Who Benefits from Information Disclosure? The Case of Retail Gasoline*

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Abstract

How does online price disclosure affect competition when both consumers and firms can use the disclosed information? This paper addresses this question exploiting the sequential implementation of an online price-disclosure policy in the Chilean retail-gasoline industry. The results show that disclosure increased margins by 9 percent on average, though the effects varied across the country depending on the intensity of local search behavior. Because margins increased the least, and even decreased, in high-search areas, where income is also higher, the results also show that price-disclosure policies may have important distributional effects.

JEL Codes: D22, D43, D83, L12, L41.

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Information-disclosure policies are meant to provide consumers with information about prices and product attributes, and to give firms the incentives to improve the quality of their

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products and to compete more intensively. Examples of industries that have seen the implementation of information-disclosure policies in the last few decades include ready-mixed concrete, retail gasoline, supermarkets, food snacks, and restaurants, in countries such as Australia, Chile, Denmark, Israel, Italy, South Korea, and the United States. A drawback of these policies, however, is that they allow firms to monitor their rivals' actions, which could facilitate coordination among firms and decrease the intensity of competition. In the end, whether information-disclosure policies intensify competition or facilitate coordination crucially depends on whether the demand- or supply-side response to disclosure dominates.

This paper studies how the implementation of a price-disclosure policy in the Chilean retail-gasoline industry impacted the intensity of competition. In February 2012, the Chilean government passed regulation requiring gas stations to post their prices on a government website and to keep prices updated as they changed at the pump. The website was introduced on March 1, 2012, and during its first month it only published information for the region where the capital (Santiago) is located. The rest of the country entered the system sequentially in the following months according to a schedule set by the government. By July 2012, the website contained information from the entire country.

The Chilean government introduced the website for two reasons.[1] First, the website would allow the *Comisión Nacional de Energía* (CNE, National Energy Commission) to have real-time price information, which would be used to evaluate the performance of the market and to forecast prices. Second, the website would allow consumers to access geocoded price information for all gas stations in the country, as well as information on stations' characteristics.

In this context, information disclosure may have both pro- and anti-competitive effects. On the one hand, disclosure may intensify competition if consumers benefit from lower search costs and firms use the website to compete more intensively. On the other hand, if stations can easily monitor their rivals' actions and consumers do not actively use the disclosed information, disclosure may facilitate coordination. Further, if there is heterogeneity in how firms and consumers use the disclosed information across the country, disclosure

[1] See "Información sobre el Sistema de Información en línea de Precios de Combustibles" at `http://www.bencinaenlinea.cl/web2/normativa.php`.

may have important distributional consequences.

I study how information disclosure affected competition in the Chilean retail-gasoline industry by asking two questions. First, what is the impact of disclosure on a firm's margin and on price dispersion? Second, how does the impact of information disclosure on local market outcomes vary with the intensity of local search behavior? To answer these questions, I combine a number of datasets that allow me to study how competition evolved between January 2010 and December 2013 across six of the largest cities in Chile. I identify the impact of disclosure on the intensity of competition, by exploiting the sequential implementation of the disclosure mechanism. The results provide strong evidence in favor of disclosure softening competition, as margins increased on average by 9 percent. Further, margins increased the most in low-income areas and increased the least (and sometimes even decreased) in high-income areas, which suggests that the intervention may have exacerbated economic inequality. Finally, the increase in margins cannot be explained by alternative mechanisms such as increasing differentiation, changes in brand- or city-specific pricing behavior, or by (joint) station ownership.

To study what drives the heterogeneity in the impact of disclosure on margins and on price dispersion, in Section 2 I introduce a model in which market outcomes depend on how firms and consumers use the disclosed information. The model shows that if firms use the disclosed information to monitor their rivals' actions and consumers do not search actively, margins increase and price dispersion decreases relative to a setting where firms also do not exploit the disclosed information. However, as more consumers became active searchers, these results reverse even if firms continue to monitor their rivals' prices and margins decrease while price dispersion increases. I then use data on the locations of smartphone users when they searched for prices through a smartphone app, to examine whether the same patterns hold in the data. The results are consistent with the model's predictions and suggest when local search intensity is low, the supply-side response to disclosure (coordination) dominates and margins increase while price dispersion decreases. However, when local search intensity increases, it has the potential to overcome price coordination and increase competition.

This paper makes two main contributions to the literature on information disclosure.

First, while most of the literature has focused on estimating the *overall* effect of disclosure on market outcomes, this paper shows that the heterogeneity in the impact of disclosure across locations crucially depends on the intensity of local search behavior. Second, this paper shows that disclosure policies may have important distributional consequences depending on who has access to and uses the newly disclosed information. Specifically, by using actual search data in gas-station neighborhoods, and by not having to infer search from aggregate measures such as website visits or Internet penetration, this paper shows that margins increased the least and even decreased in some high-income areas, where search intensity is higher. This suggests that ease of access to the disclosed information is crucial for determining how information disclosure affects market outcomes.

The literature on information disclosure can be divided into branches depending on whether it focuses on disclosure of prices or quality and whether it uses pre- and post-intervention data or only post-intervention data. This paper falls within the price-disclosure literature that uses both pre- and post-intervention data. In this context, two papers are closely related. Rossi and Chintagunta (2015) study how the introduction of signs containing price information from nearby stations affected competition in the Italian motorway and show that on average margins decreased by 20 percent following the introduction of the signs. Ater and Rigbi (2017) study how the implementation of online price disclosure in the supermarket industry in Israel affected competition. They show that disclosure caused a sharp and quick decrease in price dispersion, while price levels decreased several months after the intervention.

A larger body of work has also studied how market outcomes vary with price disclosure, but using only post-intervention data. Albæk, Møllgaard and Overgaard (1997) use price data for ready-mixed concrete from Denmark to study how prices evolved in the year after the implementation of the policy. In the context of retail gasoline, Jang (2014) and Hong (2014) study to what extent, following the introduction of a price-disclosure mechanism in the South Korean gasoline industry, market outcomes were affected by the smartphone penetration rate. While Jang finds that both price dispersion and markups slightly increased with smartphone penetration, Hong finds the opposite to be true. Byrne and de Roos (2016) show that after gas stations in Perth, Australia, had to start informing authorities about the prices they would charge the following day, it took them twelve years to learn how to use the mechanism to coordinate as an effective cartel. Finally, Lemus and Luco (2018) study how, after the implementation of disclosure in the Chilean retail-gasoline industry, some stations became price leaders and induced higher margins in their markets. In the context of the price-disclosure literature, the main contribution of this paper is its study of how the heterogeneity of the effect of disclosure depends on the intensity of local search behavior. Further, the availability of pre- and post-intervention data allows for estimating the causal effect of the policy on market outcomes.[2]

This paper is also related to the literature that studies pricing in the retail-gasoline industry. Lewis (2008) studies how price dispersion depends on both differentiation and local competition. Houde (2012) performs an ex-ante merger evaluation using data on commuting paths to estimate preferences over gas stations. Clark and Houde (2014) study pricing behavior when collusion collapsed in Québec's retail-gasoline market. Eckert (2013) reviews the empirical literature on retail-gasoline markets. This paper contributes to this literature by studying how an information-disclosure policy implemented in the retail-gasoline industry affected market outcomes depending on the extent to which firms and consumers used the disclosure mechanism.

Finally, this paper is also related to the empirical literature on search. In particular, it explains the heterogeneity in the impact of disclosure across locations as a consequence of the intensity of local search behavior. This paper is related to Sorensen (2000), Brown and Goolsbee (2002), and Baye, Morgan and Scholten (2004), who study how prices and price dispersion are affected by exposure to the Internet and the frequency of purchases. In the context of retail gasoline, Chandra and Tappata (2011) show that price dispersion increases with the number of firms and search costs, but decreases with production costs.

[2]Information-disclosure policies have also focused on disclosing measures of quality. Mathios (2000) studies the differential impact of voluntary versus mandatory information disclosure in the salad-dressing market. Dranove et al. (2003) study how health-care report cards affected patient outcomes and matching between patients and providers. Jin and Leslie (2003) study how displaying hygiene quality cards in restaurants windows affected consumers and firms. Bollinger, Leslie and Sorensen (2011) study how calorie posting by Starbucks affected both consumer behavior and profits. All these studies find evidence of agents responding to the disclosure of information.

Lewis (2011) explains slower price adjustments and higher price dispersion during periods in which prices fall, through the lens of a model in which consumers' expectations are determined by the prices at which they purchased in the past. Byrne and Roos (2017) use market-level search data to develop tests for search behavior and show that consumers in the Perth gasoline market engage in both inter-temporal and cross-sectional search. Finally, Pennerstorfer et al. (2017) use data on commuters to study how price dispersion is related to consumer search. The main contributions of this paper to this literature are twofold. First, while most papers have had to either infer local search behavior from, for example, measures of Internet penetration or use search data aggregated at the market level, in this paper I use real search data where the exact location where a search request was made is known. This allows me to create measures of search intensity in the neighborhood of a gas station to study how market outcomes are affected by local search behavior. Second, while the literature on the relationship between search and market outcomes has focused on consumer search behavior, in this paper I consider an environment in which information disclosure allows both consumers and firms to use the disclosed information. In Section 2 I model this interaction between consumers and firms, and later I use the predictions of the model to further discuss how disclosure determined market outcomes.

The paper proceeds as follows. Section 1 describes the policy intervention and the data sources. Section 2 introduces a model that illustrates how information disclosure may affect competition in a context in which both firms and consumers make use of the disclosed information. Section 3 presents the research design and discusses the results. Finally, Section 4 concludes.

1 Industry and Data

1.1 The Chilean Gasoline Industry

Chile is a net importer of oil, and it imports most of its oil through the state-owned company ENAP (85 percent in 2012). The rest is directly imported by distributors. Because ENAP competes with international producers, its prices follow those of international markets. Since 2009, ENAP has offered three different prices, which vary according to the price of oil in the Mexican Gulf and the type of purchase, but not the volume purchased. The first price applies to purchases made more than 45 days prior to expected delivery. A second price is offered to those who sign a long-term contract with ENAP, and it consists of a discount over the first price, regardless of the volume purchased. Finally, for delivery within 45 days, ENAP charges a spot price, which varies with international prices and inventory.[3]

The Chilean gasoline industry has three levels. The first level is the refinery stage, with oil either refined into gasoline by ENAP or by distributors importing fuel products from international markets. The second level corresponds to distributors. As of 2012, there where four main distributor companies in Chile: Copec, Petrobras, Shell, and Terpel. Distributors can sell in the industrial market or in the retail market through gas stations. The retail market corresponds to the third level of the industry, and it is the object of study in this paper.

Gas stations can be branded or unbranded (independent). Branded stations can either be owned by the distributor or be independently owned. Branded stations have exclusive contracts with their distributor to sell that brand's gasoline. Finally, gas stations are spatially differentiated retailers that also compete by adding additives to the gasoline they sell and by offering other services such as car wash, convenience stores, and pharmacies, among others (see, for example, Lewis 2008, Houde 2012, and Eckert 2013).

In Chile, most stations sell gasoline of 93, 95, and 97 octanes, and diesel. In this paper I focus on 93 octane gasoline, because it accounts for 53 percent of all gasoline sold in 2013 (SEC, 2013).

1.2 The Policy Intervention

On February 1, 2012, CNE passed "Resolución No. 60" (Decree N. 60) creating the "Sistema de Información en Línea de Precios de los Combustibles en Estaciones de Servicios" (Online Price Information System for Fuel Products Sold at Gas Stations). The system consists of a website where gas stations must log in to keep their price information updated every time they change prices at the pump.[4] The decree also established that the system would

[3] See ENAP (2010), pages 2 and 3.

[4] Gas stations have to update their prices within 15 minutes of prices changing at the pump. See http://www.bencinaenlinea.cl/web2/archivos/RE_CNE_N60_Sistema_de_Precios_en_Linea_DO.pdf.

be rolled out sequentially across the country during a five-month period, with groups of administrative regions entering the system each month.[5] The first region to enter the system was Región Metropolitana, which is located in the central part of the country and includes the capital, Santiago. It was followed by another four regions in April: Coquimbo, Valparaíso, Libertador Bernardo O'Higgins, and Maule, all located in the central part of the country. In May, the two regions located at the extreme south were added: Región de Aysén del General Carlos Ibáñez del Campo and Región de Magallanes y de la Antártica Chilena. In June, the four regions from the central south were added: Bío Bío, Araucanía, Los Lagos, and Los Ríos. Finally, in July, the northern part of the country was added to the system. The order of the intervention was decided by the government and, to the best of my knowledge, only technical considerations determined it. In the rest of the paper I refer to the groups of regions that entered the system at the same time as "areas of intervention."

The Chilean government enforces compliance with the policy through the "Superintendencia de Electricidad y Combustibles" (SEC), the agency that is charge of overseeing the Chilean energy market. For the policy studied in this paper, SEC is in charge of enforcing the fifteen-minute limit that stations have to update their prices on the website after they change prices at the pump.

1.3 Data

This paper uses data from six sources. The first dataset is a survey conducted by the *Servicio Nacional del Consumidor* (SERNAC, Consumer National Service). As part of the survey, SERNAC collected price information at the station level both before and after the policy intervention. SERNAC visited the stations in the sample once a week in the case of Santiago and the first week of each month in the other cities. The dataset covers almost 10 percent of the gas stations in Santiago and between 50 and 81 percent of the stations in the other cities. The original dataset covers the period 2005–2013. I focus on the period between January 2010 and December 2013 for two reasons. The first is to limit

[5] Chile is administratively divided into fifteen regions, with each region further divided into provinces and provinces divided into municipalities. In most cases, a city and a municipality overlap perfectly. The only exception is Santiago, which is composed of 37 municipalities. For this reason, when referring to cities other than Santiago, distinguishing between cities and municipalities is not important.

the extent to which changes in competition may be caused by changes in market structure, as I cannot control for changes in market structure before the introduction of the website and can only do so imperfectly afterwards. The second reason is that the stations included in the SERNAC sample before 2010 varied significantly.

