in taxes. As we learn more about demand estimation, a growing body of literature has found significant limitations in the instruments used. This body of literature has identified three main challenges: the instruments' relevance, the instruments' conditional correlation with consumer expectations, and the conditional correlation between the instruments and aggregate economic activity (Ramsey, Rasche, and Allen 1975,Coglianese et al. 2017, Li, Linn, and Muehlegger 2014). In section 3.2, I go into further detail about these challenges, and in section 3.3, I explain how outages are robust to these challenges.

The price elasticity parameter is essential to academic research and policy work alike. These new estimates should warrant a revisit of previous work that used this parameter as a key input into their analysis. For example, Holland, Hughes, and Knittel 2009 estimate the social costs of implementing the Low Carbon Fuel Standard (LCFS) and simulate different scenarios based on different supply and demand price elasticities values. My estimates exceed the range of values that they test for. Another example comes from Parry, Black, and Zhunussova 2022, who weigh the benefits and downsides of different carbon pricing policies. One of the downsides of carbon taxes is that they could lead to social unrest.[1] However, knowing that consumers are 40% more price-sensitive than previously thought would translate into a lower tax which could be more palatable to consumers and legislators alike.

3.2 Literature Review

Gasoline consumption touches several aspects of our everyday lives. Therefore, it is not surprising that the parameter of the price elasticity of demand is used to inform decisions of public policy, business decisions, and economic research as a whole (Hastings 2004, Yeh and Sperling 2010, Carter, Rausser, and Smith 2011, Knittel and Tanaka 2021). However, causally identifying the parameter using observational data has proven to be challenging.

The main challenge for parameter identification is addressing the simultaneity of supply and demand while using observational data from market outcomes. To address the parameter identification challenge, two components are necessary: exogenous variation that is uncorrelated with unobserved demand components but strongly correlated with gasoline prices (Gandhi and Nevo 2021); second, a set of controls for demand shifters (Berry and Compiani 2021). The first set of components has been historically difficult to find.

Table 3.2.1 shows selected works that have estimated the price elasticity of demand by addressing simultaneity bias, most of which use information from the crude oil market or from tax changes.

[1] See the "Yellow Vests" protests (Boyer et al. 2020)

Table 3.2.1: Selected works on the estimation of the price elasticity of demand for gasoline

Authors	Method	Instrument	Estimated price elasticity	Aggregation level	Estimate
Ramsey, Rasche, and Allen 1975	I.V.	Relative prices of other distillates	Private demand	US - 1 year	-0.65 with a s.e. of 0.36
Sweeney 1984	Case study	.	Wholesale demand	US - 10 years	-0.7 to -0.4
Hughes, Knittel, and Sperling 2008	I.V.	Weather-related oil prod. disruptions	Retail demand	US - 1 year	-0.07 to -0.03
Bento et al. 2009	Random coeff. model, moment conditions	.	Retail demand	US - 1 year	-0.35
Park and Zhao 2010	Cointegration regression	.	Retail demand	US - 1 month	-0.15 to -0.05
Davis and Kilian 2011	I.V. and Cholesky decomposition	Local & state gas taxes	Retail demand	US & states - 1 month	-1.14 to -0.46
Houde 2012	Discr. choice model, I.V.	BLP instr. & panel fixed eff.	Retail purchases	Store-level in Quebec City, CA	-10 to -14
Li, Linn, and Muehlegger 2014	I.V. and price decomposition	Gas taxes & oil prices	Retail and tax elast. of dem.	US - 1 month	-0.07 and -0.32, respectively
Levin, Lewis, and Wolak 2017	Dynamic freq. of purchase model	.	Retail demand	US - daily and 20 days	-0.45 daily, -0.29 for 20 days
Coglianese et al. 2017	I.V. controlling for anticip. behavior	Gas taxes	Retail demand	US - 1 month	-0.37
Colina 2023	Random coeff. model, I.V.	BLP instr. & price control discontinuity	Retail demand	Tijuana & Mexicali, MX 1 year	-0.64 and -0.42

As we learn more about demand estimation, these works identify different methodological concerns. I categorize these concerns into three broad groups:

- Relevance of the instruments.
- Conditional independence of the instrument from consumer expectations.
- Conditional independence of the instrument from aggregate economic activity.

In the following sections, I will describe the instruments that have been used and how they relate to the concerns other authors have expressed about their validity.

3.2.1 Instruments from the crude oil market

Traditionally, economists instrument for price using information from the crude oil market (Ramsey, Rasche, and Allen 1975). Crude oil is the primary input into gasoline production (Gary, Handwerk, and Kaiser 2007c). Therefore, crude oil prices strongly correlate with gasoline prices through a cost channel. However, crude oil prices are not uncorrelated to gasoline demand. After distilling crude oil, close to 50% of its output is gasoline blending components (Energy Information Administration 2022). Thus, making crude oil and gasoline prices interconnected through consumers' income and their expectations of future economic activity.

Another set of instruments from the crude oil market is disruptions to crude oil production. Hughes, Knittel, and Sperling 2008 find that these are not strong predictors of gasoline prices. This may be for two reasons: most of the U.S. crude oil production disruptions that the authors look into are related to weather events in the U.S. Gulf Coast (USGC). The general occurrence of these events follows a seasonal pattern, and each specific weather event can be forecasted with more than two weeks of anticipation. The seasonal pattern and the ability to forecast weather events allow refiners to adjust their purchase levels to compensate for disruptions to their supply of inputs. That is, supply disruptions have a weak first-stage regression due to anticipatory behavior from refiners.

Additionally, in the U.S. context, most refining capacity is also located near the USGC, and refiners are the main consumers of unprocessed crude oil. Therefore, if there were to be an unexpected weather-related disruption to crude oil production in the USGC, there would also be a similar demand disruption from the refineries. This means that the instruments would fail the exclusion restriction.

3.2.2 Instruments from tax changes

An alternative strategy found in the literature is to use tax changes as an instrument for price changes. This strategy has five main documented challenges; the first four are regarding exogeneity, and the last one is related to relevance.

The first challenge is documented by Li, Linn, and Muehlegger 2014, who show that the salience of the tax implementation may generate endogeneity. For example, two tax changes of the same magnitude publicized differently may produce different consumer reactions through the expectations channel. The second challenge is highlighted by Coglianese et al. 2017, who show that consumers exhibit anticipatory behavior to a tax being implemented. Since tax changes are not unexpected to consumers, they will refuel before the tax is implemented as a one-off chance to avoid paying it. Then, the quantity consumed right after the tax is passed will be abnormally lower, biasing the elasticity estimates to the upside.

A third challenge of using tax changes as an instrument is that a tax may elicit adaptative behavior different from short-term price shocks. For example, Li, Linn, and Muehlegger 2014 explain that tax changes are long-term shifts to the price level and affect consumer's expectations of future prices. This, in turn, creates a stronger long-term reaction than the one elicited by transitory price changes, as consumers may buy different-sized cars or change where they live to adjust their commuting time.

A fourth challenge is that tax implementation may not be independent of economic activity. State legislatures are more likely to pass a tax increase in periods of economic expansion (Li, Linn, and Muehlegger 2014).

