

Horizontal Mergers Post-Deregulation: The Case of the Mexico City Retail Gasoline Market

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Abstract

When prices rise after a merger, economists often attribute the increase to market power. I show a setting where this conclusion would be misleading. After Mexico deregulated retail gasoline prices in 2017, about 10 percent of gas stations in Mexico City changed ownership, and these ownership changes often coincided with brand switches, changes in upstream suppliers, and renovations. Using a difference-in-differences design, I find that merging stations raised their prices and markups. I then estimate a spatial model of gas station supply and demand and use it to decompose the increases into higher concentration, lower marginal costs, and higher station quality. Higher concentration explains less than 5 percent of the increases. Stations that switched upstream suppliers after a merger lowered their wholesale costs, which accounts for part of the higher markups, and the remaining increases are consistent with improvements in unobserved station quality. These findings highlight that post-merger price increases need not reflect market power.

Keywords: Market power, Price Deregulation, Mergers, Retail Gasoline Market

JEL Codes: G34, L13, L51, L81, Q41, Q48, R41

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1 Introduction

Economists often use a difference-in-differences analysis to study changes in prices and markups after mergers or acquisitions and attribute any estimated changes to an increase in market power. However, ownership changes may be accompanied by changes to products’ characteristics or marginal costs. For instance, in retail gasoline markets, stations that change ownership may also change their upstream supplier, renovate their facilities, or change their brand. In this paper, I study a wave of mergers that followed the deregulation of retail gasoline prices in Mexico City. I find that merging stations raised their prices and markups, but that increased concentration accounts for only a small fraction of these increases. Instead, stations that switched upstream suppliers after a merger lowered their wholesale costs, accounting for part of the higher markups. The remaining price increases are consistent with improvements in unobserved station quality. These findings highlight that post-merger price increases need not reflect market power.

Before 2017, the Mexican federal government set a single national retail gasoline price, and the state-owned company Pemex was the sole upstream supplier. Stations were privately owned and operated as Pemex franchises, and received a fixed markup per liter sold. With a fixed margin and a uniform brand, station owners had little incentive to invest in amenities or service quality, since a better station could neither charge a higher price nor distinguish itself from competitors (Davis et al., 2019). On November 30, 2017, retail gasoline prices were deregulated in the Mexico City Metropolitan Area, allowing stations to set prices freely for the first time. Stations could now choose among upstream suppliers, adopt a new retail brand, and compete on price and quality of service. Deregulation also created new incentives for consolidation, both to reduce price competition between nearby stations and to move stations to owners able to negotiate better supplier arrangements, rebrand, or invest in service quality. In the five years following price liberalization, approximately 10 percent of stations in the metropolitan area changed ownership, and these ownership changes often coincided with brand switches, changes in upstream suppliers, and renovations.

I combine a station-level panel of daily posted retail prices with proprietary information on every transaction between a gas station and its upstream supplier, which allows me to

observe wholesale prices and quantities. I also observe the identity of the permit holder for every station and all permit transfers since January 1, 2017, which I use to construct a station-level ownership panel for 2017–2022. Using a matched difference-in-differences design, I find that, over the six months after the ownership change takes effect, acquired stations charge, on average, 0.17 MXN per liter more than their matched controls and have markups 1.0 percentage points higher. Stations that switch wholesale supplier at the time of the ownership change pay 0.40 MXN per liter less than their matched controls.

To understand what drives the observed changes in prices and markups, I follow Houde (2012) and estimate a structural model of spatial competition in which stations are differentiated by location along consumers’ commuting routes. In the demand model, the distance between a consumer and a station is the detour the consumer makes from her commuting route to reach the station. On the supply side, I assume Bertrand-Nash price competition and recover each station’s marginal cost from the firms’ first-order conditions. I use the model to decompose these increases in three steps. First, holding costs and station quality fixed, I return each station to its pre-merger owner and find that increased concentration explains less than 5 percent of the changes in prices and markups. Second, I also return stations that switched upstream suppliers to their pre-merger suppliers, and find that lower wholesale costs explain only a small fraction of the markup increase, since roughly 90 percent of the decrease in marginal costs is passed on to consumers. Finally, I show that the remaining price and markup increases can be rationalized by improvements in unobserved station quality, equivalent to a price reduction of about 1.27 MXN per liter. More broadly, this work illustrates the importance of accounting for efficiency and quality gains when studying changes in prices and markups following ownership changes.

Related Literature: This paper is related to several strands of literature. First, this work is closely related to the literature on spatial competition in retail markets (Pinkse et al., 2002; Davis, 2006; Ellickson et al., 2020), and, more specifically, to the literature on mergers in the retail gasoline market. The demand model in this paper follows Houde (2012), who specifies commuting paths as the locations of consumers. Previous studies have found that mergers of large upstream suppliers or branded chains usually lead to an increase in prices and markups (Hastings, 2004; Houde, 2012; Pennerstorfer and Weiss, 2013; Erdős et al., 2022).

While these works have focused on mergers between major chains or upstream suppliers, this work studies the effect of horizontal mergers and acquisitions between retail stations. I also use the model to quantify how much of the post-merger price increase comes from changes in concentration, marginal costs, and station quality.

Second, this paper is related to the literature on price deregulation and new markets. Doraszelski et al. (2018) model firms' learning in the new market for frequency response within the UK electricity system and study how firms converge to an equilibrium. Similarly, Huang et al. (2022) analyze the evolution of firms' pricing decisions following the privatization of the retail liquor market in Washington state and find that immediately after deregulation, firms' posted prices significantly differ from profit maximization, and that retailers with previous experience in the category are initially better-informed. MacKay and Mercadal (2023) study changes in prices and markups following deregulation in the US electricity sector and find that although deregulation led to lower marginal costs, an increase in markups from energy generating firms led to an overall rise in utility prices. Relative to these papers, this work focuses on changes in the ownership structure of a market following price deregulation. Moreover, relative to the markets studied by previous authors, which are characterized by having a small number of competing firms with significant market shares (e.g., electricity generating companies), I study how ownership changes affect prices and markups in an industry with a large number of firms, most of which are small.

Third, this paper is closely related to the existing literature on the Mexican retail gasoline market. Davis et al. (2019) document differentiation in amenities in stations in Mexico City before deregulation and discuss the likely economic effects of the reform. Contreras Astizarán et al. (2020) find that Mexican municipalities with a higher density of stations have lower markups and prices. Davis et al. (2022) study the effect of the entry of gas stations on prices in a small neighborhood around them and find that the entry of a competitor significantly reduces prices and markups, with near zero effects when the incumbent and the entrant have the same owner. Colina (2023) estimates the impact of price deregulation on consumer welfare in two northern cities. Relative to these papers, I study how the ownership changes that followed deregulation affected prices and markups.

This work is structured as follows. Section 2 presents a brief description of the insti-

tutional setting of the relevant market. Section 3 provides a description of the data that I use for this project. Section 4 provides the results of the estimation of observed price and markup changes after horizontal mergers in the Mexico City Metro Area. Section 5 presents the structural model. Section 6 provides a description of the estimation and identification strategy. Section 7 shows the results from the estimation of the structural model. Section 8 presents and discusses the results from the counterfactuals. Finally, Section 9 provides concluding remarks.