The second dataset corresponds to data published on the website described in the previous section. This dataset was provided by the CNE, and it contains information about stations' characteristics and locations.[6]

The third dataset is published by the CNE—but using the stations in the SERNAC survey. In this dataset, the CNE publishes the average margin for the stations in the SERNAC survey, for stations in Santiago and five other cities.[7] In this dataset, margins are measured as the difference between the retail price (at the station level) and the sum of the wholesale price (refinery price) and taxes.[8] As the wholesale price is common to all stations in a city, it is possible to recover the sum of the distribution costs, the margin of the distributor, and the margin of the station.[9] Because this measure of margins includes distribution costs, in Section 3 I discuss how these are taken into account in the analysis to separately identify the impact of information disclosure on competition.

The fourth dataset consists of the location where the search requests were executed

[6]Though price information was also provided by CNE, I do not use this information for two reasons. First, the information provided by SERNAC coincides with that published on the website for the stations in the sample. Second, because by construction there is no pre-disclosure price information for stations not covered by the SERNAC survey, I have decided to maintain a consistent sample of stations before and after the intervention rather than adding information for some stations in the post-intervention period only.

[7]The cities in the data include Santiago (the capital), Valparaíso, Rancagua, Talca, Concepción, and Punta Arenas. These cities represented 59.3 percent of the population of the country in 2012. The area of Santiago (or *Gran Santiago*) represented 41 percent of the total population of the country in 2012. Further information about the different cities is provided in Online Appendix B.

[8]This information is published at http://www.cne.cl/estadisticas/energia/hidrocarburos under the name "Margen bruto semanal para combustibles en Santiago" and "Margen bruto nominal regional."

[9]Even though large branded companies may have access to different prices as long as they can guarantee demand for gasoline, their prices are indexed in the same way as prices for every other company (and are the same among those who can guarantee their purchases regardless of the volume they purchase). Hence, even though margins could depend on the specific brand, the way margins change as a function of the wholesale price is common to all brands. Further, in this paper I focus on stations that belong to the four biggest distributors, all of which should have the same wholesale price.

through a smartphone app. I use these data to define measures of search intensity in the neighborhood of each gas station. Importantly, these data are likely to represent a lower bound on search behavior as individuals may also access the information directly from the website. However, because CNE has records of the number of daily visits only since 2013, and these data are not georeferenced, the app data are richer and better suited for the analysis performed in this paper.[10] In Online Appendix D, I report different features of these data.

The fifth and sixth datasets provide information at the municipality level. This information includes the number of fixed Internet connections, poverty rates, population, and the fraction of the population that lives in rural areas.[11]

Similarly to most of the literature on retail-gasoline markets, I do not have access to volume data.[12] For this reason, the analysis focuses on how information disclosure affected margins and price dispersion, and how changes in these outcomes are related to station and market characteristics and to the intensity of local search behavior.

Table 1 reports summary statistics of the data at the station level. The table is divided into three panels, which differ in the variables of interest. The first panel reports statistics on margins and shows that unconditional mean margins before the implementation of disclosure were equal to 69.25 Chilean pesos per liter. This average increased to 71.64 Chilean pesos per liter once disclosure was implemented. However, as it will be shown below, these averages

[10] Importantly, the average monthly ratio of number of search requests through the app to website visits is 0.51. This suggests that though search requests through the app are a lower bound for total search, this number still represents a significant fraction of overall search.

[11] The number of fixed Internet connections is published by the "Subsecretaría de Telecomunicaciones" (the government agency in charge of telecommunications). This information can be accessed here http://www.subtel.gob.cl/estudios-y-estadisticas/internet/. The website also contains aggregate information on mobile Internet access, though these data are not available at the level of the municipality of origin but for the whole country. For this reason, these data are not used in the analysis. Demographic information is published in the SINIM dataset ("Sistema Nacional de Información Municipal" or National Municipal Information System), generated by the "Subsecretaría de Desarrollo Regional y Administrativo" (the government agency in charge of overseeing municipalities). See http://datos.sinim.gov.cl/.

[12] A notable exception is Levin, Lewis and Wolak (2017), who compute a measure gasoline purchases at the city level using daily data on both total gasoline expenditure and the average price of unleaded gasoline in each city.

hide significant heterogeneity across locations.

The second panel summarizes station characteristics and shows that 43 percent of stations had a convenience store, almost 5 percent had a pharmacy, 38 percent had public restrooms, 34 percent had a repair shop, 18 percent offered self-service pumps (in addition to full service), and 91 percent operated continuously. I later use this information to study whether changes in margins may be associated with increasing differentiation through the website, as stations could use the website to inform consumers about the services they offer.[13]

The third panel summarizes the number of monthly search requests executed in the neighborhood of each gas station, for different distance thresholds. The table shows that, though on average there is little search, there is significant heterogeneity across locations.

Table 2 reports the summary statistics of price dispersion using three different measures. Before discussing these statistics, it is necessary, however, to discuss the market definition used in this paper and how it relates to the literature. I follow most of the literature on retail gasoline and define markets as being centered at each station, and, I compute market-level statistics using a distance threshold around each station (see, Hastings 2004, Lewis 2008, and Chandra and Tappata 2011, among others). The drawback of this approach is that stations are considered multiple times if they are located within the distance threshold that sets the boundaries of the markets of other stations. An alternative approach is to define markets using a clustering algorithm that results in each station being assigned to a single market (Carranza, Clark and Houde, 2015; Lemus and Luco, 2018). This approach has the benefit of considering each station only once, but it often results in markets that may cover large areas. This approach, however, is not well suited for this application as the data consist of a survey of stations rather than the universe of stations in the country. This results in markets varying significantly depending on the parameters of the clustering algorithm. Finally, when data on commuting patterns exist, markets can be defined using these patterns (Houde, 2012). These data, however, do not exist for the Chilean setting.

[13]The website also contains information on two additional variables: whether a station accepts cash and whether it accepts credit and debit cards as means of payment. I do not include these in the analysis as essentially all stations accept them, resulting in no remaining meaningful variation.

For these reasons, I define markets as centered at each individual station, and I use different thresholds of driving distance to define the boundaries of each market.[14]

Table 2 reports summary statistics of price dispersion. The table considers markets defined using one kilometer of driving distance from each station and reports the range and standard deviation of raw prices, as well as dispersion of "clean" or "residual" prices—prices net of dispersion caused by persistent differences across gas stations (see, for example, Sorensen 2000, Brown and Goolsbee 2002, Lewis 2008, and Chandra and Tappata 2011). In all cases, it appears that within-market price dispersion increased following the implementation of disclosure, though the increase is significantly smaller in the case of dispersion of clean or residual prices. Further, the raw averages also hide significant heterogeneity across locations. In the analysis that follows, I also define markets using 3 and 5 kilometers of driving distance. The summary statistics under these definitions follow the same patterns as those reported in Table 2, though the magnitudes are larger.

2 How Can Information Disclosure Affect Competition?

Information disclosure can affect competition in two ways. First, it can reduce consumer search costs and induce more intense competition. Second, it allows firms to monitor their rivals' actions, which could induce less intense competition. In this section, I present a model that illustrates this in a context in which both firms and consumers can use the disclosed information to their advantage. The model builds on Campbell, Ray and Muhanna (2005) and Schultz (2005), who show that price transparency can facilitate collusion in a dynamic context.

In the model, firms decide whether to coordinate pricing strategies, and their decision depends on both how long it would take a firm to observe a deviation by a rival and the fraction of consumers who are informed about posted prices. The main implication of the model is that shortening the length of time it takes to observe deviations makes deviations less attractive, because deviation payoffs decrease while punishment payoffs remain unchanged. This makes coordination more attractive, allowing firms to sustain higher pay-

[14]Driving distances were computed using the algorithm developed by Huber and Rust (2016).

offs than when it takes longer to observe deviations. On the other hand, the intensity of competition increases as more consumers are informed about posted prices. This means that whether prices increase or decrease depends on whether the demand- or supply-side response to disclosure dominates.

Though gasoline may physically be a homogeneous good, two features of the industry lead to stations being able to charge different prices even if they compete in relatively narrow markets. First, consumer may face search costs that prevent them from knowing the prices that all stations charge. Second, stations themselves are spatially differentiated sellers that (may) offer different services and products. Both consumer search costs and seller differentiation may lead to observing stations charging different prices even if they face the same wholesale price and compete in the same local market.

In the model I assume that there are two sources of differentiation among gas stations: location and quality. To keep things simple, I model the problem as one of spatial competition and focus on price competition given stations' locations. For simplicity, I assume a linear city of length one with two firms, A and B, that compete by choosing prices p_A and p_B and have no production costs. I assume that firm A is located at 0 and firm B at 1.

To visit a station, consumers must pay a linear transportation cost t. It is, therefore, this cost what introduces spatial differentiation between the stations. I also assume that conditional on distance to a station, consumers value firm A more than firm B. That is, a consumer located at k, who purchases from firm A, receives indirect utility equal to $v_A - p_A - tk$. Instead, if she purchases from B, her utility is $v_B - p_B - t(1-k)$. I assume $v_A > v_B$.

I also assume that there are two types of consumers, informed and uninformed. Informed consumers represent a fraction $\phi \in (0,1)$ of all consumers and are aware of the prices that firms charge, while uninformed consumers are not. An informed consumer is indifferent between purchasing from either firm if $v_A - p_A - tx_I = v_B - p_B - t(1-x_I)$. Solving for x_I results in the familiar expression $x_I(p_A, p_B; t, \Delta) = \frac{\Delta + p_B - p_A}{2t} + \frac{1}{2}$, where $\Delta = v_A - v_B > 0$. In the case of uninformed consumers, I assume that they are uninformed about both the prices charged by the stations and any differences that may lead informed consumers to value firm A more than firm B. Therefore, half of the uninformed consumers will visit each station.[15]

In this setting, the equilibrium of the static game depends on the level of differentiation. Schultz (2005) shows that, for low levels of differentiation, the game may not have an equilibrium in pure strategies but rather in mixed strategies. On the other hand, for higher levels of differentiation, the static game does have an equilibrium in pure strategies. For the purposes of this paper, studying the equilibrium in pure strategies is enough to show how information disclosure affects equilibrium outcomes.

In a dynamic game such as the one analyzed here, the equilibrium of the static game can be used to characterize the punishment stage. Under the assumption that the market is covered (i.e., all consumers buy from one of the firms), one-period (Nash) profits are given by $\pi_A^N = \frac{(3t+\Delta\phi)^2}{18\phi t}$ and $\pi_B^N = \frac{(3t-\Delta\phi)^2}{18\phi t}$.

Consider now the case in which firms coordinate to charge prices above the Nash-equilibrium prices. Firms would, if possible, coordinate on monopoly prices. This, however, may not be possible. For example, costly verification of deviations may lead firms to coordinate on prices below those of a monopoly but above those of the Nash equilibrium. Without loss of generality, assume that coordination prices are p_A^C and p_B^C. Then, profits under coordination are given by $\pi_A^C = p_A^C\left(\frac{1}{2} + \phi\frac{\Delta + p_B^C - p_A^C}{2t}\right)$ and $\pi_B^C = p_B^C\left(\frac{1}{2} - \phi\frac{\Delta + p_B^C - p_A^C}{2t}\right)$.

For coordination to be possible, it is necessary that neither firm has unilateral incentives to deviate. To determine if coordination is possible, it is therefore necessary to find the most profitable deviation for a firm that abandons the collusive strategy. Because in this model deviations are always observed, but with a lag, a firm that decides to deviate, will deviate to a strategy that maximizes its profits conditional on its rival charging the coordination price. That is, the deviation price for firm i is $p_i^D(p_{-i}^C) = \arg\max_p \quad p \cdot D(p, p_{-i}^C; t, \Delta, \phi)$. Solving this for both firms results in static deviation profits $\pi_A^D(p_B^C) = \frac{(t+\phi\Delta+\phi p_B^C)^2}{8\phi t}$ and $\pi_B^D(p_A^C) = \frac{(t-\phi\Delta+\phi p_A^C)^2}{8\phi t}$.

[15] Assuming that uninformed consumers observe Δ results in a fraction $\frac{1-\phi}{2}\left(1 + \frac{\Delta}{t}\right)$ of the uninformed consumers visiting station A. This change does not affect the predictions of the model regarding price levels and has a minor impact on the predictions regarding price dispersion. I explain this difference below.

Coordination is then sustainable if

$$\text{Firm } A: \underbrace{\int_0^{\infty} \frac{p_A^C}{2}\Big(1+\frac{\phi}{t}(\Delta + p_B^C - p_A^C)\Big)e^{-rz}dz}_{\text{Payoffs under coordination}} \geq \underbrace{\int_0^{z^*} \frac{(t+\phi\Delta+\phi p_B^C)^2}{8\phi t}e^{-rz}dz}_{\text{Payoffs under deviation}} + \underbrace{\int_{z^*}^{\infty} \frac{(3t+\Delta\phi)^2}{18\phi t}e^{-rz}dz}_{\text{Punishment payoffs}}$$

$$\text{Firm } B: \underbrace{\int_0^{\infty} \frac{p_B^C}{2}\Big(1-\frac{\phi}{t}(\Delta + p_B^C - p_A^C)\Big)e^{-rz}dz}_{\text{Payoffs under coordination}} \geq \underbrace{\int_0^{z^*} \frac{(t-\phi\Delta+\phi p_A^C)^2}{8\phi t}e^{-rz}dz}_{\text{Payoffs under deviation}} + \underbrace{\int_{z^*}^{\infty} \frac{(3t-\Delta\phi)^2}{18\phi t}e^{-rz}dz}_{\text{Punishment payoffs}},$$

where z^* represents the instant at which a deviation, which started at $z = 0$, is observed. These equations represent incentive-compatibility (IC) constraints for both firms and have to be satisfied simultaneously for coordination to be possible. It is explicit in these constraints that the punishment strategy is to play the Nash-equilibrium outcome forever, though other strategies may also be employed.