The last documented challenge of using taxes as instruments is related to their relevance depending on the data's level of aggregation. Davis and Kilian 2011 show that state tax changes may have a noticeable effect on prices at the state level, yet the impact at the national level may be too small to create a strong relationship with national-average prices.

3.2.3 Assumptions to address potential shortcomings of instruments

Previous research has taken steps to address the shortcomings of these instruments. For example, Li, Linn, and Muehlegger 2014 control for news coverage in anticipation of a tax change; Coglianese et al. 2017 include leads and lags of retail prices to control for anticipatory and forward-looking behavior; Levin, Lewis, and Wolak 2017 use highly disaggregated daily panel data and use city and day-of-sample fixed effects to control for supply and demand simultaneity. All of these works provide reasonable evidence that endogeneity concerns are solved yet require strong assumptions on consumer behavior.

3.3 Refinery outages as instruments for price

I propose refinery outages as a new set of instruments to causally estimate the price elasticity of demand. This set of instruments solves the three main documented issues mentioned in Section 3.2 and require less stringent assumptions on consumer behavior. Due to the institutional arrangement of gasoline production, a refinery outage reduces available installed capacity and increases costs for the producers.

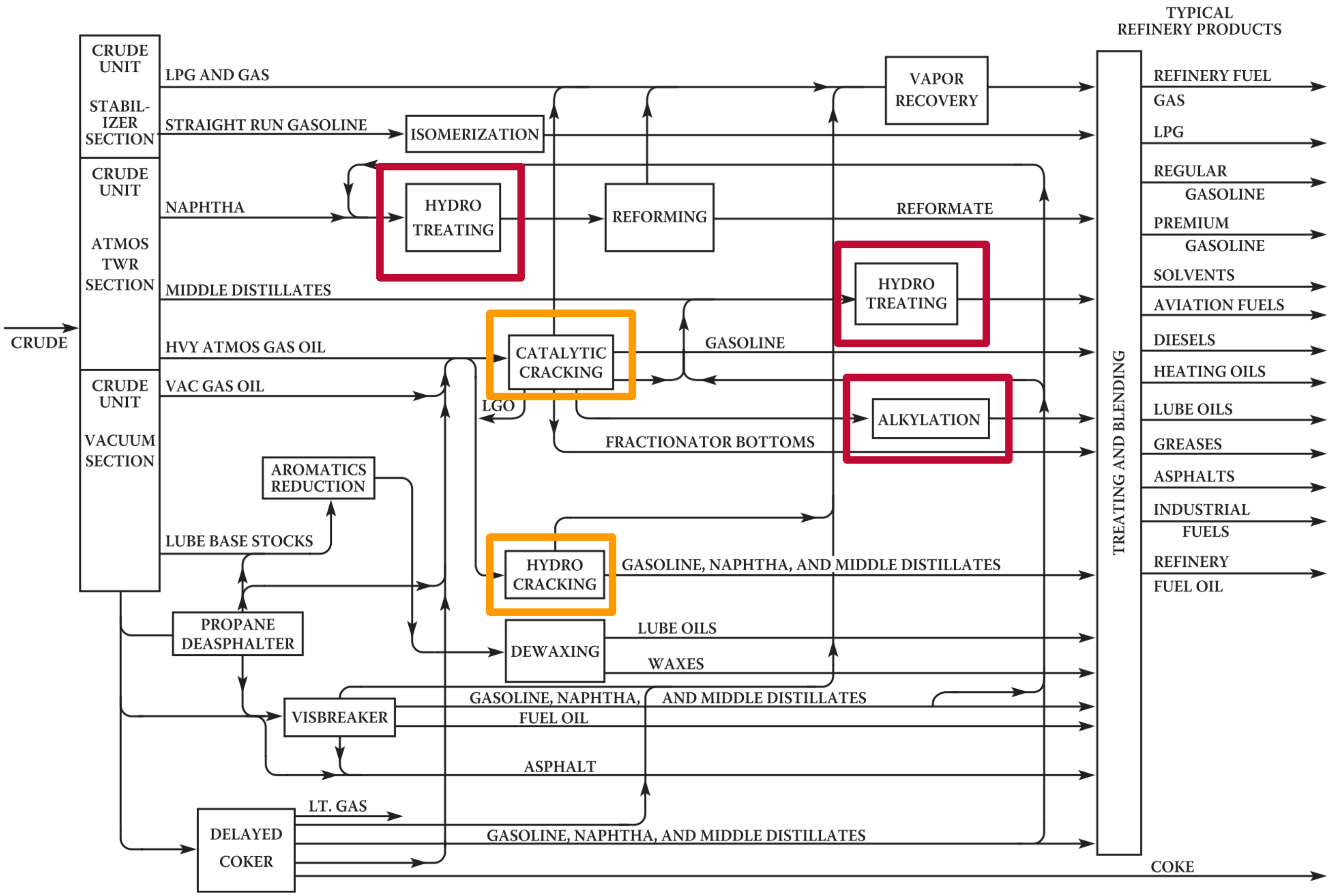
Gasoline production follows a multi-step process. Refineries produce gasoline blending components and these blending components are mixed to achieve specific performance properties (Gary, Handwerk, and Kaiser 2007c). The blend is transported to a city terminal, mostly by pipelines, and then is mixed with ethanol to produce finished gasoline. Finished gasoline is then distributed within the city to gasoline stations (Borenstein, Cameron, and Gilbert 1992).

Different markets need different performance properties from their finished gasoline. Engineers build refineries to achieve these properties and optimize their configuration by choosing, amongst other things, which refinery units to install and how to connect them together. In this process, the outputs of one refining unit are used as inputs to another refining unit.

This combination of products is meant to maximize the refiner's profits, conditional on achieving performance requirements. This configuration results in refining units connected in a complex multi-stage process (See figure 3.3.1 for further details).

Heat, pressure, catalysts, and other chemicals are used throughout the refining stages. Because of the nature of these processes, every so often, refineries need to stop operating one of the refining units for maintenance. Sometimes, a specific stage of the refining process suffers an accident or a malfunction. These incidents lead to unplanned stops in the operation of a refining unit. I refer to the loss in refining capacity in a specific refining unit as an outage.

Figure 3.3.1: Refinery flowchart from Gary, Handwerk, and Kaiser 2007d.



Several circumstances lead to outages. Some examples are:

- An unplanned power outage.
- An unplanned flaring event.[2]
- A malfunction in the refining unit caused by:
  - A leak, a crack, or loss in pressure.
  - A fire or an explosion.
- Unexpected high winds.
- Unexpected malfunction of the crude pipeline supplying the refinery.
- Replacing an old unit with a newer one.
- Replacing a part due to wear and tear.

3.3.1 Validity of the instruments

In the section 3.2, I summarized three documented concerns about instruments for the price of gasoline. I will now relate those concerns to gasoline outages.