2 Industry Setting

Before 2017, the Mexican federal government set a single national retail gasoline price, and the state-owned company Pemex was the sole upstream supplier. All gas stations in the Mexico City Metropolitan Area sold an identical product under the Pemex brand at an identical price. Stations were privately owned and operated, but wholesale prices were also set uniformly across stations regardless of distance to the nearest distribution terminal, and franchisees received a fixed markup per liter sold, typically between 5 and 6 percent of the retail price (Davis et al., 2019). Stations could not differentiate on price, brand, supplier, or product; the only meaningful source of variation across stations was their location, which determined the volume of liters sold and, given the fixed per-liter markup, the station's profitability. With a fixed margin and a uniform brand, station owners had little incentive to invest in amenities or service quality, since a better station could neither charge a higher price nor distinguish itself from competitors. A survey of all Mexico City stations conducted by Davis et al. (2019) on the eve of deregulation confirms this: two-thirds had no store attached, most had trash or oil on the ground, and fewer than half of bathrooms had toilet paper or soap.

In April 2016, the federal government ended Pemex's monopoly over gasoline supply, allowing private firms to import, transport, and distribute gasoline in Mexico. On November 30, 2017, retail gasoline prices were deregulated in the Mexico City Metropolitan Area, allowing stations to set prices freely for the first time.¹ Stations could now choose among

¹The implementation of price deregulation was staggered across the country, with northern states liberalizing first beginning in March 2017. Mexico City was part of the final round on November 30, 2017.

upstream suppliers, adopt a new retail brand, and compete on price and quality of service. A station’s profitability no longer depended solely on its location and volume—it depended on its owner’s choice of supplier, brand, and pricing strategy.

Deregulation also created new incentives for consolidation. When stations compete on price, a multi-station firm accounts for the fact that raising the price at one of its stations diverts some customers to its other nearby stations rather than losing them to a competitor, leading to higher equilibrium prices. This incentive to consolidate did not exist when the government set all prices. Additionally, deregulation allowed greater differentiation across stations in brand, service quality, and amenities. Before deregulation, every station sold gasoline under the Pemex brand, so station owners could not build brand recognition. Similarly, before deregulation, all stations bought gasoline from Pemex at roughly the same wholesale price. After deregulation, stations could negotiate with competing upstream suppliers, and some firms could secure better deals than others. If small independent owners from the pre-deregulation era lacked the experience or skill to negotiate better wholesale prices, rebrand, or invest in their station’s quality, firms with these capabilities could earn higher profits from the same stations than their current owners, and therefore had an incentive to acquire them. In the five years following price liberalization, almost 10 percent of stations in the Mexico City Metropolitan Area changed ownership. The majority of these ownership changes involved small, independent stations being acquired by larger firms. I document the pattern of these ownership changes and their effects on prices in Section 4.

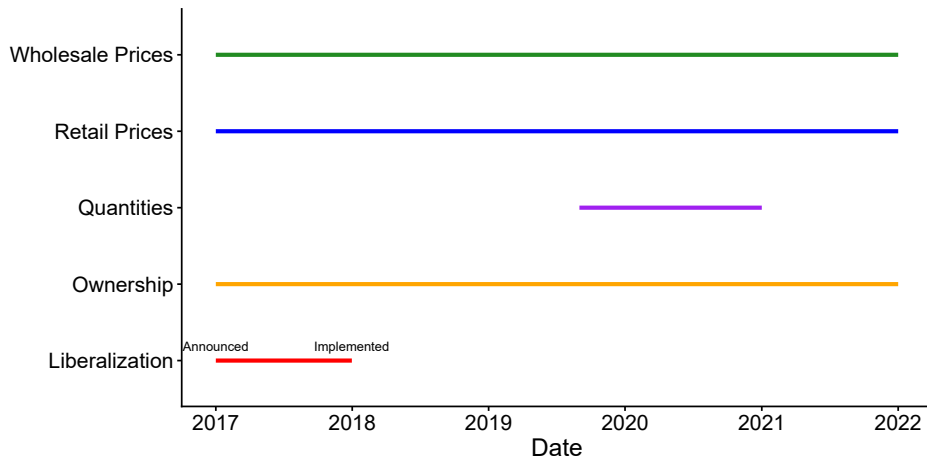
3 Data

I construct station-level panels from administrative records of the Mexican Federal Energy Regulatory Commission (CRE by its acronym in Spanish), which regulates and oversees all downstream fuel activities in Mexico.² The CRE data include station geographic coordinates, a daily panel of posted retail prices, transaction-level wholesale records between stations and their upstream suppliers, and operating permits that identify each station’s owner. I complement the CRE data with a household commuting survey and a routing engine for

²The CRE was dissolved in March 2025 as part of a broader energy reform. Its regulatory functions were assumed by the newly created Comisión Nacional de Energía (CNE).

computing travel times. I focus the analysis on the Mexico City Metropolitan Area, which contains approximately 1,000 gas stations. Data availability varies across sources: while I observe retail and wholesale prices and ownership transfers for the full 2017–2022 period, wholesale transactions and quantities are only available for a twelve-month window. Figure 1 shows the timeline of events and data availability.

FIGURE 1. Timeline of events and data availability for the Mexico City retail gasoline market.



Retail prices. I obtain the daily posted price of regular gasoline at every gas station in Mexico from January 1, 2017, to May 31, 2022, from the CRE. The CRE requires all gas stations to report their posted prices daily. I focus on regular gasoline, which accounts for approximately 78% of total retail fuel volume. The retail price panel for stations in the Mexico City Metropolitan Area contains approximately 1.5 million station-day observations.

Wholesale prices. Gas stations are also required to report to the CRE the wholesale price they pay for gasoline. I use these reports to construct a monthly panel of the average wholesale price paid by each station from January 2017 to March 2022, which I use to measure markups in Section 4.

Wholesale transactions and quantities. I obtain proprietary transaction-level records from the CRE covering all wholesale gasoline transactions in Mexico from December 1, 2019, to November 30, 2020. The CRE requires both gas stations and their upstream suppliers to report all transactions between them, including the number of liters sold and the price per liter. This dataset contains 1,624,260 transactions. For each transaction, I observe

the identity of the buyer (gas station) and seller (upstream supplier), the number of liters purchased, and the wholesale price per liter. I use total liters purchased as a proxy for station-level sales. Because I only observe quantities for this twelve-month window, I estimate the structural model using observations from this period.

Ownership structure. Under Article 48 of the Ley de Hidrocarburos, all gas stations in Mexico must hold a CRE-issued operating permit. I obtain proprietary records from the CRE containing the identity of the permit holder for every station as of December 2019, as well as all permit transfers since January 1, 2017—the date on which the Mexican federal government announced the deregulation calendar. This panel contains 94 transfers of permits for stations in the Mexico City Metropolitan Area. I combine the December 2019 ownership snapshot with the transfer records to construct a station-level ownership panel for 2017–2022.

Station characteristics. For each station, I observe three additional characteristics: the upstream supplier, the retail brand, and the number of pump modules. I identify each station’s upstream supplier from the wholesale transaction records described above. The upstream supplier is an important station characteristic for two reasons. First, all stations with the same supplier sell the same brand of gasoline. Second, upstream suppliers are correlated with other non-gasoline amenities. For instance, all gas stations supplied by Oxxo Gas have an Oxxo convenience store. I obtain the retail brand and the number of pump modules from each station’s CRE operating permit. While Pemex remains the dominant brand, international brands such as Shell, BP, Chevron, and Repsol entered following the reform.

Consumer commuting patterns and travel times. I simulate the distribution of commuting patterns from the Survey of Origin and Destinations of the Mexico City Metropolitan Area (INEGI, 2017), a representative survey of 66,625 households. The survey divides the metropolitan area into 194 traffic analysis zones (TAZs) and records the origin, destination, and mode of transportation for every trip made by household members. I use the survey to construct an origin-destination matrix of the number of commuters traveling between each pair of TAZs. For the spatial distribution of commuters within each TAZ, I use population density maps from CIESIN (2016). I compute driving times and distances between stations and TAZ centroids using the Open Source Routing Machine (OSRM; Luxen

and Vetter, 2011), an open-source routing engine that computes the fastest car route between two points using the OpenStreetMap road network.