The IC constraints presented above must be met simultaneously for coordination to be possible. Without further assumptions, it can be shown that, for fixed values of the parameters of the model, the intersection of the IC constraints defines a set of prices, in the space (p_A^C, p_B^C), that can be sustained under coordination. To perform clear comparative statics on equilibrium prices, further assumptions are needed. I explore two of these assumptions, both of which provide similar results. In principle, it would be natural to be interested in the prices that maximize joint collusive surplus, subject to the IC constraints. These prices correspond to the solution of the Nash bargaining problem associated with this model, where disagreement payoffs correspond to the sum of deviation and punishment payoffs. The solution to the problem then implicitly defines coordination prices, as disagreement payoffs also depend on the collusive prices. I present these results in Online Appendix A.

Here, I focus on a more extreme case that does result in a unique pair of equilibrium prices for fixed values of the parameters of the model and provides similar results in a more tractable and intuitive manner. To obtain these unique coordination prices, it is necessary to assume that the firm for which consumers have a higher willingness to pay (firm A) makes a take-it-or-leave-it offer to firm B that maximizes A's payoffs, subject to leaving B indifferent between coordinating and deviating.[16] The results associated with this approach are presented in Figure 1.

[16] Importantly, firm B is better off accepting this offer than rejecting it, as rejecting the offer would leave it with (lower) static profits.

Figure 1 presents equilibrium prices and equilibrium price dispersion as a function of the fraction of informed consumers ϕ and the time it takes to observe a deviation by a rival firm z^*. The top panel shows that, in equilibrium, prices decrease as more consumers become informed. However, prices increase as the length of time it takes to observe a deviation decreases (moving from high to low z^*).

The bottom panel examines how equilibrium price dispersion *under coordination* changes with the fraction of informed consumers and the time it takes to observe a deviation by a rival. The figure shows that equilibrium price dispersion under coordination first decreases and then increases with the fraction of informed consumers. Further, the shorter the time it takes to observe a deviation, the lower the price dispersion. That is, as more consumers become informed, price dispersion tends to decrease and then increase. When all consumers are informed, the price differential arises because of the differences in valuations, though prices are lower than when fewer consumers are informed.[17]

Finally, the model is also informative about how market outcomes vary across markets in which firms and consumers respond differently to disclosure. To illustrate this, consider the example presented in Figure 2. Figure 2a presents the inputs that are used in this example. On the horizontal axis, the figure presents the fraction of informed consumers. On the vertical axis, the figure presents different values of the time it takes to observe deviations from rivals. The pairs (ϕ, z^*) presented in the figure are chosen to reflect cases in which, starting from a reference point at the extreme left, the length of time required to observe deviations decreases at a decreasing rate until converging, while the fraction of informed consumers increases linearly. This is, the example is meant to represent a situation in which firms react faster to disclosure than consumers.

Figure 2b presents equilibrium prices and equilibrium price dispersion, measured as the difference between the price of firm A and the price of firm B (i.e., the range of prices), for each of the input pairs presented in Figure 2a. The figure shows that when the time to detect deviations decreases sharply, while the fraction of informed consumers increases slowly, prices increase and dispersion decreases. However, as more consumers become informed

[17]When uninformed consumers observe Δ, price dispersion is always decreasing in the fraction of informed consumers.

and the time it takes to observe deviations converges, these results change and prices start to decrease and dispersion to increase. I come back to these results when discussing the empirical findings in Section 3.

In summary, the model shows that i) prices under coordination increase when it takes less time to observe deviations and decrease as more consumers are informed; ii) price dispersion under coordination first decreases as more consumers are informed and induce lower collusive prices, but it increases again as more consumers become informed, though prices continue to decrease; and iii) sharp decreases in the length of time it takes to observe deviations increase prices and decrease price dispersion, if the fraction of informed consumers is increasing slowly. These results reverse, however, as more consumers become informed.[18]

3 Information Disclosure and the Intensity of Competition

I now turn to empirically examining how information disclosure affected the intensity of competition in the Chilean retail-gasoline market. I first present the framework used in the analysis. Section 3.1 then presents the results regarding the impact of disclosure on margins, and Section 3.2 presents the results regarding price dispersion.

To estimate the overall effect of disclosure on competition, I estimate regressions of the form

$$Y_{it} = \beta_0 + \beta_1 \mathbb{1}\{\text{Website operative}\}_{it} + X_{it}'\gamma + \xi_i + \eta_t + \epsilon_{it}, \tag{1}$$

where Y_{it} corresponds to the outcome of interest (e.g., inflation-adjusted margins or measures of local price dispersion), and the indicator function is equal to one if station i is located in an area in which the website is operative at time t and zero otherwise. X_{it} corresponds to time-varying covariates, such as the interaction between distance to the main pipeline and oil prices (that measure changes in distribution costs) and measures of local search behavior. ξ_i corresponds to unobserved station characteristics, which I assume constant over time and control for using station fixed effects. Finally, η_t corresponds to time fixed effects, which allow for taking country-wide shocks into account. ϵ_{it} is the error term.

[18] The results presented in Online Appendix A for the case of the Nash bargaining solution provide similar insights, though it is not possible to pin down unique equilibrium prices.

Regarding the identification of the impact of disclosure on market outcomes, a pre- and post-analysis at the city level could confound a number of factors, preventing me from interpreting the effects as representing changes in competition due to the interaction between consumer behavior and supply-side pricing. For this reason, I exploit the rollout of the policy and use a differences-in-differences approach that allows me to control for potentially confounding effects. Further, measures of distribution costs are incorporated as controls to take into account changes in wholesale supply.

Because the policy was implemented across the whole country during a five-month window, it is important to clarify two aspects of the empirical approach that I follow. First, because of the rollout period, the number of cities in the control group decreases from month to month as new cities enter the disclosure system. This feature is not related to the sample used in the analysis but to the nature of the policy design. Figure D.1 in Online Appendix D presents the evolution of margins for the different "areas of intervention," where the area of intervention corresponds to the group of regions that entered the system at the same time. The figure shows that the evolution of margins is similar across the areas of intervention before the website was introduced and that margins increased afterwards.

Second, because the policy was implemented by geographic areas that grouped administrative regions of the country, a large number of stations are simultaneously affected by the policy. Therefore, treatment takes place at the area-of-intervention level, while outcomes are observed at the station level. For this reason, it is necessary to cluster standard errors at the area-of-intervention level. However, because of how the system was rolled out, and as a consequence of the data available from CNE, there are only four areas of intervention (though areas of intervention include stations located on administrative regions that are hundreds of kilometers apart). Because standard bootstrap methods may lead to incorrect inference in the presence of a small number of clusters, I implement the six-point bootstrap-weight distribution approach proposed by Webb (2014) and also provide robustness analysis that follows Conley (1999) to take spatial correlation into account.[19]

[19] All implementations of the six-point bootstrap-weight distribution approach use 1,000 replications.

3.1 Impact of disclosure on margins

To study how disclosure affected margins, I estimate different specifications of Equation 1. In these specifications, the dependent variable is the inflation-adjusted margin of each station, and the covariates differ across specifications. To include Santiago with the same data frequency as the other cities, I only use the first week of each month for stations in Santiago.[20]

The results are reported in Table 3. The first specification shows that margins increased by 6.8 Chilean pesos per liter following the implementation of disclosure. This represents a 9.7 percent increase in margins caused by the disclosure of information. Column 2 repeats the analysis replacing a common trend with region-specific trends and shows that disclosure increased margins by 6.5 pesos per liter, or 9.2 percent. That is, both specifications show that disclosure caused a significant increase in margins both in statistical and economic terms.

The results reported above show that the implementation of disclosure is associated with a significant increase in margins that is consistent with a decrease in the intensity of competition. It is not yet possible, however, to determine the mechanism that led to these changes in margins. Before discussing potential mechanisms, I discuss two threats to identification and how these are considered in the research design. I then return to studying the mechanism behind the observed changes in margins.

First, it is important to discuss where identification comes from in this application, as the policy was rolled out over a five-month period. This means that by August 2012, the entire country was already under the disclosure policy. Hence, even though there may be a lag between the moment the website was operative and when both consumers and firms started using it, most of the variation in the data should come from the months during

[20]Importantly, I do not aggregate data at the month level, but use the data from the first week of each month for stations in Santiago. Aggregating the data at the month level for Santiago would not allow me to compare margins across cities, as the data for cities different from Santiago are only available for the first week of each month. Because most stations in Chile change prices once a week (89 percent, as shown in Lemus and Luco, 2018), the loss is not as important as it would be if the object of study was the retail-gasoline industry in, for example, the United States, where stations may change prices several times in a day.

which the system was rolled out. For this reason, in Table 3, column 3 replicates column 2 but drops all observations following August 2012. In this case, we find that disclosure increased margins by 6.2 pesos per liter, a 8.9 percent increase relative to the mean. This is of particular importance as it provides support for the empirical approach followed. In other words, though the additional data allow for fully taking into account any lag in learning about the policy and how to use the website, the estimates reported in column 3 show that most of the effect was already present by one month after the entire country was under the new policy.

Second, it is possible that there are city-specific effects that may have caused the observed changes in margins. I take this into account, estimating a series of specifications that replicate the main regression but drop one city at a time. If the effects are driven by a specific city, this should be reflected in the estimates that consider the subsample without that city. The results from this exercise are presented in Table C.1 in Online Appendix C.1 and show that this was not the case. That is, regardless of which city is dropped from the analysis, disclosure increased margins by 8 to 11 percent.

3.1.1 Possible mechanisms

Having identified the average effect of the intervention, I now explore possible mechanisms that may have caused them, as well whether the effects were heterogeneous across locations. I discuss two potential mechanisms in the main text and four in Online Appendix C.1 that also provide robustness analyses.

The first mechanism considered is whether the effects could have been caused by changes in the pricing behavior of a specific brand of gas stations. This is important because pricing decisions vary with the contractual relationship between a station and the parent company. Informal conversations with gas-station managers suggest that, even if branded stations are independently owned and choose prices themselves, parent companies may influence these decisions. For this reason, if the website allows parent companies to monitor the prices of stations in an area, this could lead to increases in margins that are brand-specific, unless all brands use the website in a similar way. If the effect is driven by changes in the pricing behavior of a specific brand, this would be evidence against the website facilitating coordination. On the other hand, if changes are common across brands, then increased coordination would be more likely.

The results are reported in Table 4. The omitted category across specifications corresponds to Copec stations (36 percent of the stations in the sample, in line with the company's share of total stations in the country). The first two specifications replace station fixed effects with brand dummies and include region-of-the-country fixed effects. In addition, column 2 includes the interaction between brand dummies and the disclosure dummy as regressors. Column 1 shows that dropping the station fixed effects and introducing the brand dummies results in a larger estimated coefficient on the disclosure dummy, representing an 11.9 percent increase relative to the mean. The results also show that margins are similar across brands. This is not surprising as all stations in the sample are associated with the four largest brands that operated in Chile during the sample period and had access to the same price from ENAP.

The estimates in column 2, however, are more interesting. First, including the interaction between brand dummies and the disclosure indicator reduces the estimated increase in margins to the same level as that reported in Table 3 (a 9.1 percent increase). However, the most important result associated with this specification is that margins were not only similar across brands before disclosure but also afterwards, meaning that margins increased similarly across brands after the intervention.

Column 3 brings back the station fixed effects and drops the brand and region indicators, while keeping the interaction between the brand and the disclosure indicator. The results are similar to the ones in the previous specifications: margins increased significantly and similarly across all brands. Overall, disclosure increased margins by 8.6 percent.

The last two columns in Table 4 include demographic information at the municipality level as regressors. Because these specifications include station fixed effects, demographic information is interacted with the disclosure indicator (continuous variables are standardized). These specifications show that margins increased between 8.9 and 9.5 percent on average. Further, though margins increased on average, they increased the most in low-income areas, suggesting that disclosure of information may have had important distributional consequences, which are further explored in Figure D.2 in Online Appendix D, that reports the estimated percentage changes in margins across household income levels. The figure shows that while in the lowest income areas margins increased by around 12 percent, margins decreased by 4 percent in the highest income areas, suggesting that disclosure affected low income areas the most.

Including the interaction between demographic information and the disclosure indicator also causes one of the interactions between brand dummies and the disclosure indicator to increase significantly, suggesting that Shell stations experienced a larger increase in margins than other brands, though margins increased for all of them. The table also shows that none of the other interactions between the disclosure indicator and information at the municipality level is significant. Finally, though the point estimate on the interaction between the number of competitors in the market and the disclosure indicator is negative, suggesting that margins increased less in markets with more stations, the coefficient is neither economically relevant, nor statistically significant. This suggests that the increase in margins did not vary significantly with market structure, though it was smaller in markets with more stations. This finding, and that all brands reacted similarly to disclosure, suggests that parent companies may have played a role in counteracting the effect of facing more rivals. One way to do this is examined by Lemus and Luco (2018), who rely on post-disclosure data to show that stations of the main brand in the country where often price leaders in their markets.

Overall, the results presented in Table 4 suggest that the decrease in the intensity of competition that followed the introduction of the website was homogeneous across brands, consistent with the website facilitating coordination.

In Online Appendix C.1, I explore four additional reasons that may explain the increase in margins that followed the policy intervention. These mechanisms consider whether the increase in margins could be explained by i) gas stations using the website to further differentiate from each other by advertising the services they offer (Table C.2); ii) a merger that took place in 2013 (Table C.3); iii) common station ownership (Table C.4, columns (1) to (4)); and iv) demand relocation from more visible to less visible stations (Table C.4, columns (5) and (6)). I find that none of these mechanisms explains the increase in margins that followed the policy intervention.

Finally, in Online Appendix C.2 I further examine the robustness of the estimates by estimating the main equation on two placebo specifications that randomly assign the moment at which treatment starts in each area of intervention. The results suggest that it is unlikely that the estimated effects were obtained by chance.