The first concern is the relevance of the instruments. Outages in specific refining units result in increased costs to the refiner. As one of the components of the optimized blend is missing, refiners either: source the missing component from an outside supplier, which is costly (American Petroleum Institute 2013); reduce total output while maintaining the optimal blend, which increases inventory costs due to the unused components (Energy Information Administration 2007); or produce a suboptimal blend subject to achieving the performance requirements (Valentine and Josefson 2017). In any case, there is an increase in operational costs and the possibility of reduced output which will impact market prices.

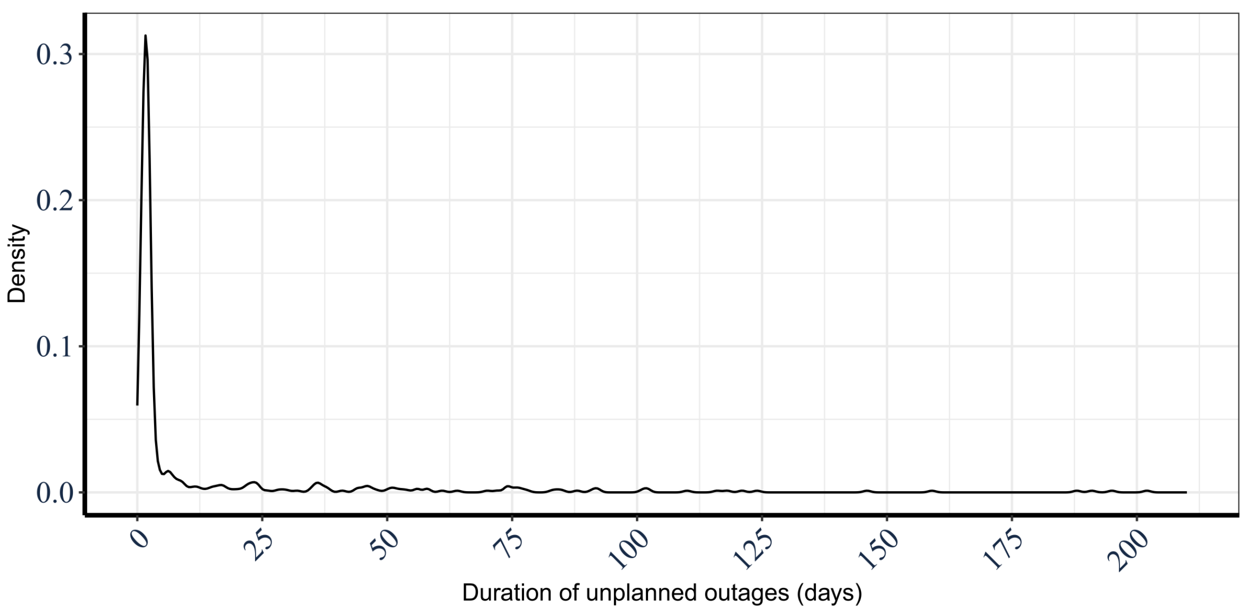
A second concern is the conditional independence of the instrument from consumer expectations. For example, if consumers expect higher prices in the future, they can buy gasoline before a price increase happens. However, due to the unexpected nature of accidents, consumers cannot engage in anticipatory buying before a specific operational problem occurs when dealing with refining accidents.

Another concern is that the salience of the coverage of an event affects consumer expectations of the magnitude of the impact. Regarding refinery outages, news agencies cannot cover an accident in anticipation

[2]A flaring event happens when excess hydrocarbons are burned rather than released straight into the atmosphere. Plants usually inform local authorities about planned flaring. But sometimes, pressure builds up to dangerous levels resulting in an unplanned flaring event. For more information see Gary, Handwerk, and Kaiser (2007b) and Precognize (2023)

of it happening. Therefore the level of coverage cannot affect expectations before the incident. However, once the unplanned outage occurs, it may be covered by the news, but it is unlikely. Most unplanned outages in the U.S. are reported to the Occupational Safety and Health Administration (OSHA). Large, unplanned outages are reported in specialized news outlets. On some rare occasions, the accident will appear in mainstream news channels. To account for possible salience effects, I will include lagged consumption variables to include the information available in the market.

Figure 3.3.2: Distribution of the duration of outages from January 2011 to March 2023



Another possibility is that consumers may expect the duration of the outage to be long-lived, and they react differently from a regular price change. Yet, the vast majority of outages are resolved in a short period of time; 83% of them are solved in less than a month. Therefore, outages are unlikely to elicit changes in long-term consumer behavior, such as buying a more fuel-efficient vehicle, moving closer to their job to reduce commuting distances, or choosing alternative modes of transportation. See Figure 3.3.2 and Table 3.3.1 for further details.

Another concern is the conditional independence of the instrument from aggregate economic activity. It is possible that accidents in a refinery are more likely to occur when the units are running at full capacity. This would violate the assumption that accidents happen randomly. To account for the possible systemic variation in accidents, I control for the percentage of operating capacity that refineries are running at.

Table 3.3.1: Cumulative distr. of the duration of outages

Duration (days)	*Prob. of outage being at least X days*
5	72.16%
10	76.90%
15	78.55%
20	80.20%
25	82.47%
30	83.29%
70	90.00%
125	95.00%

Using daily data from Jan 3 2011 to Dec 31 2020

3.4 Applying the instruments to the California context

California's gasoline market faces a set of regulatory and infrastructure constraints that make it a partially isolated market from the rest of the 47 contiguous states and the District of Columbia. This unique setting causes the proposed instrument to have a strong first-stage regression because it is relatively difficult to substitute for the loss of local production capacity.

Due to environmental regulations, Californians consume the cleanest burning gasoline in the world. However, within the U.S., only California refineries produce this blend (Pyziur 2016). Therefore, when there is an outage and refining capacity is lost, wholesalers cannot substitute local production with refined products produced elsewhere in the U.S.