4 Descriptive Evidence

I observe 94 ownership changes among gas stations in the Mexico City Metropolitan Area between 2017 and 2022. The pattern is one of consolidation: the majority of sellers are independent operators who own a single station (69%), and most sellers fully exit the market by selling all of their stations (90%). On the acquiring side, a small number of firms account for a disproportionate share of acquisitions—the five largest acquirers account for half of all ownership changes. Appendix Table 4 reports the full decomposition.

Empirical design. I estimate the effect of ownership changes on station-level prices and markups using a difference-in-differences design with staggered treatment timing, following Callaway and Sant’Anna (2021). I define treatment as the month in which a station applies for a permit transfer. I match each treated station to ten control stations using Mahalanobis distance on three pre-treatment lags of retail price, wholesale price, and station size (measured by the number of pump modules). Control stations are drawn from stations not involved in any ownership change during the observation window.³

Let j denote a gas station, t a month, and G_j the month in which station j applies for a change in ownership ($G_j = \infty$ for stations that never change ownership). For each treated station j with $G_j = g$, I compute the difference-in-differences estimator at event time e as

$$\text{DiD}_{j,e} \equiv (Y_{j,g+e} - Y_{j,g-1}) - \frac{1}{|C_j|} \sum_{j' \in C_j} (Y_{j',g+e} - Y_{j',g-1}),$$

where $Y_{j,t}$ is the outcome of station j in month t and C_j denotes the set of matched control stations for j . I then average across all treated stations and cohorts to obtain the event-study

³I also exclude from the control group stations owned by firms that acquire other stations, since acquiring firms may adjust pricing across all of their stations following a deal.

coefficient at event time e :

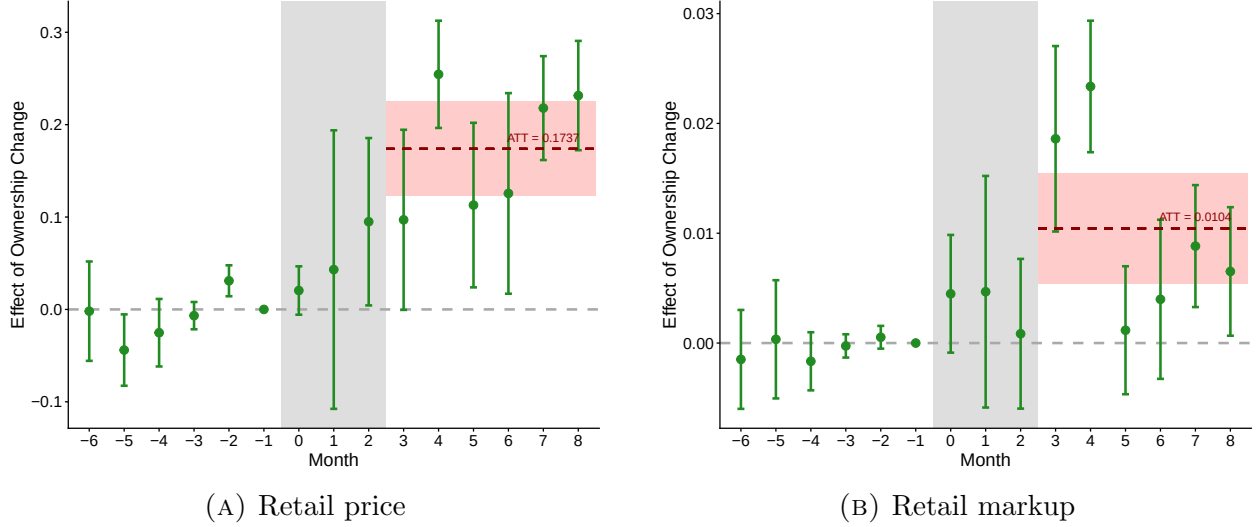
$$\text{DiD}_e \equiv \sum_g \omega_g \frac{1}{|\mathcal{G}_g|} \sum_{j \in \mathcal{G}_g} \text{DiD}_{j,e}, \quad \omega_g \equiv \frac{|\mathcal{G}_g|}{\sum_{g'} |\mathcal{G}_{g'}|},$$

where $\mathcal{G}_g$ is the set of stations that change ownership in month g . I report event-study coefficients for six months before and eight months after the ownership change, along with the average treatment effect on the treated (ATT) computed over months three through eight.

Retail prices and markups. Figure 2 presents the event-study estimates with retail price (panel a) and the retail markup (panel b) as outcomes. The retail markup is defined as (retail price – wholesale price) / retail price. In both panels, the pre-treatment coefficients are small in magnitude; the average pre-treatment effects are -0.01 MXN per liter ($\text{SE} = 0.01$) for prices and -0.07 percentage points ($\text{SE} = 0.10$) for markups, supporting the parallel trends assumption. Under Article 53 of the Hydrocarbons Law, the Energy Regulatory Commission has 90 calendar days to resolve a permit transfer application, so the ownership change does not take effect until approximately three months after the application date. Consistent with this timeline, the estimated effects are small and insignificant during the regulatory review period (months zero through two, shaded) and become significant thereafter. Over months three through eight, acquired stations charge 0.17 MXN per liter more than their matched controls on average ($\text{SE} = 0.03$) and have markups 1.0 percentage points higher ($\text{SE} = 0.3$), though the post-treatment markup estimates are noisy: the effect is largest in months three and four and attenuates before recovering. Appendix Table 5 reports the event-study coefficients.

Wholesale prices. Figure 3 presents the results on how wholesale prices paid by stations to their upstream suppliers change following ownership changes. Panel (a) pools all acquired stations: the pre-treatment coefficients are small in magnitude (average pre-treatment effect -0.00 MXN per liter, $\text{SE} = 0.01$), and the post-treatment ATT is -0.01 MXN per liter ($\text{SE} = 0.03$), statistically indistinguishable from zero. However, this null average masks substantial heterogeneity by whether the station switches wholesale supplier. Panel (b) restricts the sample to stations that switch wholesale supplier at the time of the ownership change. The

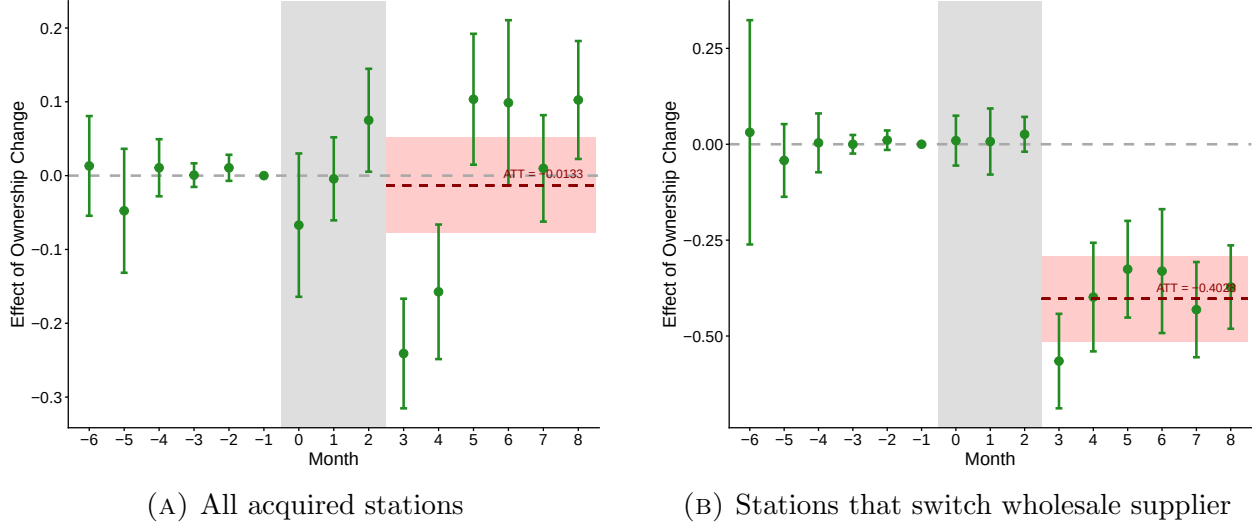
FIGURE 2. Effect of ownership change on retail price and markup. Event-study coefficients from the matched difference-in-differences design described in Section 4. Bars show 95% confidence intervals. The shaded region marks the regulatory review period. The ATT is averaged over months three through eight.



pre-treatment average is again close to zero (0.00 MXN per liter, $SE = 0.03$). Over months three through eight, these stations pay 0.40 MXN per liter less than their matched controls ($SE = 0.06$).