3.1.2 The role of local-search behavior

Having established that margins increased across the entire country, increased more in low-income areas, increased similarly across brands and cities, and that the increase was not related to ownership of gas stations or their exposure to consumers on the road, I now turn to studying whether the increase in margins was related to the intensity of local search behavior. To do this, I rely on search data collected by an app that smartphone users can access to search for price information. The search data include the location (coordinates) where users were when they executed search requests but do not allow me to distinguish between search requests executed by potential customers of a gas station or, for example, the manager of the station. For this reason, the analysis that follows uses the number of search requests per capita (relative to the population of the municipality in which a station is located), executed within a distance threshold of a station, as the main variable of interest.

Table 5 reports the estimated coefficients associated with the specification that control for the intensity of local search behavior. The specifications replicate those presented above and include, for each observation, the standardized number of search requests per capita (with population measured at the municipality level) executed within a distance threshold of a station during the month before the observation. Finally, the different specifications include the same controls as the specifications presented above, such as the interaction between the distance from a station to the main pipeline and oil prices, the interaction of the disclosure indicator and demographics, the interaction of the disclosure dummy and the number of competitors within the corresponding distance threshold, among others.[21]

[21] Even though search behavior is likely endogenous, I focus on OLS correlations rather than on implementing an instrumental-variables estimator because of the difficulty of finding a valid instrument for search behavior. Though variables such as the number of fixed Internet connections at the municipality level could serve as instruments, there is little variation within a municipality over time (though the number of con-

The estimates reported in Table 5 are interesting. First, it is important to note that, by construction, the disclosure indicator captures the average effect of disclosure on margins, as there is no search during the pre-intervention period. For this reason, the search covariates examine how the post-intervention heterogeneity, relative to the average effect, is related to local search intensity.[22] Second, in all cases, the relationship between search and margins is concave, with margins first increasing with search and later decreasing. Finally, though the magnitude of the coefficients on income do not change relative to those reported above, the inclusion of the search variables turns them insignificant, suggesting that it is local search, and not local income itself, what drives the effect reported above.[23]

Figure 3 plots the relationship between the predicted level of margins (according to the regression estimates) and local search intensity (the figure also plots the relationship between price dispersion and search, to which I return later), for markets defined using a 3-kilometer radius around gas stations (Figure D.6 in Online Appendix D report the same findings using a 1- and a 5-kilometer radius). The figure shows that at very low levels of search, margins vary significantly but start increasing as search intensity increases. However, when search intensity is large enough, margins start to decrease with search.

These findings are consistent with the predictions of the model presented in Section 2, where market outcomes varied with the relative usage of the disclosed information between firms and consumers (see Figure 2). That is, the empirical findings presented here are consistent with markets that vary in how consumers reacted to disclosure, while stations react quickly to disclosure, sharply decreasing the length of time it takes to observe deviations. When there is little consumer search, the decrease in the length of time it takes to observe deviations increases margins. However, in markets with more informed consumers, the demand-side response to disclosure dominates, it intensifies competition among firms,

nections increases over time). Alternatively, one could expect lagged search to be a valid proxy for current search, but if consumers adopted the app because of their expectations of future prices, then the same endogeneity problem would arise. Finally, the data on search requests do not allow me to distinguish between customers searching for low prices and station managers searching for their rivals' prices.

[22] I thank a referees for suggesting this approach.

[23] The correlation between search per capita and income is 0.41 when considering markets defined using a 1-kilometer radius around gas stations. The correlation decreases as the radius increases, reaching 0.22 when markets are defined using a 5-kilometer radius around gas stations.

and margins decrease. For this reason, the results presented here have important policy implications in that they show that whether the intensity of competition increases or decreases with information disclosure depends, critically, on the intensity of local consumer search behavior.

Finally, in Online Appendix C.1 I report robustness analyses that take into account market-specific seasonality (columns 1–4 in Table C.5), stations that do not belong to the top and bottom 1 percent of the distribution of search intensity (Table C.6), and spatial correlation (columns 1–3 in Table C.7). The results do not change.

3.2 Impact of disclosure on price dispersion

Having established that disclosure of price information increased margins on average, but that the effect varied depending on local search behavior, I now turn to studying how it affected price dispersion. Because stations differentiate from each other through attributes such as their location and the services they offer, I study how price dispersion was affected by disclosure and local search behavior computing a measure of price dispersion net of station-specific effects. I do this following the approach used by Sorensen (2000), Brown and Goolsbee (2002), Lewis (2008), and Chandra and Tappata (2011), among others, to study how disclosure and search affected dispersion of "clean" or "residual" prices. This approach relies on studying dispersion of the residuals of a regression of prices on station and time fixed effects. However, because competition in retail gasoline is mainly local, Lewis (2008) proposes to consider a measure of price variation relative to the price of direct competitors. This residual measure of *local* price dispersion is then regressed on the variables of interest, such as local search intensity.[24]

The results associated with this approach are presented in Table 6. The table presents estimates for markets defined using 1, 3, and 5 kilometers of driving distance around each station. All specifications include the same controls as the specifications presented above, such as an indicator variable for the disclosure period, local search intensity, the interaction

[24] I also repeat the analysis using other measures of price dispersion such as the range and standard deviation of prices, in markets defined using 1, 3, and 5 kilometers of driving distance. The results follow the same patterns as the ones described in the text. The relationship between price dispersion and search for these alternative measures of dispersion is presented in Figure D.7 in Online Appendix D.

between distance from a station to the main pipeline in the country and oil prices, among others.

The estimates reported in Table 6 show that price dispersion is a convex function of local search intensity, consistent with the outcome of the model presented in Section 2. Starting from low or no search, margins first increase and dispersion decreases with search, and it is only at higher levels of search intensity that these results reverse, with margins decreasing and dispersion increasing.[25]

These results are consistent with the predictions of the model presented in Section 2, and show that firms benefit from being able to monitor their rivals' actions when consumer search is low. The shorter time required to observe deviations drives margins up and price dispersion down. However, once local search behavior becomes more intense, these results are reversed and margins start to decrease while price dispersion increases. Finally, the relationship is the same when the analysis is performed on the within-market range and standard deviation of prices instead of the dispersion of clean prices (Figure D.7 in Online Appendix D).[26]

3.3 Who benefits from information disclosure?

The results presented in this paper show that whether margins and price dispersion increase or decrease following information disclosure depends on whether firms or consumers use the disclosure mechanism more intensively. For this reason, I finish this section by quantifying the extent to which consumers and firms benefited from the disclosure policy. To do this, I compute the expected gain from buying gasoline from the cheapest station in a market. Here, gains are defined as the difference between what a consumer would pay if purchasing at random versus visiting the cheapest gas station in the market. Because I do not allow

[25]Interestingly, the results regarding price dispersion are different from those reported in, for example, Brown and Goolsbee (2002), where price dispersion is a concave function of consumer search. This difference is driven by the dynamics of the game analyzed here. In a static context, the model presented here also predicts that price dispersion is a concave function of search. However, it is sufficient to introduce an arbitrary small lag between the time a deviation takes place and when it is observed, for the model to predict a convex relationship between price dispersion and search.

[26]In Online Appendix C.1 I show that the results remain when taking into account market-specific seasonality (columns 5–7 in Table C.5) or spatial correlation (columns 4 and 5 in Table C.7).

firms to react to consumers search (i.e., prices are kept fixed as they are observed in the data), the estimated gains are a lower bound relative to what a consumer would obtain if either firms were to compete more intensively to attract searchers or a consumer were to search across the different markets she would go through when commuting.[27]

In this setting, the results show that gains from search are, on average, \$1.8, \$5.4, and \$8.5 Chilean pesos per liter for markets defined based on a 1, 3, and 5 kilometer driving distance, respectively. This is equivalent to between 8 and 38 dollars in savings per year, depending on the market definition, for a car with a 50-liter tank that is filled once a week.[28] Though this does not seem impressive, it is a lower bound for the reasons described above. Hence, gains from search exist and, though they are relatively modest, they are consistent with those reported in other studies in similar settings (e.g., Jang, 2014). On the other hand, a back-of-the-envelope calculation using total volume of gasoline sold in 2013 shows that the average gas station increased its profits by around US\$27,000 in that year alone, suggesting that gas stations benefit the most from the introduction of the website, as they can use it to monitor the prices charged by their rivals and increase overall payoffs.[29]

In summary, the findings presented in this paper are consistent with both a supply- and demand-side response to the implementation of information disclosure, with each of these

[27] Importantly, because all stations in the sample are branded and ENAP produces most of the gasoline sold in the country, in the analysis I assume there are no differences in the quality of the gasoline sold by the different gas stations. However, the calculations presented here are limited to price differences across stations and do not consider quality differences in dimensions other than gasoline. To take into account both differences in gasoline prices and differences in quality and prices along other dimensions, it is necessary to compute differences in utility associated to changes in purchase behavior induced by search, which is beyond what I can do in this paper. For this reason, I limit the analysis to expected monetary gains from purchasing gasoline from the cheapest gas station.

[28] If one considers the case of someone who switches from paying the highest price in the market to paying the lowest one, the consumer would save between 16 and 70 dollars per year.

[29] This number is computed using data from different sources. Total volume sold in Chile, in cubic meters, is published at http://www.cne.cl/wp-content/uploads/2015/05/Venta_mensual_combustibles7.xls. This shows that 53 percent of gasoline sold in Chile corresponded to gasoline of 93 octanes. I use this number and the number of gas stations that operated in Chile in 2013 to calculate the average number of liters sold by gas stations that year. Then, I calculated the additional revenues associated with the increase in margins estimated above. Finally, I use the exchange rate from December 30, 2013, to compute gains in dollars.

dominating in different cases. These findings suggest that price disclosure allowed firms to monitor their rivals' actions and to increase their payoffs on average. However, when consumers actively engaged in search, the demand-side response to disclosure dominated and competition intensified.

4 Conclusions

Price-disclosure policies can have pro- or anti-competitive effects depending on whether consumer search—the demand-side response to disclosure—or price coordination—the supply-side response—dominates. I study how the implementation of an online price-disclosure mechanism affected consumer and firm behavior in the Chilean retail-gasoline industry, as well as the distributional consequences of the intervention. To identify the impact of price disclosure on market outcomes, I rely on the sequential implementation of the system across the country. The implementation started in March 2012 with the capital, and the rest of the country was added sequentially in the following months.

The results show that price disclosure decreased the intensity of competition on average, though there is significant heterogeneity across the country. Margins increased by 9 percent on average after the disclosure mechanism was implemented. However, margins increased the least and even decreased in high-income areas, while they increased the most in low-income areas. This suggests that the implementation of an online price-disclosure mechanism may have had important distributional consequences. Finally, the paper also shows that the heterogeneity in the impact of disclosure across locations depends on the intensity of local search behavior. While the intensity of competition decreased on average, competition increased in areas with high local search intensity.

A critical question is whether the observed change in behavior is a consequence of optimal responses to online price disclosure or to confounding factors. Based on a number of robustness checks, such as testing for increasing differentiation, changes in market structure, changes in wholesale supply, and changes in firm- or city-specific pricing behavior, this paper concludes that it is unlikely that factors other than coordination facilitated by the online price-disclosure mechanism may have caused the findings presented here.

Regarding disclosure policies in general, this paper shows that mechanisms that increase market transparency may increase competition and benefit consumers only if consumers can easily access and use the disclosed information. Otherwise, the supply-side response to disclosure (coordination) is likely to dominate, and the intensity of competition will decrease. Hence, this paper provides evidence showing that policy makers should consider ease of access to the newly disclosed information to be of major importance.

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Tables and Figures

Table 1: Summary statistics: Margins

	Unit	Mean	Std. Deviation
Inflation-adjusted margins			
Before disclosure	(CLP $/liter)	69.26	23.12
After disclosure	(CLP $/liter)	71.64	22.24
Number of observations	5795		
Station characteristics	(% of stations)		
Convenience store		42.97	
Pharmacy		4.69	
Public restrooms		37.50	
Repair shop		33.59	
Self-service pumps		17.97	
Open 24 hours		91.41	
Search requests near a	Number of requests		
station (within a month)	Per capita (mean)	Level (mean)	Level (Std. Deviation)
1 kilometer	0.0005	86.87	199.05
3 kilometers	0.0046	627.95	1324.03
5 kilometers	0.0113	1413.59	2996.35

Note: CLP$ stands for Chilean pesos.

Table 2: Summary statistics: Price dispersion (markets defined using 1 kilometer of driving distance)

	Mean	Std. Deviation
Range of prices		
Before disclosure	2.28	4.48
After disclosure	5.17	10.09
Standard deviation of prices		
Before disclosure	2.14	3.00
After disclosure	4.77	6.76
Local unexplained price variation		
Before disclosure	1.36	2.41
After disclosure	1.98	2.74
Number of markets	3537	

Note: All variables are measured in Chilean pesos per liter. The local unexplained price variation corresponds to the outcome of the two-step procedure proposed in Lewis (2008) in which prices dispersion is measured net of station-specific characteristics and common temporal shocks. The table considers markets defined using 1 kilometer of driving distance around each station. Summary statistics show a similar pattern for markets defined using 3 and 5 kilometers, though all measures are larger than for markets defined using 1 kilometer.

Table 3: Effect of disclosure on margins

	Dependent variable: margin_{it}		
	(1)	(2)	(3)
Disclosure	6.794	6.484	6.169
	[0.020]**	[0.030]**	[0.058]*
Station FE	Yes	Yes	Yes
Cost controls	Yes	Yes	Yes
Common trend	Yes	No	No
Region-specific trend	No	Yes	Yes
Year and month FE	Yes	Yes	Yes
Observations dropped			Post-August 2012
Mean margins (CLP$ per liter)	70.35	70.35	69.71
Effect as percentage of the mean	9.66%	9.22%	8.85%
R^2	0.771	0.793	0.903
N	5795	5795	3777

Note: All specifications report, in square brackets, the p-value associated with the 6-point distribution Bootstrap procedure. Clustering is at the area of intervention level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in all regressions is the (inflation-adjusted) margin of station i in period t. Margins are measured in Chilean pesos per liter (CLP$). Cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs. Specification 3 drops all observations following August 2012.