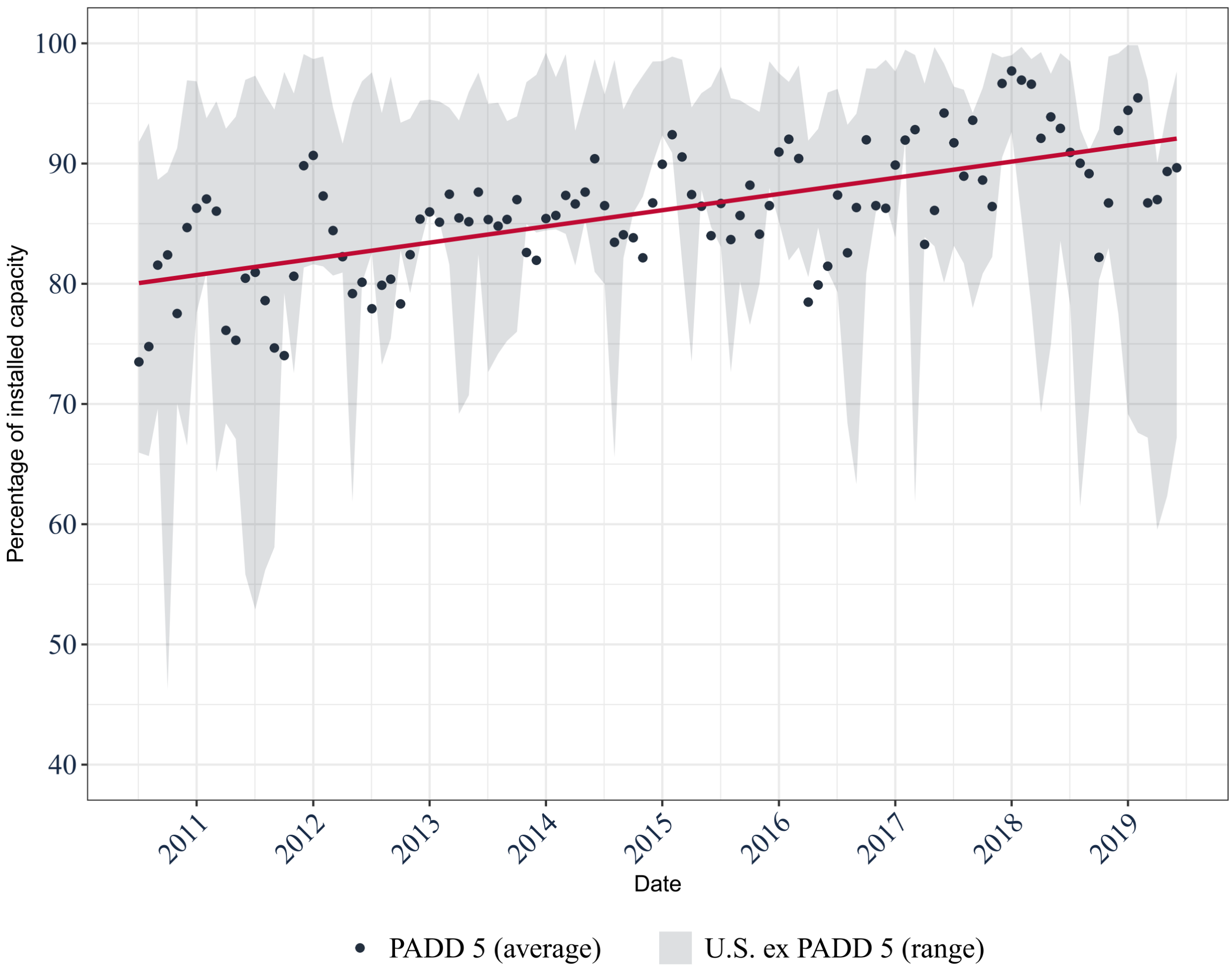
An alternative to sourcing refined products from outside the state is to substitute with products made within the state. However, the refineries in California have been running increasingly close to their installed capacity, making it harder to increase regional production in response to a local outage. Figure 3.4.2 shows the throughput of refineries in PADD 5 as a percentage of the installed available capacity.[3] PADD 5, encompasses California and other states along the West of the U.S., of which California is by far the largest.

A second alternative to substitute for the loss of local production capacity is to import refined products into California from outside of the U.S. There are other two countries that produce the refined products needed to achieve the required blend for California: Singapore and South Korea. According to the California Energy Commission 2020a, the minimum number of days needed for a vessel to reach California and be fully unloaded is 19 and 13 days, respectively. However, weather conditions across the Pacific Ocean and local logistics constraints at California's ports can extend this process. The lag between an outage and when the imported products may arrive creates a temporary contraction in supply.

One of the possible local logistics constraints when importing distillates is scheduling their transportation

[3] A Petroleum Administration for Defense Districts (PADD) is a geographic division of crude and fuels markets established during World War 2 to ration gasoline consumption. Now at days, market participants use the division to analyze regional trends (Energy Information Administration 2012).

Figure 3.4.1: Utilization of refining capacity



once the vessel is unloaded. Schremp 2015 explains that only two sets of pipelines transport products in California. The first one starts in San Francisco and finishes in Reno passing through several refineries along the way. The second set of pipelines starts in Los Angeles and forks to Las Vegas and Phoenix. The limited number of pipelines leads to a strict scheduling system in which users need to buy space and time in the refinery in advance. Then, it is likely that an importer would have to buy already reserved capacity on the pipeline to move the imported products (California Energy Commission 2020a). This would increase transportation costs which may be ultimately passed on to the retail price resulting in a strong first-stage regression.

3.4.1 Differentiating by outage type

As explained in Section 3.3, gasoline production is a multi-stage process. Refinery units are involved in different stages in this process, each with a different installed capacity. Then, an outage of 10 million gallons per month will have a very different impact depending on which stage of the process it occurs. To improve the power of the instruments, I differentiate by the source of the outage at the refinery unit level.

Not all outages are the same; simply aggregating the capacity loss would translate into noisier estimates. For example, the crude distilling unit (CDU) is usually the largest refining unit within a refinery, and all refineries have one. This unit is the first one to receive the crude oil at the refinery; it then applies heat and produces the first batch of distillates. Losing 10 million gallons per month will not have a big impact since its output would not be a limiting factor in producing California-compliant gasoline. In contrast, the alkylation unit has a smaller capacity as it is used mostly at the end of the refining process and produces "boutique" distillates that make the refining blend California-compliant. The alkylation unit is expensive to build and install. Therefore, only select refiners have one. Losing 10 million gallons per month would create a large disruption in the market.

I use a very detailed data set from the Bloomberg Terminal, where I can observe the output of each individual refinery unit within a refinery. Having this granularity in the data results in a stronger first stage and more precise estimates. For explanatory purposes, I group the relevant refinery units into middle-stage units that produce a sizeable share of the finished output and sulfur-reducing units that produce "boutique" distillates. The latter produce smaller amounts of distillates but are essential to achieve the regulatory requirement; therefore, a small outage has an outsized effect.

Middle-stage refining units

The fluid catalytic cracking unit (FCC) and hydrocracking unit (HCU) units are part of the middle stages of the refining process. The units are shown in figure 3.3.1 highlighted in orange. The main task of these units is to transform heavy and medium hydrocarbons into lighter distillates by "cracking" them.[4] These lighter distillates have higher octane levels.

- FCC unit: transforms heavy hydrocarbons into lighter products like gasoline and naphtha by applying heat and catalysts.
- HCU unit: transforms blends with high sulfur content into naphthas and gasoline by using high pressure, hydrogen, and catalysts.

The output of the FCC and HCU units contributes to roughly 40% of the volume of the finished gasoline blend (Pugliaresi and Pyziur 2015). Therefore, an outage in these units constrains overall output by volume.

[4]Cracking is the process where heavy hydrocarbon molecules are broken up into lighter molecules, usually with higher octane levels.

Sulfur-reducing refining units

As mentioned at the beginning of the section, one thing that makes California's gasoline market unique is its environmental regulations. Specifically, California Air Resources Board (CARB) mandates specifications that reduce the pollution from gasoline consumption when compared to conventional gasoline. These specifications are reached largely thanks to the alkylation and hydrotreating units.

Finished gasoline is a blend of petroleum distillates and ethanol. According to Larson 2018, most geographies in the U.S. use a blend known as Conventional Blendstock for Oxygenate Blending (CBOB), while some highly populated areas along the Northeast coast of the U.S. use a blend with more stringent environmental requirements known as Reformulated Blendstock for Oxygenate Blending (RBOB).