The wholesale price results suggest that lower input costs may explain part of the markup increase for stations that switch suppliers. However, these estimates do not tell us how changes in market power, marginal costs, and product characteristics contribute to the observed changes in prices and markups. To disentangle these channels, I follow Houde (2012) and estimate a structural model of demand and supply in Sections 5–6 and use counterfactual simulations to separately quantify the contribution of each channel in Section 8.

FIGURE 3. Effect of ownership change on wholesale price. See Figure 2 for details on the estimation design. The shaded region marks the regulatory review period. The ATT is averaged over months three through eight.



5 Model

5.1 Demand Model

Following Houde (2012), I model demand for gasoline as a discrete choice problem over $J + 1$ options (where J denotes the total number of stations and option 0 denotes the outside option of using a mode of transportation different from a car). Let u_{ijt} denote the indirect utility obtained by consumer i from buying gasoline at station j during time period t :

$$u_{ijt} = \alpha p_{jt} + \lambda D(r(s_i, d_i), l_j) + X'_{jt} \beta + \psi_t + \xi_{jt} + \varepsilon_{ijt}, \quad (1)$$

where s_i denotes consumer i 's origin point and d_i denotes i 's destination point. Let $r(s_i, d_i)$ denote the route taken by consumer i to drive from s_i to d_i . Following Houde (2012), I assume that $r(s_i, d_i)$ will be the fastest route to travel between these two points. Let l_j denote the location of station j . I follow Houde (2012) in defining the distance between consumer i and station j ($D(r(s_i, d_i), l_j)$) as follows:

$$D(r(s_i, d_i), l_j) = t(s_i, l_j) + t(l_j, d_i) - t(s_i, d_i),$$

where $t(a, b)$ denotes the time it takes to travel from point a to point b (in minutes). See Appendix B.1 for more information on how I simulate the distribution of commuting patterns in the empirical application of this paper. p_{jt} is the average price posted by station j at month t . ψ_t denotes a time-fixed effect capturing period-specific shocks common to all gas stations (such as seasonal variation). X_{jt} is a vector of dummy variables for the identity of the upstream supplier of station j , which captures the brand of gasoline the station sells and amenities correlated with its supplier (see Section 3). Finally, ξ_{jt} denotes station j 's unobserved non-gasoline quality that is not captured by X_{jt} .

As usual, we normalize the utility of the outside option to be mean zero across consumers:

$$u_{i0t} = \varepsilon_{i0t}.$$

We assume that ε_{ijt} is distributed according to a Type 1 extreme value distribution. We can express j 's common utility component for all consumers as $\delta_{jt} = \alpha p_{jt} + \psi_t + X'_{jt}\beta + \xi_{jt}$. The consumer-specific utility component of station j for consumer i is given by the distance between station j and i 's commuting path and the consumer-specific utility shock: $\mu_{ijt} + \varepsilon_{ijt} = \lambda D(r(s_i, d_i), l_j) + \varepsilon_{ijt}$.

Given the distributional assumptions we made over ε_{ijt} , the probability that consumer i buys from station j is given by:

$$\mathbb{P}_{ijt}(r(s_i, d_i) | \boldsymbol{\delta}_t, \mathbf{p}_t) = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_k \exp(\delta_{kt} + \mu_{ikt})},$$

where $\boldsymbol{\delta}_t$ and $\mathbf{p}_t$ denote vectors with δ_{jt} and p_{jt} for each station.

We also assume that, if consumers choose to buy from a station, they will demand heterogeneous quantities $\bar{q}_i$ of gasoline depending on the length of the path they use to commute:

$$\bar{q}(s_i, d_i) = c_1 m(s_i, d_i),$$

where $m(s_i, d_i)$ denotes the length of the shortest path from s_i to d_i . Following Houde (2012), I fix $c_1 = 0.2$ liters per kilometer, which is roughly the average fuel consumption of cars. The demand faced by station j as a function of the price vector $\mathbf{p}_t$ can then be expressed as:

$$Q_{jt}(\mathbf{p}_t) = \int \bar{q}(s_i, d_i) \mathbb{P}_{ijt}(r(s_i, d_i) | \boldsymbol{\delta}_t, \mathbf{p}_t) dF(s_i, d_i),$$

where $F(s_i, d_i)$ denotes the distribution of consumers' origin and destination points. Finally, in order to obtain shares for each station, we must divide this quantity by the theoretical market size

$$M = \int \bar{q}(s_i, d_i) dF(s_i, d_i).$$

Note that M is equal to the total number of liters that consumers would buy if everyone decided to commute using a car.

5.2 Supply Side Model

We model the supply side as a differentiated product Bertrand-Nash price competition model. We assume that each period t , firm k owning the stations in the set $\mathcal{F}_k$ plays a static, full information, simultaneous move pricing game. Each period t , firm k solves the following problem:

$$\max_{\mathbf{p}_k} \sum_{j \in \mathcal{F}_k} (p_j - c_j) Q_j(\mathbf{p}_k, \mathbf{p}_{-k}),$$

where $\mathbf{p}_k$ is a vector containing the prices of all stations that belong to k , and $\mathbf{p}_{-k}$ is a vector with the prices of all competing stations.

Let Ω denote the ownership matrix of the market ($\Omega_{ij} = 1$ if station i and station j have the same owner, $\Omega_{ij} = 0$ otherwise). In matrix notation, the solution to the Bertrand-Nash Equilibrium is given by:

$$Q(\mathbf{p}) + (\Omega \odot \mathbf{J}(\mathbf{p}))(\mathbf{p} - \mathbf{c}) = 0, \tag{2}$$

where $\mathbf{p}$ denotes the vector of prices of all stations, $\mathbf{c}$ denotes the vector of marginal costs of all stations, and $\odot$ denotes element-by-element multiplication of matrices of the same dimensions. $\mathbf{J}(\mathbf{p}) \equiv \partial Q(\mathbf{p}) / \partial \mathbf{p}'$ denotes the $J \times J$ Jacobian matrix of derivatives of quantities with respect to prices. We can back out the implied marginal cost of each station from the

model by inverting equation (2):

$$\mathbf{c} = \mathbf{p} + (\Omega \odot \mathbf{J}(\mathbf{p}))^{-1} Q(\mathbf{p})$$

6 Estimation and Identification

6.1 Estimation

I follow the procedure from Berry et al. (1995) to estimate the vector of parameters θ from the demand model. For every product j and every time period t , let Z_{jt}^D be a vector of demand-side instruments that satisfy

$$\mathbb{E}[\xi_{jt} Z_{jt}^D] = 0. \quad (3)$$

Following Berry et al. (1995), I parametrize the marginal costs implied by the model as

$$f_{MC}(c_{jt}) = \phi \text{Wholesale_Price}_{jt} + X_{jt}' \gamma + \eta_t + \omega_{jt},$$

where $f_{MC}(c) = \log(c)$, c_{jt} denotes the marginal cost for station j at time t implied by the model, $\text{Wholesale_Price}_{jt}$ denotes the wholesale price paid by station j at time t , X_{jt} is a vector of dummy variables for the identity of the upstream supplier of station j , η_t denotes a time fixed effect, and ω_{jt} is a mean-zero unobserved component.