Table 4: Effect of disclosure on margins across brands

	Dependent variable: margin_{it}				
	(1)	(2)	(3)	(4)	(5)
Disclosure	8.369	6.416	6.061	6.856	6.405
	[0.076]*	[0.014]**	[0.073]*	[0.048]**	[0.064]*
Petrobras	0.188	-0.153			
	[0.615]	[0.627]			
Shell	-0.499	-0.74			
	[0.815]	[0.849]			
Terpel	-0.571	-0.499			
	[0.885]	[0.715]			
Petrobras×Disclosure		0.579	0.909		0.808
		[0.627]	[0.0627]		[0.633]
Shell×Disclosure		0.142	0.551		1.546
		[0.743]	[0.454]		[0.028]**
Terpel×Disclosure		-0.12	0.346		0.417
		[0.845]	[0.627]		[0.491]
Disclosure×Income				-2.349	-2.294
				[0.074]*	[0.077]*
Disclosure×Number of fixed Internet connections				0.338	0.239
				[0.887]	[0.887]
Disclosure×Poverty rate				-0.044	-0.116
				[0.999]	[0.961]
Disclosure×Rural population				-3.662	-3.643
				[0.224]	[0.288]
Disclosure×Number of rivals within 3 km.				-0.012	-0.02
				[0.823]	[0.601]
Station FE	No	No	Yes	Yes	Yes
Region FE	Yes	Yes	No	No	No
Cost controls	Yes	Yes	Yes	Yes	Yes
Region-specific trends	Yes	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	70.35	70.35	70.35	71.85	71.85
Effect as percentage of mean dependent variable	11.90%	9.12%	8.62%	9.54%	8.91%
R^2	0.738	0.738	0.793	0.787	0.787
N	5795	5795	5795	5020	5020

Note: All specifications report, in square brackets, the p-value associated with the 6-point distribution Bootstrap procedure. Clustering is at the area of intervention level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in all regressions is the (inflation-adjusted) margin of station i in period t. Margins are measured in Chilean pesos per liter (CLP$). Cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs.

Table 5: Effect of disclosure and search on margins

	Dependent variable: margin_{it}					
	1 kilometer		3 kilometers		5 kilometers	
	(1)	(2)	(3)	(4)	(5)	(6)
Disclosure	6.640	5.809	6.405	6.298	7.170	7.542
	[0.048]**	[0.088]*	[0.064]*	[0.064]*	[0.026]**	[0.026]**
Petrobras×Disclosure	0.837	0.829	0.808	0.843	0.764	0.783
	[0.639]	[0.645]	[0.633]	[0.631]	[0.653]	[0.647]
Shell×Disclosure	1.394	1.177	1.536	1.436	1.569	1.489
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Terpel×Disclosure	0.251	0.062	0.417	0.377	0.467	0.502
	[0.713]	[0.939]	[0.490]	[0.533]	[0.424]	[0.418]
Disclosure×Income	-2.365	-2.428	-2.294	-2.327	-2.419	-2.559
	[0.075]*	[0.249]	[0.074]*	[0.372]	[0.072]*	[0.240]
Search requests per capita		2.578		2.399		2.097
(within distance threshold)		[0.034]**		[0.067]*		[0.182]
Search requests per capita^2		-0.230		-0.216		-0.185
(within distance threshold)		[0.077]*		[0.085]*		[0.248]
Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Cost controls	Yes	Yes	Yes	Yes	Yes	Yes
Region-specific trends	Yes	Yes	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls×Disclosure	Yes	Yes	Yes	Yes	Yes	Yes
Number of rivals within distance threshold×Disclosure	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	71.85	71.85	71.85	71.85	71.85	71.85
Effect as percentage of mean dependent variable	9.24%	8.08%	8.91%	8.77%	9.98%	10.50%
R^2	0.787	0.788	0.787	0.788	0.787	0.788
N	5020	5020	5020	5020	5020	5020

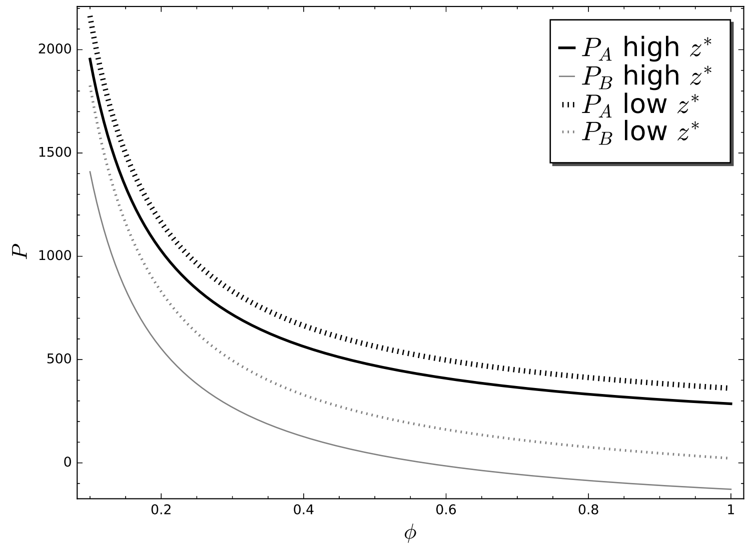
Note: All specifications report, in square brackets, the p-value associated with the 6-point distribution Bootstrap procedure. Clustering is at the area of intervention level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in all regressions is the (inflation-adjusted) margin of station i in period t. Margins are measured in Chilean pesos per liter (CLP$). Cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs. Demographic controls that are interacted with the disclosure indicator include the number of fixed Internet connections, the poverty rate, and the percentage of the population classified as rural, all at the municipality level.

Table 6: Effect of disclosure on price dispersion

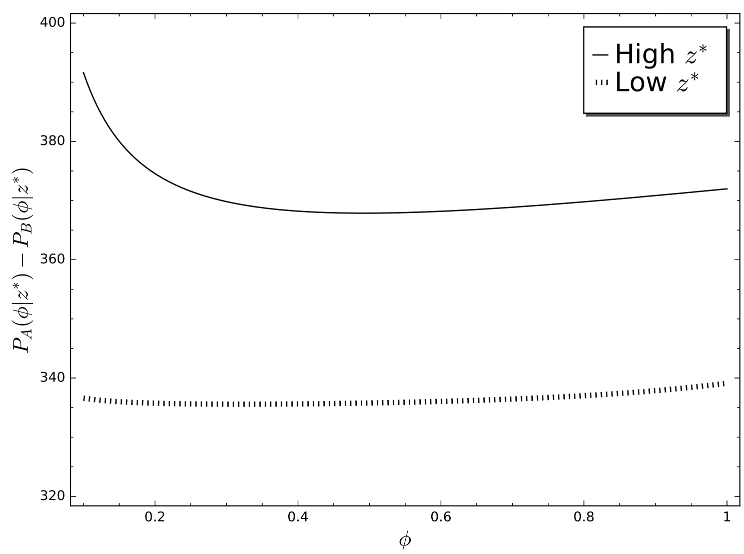
	Dep. var.: residual price dispersion					
Market definition	1 km.		3 km.		5 km.	
	(1)	(2)	(3)	(4)	(5)	(6)
Disclosure	-0.27	-0.199	0.0785	0.059	0.309	0.284
	[0.575]	[0.581]	[0.907]	[0.925]	[0.713]	[0.729]
Disclosure×Income	-0.307	-0.238	-0.216	-0.198	-0.102	-0.094
	[0.138]	[0.376]	[0.138]	[0.382]	[0.181]	[0.181]
Search requests		-0.479		-0.236		-0.234
(within distance threshold)		[0.026]**		[0.084]*		[0.221]
Search requests^2		0.052		0.034		0.039
(within distance threshold)		[0.058]*		[0.086]*		[0.201]
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Cost controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of rivals within distance threshold×Disclosure	Yes	Yes	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	1.661	1.661	1.528	12.023	1.567	1.56
R^2	0.221	0.225	0.251	0.451	0.233	0.236
N	3248	3248	4776	4782	4975	4975

Note: All specifications report, in square brackets, the p-value associated with the 6-point distribution Bootstrap procedure. Clustering is at the area of intervention level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in all regressions is the residual price dispersion after taking into consideration local competition and persistent heterogeneity across competitors. This is done following the two-step estimation approach described in Lewis (2008). Cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs.

FIGURE 1: Equilibrium prices and price dispersion as a function of parameter values



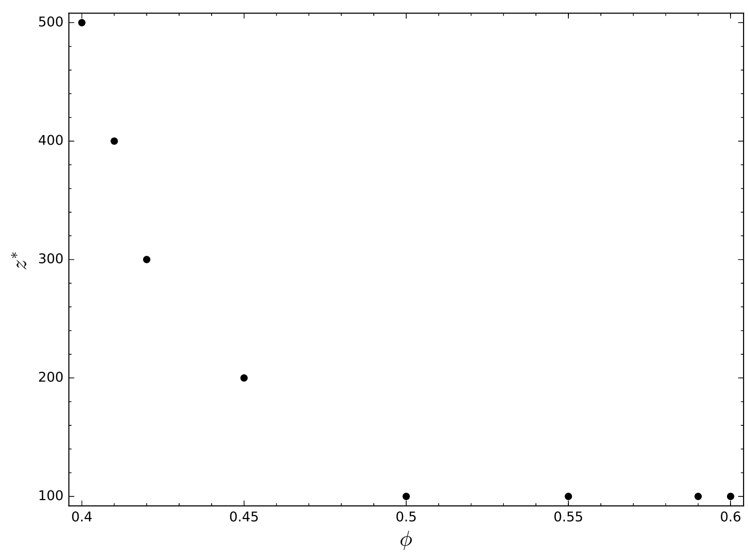
(a) Equilibrium prices



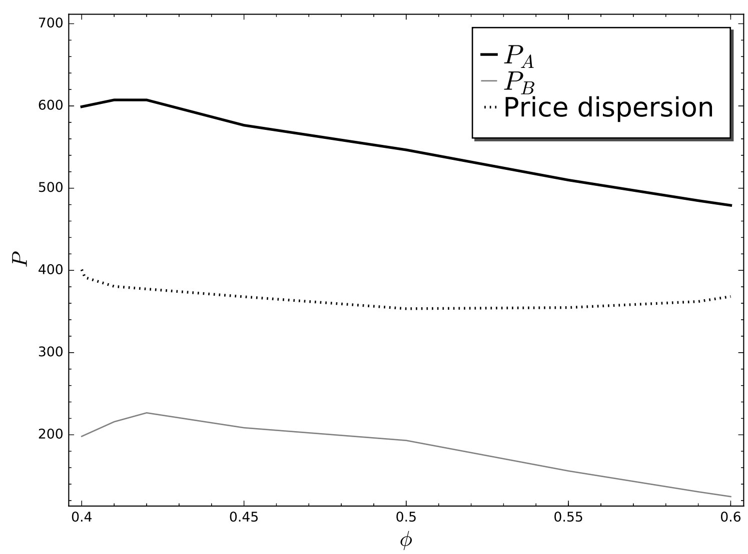
(b) Equilibrium price dispersion

Figures 1a and 1b report equilibrium prices and price dispersion as a function of the fraction of informed consumers ϕ, for two lengths of time it takes to observe deviations (high and low z^*, respectively).

Figure 2: Examples of equilibrium prices and price dispersion for different parameter values



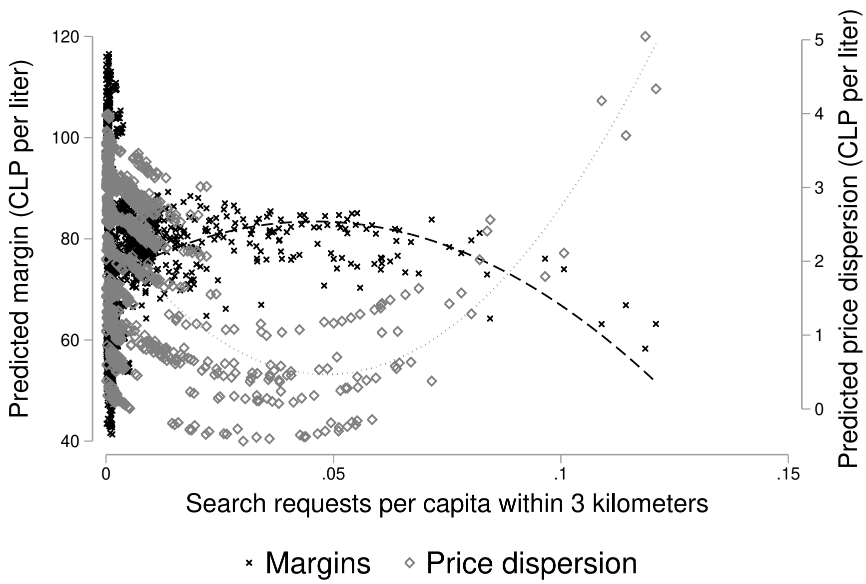
(a) Arbitrary pairs of the fraction of informed consumers and time to detection



(b) Prices and price dispersion for different parameter values

The figure examines, through examples, how prices and price dispersion change with the length of time it takes to observe deviations and the fraction of informed consumers. Figure 2a presents the inputs used in the example. From left to right, the time it takes to observe deviations first decreases sharply and then it converges to a low value, while the fraction of informed consumes increases smoothly. Figure 2b shows how these changes result in prices first increasing firms and price dispersion decreasing. However, as more consumers become informed, prices fall and price dispersion starts to increase.

Figure 3: Predicted margins and price dispersion



The figure reports predicted margins and dispersion of clean prices for markets defined using a 3-kilometer radius around gas stations. The underlying regressions correspond to Column (4) in Table 5 and Table 6. Figure D.6 in Online Appendix D presents the same figure for markets defined using a 1- and 5-kilometer radius.

Online Appendix: Not for Publication

Who Benefits from Information Disclosure?
The Case of Retail Gasoline

Fernando Luco

A Model: Nash Bargaining Solution

In this Appendix, I propose a different solution concept to the model introduced in the main text. To obtain unique predictions for equilibrium prices and price dispersion under coordination, the model in the text assumed that the firm for which consumers are willing to pay more (firm A) made a take-it-or-leave-it offer that left firm B indifferent between coordinating and deviating. Here, instead, I study how market outcomes that follow from the solution to the Nash bargaining model change as both the fraction of informed consumers and the time it takes to observe deviations by rivals changes. In all other aspects, the model is identical to that presented in the main text.