However, a different blend known as California Reformulated Gasoline Blendstock for Oxygenate Blending (CARBOB) is mandated in California. When compared to RBOB, this blend has even lower volatility, or tendency to vaporize, as measured by Reid Vapor Pressure (RVP); it also has lower levels of toxic pollutants like sulfur and benzene than conventional blends.

Table 3.4.1: Specifications for different types of gasoline

Gasoline parameter	*CBOB* (1)	*RBOB* (2)	*CARBOB* (3)	Units
Benzene content	.	1.3	1.22	% of volume
Reid Vapor Pressure	7.9	7	5.99	psi
Sulfur content	80	80	21	ppm

Source: California Air Resources Board 2014 and TransportPolicy.net 2017.

To achieve CARB's standards, California refiners need to include components into the blend that will accomplish two opposing objectives: reach the desired octane level and reach the desired environmental regulations. There are two refining units that are instrumental in reaching these dual objectives: the alkylation unit and the hydrotreating units.

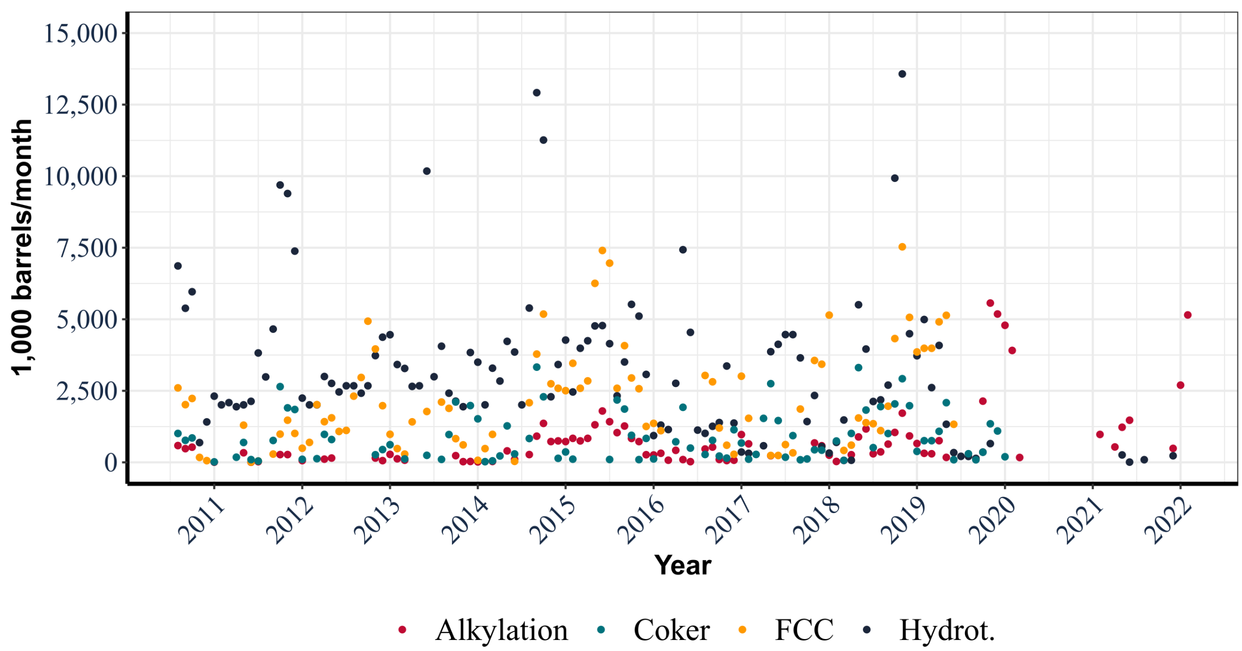
While the volume of output from these units is low compared to the FCC and HCU, these units are essential to meeting environmental regulations. Therefore, their outages strongly affect the ability to produce CARB-compliant gasoline. Figure 3.3.1 shows a flowchart of the refinery process and highlights in red where the alkylation and hydrotreating units participate in creating the gasoline blend.

Alkylation units produce alkylates, a distillate with low RVP, low sulfur, and high octane levels (Peterson 1996). There are two downsides to alkylation units, though: the first one is that they have high fixed costs; the second one is that one of the main inputs into the unit is isobutane.

Isobutane is a chemical produced during one of the refining stages and has limited availability. Isobutane is also a main input to another process called polymerization, which produces a high-octane distillate, yet this distillate is more polluting than the alkylates. Installing a polimerization unit is substantially cheaper than an alkylation unit and yields a high-octane product, making it more attractive for refiners to have (Gary, Handwerk, and Kaiser 2007a). Therefore, alkylation units tend to be used only in regions with very strict RVP requirements, such as California (Peterson 1996).

Hydrotreating units are the second set of units that help refiners achieve CARB's standards. The main objective of these units is to reduce a product's sulfur content. These units are common throughout the U.S. and not only in California, as opposed to alkylation units. However, California refineries tend to rely more on hydrotreating units than their counterparts in the contiguous U.S. (California Energy Commission 2020b). Therefore, an outage in these units noticeably affects the ability of refiners to meet CARB's standards.

Figure 3.4.2: Refining capacity lost fur outages in different refining units



3.5 Model & Data

I use a traditional log-log linear specification that relates quantities consumed to the prices observed in the market. I use equation (3.1) to estimate the parameters of interest: the contemporaneous price elasticity of demand, β_1, and the long-term price elasticity of demand, $\beta^\star \equiv {}^{\beta_1}/_{1-\rho}$.

I use additional lagged covariates to control for contemporaneous demand shifts. I control for the level of inventories, the level of imports, the refinery utilization rate, and the price of crude oil. To control for autocorrelation, I estimate different model specifications given by k lagged covariates in the following model:

$$\begin{aligned} q_t = &\beta_0 + \beta_1 p_t + \\ &\sum_{h=1}^{k} \gamma_h Inv_{t-k} + \sum_{h=1}^{k} \delta_h Imp_{t-k} + \sum_{h=1}^{k} \theta_h caputil_{t-k} + \sum_{h=1}^{k} \lambda_h wti_{t-h} + \\ &\rho q_{t-1} + \alpha m_t + \varepsilon_t \end{aligned} \tag{3.1}$$

where $[\beta_0, \beta_1, \rho, \gamma_h, \delta_h, \theta_h, \lambda_h$ for h = $\{1 \ldots K\}]$ are parameters.

The variable q_t is the logarithm of the level of millions-gallons of gasoline sold during month t. The variable p_t is the logarithm of the monthly retail price of regular gasoline; Inv_t is the logarithm of the level of blending components in inventories; Imp_t is the logarithm of imports into California of motor gas blending components; wti_t is the spot price of a barrel of West Texas Intermediate crude oil (WTI).

I report the summary statistics of the variables used in the estimating equation (3.1) in table 3.5.1. Fuel sales are taken from the California Department of Tax and Fee Administration; retail prices, inventories, imports, capacity utilization, and WTI prices are sourced from the U.S. Energy Information Administration. The outage data set is sourced from The Bloomberg terminal.