Let Z_{jt}^S denote a vector of supply-side instruments such that

$$\mathbb{E}[\omega_{jt} Z_{jt}^S] = 0. \quad (4)$$

Let $\bar{g}$ be a vector created by stacking the sample analog of the demand and supply moment conditions given by Equations (3) and (4):

$$\bar{g} = \begin{bmatrix} \bar{g}_D \\ \bar{g}_S \end{bmatrix} = \frac{1}{N} \begin{bmatrix} \sum_{j,t} Z_{jt}^{D'} \xi_{jt} \\ \sum_{j,t} Z_{jt}^{S'} \omega_{jt} \end{bmatrix}.$$

I estimate the parameters of the model by solving the GMM problem

$$\min_{\theta} \bar{g}(\theta)' W \bar{g}(\theta),$$

where W denotes a positive-definite weighting matrix. I concentrate out the demand and supply linear parameters (the inclusion of the supply-side moments implies α cannot be concentrated out) so that $\theta = \{\lambda, \alpha\}$. For the estimation procedure, to evaluate the objective function at θ , for each period t , I solve for the vector $\hat{\delta}(\theta)$ that equates the observed shares to those from the model using the contraction mapping from Berry et al. (1995). I then use the supply-side model to obtain

$$\mathbf{c}(\theta) = \mathbf{p} + (\Omega \odot \mathbf{J}(\mathbf{p}; \theta))^{-1} Q(\mathbf{p}; \theta),$$

and perform linear IV regressions of the form

$$\hat{\delta}_{jt}(\theta) - \alpha p_{jt} = X'_{jt} \beta + \psi_t + \xi_{jt} \quad (5)$$

$$f_{\text{MC}}(c_{jt}(\theta)) = \phi \text{Wholesale_Price}_{jt} + X'_{jt} \gamma + \eta_t + \omega_{jt} \quad (6)$$

and use the residuals from Equations (5) and (6) to create

$$\bar{g}(\theta) = \begin{bmatrix} \frac{1}{N} \sum_{jt} \hat{\xi}_{jt}(\theta) Z_{jt}^D \\ \frac{1}{N} \sum_{jt} \hat{\omega}_{jt}(\theta) Z_{jt}^S \end{bmatrix}$$

The estimation of the parameters of the model is done using two-step GMM. In the first step, I start by computing a set of pilot estimates θ^p using the optimal weight matrix under the assumption of homoskedasticity:

$$W = \begin{bmatrix} (Z^{D'} Z^D / N)^{-1} & 0 \\ 0 & (Z^{S'} Z^S / N)^{-1} \end{bmatrix}.$$

In the second step, I use the residuals $\hat{\xi}(\theta^p)$ and $\hat{\omega}(\theta^p)$ from the first step to construct the optimal heteroskedasticity robust weight matrix $\hat{W}(\theta^p)$.

6.2 Identification

Identification of the price parameter α requires that the variables in Z_{jt}^D are correlated with station j 's posted retail price p_{jt} but uncorrelated with its unobserved quality component ξ_{jt} . In the retail gasoline market, it is reasonable to assume that most of the utility that consumers derive from a station's location is related to its closeness to their commuting route. The inclusion of $\lambda D(r(s_i, d_i), l_j)$ in the utility specification for each consumer i removes the utility that consumers get from station j 's distance to their commuting path from ξ_{jt} . Moreover, gasoline is mostly a homogeneous product, and any differences in gasoline quality will be captured by the upstream supplier dummies in X_{jt} . Therefore, this assumption mostly requires that the instruments Z_{jt}^D are uncorrelated with non-gasoline characteristics of stations (such as station-specific amenities that are not captured by X_{jt}).

To identify the price coefficient, I include the contemporary and lagged wholesale price of gasoline that station j paid to its upstream supplier during period t in Z_{jt}^D . I also include the average current and lagged wholesale prices that station j 's close competitors (as defined by driving distance) paid at time t . Wholesale prices are correlated with retail prices since they are a crucial component of marginal costs in the retail gasoline market. However, they do not directly impact consumers' utility. Therefore, I leverage the fact that my dataset allows me to observe the wholesale price paid by each station in every period.

Following Davis (2006), I also include instruments in Z_{jt}^D that are correlated with the distribution of consumers faced by each station. Specifically, I include the average distance between station j and all consumers in the market ($\bar{D}_j = \int D(r_i, l_j) dF(s_i, d_i)$) and the number of consumers who commute close to station j ($C_j = \int_{\{i: D(r_i, l_j) < 35\}} dF(s_i, d_i)$) as part of the demand instruments Z_{jt}^D . Therefore, we require that the distribution of commuters that station j faces is uncorrelated with ξ_{jt} . Note that this assumption does allow for the possibility that stations choose their location based on traffic patterns since the inclusion of $\lambda D(r(s_i, d_i), l_j)$ implies that ξ_{jt} does not contain the utility that consumers get from their distance to station j . However, this assumption rules out the possibility of stations with high (or low) quality amenities choosing to locate close to roads with a high number of close commuters. While this is a strong assumption, it is ameliorated by the fact that gas stations in the Mexico City Metropolitan Area are not highly differentiated by their amenities (Davis

et al., 2019) and that several of the non-gasoline attributes of stations will be captured by X_{jt} .

Finally, the linear demand parameters (β, ψ_t) are identified by assuming that the observable product attributes are uncorrelated with ξ_{jt} . The supply-side parameters (ϕ, γ, η_t) are identified by assuming that the wholesale price paid by each station and the observed product attributes are orthogonal to ω_{jt} .

7 Model Estimation Results

Table 1 presents the estimated coefficients of prices (α) and distance (λ). Column (1) contains the coefficients obtained from estimating the demand model using the procedure described in Section 6.1. Column (2) reports the coefficients obtained by estimating the model while imposing the assumption that

$$c_{jt} = \text{Wholesale.Price}_{jt} + \omega_{jt},$$

where c_{jt} denotes the marginal cost implied by the model. This condition implies that marginal costs are equal to the wholesale price paid by each station plus a mean zero error term. In practice, I implement this assumption by adding the following supply-side moment conditions:

$$\mathbb{E}[\text{Wholesale.Price}_{jt} - c_{jt}] = 0 \tag{7}$$

$$\mathbb{E}[\text{Wholesale.Price}_{jt}\omega_{jt}] = 0 \tag{8}$$

Finally, Column (3) reports the coefficients estimated by only using the demand-side moment conditions. As expected, the coefficients for prices and distance are negative and statistically significant in all specifications, except for the price coefficient obtained using only the demand side (Column (3)), which is imprecisely estimated.

The first line of Table 2 presents the mean own-price elasticities implied by the estimated coefficients from the demand model. Column (1) presents the results obtained from using

TABLE 1: Demand model estimation results

Variable	Specification		
	(1)	(2)	(3)
Price	-1.149 (0.318)	-0.447 (0.014)	-0.531 (0.319)
Distance	-3.029 (1.376)	-2.539 (0.422)	-3.186 (1.522)
Note: GMM standard errors in parentheses.			

both supply and demand moment conditions. Columns (2) and (3) present the mean elasticities obtained from the coefficients we estimate by imposing the condition that marginal costs are, on average, equal to wholesale prices and by only using the demand-side moment conditions, respectively. The mean own-price elasticities for all specifications are approximately between -8 and -19, which shows that consumers are very price-sensitive and the market is highly elastic. As argued by Houde (2012), this is consistent with the fact that gas stations are not highly differentiated from each other and that most consumers have a high number of gas stations close to their commuting routes, making it easy for them to substitute between stations. The own elasticities implied by the model are also roughly in line with the ones found by Houde (2012), who estimates average station-level own price elasticities of between -10 and -15 for the Quebec City retail gasoline market. Appendix B.2 presents the plot of the distribution of own-price elasticities.