In order to simplify exposition, I first introduce some notation. Let discounted payoffs under coordination be

$$\begin{aligned}
\Pi_A^C(p_A^C, p_B^C) &= \int_0^\infty \frac{p_A^C}{2}\Big(1+\frac{\phi}{t}(\Delta+p_B^C-p_A^C)\Big)e^{-rz}dz \\
&= \frac{p_A^C}{2r}\Big(1+\frac{\phi}{t}(\Delta+p_B^C-p_A^C)\Big) \\
\Pi_B^C(p_A^C, p_B^C) &= \int_0^\infty \frac{p_B^C}{2}\Big(1-\frac{\phi}{t}(\Delta+p_B^C-p_A^C)\Big)e^{-rz}dz \\
&= \frac{p_B^C}{2r}\Big(1-\frac{\phi}{t}(\Delta+p_B^C-p_A^C)\Big).
\end{aligned}$$

Let discounted payoffs under deviation be

$$\begin{aligned}
\Pi_A^D(p_B^C) &= \frac{(t+\phi\Delta+\phi p_B^C)^2}{8\phi rt}(1-e^{-rz^*}) + \frac{(3t+\Delta\phi)^2}{18\phi rt}e^{-rz^*} \\
\Pi_B^D(p_A^C) &= \frac{(t-\phi\Delta+\phi p_A^C)^2}{8\phi rt}(1-e^{-rz^*}) + \frac{(3t-\Delta\phi)^2}{18\phi rt}e^{-rz^*}
\end{aligned}$$

Then, coordination prices that are a solution to the Nash bargaining problem with equal bargaining weights solve

$$\max_{p_A^C, p_B^C} \quad \Big(\Pi_A^C(p_A^C, p_B^C) - \Pi_A^D(p_B^C)\Big)^{\frac{1}{2}} \Big(\Pi_B^C(p_A^C, p_B^C) - \Pi_B^D(p_A^C)\Big)^{\frac{1}{2}}.$$

The first-order conditions of this problem, without specifying the arguments for each expression, can be written as

$$\begin{aligned}
\frac{\partial}{\partial p_A^C} : \ & \frac{1}{2}\Big(\Pi_A^C - \Pi_A^D\Big)^{-\frac{1}{2}}\Big(\Pi_B^C - \Pi_B^D\Big)^{\frac{1}{2}}\Big[\frac{\partial \Pi_A^C}{\partial p_A^C} - \frac{\partial \Pi_A^D}{\partial p_A^C}\Big] + \\
& \frac{1}{2}\Big(\Pi_A^C - \Pi_A^D\Big)^{\frac{1}{2}}\Big(\Pi_B^C - \Pi_B^D\Big)^{-\frac{1}{2}}\Big[\frac{\partial \Pi_B^C}{\partial p_A^C} - \frac{\partial \Pi_B^D}{\partial p_A^C}\Big] = 0 \\
\frac{\partial}{\partial p_B^C} : \ & \frac{1}{2}\Big(\Pi_A^C - \Pi_A^D\Big)^{-\frac{1}{2}}\Big(\Pi_B^C - \Pi_B^D\Big)^{\frac{1}{2}}\Big[\frac{\partial \Pi_A^C}{\partial p_B^C} - \frac{\partial \Pi_A^D}{\partial p_B^C}\Big] + \\
& \frac{1}{2}\Big(\Pi_A^C - \Pi_A^D\Big)^{\frac{1}{2}}\Big(\Pi_B^C - \Pi_B^D\Big)^{-\frac{1}{2}}\Big[\frac{\partial \Pi_B^C}{\partial p_B^C} - \frac{\partial \Pi_B^D}{\partial p_B^C}\Big] = 0,
\end{aligned}$$

which can be simplified to

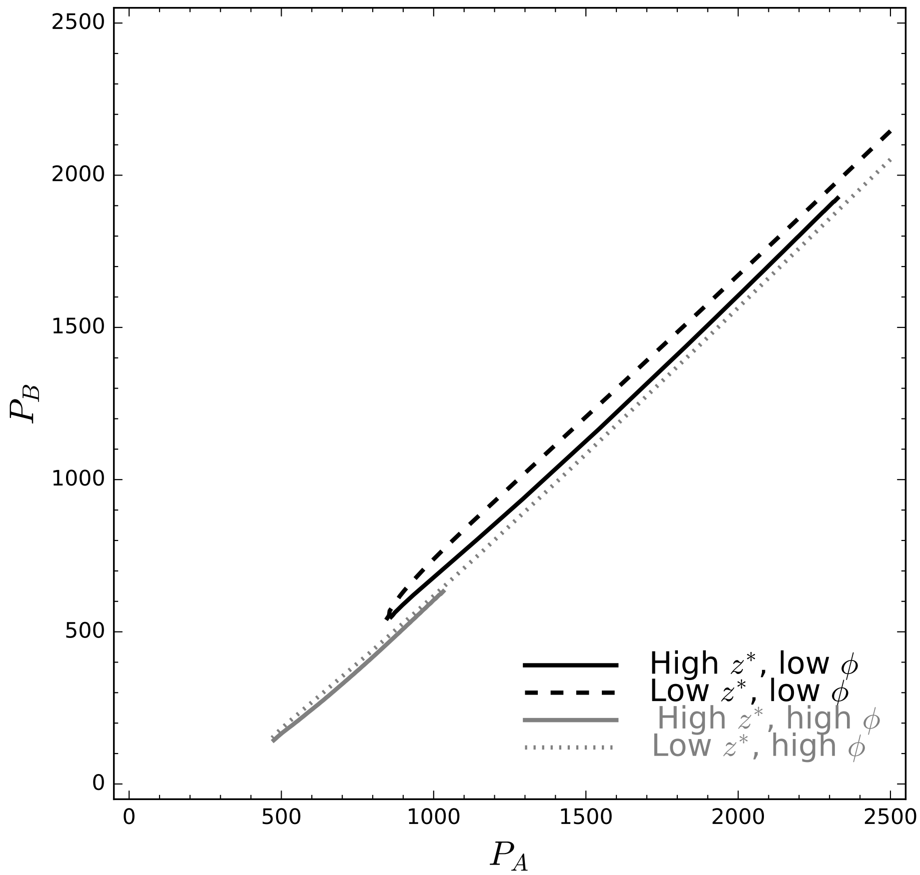
$$\frac{\Big[\frac{\partial \Pi_B^C}{\partial p_A^C} - \frac{\partial \Pi_B^D}{\partial p_A^C}\Big]}{\Big[\frac{\partial \Pi_A^C}{\partial p_A^C} - \frac{\partial \Pi_A^D}{\partial p_A^C}\Big]} = \frac{\Big[\frac{\partial \Pi_B^C}{\partial p_B^C} - \frac{\partial \Pi_B^D}{\partial p_B^C}\Big]}{\Big[\frac{\partial \Pi_A^C}{\partial p_B^C} - \frac{\partial \Pi_A^D}{\partial p_B^C}\Big]}, \tag{2}$$

which implicitly defines all pairs p_A^C and p_B^C that can be sustained under coordination for the Nash bargaining problem with equal bargaining weights of $\frac{1}{2}$. This relationship is presented in Figure A.1 for different values of the fraction of informed consumers ϕ and the time it takes to observe a deviation from a rival z^*.

Figure A.1 provides a number of useful insights. First, sustainable prices are below the 45-degree line (not shown) because of vertical differentiation. That is, firm A is able to charge higher prices.

Second, the solid lines present two cases that differ in the fraction of informed consumers, for the same length of time that it takes to observe a deviation. That is, comparing the solid black (low ϕ) and gray (high ϕ) lines allows me to compare how increasing the fraction of informed consumers affects prices and price dispersion under coordination. This comparison gives two interesting results. First, price dispersion is lower when fewer consumers are informed, as the set of prices that is sustainable under coordination for low values of ϕ is

Figure A.1: Equilibrium prices under Nash bargaining



The figure examines how the set of prices that are a solution to the Nash bargaining problem with equal bargaining weights varies with the fraction of informed consumers and the time it takes to observe deviations by rivals.

closer to the 45-degree line than under higher values of ϕ. Second, prices are lower as more consumers are informed.

Third, same-colored lines (say, dashed black and solid gray) compare situations with the same fraction of informed consumers but different lengths of time that it takes to observe deviations from a rival. In both cases, we observe that dashed lines, which represent lower times needed to detect deviations, result in higher prices and lower price dispersion, consistent with the results presented in Figure 1 in Section 2.

Finally, to compare how changes in both the fraction of informed consumers ϕ and the time it takes to observe deviations z^* affect market outcomes, we need to compare, for example, the solid black line (low ϕ, high z^*) with the dotted gray line (high ϕ, low z^*). In this case, the comparison is not obvious. On the one hand, for most price pairs it is possible to say that prices decrease when moving from the solid black to the dotted gray line. However, there is a region in which prices could be higher under the dotted gray line relative to the solid black one. Similarly, for most price pairs dispersion appears to be lower under the solid black line as it is closer to the 45-degree line, but depending on the parameter values, dispersion is lower under the dotted gray line for low price pairs. That is, the overall impact of information disclosure on market outcomes depends on the region in which outcomes lay as more consumers become informed and it takes firms less time to observe deviations.

B The Cities in the Data

The cities considered in this paper are determined by the data published by the CNE, which provides information on cities in six regions of the country. These cities are regional capitals, meaning that the regional administrative offices are located within them and they comprise most of the population (59.3 percent in 2012) and services in the region. Table B.1 summarizes demographic information at the municipality level obtained from the SINIM (2016) dataset. The table shows that, on average, these municipalities have slightly less than 200,000 people, the mean poverty rate is 12 percent, and very few people live in rural areas (and none in the city of Santiago). Hence, the cities studied in this paper are large relative to those in the rest of the country.

Table B.1: Summary statistics. Demographic information by municipality (year is 2013)

	Poverty rate (%)	Population	Rural population (% of total)
Valparaíso	16.13	267853	0.156
Rancagua	8.99	253189	4.46
Talca	17.51	253742	4.88
Concepción	21.48	230255	2.88
Punta Arenas	5.42	125712	2.16
Santiago	5.71	156049	0
Cerro Navia	14.64	129630	0
Conchalí	10.83	101796	0
Estación Central	17.61	107335	0
Independencia	8.23	48565	0
La Cisterna	7.46	68370	0
La Florida	9.21	396684	0
La Granja	15.94	120144	0
La Reina	7.12	94037	0
Las Condes	1.38	291971	0
Maipú	9.2	931211	0
Ñuñoa	5.16	140531	0
Quinta Normal	11.44	83187	0
Recoleta	11.53	119303	0
San Joaquín	26.87	73197	0
San Miguel	12.97	68855	0

Note: The table summarizes demographic information obtained from the SINIM (2016) dataset for each of the municipalities in the analysis. The first five municipalities correspond to cities other than Santiago. All municipalities that follow, starting with Santiago, are within the urban area of the city of Santiago (which explains why the rural population is zero for all of them). Further, though all municipalities located in cities other than Santiago do have rural population, the stations in the sample are located within their urban areas.

C Tables

C.1 Alternative mechanisms

In this Section, I explore five reasons that could lead to increasing margins following the implementation of online price disclosure.

First, I explore whether changes in margins could be explained by changes in city-specific pricing practices. To do this, I estimate a series of specifications that replicate the main regression but drop one city at a time. The results from this exercise are presented in Table C.1, where each column corresponds to a specification that does not consider the city that is specified at the top of each column. The results show that, though the point estimates do change when the cities under consideration change, the main finding remains, as margins increased between 8 and 11 percent.

TABLE C.1: Effect of disclosure on margins (Robustness analysis 1: excluding one city at a time)

	Dependent variable: margin_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
Excluding:	Valparaíso	Rancagua	Talca	Concepción	Punta Arenas	Santiago
Disclosure	6.857	5.284	6.455	5.463	7.999	7.997
	[0.038]**	[0.052]*	[0.032]**	[0.102]	[0.064]*	[0.066]**
Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Cost controls	Yes	Yes	Yes	Yes	Yes	Yes
Region-specific trends	Yes	Yes	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	69.74	66.02	68.98	66.65	70.594	82.899
Effect as percentage of mean dependent variable	9.83%	8.00%	9.36%	8.20%	11.33%	9.65%
R^2	0.824	0.774	0.806	0.793	0.811	0.527
N	4906	4825	5224	4789	5420	3811

Note: All specifications report, in square brackets, the p-value associated with the 6-point distribution Bootstrap procedure. Clustering is at the area of intervention level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in all regressions is the (inflation-adjusted) margin of station i in period t. Margins are measured in Chilean pesos per liter (CLP$). Each specification drops all observations from stations located in the specified city. Cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs.

Second, I explore whether the website allowed stations to inform consumers about the services they offer. This would allow stations to further differentiate from each other, potentially increasing the margins of some stations. Importantly, I do not assume that stations change the services they offer following disclosure, but that they use the website to inform consumers of the services they already offered before the website was available. Though stations could change the services they offer following disclosure, this type of response is likely to take longer to be implemented and the data available would not allow me to identify it. For this reason, I focus on whether stations make use of the website to advertise the services they already offered before the website was implemented. The results, reported in Table C.2, show that this is not the case. In general, neither the indicator variables associated with each of the services offered nor the interaction of these indicators and the indicator for disclosure are significant.

Third, I explore whether margins could have increased because of a merger that took place in 2013. In 2013, the Chilean Supreme Court ruled against a previous decision of the Chilean *Tribunal de Defensa de la Libre Competencia* (the Chilean Competition Court) and authorized, with a number of remedies, a merger between Shell and Terpel. The ruling by the Supreme Court took place in January 2013, while the merger took place in June of the same year. I take this into account in two ways. First, I drop all observations that correspond to the merging parties for the period after the merger was approved (January 2013). Second, instead of dropping all observations that followed the approval of the merger, I drop all observations of the merging parties that followed the moment when the merger took place (June 2013). The results are reported in the first two columns of Table C.3 and show that the merger did not cause increases in prices that could be confounded with those of disclosure, which is consistent with the results reported in the last specification of Table 3.