Table 3.5.1: Summary statistics

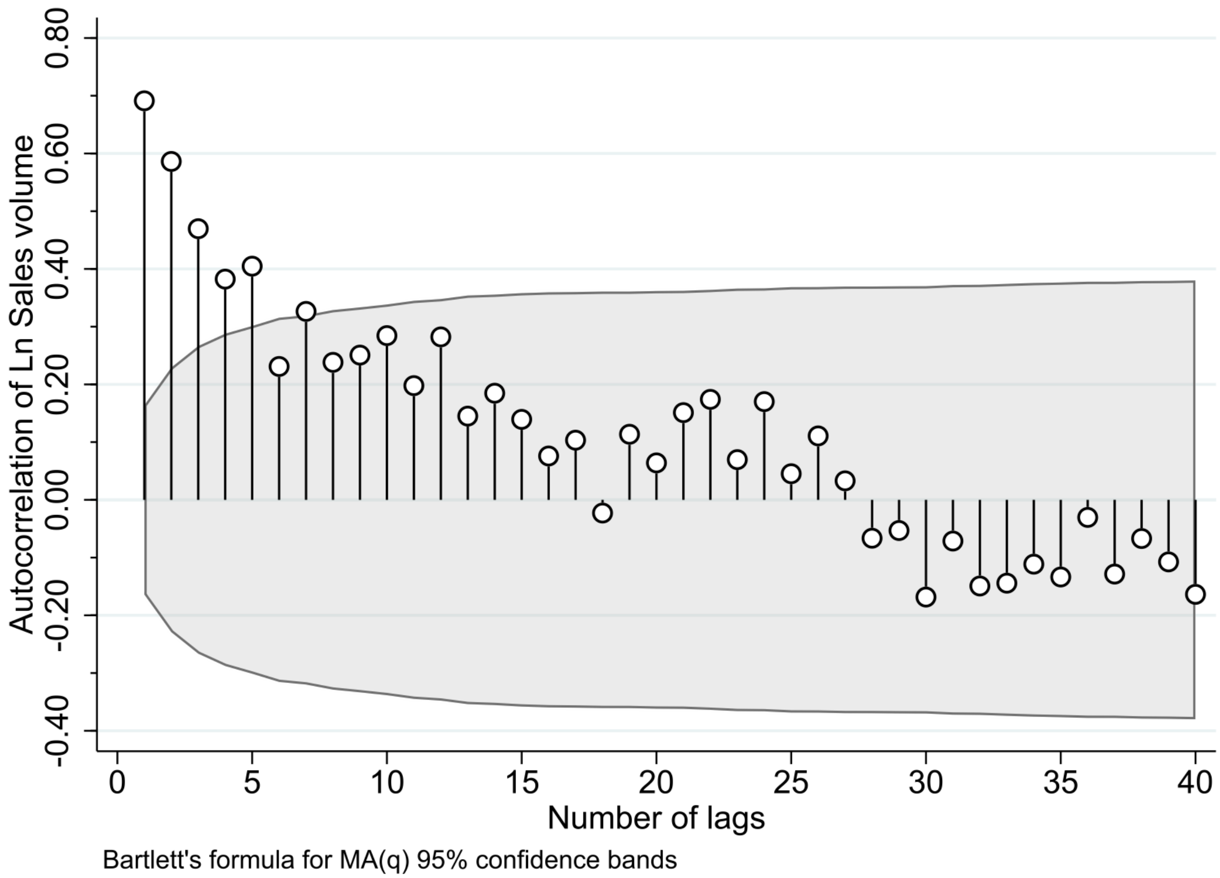
Variable	N	Mean	SD	Min	Max
Date (monthly)	147	.	.	Jan 2011	Mar 2023
Sales (MMgals/month)	143	1,218.8	97.8	713.6	1,514.2
Retail price (USD/gal)	147	3.7	0.7	2.4	6.2
Inventories (MMgals)	144	752.1	70.2	586.0	952.6
Imports (MMgals/month)	139	946.8	209.0	419.4	1,641.4
Capacity util. (%)	147	84.4	6.5	60.5	97.7
WTI (USD/barrel)	147	70.7	23.3	16.5	114.8
Outages :					
:: Alkylation unit (MMgals/month)	139	21.1	41.6	0.0	233.8
:: Coker unit (MMgals/month)	139	23.2	33.1	0.0	130.8
:: Hydrocracking unit (MMgals/month)	139	29.4	41.6	0.0	233.2
:: FCC unit (MMgals/month)	139	57.2	73.8	0.0	316.3

Notes: MM denotes millions

The model in equation (3.1) includes the variable q_{t-1} to control for autocorrelation, and m_t are monthly fixed effects to account for demand seasonality. The variable ε_t is an independent shock of unobserved time-varying factors with mean zero.

Figure 3.5.1 shows that the quantity sold, q_t, exhibits autocorrelation for up to six months. Then, to ensure that ε is truly independent across time, I will use lagged control variables up to 12 months, that is,

Figure 3.5.1: Autocorrelogram of the natural logarithm of retail gasoline sales.



$k <= 12$. I will conduct further analytical tests to ensure the white-noise hypothesis holds.

Aside from the possibility of biased estimates due to time dependence on the unobserved factors, another source of bias stems from supply and demand simultaneity. In sections 3.3 and 3.4, I discuss how refining outages satisfy the exclusion restriction and are likely to satisfy the relevance requirement. In section 3.6, I provide analytical evidence that the assumptions are satisfied.

3.6 Results

The model's parameter estimates described in equation (3.1) are presented in table 3.6.1. There are three model specifications, each with different lags in the control variables. The estimates of each model specification are presented side by side, comparing two estimation techniques.

The first estimation technique uses an ordinary least squares (OLS) estimation procedure and controls for autocorrelation and heteroskedasticity in the standard errors using the covariance matrix proposed by Newey and West 1987. I label these columns as *OLS*. However, this estimation procedure does not address the simultaneity of supply and demand. Therefore, the OLS estimates provide a lower bound to the elasticity estimates. The second estimation technique uses an instrumental variable estimation procedure to control for simultaneity. I label these columns as *I.V.*

Across all estimations, autocorrelation is accounted for correctly; the null hypothesis of white noise in unobserved shocks cannot be rejected at the 5% confidence level. I use the Arellano and Bond 1991 test for autocorrelation from 1 to 12 lags and report the results in panel C of table 3.6.1. This validates the assumption that ε is weakly sequentially exogenous.