TABLE 2: Combined Summary Statistics of Elasticities

Mean	Specification		
	(1)	(2)	(3)
Own Elasticities	-19.274	-7.707	-8.833
Cross Price Elasticities (5-10 min dist.)	0.065	0.027	0.030
Cross Price Elasticities (1-5 min dist.)	0.330	0.130	0.152
Cross Price Elasticities (0-1 min dist.)	1.938	0.694	0.915

Given the spatial component of competition in the retail gasoline market, we expect stations that share a large fraction of close commuters to compete more closely with each

other (e.g., stations in the same street or stations in close proximity to each other). Figure 4 plots the relationship between the cross-price elasticities between pairs of stations and the distance between them (in driving time), and fits a curve based on a nonparametric regression. Due to the high number of pairs between stations, I do this for a random sample of 2,000 pairs of stations. The second, third, and fourth rows of Table 2 present summary statistics of the distribution of cross-price elasticities for all pairs of stations depending on their distance. As expected, these results show that pairs of stations that are in close proximity to each other have significantly higher cross-price elasticities.

FIGURE 4. Relationship between cross-price elasticity and distance between stations (in driving time), for a random sample of 2,000 pairs

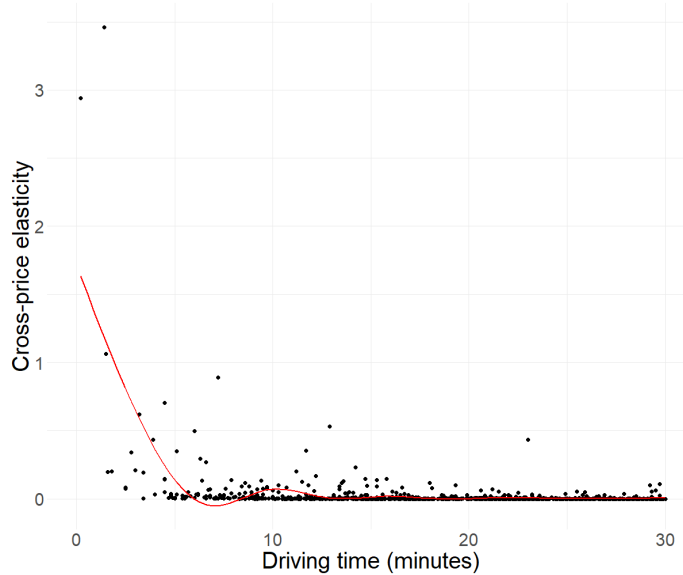
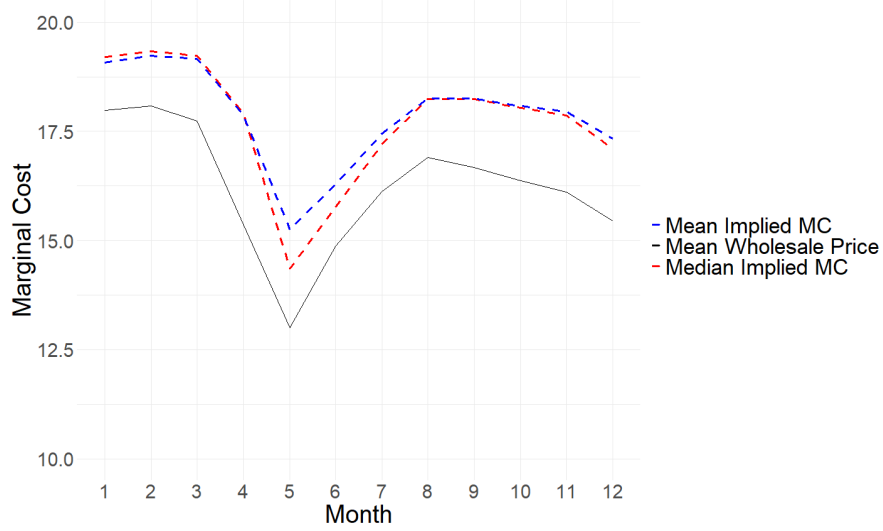


Figure 5 compares the average and median marginal cost implied by the estimated parameters of the model using both the demand and supply moment conditions (specification (1)) to the average wholesale price paid by stations during each period. The estimated marginal costs follow the average wholesale price stations pay very closely. Under this specification, on average, the wholesale price paid by stations represents approximately 90% of all marginal costs. Appendix B.3 presents equivalent plots for specifications (2) and (3).

FIGURE 5. Comparison between the marginal costs implied by the model and the mean wholesale price.



8 Counterfactual Equilibrium Prices

We are interested in determining the extent to which changes in the ownership structure following price deregulation affected prices and markups. In order to quantify these effects, for each period t I use the Bertrand-Nash competition model to solve for the optimal counterfactual prices under an alternative ownership structure Ω^{original} , where Ω^{original} is a $J \times J$ matrix such that $\Omega_{ij}^{\text{original}} = 1$ if station i and station j had the same owner before price deregulation.

In order to determine to what extent the observed increases in prices and markups were due to an increase in market power caused by changes in the ownership structure of this market, I start by estimating counterfactual prices under the pre-deregulation ownership structure, while keeping all other variables fixed. Formally, the vector of counterfactual prices $\mathbf{p}^{\text{count}}$ is defined as the vector $\mathbf{p}$ solving the system of equations of the firms' first order conditions:

$$Q(\mathbf{p}) + (\Omega^{\text{original}} \odot \mathbf{J}(\mathbf{p}))(\mathbf{p} - \hat{\mathbf{c}}) = 0,$$

where $\hat{\mathbf{c}}$ denotes the vector of marginal costs estimated in the previous section. Given the high number of products in each market, finding the vector of counterfactual prices requires

solving a large system of nonlinear equations. I, therefore, use the fixed point approach from Morrow and Skerlos (2011) to find the vector of prices that solves for the firms' first order conditions in each market.

The first column of Table 3 presents the average difference (in cents) between the observed and counterfactual prices under the pre-deregulation ownership structure while keeping all else fixed, for stations that changed ownership. For comparison, the third column of Table 3 presents the average differences estimated in the DiD analysis from Section 4, averaged over months three through eight after the ownership change. These results show that an increase in market power caused by changes in the ownership structure cannot explain the observed increases in prices and markups.

TABLE 3: Average differences (in cents) for stations that changed ownership

	Counterfactual		DiD (3)
	Ownership only (1)	Ownership & MC (2)	
Margin (all)	0.102	0.217	21.6
Margin (changed supplier)	-	0.910	57.8
Price (all)	0.102	-3.511	17.4
Price (changed supplier)	-	-8.633	17.6
Marginal cost (changed supplier)	-	-9.544	-40.3

Note: Column (3) reports difference-in-differences estimates using the design in Section 4, averaged over months three through eight after the ownership change. Margins are price minus marginal cost in columns (1) and (2), and retail minus wholesale price in column (3). For marginal costs, column (3) reports the estimate for wholesale prices.