Fourth, I examine whether the estimated effects may have been caused by (common) station ownership. The second one deals with possible demand relocation depending on the relative exposure of a station to traffic and consumers. The estimated coefficients associated with specifications that take these possible mechanisms into account are presented in Table C.4. The first column controls for the identity of the owner or manager of a station

Table C.2: Effect of disclosure on margins (Robustness analysis 2: controlling for station characteristics)

	Dependent variable: margin_{it}	
	(1)	(2)
Disclosure	9.56	9.076
	[0.034]**	[0.042]**
Convenience store	3.138	3.326
	[0.322]	[0.290]
Convenience store×Disclosure	-0.688	-1.015
	[0.414]	[0.314]
Pharmacy	-6.432	-7.099
	[0.663]	[0.324]
Pharmacy×Disclosure	5.891	6.85
	[0.128]	[0.112]
Public restrooms	0.663	1.326
	[0.699]	[0.096]*
Public restrooms×Disclosure	-1.855	-2.668
	[0.146]	[0.058]*
Repair service	1.76	1.715
	[0.108]	[0.108]
Repair service×Disclosure	-1.977	-1.844
	[0.048]**	[0.062]*
Has self-service pumps	-1.882	-1.95
	[0.294]	[0.210]
Has self-service pumps×Disclosure	0.832	0.526
	[0.673]	[0.647]
Open 24 hours	2.455	2.128
	[0.881]	[0.857]
Open 24 hours×Disclosure	-1.855	-1.467
	[0.919]	[0.903]
Station FE	No	No
Brand FE	No	Yes
Brand FE×Disclosure	No	Yes
Cost controls	Yes	Yes
Region FE	Yes	Yes
Region-specific trends	Yes	Yes
Year and month FE	Yes	Yes
Mean dep. Var.	70.12	70.12
Effect as % of dep. Var.	13.63%	12.94%
R^2	0.745	0.746
N	5676	5676

Note: All specifications report, in square brackets, the p-value associated with the 6-point distribution Bootstrap procedure. Clustering is at the area of intervention level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in all regressions is the (inflation-adjusted) margin of station i in period t, with margins measured in Chilean pesos per liter (CLP$). Cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs.

Table C.3: Effect of disclosure on margins (Robustness Analysis 3: mergers)

	Dependent variable: margin_{it}	
	(1)	(2)
Disclosure	6.392	6.607
	[0.028]**	[0.028]**
Station FE	Yes	Yes
Cost controls	Yes	Yes
Region-specific trends	Yes	Yes
Year and month FE	Yes	Yes
Merger defined on	January 2013	June 2013
Mean dependent variable	70.33	70.41
Effect as percentage of mean dependent variable	9.09%	9.38%
R^2	0.81	0.803
N	5260	5486

Note: Both specifications report, in square brackets, the p-value associated with the 6-point distribution Bootstrap procedure. Clustering is at the area-of-intervention level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In both regressions the dependent variable is the (inflation-adjusted) margin of station i in period t, with margins measured in Chilean pesos per liter (CLP$). The first specification drops all observations following the approval of the merger for the parties involved in the transaction. The second specification drops all observations of the parties involved in the transaction following the moment when the merger took place (June 2013). Cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs.

and shows that adding this control has little impact on the coefficient of disclosure. This is due to 83 percent of the stations in the sample being owned by a single-station owner.[30] Column 2 adds municipality fixed effects and shows that these have little impact on the estimates. Column 3 replaces the owner fixed effects by an indicator showing the number of stations with which a station shares ownership. The difference between this specification and the previous two is that the number of stations with common ownership is computed over the universe of stations in Chile rather than just those in the sample. Controlling for this, however, has no impact on the results. Finally, column 4 includes an interaction between the number of stations with common ownership and the disclosure indicator. Overall, the results show that margins increased by around 9 percent and that this increase was not related to station ownership.

Fifth, Table C.4 also examines whether the intervention may have reallocated demand across stations. In other words, consumers can use the website to search for prices at gas stations that were not on their commuting path before the intervention. In this case, demand for gasoline at these "less visible" stations may have increased as consumers deviated from their commuting paths to visit them. To test this hypothesis, one would need information about purchases both before and after the intervention, or on commuting paths, also before and after the intervention. These data, however, are not available.[31] For this reason, I follow an alternative approach that relies on the importance of the location of a station relative to its competitors in the same geographical area. I do this by classifying stations depending on whether they operate on a major street, as stations that operate on major streets are more visible and exposed to more traffic than stations that operate on other streets, within the same municipality. In this setting, the policy intervention could lead gas stations to sort into serving searchers or non-searchers, decreasing margins in the former case and increasing them in the latter. The results, reported in Table C.4, columns (5) and

[30]Ownership information was provided by SEC and corresponds to the identity of the person registered in their records as being responsible for a station.

[31]The Chilean government has performed Origin–Destination studies on a number of cities at different points in time. None of these studies, however, is useful for this application as they either focus on a single point in time without covering the areas in which the stations in the SERNAC sample are located or do not cover the same cities as this paper.

(6), show that this was not the case and margins increased across all stations, though they increased the most across stations located on major streets. Because in the example just given, stations located on major streets are more likely to serve a higher fraction of non-searchers after the intervention, this result suggests that some demand relocation may have taken place. However, because margins increased across all stations, coordination seems to have dominated in the context studied in this paper.

Table C.4: Effect of disclosure on margins (Robustness Analysis 4: ownership and location)

	Dependent variable: margin_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
Disclosure	6.809	6.068	6.251	6.238	5.299	5.082
	[0.018]**	[0.022]**	[0.016]**	[0.016]**	[0.042]**	[0.064]*
Major street×Disclosure					2.146	2.286
					[0.068]*	[0.062]*
Station FE	No	No	No	No	No	Yes
Major street FE	No	No	No	No	Yes	No
Owner FE	Yes	Yes	No	No	No	No
Municipality FE	No	Yes	Yes	Yes	Yes	No
Number of stations with the same owner	No	No	Yes	Yes	No	No
Number of stations with the same owner×Disclosure	No	No	No	Yes	No	No
Number of rivals within 3 km.	No	No	Yes	Yes	Yes	No
Number of rivals within 3 km×Disclosure	Yes	Yes	Yes	Yes	Yes	Yes
Cost controls	Yes	Yes	Yes	Yes	Yes	Yes
Region-specific trends	Yes	Yes	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	71.85	71.85	71.85	71.85	70.12	70.35
Effect as percentage of mean dependent variable	9.48%	8.45%	8.70%	8.68%	7.56%	7.22%
R^2	0.771	0.784	0.77	0.768	0.775	0.793
N	5020	5020	5020	5020	5676	5795

Note: All specifications report, in square brackets, the p-value associated with the 6-point distribution Bootstrap procedure. Clustering is at the area of intervention level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in all regressions is the (inflation-adjusted) margin of station i in period t. Margins are measured in Chilean pesos per liter (CLP$). Specifications (1)–(4) study whether (common) ownership across stations affects margins. Specifications (5) and (6) study whether stations located on major streets experience different changes in margins than stations located on secondary streets. Cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs.

C.1.1 Robustness

I now consider a number of robustness checks related to the main specification reported in Table 3. Thee robustness specifications examine whether the results are driven by i) market-specific seasonality, ii) stations located at the extremes of the search distribution, and iii) whether considering spatial correlation may affect inference.

I first consider whether the different locations may have experienced market-specific seasonality that could be confounded with the effects of implementing an online price-disclosure mechanism. To do this, I introduce market–month-of-year fixed effects, which capture any market-specific seasonality that could be confounded with the impact of the policy. The results, presented in Table C.5, show that this is not the case.

Second, I now turn to examining whether the results are driven by stations that are located at the extremes of the search-request distribution. I do this by eliminating observations from stations in the top and bottom 1 percent of the search distribution.

Finally, to consider whether spatial correlation may play a role in inference, I estimate a number of specifications in which standard errors are computed according to Conley (1999) and show that this is not the case.

Table C.5: Effect of disclosure on margins (Robustness Analysis 5: market-specific seasonality)

	Inflation-adjusted margins				Residual price dispersion		
	Baseline	1 km.	3 km.	5 km.	1 km.	3 km.	5 km.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Disclosure	6.165	5.867	6.024	6.757	-0.104	0.123	0.141
	[0.054]*	[0.091]*	[0.044]**	[0.136]	[0.657]	[0.981]	[0.798]
Search requests per capita		3.074	2.585	2.147	-0.523	-0.162	-0.15
(within distance threshold)		[0.038]**	[0.058]*	[0.172]	[0.044]**	[0.050]*	[0.188]
Search requests per capita^2		-0.308	-0.252	-0.208	0.058	0.028	0.035
(within distance threshold)		[0.098]*	[0.085]*	[0.134]	[0.048]**	[0.043]**	[0.142]
Cost controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of rivals within distance threshold$\times$Disclosure	No	Yes	Yes	Yes	Yes	Yes	Yes
Region-specific trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and market-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	70.12	71.85	71.85	71.85	1.661	1.661	1.567
Effect as percentage of mean dependent variable	8.79%	8.17%	8.38%	9.40%	-6.26%	7.41%	9.00%
R^2	0.804	0.815	0.815	0.814	0.413	0.413	0.397
N	5676	5020	5020	5020	3248	3248	4975

Note: All specifications report, in square brackets, the p-value associated with clustering at the intervention level using the 6-point distribution Bootstrap procedure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports estimates for four specifications in which the dependent variable corresponds to inflation-adjusted margins and three in which it corresponds to residual price dispersion. Measures of search intensity are standardized. In all specifications, cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs.

Table C.6: Effect of disclosure on margins (Robustness Analysis 6: dropping stations at the top and bottom 1 percent of the search distribution)

	Dep. var.: Inflation-adjusted margins		
Market definition	1 km.	3 km.	5 km.
	(1)	(2)	(3)
Disclosure	5.840	6.194	6.691
	[0.067]*	[0.065]*	[0.080]*
Petrobras×Disclosure	0.952	0.883	0.494
	[0.639]	[0.657]	[0.857]
Shell×Disclosure	1.647	1.717	2.108
	[0.000]***	[0.000]***	[0.000]***
Terpel×Disclosure	0.201	0.301	0.327
	[0.803]	[0.643]	[0.651]
Disclosure×Income	-2.674	-2.707	-2.399
	[0.193]	[0.259]	[0.787]
Search requests per capita	2.716	2.117	0.699
(within distance threshold)	[0.087]*	[0.093]*	[0.311]
Search requests per capita^2	-0.416	-0.347	-0.149
(within distance threshold)	[0.071]*	[0.189]	[0.312]
Station FE	Yes	Yes	Yes
Cost controls	Yes	Yes	Yes
Region-specific trends	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes
Demographic controls×Disclosure	Yes	Yes	Yes
Number of rivals within distance threshold×Disclosure	Yes	Yes	Yes
Mean dependent variable	72.15	72.09	71.85
Effect as percentage of mean dependent variable	6.98%	8.51%	9.31%
R^2	0.785	0.784	0.792
N	4644	4675	4641

Note: All specifications report, in square brackets, the p-value associated with clustering at the intervention level using the 6-point distribution Bootstrap procedure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in all regressions corresponds to inflation-adjusted margins. The regressions exclude the lower and upper 1 percent of observations in the distribution of search requests. In all specifications, cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs.

TABLE C.7: Effect of disclosure on margins (Robustness Analysis 7: standard errors as in Conley 1999)

	Inflation-adjusted margins			Residual price dispersion	
	Baseline	1 km.	3 km.	1 km.	3 km.
	(1)	(2)	(3)	(4)	(5)
Disclosure	6.484	6.394	5.757	0.821	0.809
	[0.034]**	[0.070]*	[0.068]*	[0.038]**	[0.167]
Search requests per capita		4.865	4.238	-0.611	-0.260
(within distance threshold)		[0.071]*	[0.105]	[0.001]***	[0.084]*
Search requests per capita^2		-0.501	-0.433	0.051	0.024
(within distance threshold)		[0.052]*	[0.087]*	[0.022]**	[0.022]**
Station FE	Yes	Yes	Yes	Yes	Yes
Cost controls	Yes	Yes	Yes	Yes	Yes
Number of rivals within distance threshold×Disclosure	No	Yes	Yes	Yes	Yes
Region-specific trends	Yes	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	70.33	71.85	71.85	1.661	1.528
R^2	0.810	0.788	0.788	0.2243	0.252
N	5260	5020	5020	3248	4776

Note: The table reports estimates for three specifications in which the dependent variable corresponds to inflation-adjusted margins and two in which it corresponds to residual price dispersion. p-values are based on standard errors computed following Conley (1999), with a distance threshold of 100 kilometers. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Measures of search intensity are standardized. In all specifications, cost controls refer to the interaction between oil prices and the distance from each station to the main pipeline in the city of Santiago, to control for changes in distribution costs.