Table 3.6.1: Estimation results

Dep. Var.: Ln Retail Sales	*Specification 1*		*Specification 2*		*Specification 3*	
	OLS (1)	*I.V.* (2)	*OLS* (3)	*I.V.* (4)	*OLS* (5)	*I.V.* (6)
A) Coefficient estimates						
Ln Retail price (β_1)	-0.109***	-0.410***	-0.114***	-0.366***	-0.098**	-0.272***
:: s.e.	(0.028)	(0.185)	(0.037)	(0.161)	(0.041)	(0.093)
Lagged Ln Retail sales (ρ)	0.615***	0.252	0.628***	-0.300	0.637***	0.346***
:: s.e.	(0.085)	(0.206)	(0.111)	(0.190)	(0.131)	(0.168)
Ln Inventories (num lags)	3	3	6	6	12	12
Ln Imports (num lags)	3	3	6	6	12	12
Ln Capacity util. (num lags)	3	3	6	6	12	12
Ln WTI (num lags)	3	3	6	6	12	12
Constant (β_0)	8.122***	15.862***	8.447***	15.565***	9.125***	53.784**
:: s.e.	(1.707)	(4.629)	(2.231)	(4.379)	(2.859)	(25.837)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	137	136	134	133	128	127
R-squared	0.713	0.408	0.708	0.276	0.848	0.243
Lags in OLS cov. matrix	3	.	6	.	12	.
B) Steady-state estimates						
Long term elasticity ($\beta_1/1-\rho$)	-0.282***	-0.550***	-0.305***	-0.523***	-0.269***	-0.417***
:: s.e.	(0.064)	(0.124)	(0.067)	(0.115)	(0.083)	(0.067)
:: 95% conf. interval	-0.40,-0.15	-0.79,-0.30	-0.43,-0.17	-0.75,-0.29	-0.43,-0.10	-0.54,-0.28
C) Test autocorr.						
AR(1): Test statistic	0.710	1.840*	0.980	1.660*	0.060	1.800*
:: p-value	0.475	0.065	0.327	0.097	0.950	0.073
AR(6): Test statistic	0.660	1.310	0.850	0.750	1.080	1.410
:: p-value	0.509	0.191	0.396	0.455	0.281	0.159
AR(12): Test statistic	-1.440	-1.360	-1.100	-1.430	-1.620	-1.230
:: p-value	0.150	0.173	0.270	0.152	0.106	0.220

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel A in table 3.6.1 shows the estimates of the model parameters. The price coefficients in all specifications are negative and statistically significant at the 1% level. The estimates from columns 1, 3, and 5 provide a lower bound of the price elasticity and are similar in magnitude to the latest estimates for the U.S.

The estimates from columns 1, 3, and 5 are noticeably smaller in magnitude when compared to their counterparts in columns 2, 4, and 6. This is consistent with the well-documented case that estimates of demand elasticity that control poorly for simultaneity tend to be biased towards zero (see Davis and Kilian 2011 and Coglianese et al. 2017 for further details). The change in magnitude in the elasticity estimates validates the assumption that instruments control for simultaneity bias.[5]

The assumption of the validity of the instruments is further validated in Panels C and D in table 3.A.2, where I show the results of the underidentification test (Kleibergen and Paap 2006) and the overidentifying restriction tests (Sargan 1958 and Hansen 1982). The underidentification test has the null hypothesis that the external instruments are weakly correlated with the endogenous variable. Panel C shows that the null hypothesis is rejected at least at the 5% level in every specification in favor of the strong-instrument hypothesis.[6]

The overidentification test has the null hypothesis that the instruments are jointly valid. In every specification, the test fails to reject the null hypothesis at the 5% level. That is, there is strong evidence in favor of the excluded instruments being uncorrelated with the unobserved factors, ε, and that they are correctly excluded from the main estimating equation 1.3.

A well-established property of I.V. estimators is the existence of finite-sample bias even if they are asymptotically consistent (Cameron and Trivedi 2005). This is particularly relevant for empirical work where the instruments are weak. Despite rejecting the weak-instrument hypothesis in all three specifications, as shown in Panel C of table 3.A.2, I show that the bias from the I.V. estimates would be relatively small. I follow the approach of Stock and Yogo 2005 and find that the estimates could have between the 20% and 30% of the bias of the OLS estimates at most. This provides further evidence that the proposed instruments are valid.

Despite different model specifications, all I.V. estimates for the long-term price elasticity of demand have small standard errors and joint statistical significance at the 2% level or lower. The lowest long-term elasticity estimate is -0.417; this estimate is statistically larger than the latest estimates in the literature from Park and Zhao 2010, Li, Linn, and Muehlegger 2014, Levin, Lewis, and Wolak 2017, and Coglianese et al. 2017. Panel B of table 3.6.1 shows the 95% confidence interval around the central estimates of the long-term elasticity of demand as a reference point.

My preferred model specification is Specification 2 with an I.V. estimation procedure as reported in column 4 in table 3.6.1. This specification yields the highest Kleibergen-Paap LM statistic at 12.81, suggesting the strongest first-stage regression. This specification yields a central estimate of -0.36 for the one-month price elasticity of demand and an estimate for the long-run elasticity of -0.52 . The difference in magnitude is consistent with economic theory that shows that consumers smooth consumption across time in response to price changes. Additionally, specification 2 satisfies the weak exogeneity assumption regarding unobserved

[5]See table 3.A.1 for further model specifications that show how model estimations that control poorly for simultaneity yield estimates that are biased towards zero.

[6]The outages of the hydrotreating unit have a significant and negative coefficient. The negative coefficient follows a negative correlation of the occurrence between alkylation and hydrotreating outages. For further information see table 3.6.3

Table 3.6.2: First-stage estimation results.

Dep. Variable: Ln Retail Prices	First stage regression		
	Specification 1	*Specification 2*	*Specification 3*
	(1)	(2)	(3)
A) Coefficient estimates			
Alkylation unit outage	0.503	0.648	0.422
:: s.e.	(0.249)	(0.439)	(0.401)
Hydrotreating unit outage	-0.442***	-0.335**	-0.267**
:: s.e.	(0.128)	(0.133)	(0.120)
FCC unit outage	0.516**	0.667***	0.816***
:: s.e.	(0.233)	(0.236)	(0.276)
Hydrocracking unit outage	1.088***	0.763*	1.347**
:: s.e.	(0.391)	(0.401)	(0.580)
Lagged Ln Retail sales	-0.910***	-0.995***	-1.491***
:: s.e.	(0.216)	(0.251)	(0.26168)
Ln Inventories	Lags: 3	Lags: 6	Lags: 12
Ln Imports	Lags: 3	Lags: 6	Lags: 12
Ln Capacity util.	Lags: 3	Lags: 6	Lags: 12
Ln WTI	Lags: 3	Lags: 6	Lags: 12
Constant	19.906***	21.943***	36.971***
:: s.e.	(5.276)	(5.868)	(8.056)
Month fixed effects	Yes	Yes	Yes
B) Model stats.			
Observations	136	133	127
R-squared	0.811	0.843	0.8954
F stat.	3.53	3.10	3.14
:: p-value	0.009	0.019	0.020
C) Test underidentif.			
Kleibergen-Paap LM stat. $\chi^2(4)$	10.83	12.81	11.38
:: p-value	0.028	0.012	0.022
D) Test overid. restr.			
Sargan-Hansen stat. $\chi^2(3)$	2.397	3.867	5.81
:: p-value	0.494	0.276	0.121
E) Weak ident. test			
F stat. (Cragg-Donald)	5.86	5.56	5.21
:: Stock-Yogo (30%/20% relat. bias)	5.34/6.71	5.34/6.71	5.34/6.71

Standard errors in parentheses.