I now study the extent to which the observed changes in markups can be explained by efficiency gains for stations for which a change in their upstream supplier accompanied changes in ownership. To obtain counterfactual marginal costs for stations where changes in ownership also implied changes in their upstream supplier, I start by parametrizing marginal costs as follows:

$$\hat{c}_{jt} = X_{jt}'\varsigma + \varphi_t + u_{jt}, \quad (9)$$

where $\hat{c}_{jt}$ denotes the marginal cost implied by the model for station j at time t , X_{jt} denotes a vector of supplier dummies, and φ_t denotes a time fixed effect. Then, for each station that

changed ownership, I determine the counterfactual supplier as the supplier of other stations from the same firm as the original owner (if there are any) or, if there are no stations left that belong to the original owner, as the state-owned supplier Pemex. I then compute the counterfactual marginal cost as $\hat{c}_{jt}$ plus the difference between the estimated dummies for the observed and counterfactual suppliers.

The last row of column (2) in Table 3 presents the mean difference (in cents) between the baseline and counterfactual marginal cost for stations that changed their upstream supplier after an ownership change. These results imply that there were efficiency gains for stations that changed their upstream supplier following an ownership change. The decrease in marginal costs is consistent with the DiD estimates in Section 4, where stations that switch suppliers at the time of the ownership change pay 0.40 MXN per liter less than their matched controls (Figure 3b), although the DiD estimate is larger than the decrease in marginal costs implied by the model.

I then estimate each station's optimal prices under the pre-deregulation ownership structure and the pre-deregulation counterfactual marginal costs by solving the following system of equations from the firms' first order conditions:

$$Q(\mathbf{p}) + (\Omega^{\text{original}} \odot \mathbf{J}(\mathbf{p}))(\mathbf{p} - \hat{\mathbf{c}}^{\text{count}}) = 0,$$

where $\hat{\mathbf{c}}^{\text{count}}$ is defined as the vector of counterfactual marginal costs estimated from equation (9). The second column of Table 3 shows the difference between the observed prices and markups and those estimated under the counterfactual allowing for changes in ownership and marginal costs. While these results predict higher markup gains than the ones obtained in counterfactual (1), they are much lower than the ones estimated in the DiD analysis. These results suggest that gains in efficiency and market power explain only a small fraction of the observed markup increases. This is because, in this counterfactual, roughly 90% of the decrease in marginal costs for stations with efficiency gains is passed on to the consumers.

In both of the counterfactuals presented in Table 3, I have held the vector of unobserved quality of stations $\boldsymbol{\xi} = (\xi_1, \dots, \xi_J)$ fixed to the fitted values from the model $\hat{\boldsymbol{\xi}} = (\hat{\xi}_1, \dots, \hat{\xi}_J)$. However, it is possible that ownership changes were accompanied by changes in stations' amenities (such as renovations to their facilities). Therefore, I estimate the average change

in quality that rationalizes the observed changes in prices.

As before, let $\hat{\mathbf{c}}^{\text{count}}$ be defined as the vector of counterfactual marginal costs estimated from equation (9), and let $\hat{\mathbf{p}}^{\text{count}}$ be a vector of prices defined as follows:

$$\hat{\mathbf{p}}_j^{\text{count}} = \begin{cases} p_j - 0.15 & \text{if station } j \text{ changed ownership} \\ p_j & \text{otherwise} \end{cases},$$

where p_j denotes the observed price of station j . $\hat{\mathbf{p}}_j^{\text{count}}$ is the vector of counterfactual prices assuming that stations that changed ownership would have charged 15 fewer cents (approximately the DiD estimate for price increases) if there had been no changes to the ownership structure of the market following deregulation.

Note that the functions $Q(\cdot)$ and $\mathbf{J}(\cdot)$ of the firms' FOCs are implicitly a function of the vector of unobserved qualities $\boldsymbol{\xi}$. I estimate the average change in (unobserved) quality $\Delta\xi$ that rationalizes the observed changes in prices and markups as the number that minimizes the following expression:

$$\|Q(\hat{\mathbf{p}}^{\text{count}}; \hat{\boldsymbol{\xi}}^{\text{count}}) + (\Omega^{\text{original}} \odot \mathbf{J}(\hat{\mathbf{p}}^{\text{count}}; \hat{\boldsymbol{\xi}}^{\text{count}}))(\hat{\mathbf{p}}^{\text{count}} - \hat{\mathbf{c}}^{\text{count}})\|,$$

with

$$\hat{\boldsymbol{\xi}}^{\text{count}} = \begin{cases} \hat{\xi}_j - \Delta\xi & \text{if station } j \text{ changed ownership} \\ \hat{\xi}_j & \text{otherwise} \end{cases},$$

where $\hat{\xi}_j$ denotes the residuals from the model and $\|\cdot\|$ denotes the Euclidean norm.

The solution to this problem is given by $\Delta\xi = 1.457$. In monetary terms, this result implies that after accounting for changes in market power and efficiency gains, the observed changes in prices can be rationalized by an average increase in the unobserved quality of stations equivalent to a price reduction of 1.268 MXN (roughly 6.3 USD cents) per liter.

9 Concluding Remarks

In this paper, I have studied how changes in the ownership structure of a market following price deregulation affect prices, marginal costs, and markups. To answer this question, I use data from the Mexico City retail gasoline market, which underwent a price deregulation in 2017. Overall, I draw three main conclusions from this study.

First, using a matched difference-in-differences design, I find that acquired stations raised their prices and markups relative to stations that did not change ownership. I then estimate a differentiated demand model and use these results with a model of Bertrand-Nash price competition to study the mechanisms behind the observed price increases. My second main finding is that the increases in prices cannot be explained by the rise in market power caused by ownership changes. Using both the results from my model and a DiD analysis, I also find that changes in ownership led to efficiency gains for stations that changed their upstream supplier. Finally, I estimate that the observed price increases could be rationalized by an increase in the unobserved quality of stations that changed ownership.

It is important to note that this work has several limitations. I make strong conduct assumptions by assuming that firms set prices to maximize the sum of profits from all stations they own. This assumption rules out the possibility of collusion between firms or upstream suppliers setting prices via resale price maintenance. Moreover, the assumption that all firms set prices optimally also rules out the possibility that the observed price changes are caused by acquiring firms being better at choosing profit-maximizing prices than the original owners.

More broadly, this paper speaks to the literature on antitrust policy. Often, economists use a DiD analysis to study changes in prices and markups after mergers or acquisitions and attribute any estimated changes to an increase in market power. However, ownership changes are usually accompanied by changes in marginal costs and product characteristics. This work illustrates the importance of accounting for efficiency and quality gains when studying changes in prices and markups following ownership changes.

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A Reduced-Form Appendix

TABLE 4: Ownership Change Descriptive Statistics

Panel A: Decomposition of Ownership Changes		
	Cases	Percentage
Total ownership changes	94	100.0%
<i>By seller pre-merger size</i>		
Seller was independent (1 station)	65	69.1%
Seller was small chain (2–5 stations)	18	19.1%
Seller was larger chain (6+ stations)	11	11.7%
<i>By seller outcome</i>		
Seller fully exits (all stations sold)	85	90.4%
Seller retains some stations	9	9.6%
Panel B: Acquiring Firms		
	Value	Percentage
Stations acquired by top 3 acquirers	35	37.2%
Stations acquired by top 5 acquirers	47	50.0%

B Appendix

B.1 Empirical Distribution of Commuters

In order to estimate the empirical distribution of traveling patterns from the Mexico City Metropolitan Area, I use the 2017 Survey of Origin and Destination. This is a representative survey of 66,625 households. This survey partitions the Mexico City Metropolitan Area into 194 different traffic area zones (TAZs). For each sampled household, the survey contains information on all daily trips taken by each household member, including the TAZ where the trip originated, the TAZ of the trip’s destination, and the mode of transportation (e.g., car, public transportation, etc.). The Survey of Origin and Destination also contains information on household characteristics, such as car ownership.