First-stage test statistics are robust to heteroskedasticity and autocorrelation, Bartlett kernel = 4.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Outage units are in billion barrels per month to improve legibility.

shocks and the relevance requirement for the instruments.

The estimates in column 4 are not statistically different from those reported by Davis and Kilian 2011 and Colina 2023. However, using refinery outages as instruments requires considerably less stringent assumptions about the structural modeling of consumer behavior. Furthermore, the long-run estimates using outages are similar in magnitude despite having different controls to estimate them. This suggests that the estimates are consistent and robust to model specifications.

Table 3.6.3: Correlation of capacity lost due to outages in different refining units

Correlations of outages in refining units

	Alkylation	Hydrotreating	FCC	Hydrocracking
Alkylation	1.000			
Hydrotreating	-0.035	1.000		
FCC	0.136	0.464	1.000	
Hydrocracking	0.016	0.526	0.216	1.000

3.7 Conclusion

In this paper, I propose refinery outages as a new set of instruments to estimate the price elasticity of demand for gasoline at retail. This set of instruments solves the three main documented issues with previous instruments: relevance, conditional independence from consumer expectations, and conditional independence from aggregate demand. I find that the one-month price elasticity is -0.36 and that the long-term elasticity is -0.52 . This is consistent with economic theory that shows that consumers smooth consumption over time.

The long-term elasticity estimate is statistically larger than the latest state-of-the-art estimates for the U.S. (Levin, Lewis, and Wolak 2017 and Coglianese et al. 2017); the central estimate is 40% to 80% larger than estimates in previous work. My estimates are not statistically different from the ones reported by Davis and Kilian 2011 and Colina 2023, yet require less stringent assumptions about the structural modeling of consumer behavior.

I apply this new set of instruments to the California context and differentiate by the source of the outage at the refinery unit level. I focus on HCU and FCC units since they produce naphtha, a major blending component by volume of finished gasoline. I also use outages in the alkylation and hydrotreating units. While these units contribute less in volumetric terms to the finished product, the chemical properties of their output are essential to make CARB-compliant gasoline having an outsized effect.

Due to the granularity of the outage data set and the conditions in the California gasoline market, the proposed instruments have a strong first stage. This is confirmed by performing the Kleibergen-Paap LM test. Similarly, due to the haphazard nature of the outages, these are conditionally independent from unobserved demand components. This is further confirmed by the Sargan-Hansen test.

Gasoline consumption touches several aspects of our everyday lives, and knowing the price sensitivity of consumers is essential to the design of public policies and to informing business decisions. My estimates satisfy all the latest methodological concerns and show that consumer price sensitivity is substantially higher than previously thought. Based on this new evidence, policymakers, investors, and researchers should re-evaluate their previous assumptions about consumer behavior. For example, Holland, Hughes, and Knittel 2009 estimate the welfare costs of implementing the Low Carbon Fuel Standard (LCFS) and simulate different scenarios based on different supply and demand price elasticities values. My estimates exceed the range of values for which they simulate welfare outcomes, but based on their argumentation, the conclusion follows that welfare costs of adjusting to the new standards would be lower since consumers are more responsive to the implied subsidies of the LCFS. Similarly, knowing that consumers are more price-sensitive than previously thought could open the door to carbon tax policies that are more palatable to elected officials; this could avoid social unrest scenarios, as explained by Parry, Black, and Zhunussova 2022.

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Appendix

3.A Alternative model specifications

I present the results of an additional model specification that controls poorly for simultaneity to show further how estimations that are affected by supply and demand simultaneity bias produce estimates that are biased towards zero. In this specification, I do not use lags on the controls but use their contemporaneous values instead. These contemporaneous controls are market outcome variables that are simultaneously determined by current demand and supply and by unobserved expectations of future economic activity. 3.6.1.

By including contemporaneous variables as controls, I will have some endogeneity problems, and my estimates will be biased. The estimation results from table 3.A.1 show that the price elasticity is still negative and significant; furthermore, the magnitude of the elasticity estimate is smaller than the I.V. estimates but larger than the OLS estimates reported in table 3.6.1. The results from table 3.A.1 provide further evidence that suggests Specification 2 addresses simultaneity bias correctly.

For completeness, I report the first-stage estimates of Specification 4. While the instruments pass the underidentification test, the weak identification test, and the overidentification test, this specification has a lower Kleibergen-Paap LM statistic than Specification 2 in table 3.6.1.

Table 3.A.1: Estimation results with endogeneity in contemporaneous controls

Dep. Var.: Ln Retail Sales	*Specification 4*
	I.V.
	(1)
A) Coefficient estimates	
Ln Retail price (β_1)	-0.264***
:: s.e.	(0.096)
Lagged Ln Retail sales (ρ)	0.343***
:: s.e.	(0.145)
Ln Inventories (contemp.)	-0.140*
Ln Imports (contemp.)	0.072**
Ln Capacity util. (contemp.)	0.005***
Ln WTI (contemp.)	0.114**
Constant (β_0)	13.75***
:: s.e.	(3.143)
Month fixed effects	Yes
Observations	137
R-squared	0.713
Lags in OLS cov. matrix	.
B) Steady-state estimates	
Long term elasticity ($^{\beta_1}/_{1-\rho}$)	-0.402***
:: s.e.	(0.090)
:: 95% conf. interval	-0.58,-0.22
C) Test autocorr.	
AR(1): Test statistic	1.50
:: p-value	0.133
AR(6): Test statistic	0.75
:: p-value	0.453
AR(12): Test statistic	-1.66
:: p-value	0.096

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.2: First-stage estimation results with contemporaneous controls.

Dep. Variable: Ln Retail Prices	First stage regression *Specification 4* (1)
A) Coefficient estimates	
Alkylation unit outage	0.954***
:: s.e.	(0.361)
Hydrotreating unit outage	-0.548***
:: s.e.	(0.153)
FCC unit outage	0.490**
:: s.e.	(0.220)
Hydrocracking unit outage	1.123**
:: s.e.	(0.569)
Lagged Ln Retail sales	-0.224
:: s.e.	(0.299)
Ln Inventories	-0.097
Ln Imports	0.097
Ln Capacity util.	0.002
Ln WTI	0.456***
Constant	4.429
:: s.e.	(6.271)
Month fixed effects	Yes
B) Model stats.	
Observations	138
R-squared	0.811
F stat.	12.00
:: p-value	0.000
C) Test underidentif.	
Kleibergen-Paap LM stat. $\chi^2(4)$	11.71
:: p-value	0.019
D) Test overid. restr.	
Sargan-Hansen stat. $\chi^2(3)$	3.995
:: p-value	0.262
E) Weak ident. test	
F stat. (Cragg-Donald)	9.98
:: Stock-Yogo (20%/10% relat. bias)	6.71/10.27

Standard errors in parentheses.

First-stage test statistics are robust to heteroskedasticity and autocorrelation, Bartlett kernel = 4.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Outage units are in billion barrels per month to improve legibility.