I selected the subsample of households that own at least one car and aggregated all trips with the same origin and destination traffic area zones to create an aggregate Origin-Destination matrix. This is a 194×194 matrix, where element (i, j) contains the number

TABLE 5: Event-study estimates of the effect of ownership changes

Month	(1) Retail price	(2) Markup	(3) Wholesale price	(4) Wholesale price Supplier switchers
	MXN/liter	p.p.	MXN/liter	MXN/liter
−6	−0.002 (0.027)	−0.15 (0.23)	0.013 (0.034)	0.031 (0.149)
−5	−0.044 (0.020)	0.03 (0.27)	−0.048 (0.043)	−0.042 (0.048)
−4	−0.025 (0.019)	−0.17 (0.13)	0.011 (0.020)	0.004 (0.039)
−3	−0.007 (0.008)	−0.03 (0.05)	0.001 (0.008)	0.000 (0.012)
−2	0.031 (0.009)	0.05 (0.05)	0.011 (0.009)	0.011 (0.013)
0	0.020 (0.013)	0.45 (0.27)	−0.067 (0.050)	0.009 (0.033)
1	0.043 (0.077)	0.47 (0.54)	−0.004 (0.029)	0.007 (0.044)
2	0.095 (0.046)	0.08 (0.35)	0.075 (0.036)	0.026 (0.023)
3	0.097 (0.050)	1.86 (0.43)	−0.241 (0.038)	−0.565 (0.063)
4	0.254 (0.030)	2.34 (0.31)	−0.157 (0.046)	−0.398 (0.072)
5	0.113 (0.045)	0.12 (0.30)	0.103 (0.045)	−0.326 (0.064)
6	0.126 (0.055)	0.40 (0.37)	0.099 (0.057)	−0.331 (0.082)
7	0.218 (0.029)	0.88 (0.28)	0.010 (0.037)	−0.431 (0.063)
8	0.231 (0.030)	0.65 (0.30)	0.102 (0.041)	−0.372 (0.055)
Average, months −6 to −2	−0.013 (0.013)	−0.07 (0.10)	−0.001 (0.013)	0.002 (0.031)
Average, months 3 to 8	0.174 (0.026)	1.04 (0.26)	−0.013 (0.033)	−0.403 (0.057)

Note: Matched difference-in-differences estimates from Section 4 (Figures 2 and 3). Month 0 is the month in which the station applies for the permit transfer, and month −1 is the base month. Standard errors in parentheses. Markups are (retail price − wholesale price) / retail price, in percentage points. Column (4) restricts the sample to stations that switch wholesale supplier at the time of the ownership change.

of daily trips from TAZ i to TAZ j . In the empirical application for this paper, I use this matrix to jointly draw the origin and destination TAZ for 10,000 simulated trips.

Once I have the origin and destination TAZ of each of the simulated trips, for each trip i , I randomly draw an origin point s_i inside i 's origin TAZ and a destination point d_i from i 's destination TAZ. I draw these points with weights given by the population density of each TAZ, with more densely populated areas receiving higher weights. I then use the *Open Source Router Machine* (Luxen and Vetter, 2011) to estimate the shortest path to travel from s_i to d_i . I also use the *Open Source Router Machine* (Luxen and Vetter, 2011) to estimate the travel time (in minutes) between s_i and d_i . Finally, I estimate a distance matrix with the distance between each consumer i and every station j . Let $r(s_i, d_i)$ denote the shortest route to travel from s_i to d_i . Let l_j denote the location of station j . I follow Houde (2012) in defining the distance between consumer i and station j ($D(r(s_i, d_i), l_j)$) as follows:

$$D(r(s_i, d_i), l_j) = t(s_i, l_j) + t(l_j, d_i) - t(s_i, d_i)$$

Where $t(a, b)$ denotes the time it takes to travel from point a to point b (in minutes).

B.2 Distributions

FIGURE B1. Distribution of own price elasticities

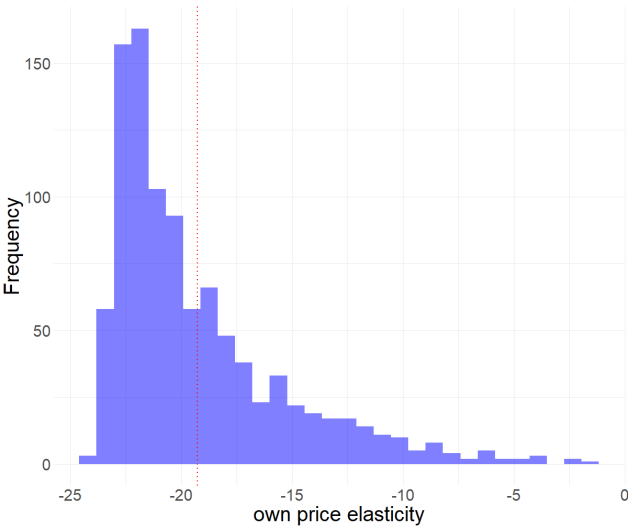
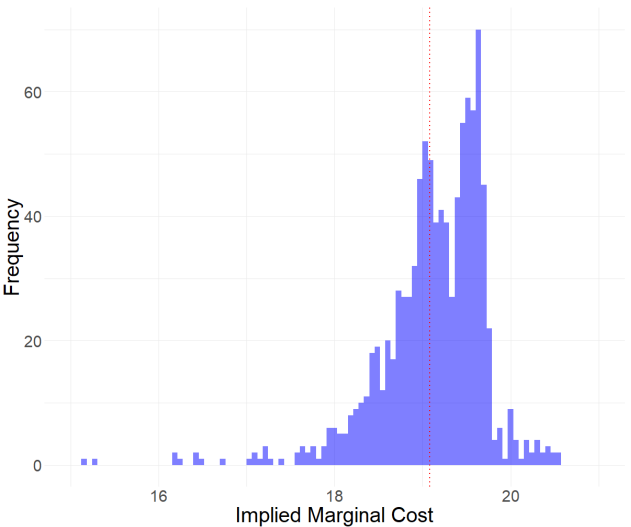


FIGURE B2. Distribution of implied marginal costs



B.3 Marginal Costs

FIGURE B3. Comparison between the marginal costs implied by specification (2) and the mean wholesale price.

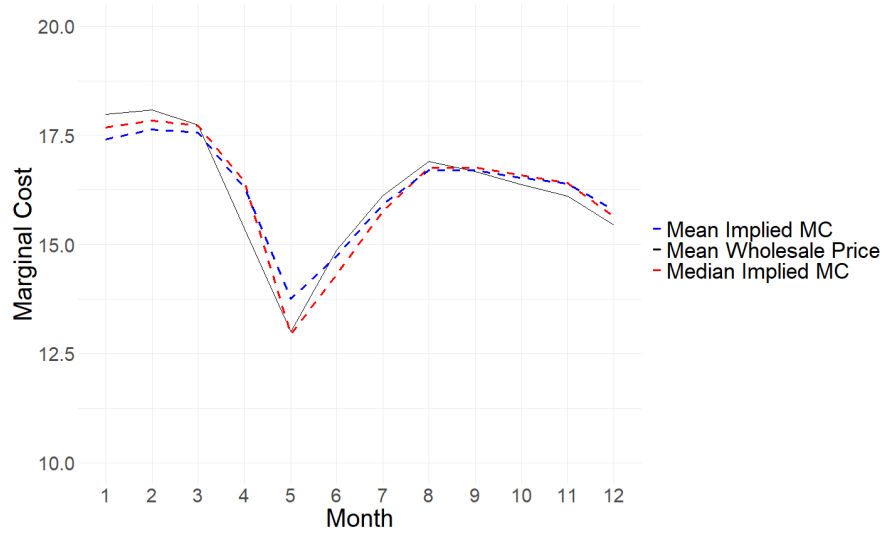


FIGURE B4. Comparison between the marginal costs implied by specification (3) and the mean wholesale price.