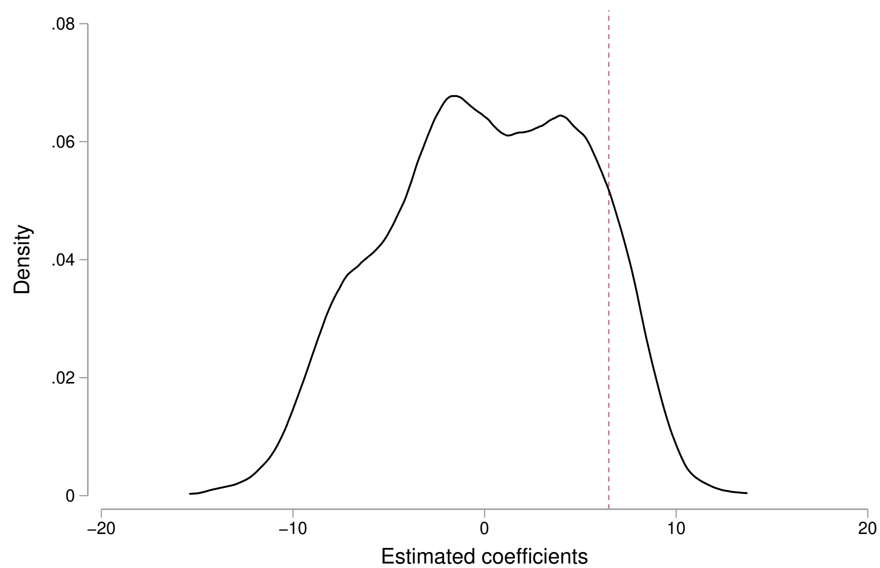
C.2 Placebos

To examine to what extent the estimated effects could have happen by chance, I perform two placebo exercises. In both exercises, the moment at which treatment starts in each intervention area is randomly drawn from the sample period. An area is considered treated for all periods following the moment at which it was assigned treatment. The difference between the two exercises is that in the first one I do not consider the order in which the intervention actually took place, while in the second one I do. This is, while in the first exercise the moment of treatment is drawn independently for each intervention area, in the second exercise the order of intervention is the same as in the data but the moment at which the intervention starts is drawn randomly. This means that in the first exercise the resulting rollout sequence differs from the real rollout sequence in both the moment when interventions take place and also in the order in which regions are treated. The rollout sequence in the second case, however, only differs from the real rollout sequence in the moment at which the intervention starts.

It is important to note that because all areas of intervention are treated in the data, and the placebos only consider randomly assigning the moment at which treatment starts, the resulting treatment periods consider months during which the different areas where actually treated. In other words, if an area of intervention is randomly assigned treatment before the moment in which it was actually treated, the resulting placebo considers as treated both months in which the area was not treated (e.g., the months between the randomly-drawn initial treatment period and the month before when that area was actually treated) and months in which it was (e.g., the months during which that area was actually treated). Similarly, if an area is assigned treatment after it was actually treated, the resulting placebo considers as treated a subset of the months in which the area was actually treated.

I perform both placebo exercises 10,000 times and recover the distribution of the estimated effects. I use these distributions to compute the p-value associated with the estimated effect reported in Table 3. Figure C.1 reports both the distribution of the estimated placebo effects and the effect reported in Table 3. The figure shows that the distribution is centered at zero and that the estimated effect is at the top of the distribution, with an associated p-value of 0.0916, which suggest that there is a low probability that the effect was estimated by chance. I do not report the distribution associated with the second placebo exercise because imposing the same order of treatment across areas as in the data, results in only 48 possible placebos as the month in which the first area of intervention is treated defines the placebo exercise. Nonetheless, the p-value of the estimated effect in this case is 0.0652, which also suggests that the effects have a low probability of being estimated by chance.

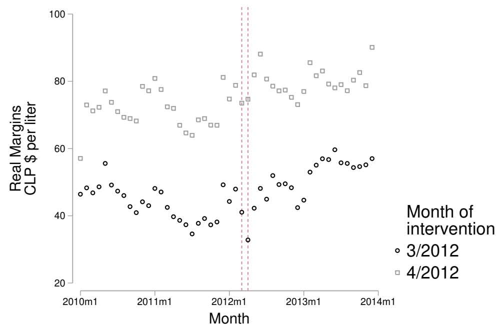
FIGURE C.1: Distribution of placebo estimates



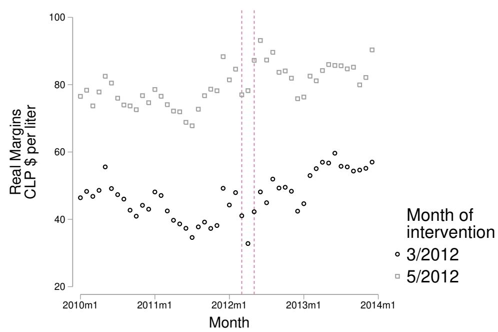
The figure reports the distribution of the placebo estimate, based on 10,000 repetitions, where the moment at which treatment starts in each intervention area is randomly drawn from the sample period. The vertical line corresponds to the estimated value of 6.48, with a p-value of 0.0916.

D Figures

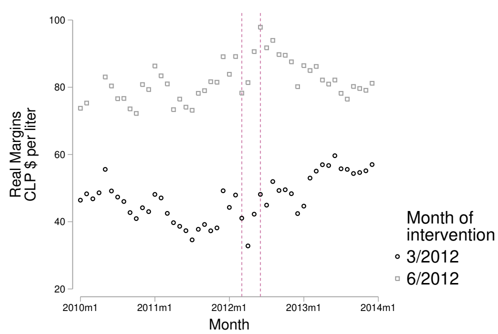
Figure D.1: Mean margins by area of intervention



(a) Areas 1 and 2



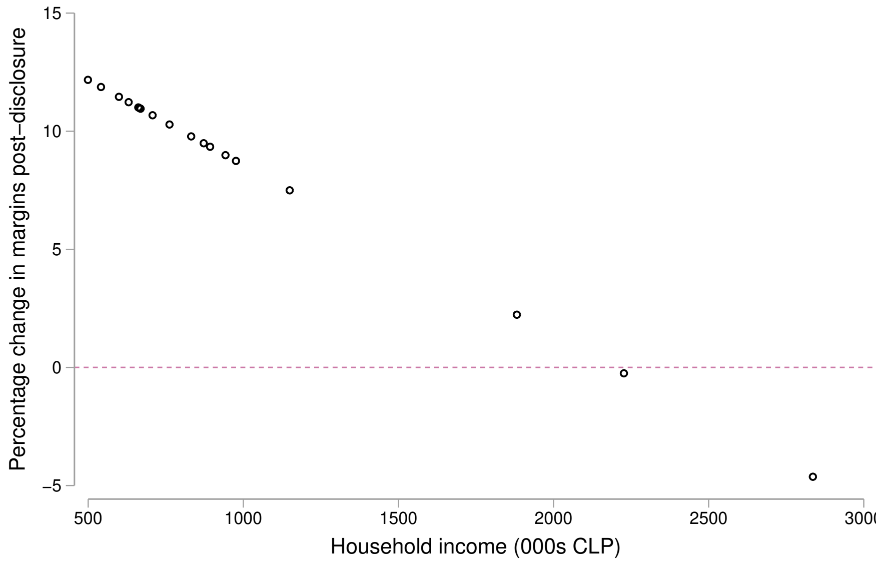
(b) Areas 1 and 3



(c) Areas 1 and 4

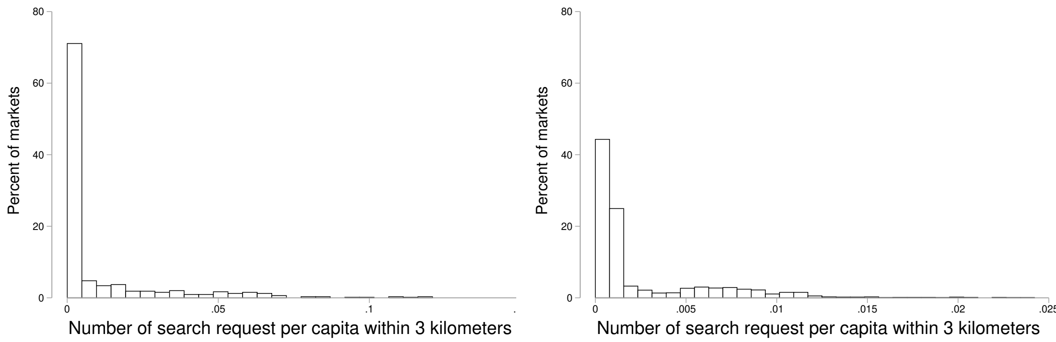
The figure presents the evolution of mean margins across areas of intervention. The vertical red lines denote the moment the website became operative in the areas of intervention presented in the figure.

Figure D.2: Estimated percentage change in margins by household income level



The figure reports the estimated percentage changes in margins over the range of household income observed in the data. In the figure, household income is measured in thousands of Chilean pesos per month. In the data, monthly household income ranges between 430,000 and 2,837,000 Chilean pesos per month. At the average exchange rate between US dollars and Chilean pesos of 2012, monthly household income in US dollars ranged between $886 and $5,826. The underlying regressions correspond to Column (4) in Table 4.

Figure D.3: Distribution of search intensity across markets

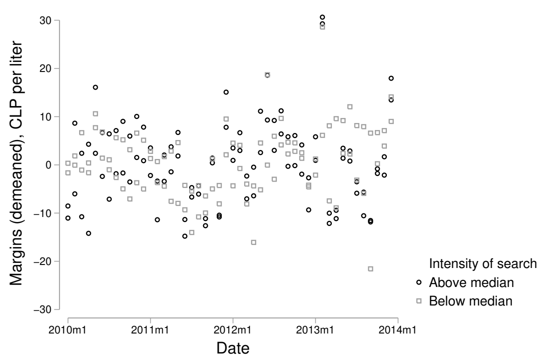


(a) 2012

(b) 2013

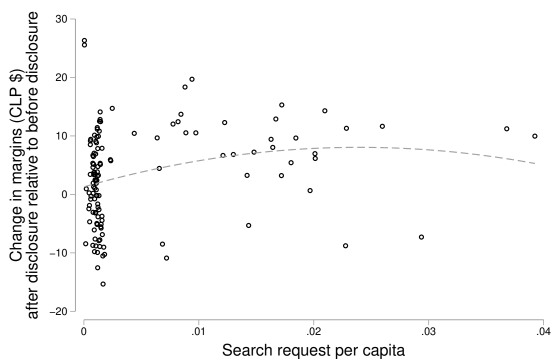
The figures report the distribution of search intensity in the neighborhood of gas stations for 2012 and 2013.

Figure D.4: Margins and ex-post search intensity



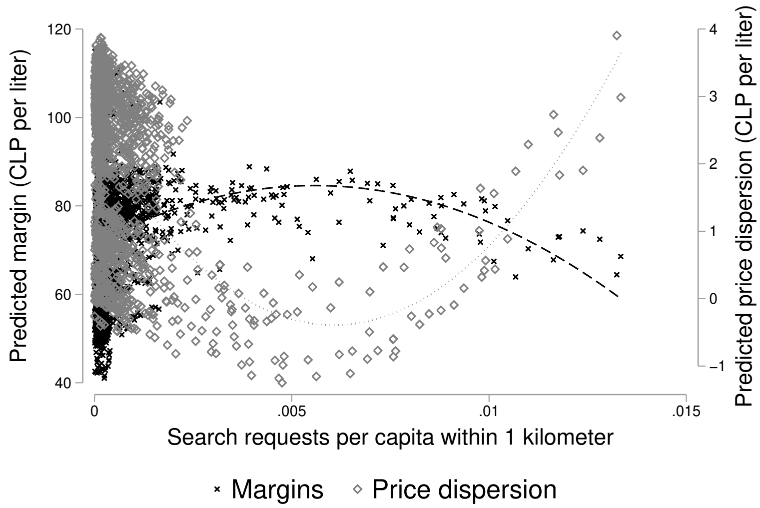
The figure reports the evolution of margins classifying stations by the intensity of search during the post-disclosure period.

Figure D.5: Margins and ex-post search intensity

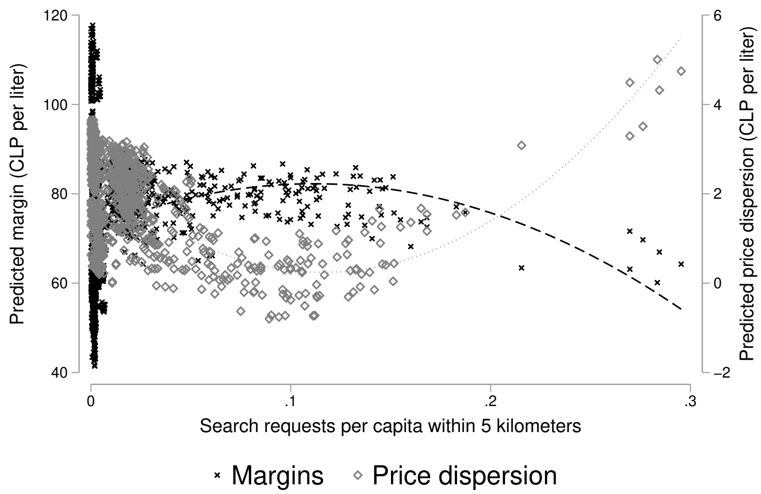


The figure reports changes in margins after disclosure relative to before disclosure, at the station level, as a function of average search intensity in the neighborhood of each station during the post-disclosure period. In the figure, markets are defined using a 3-kilometer radius around gas stations. The figures are similar using both a 1- and 5-kilometer radius.

FIGURE D.6: Predicted margins and price dispersion by market definition



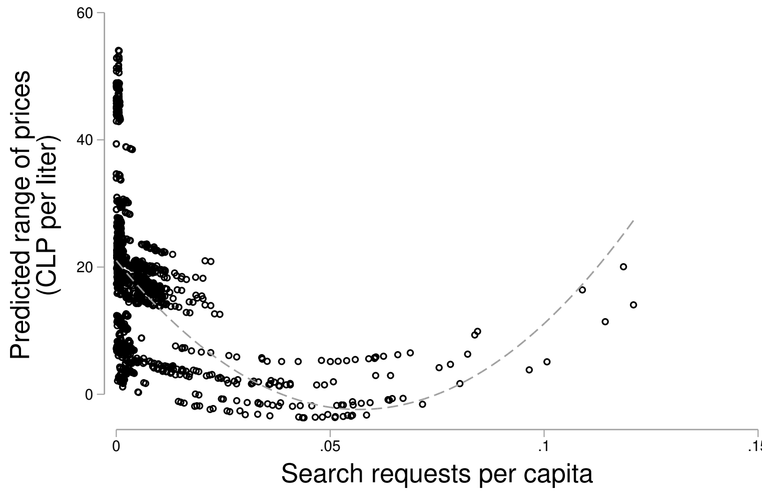
(a) 1 kilometer



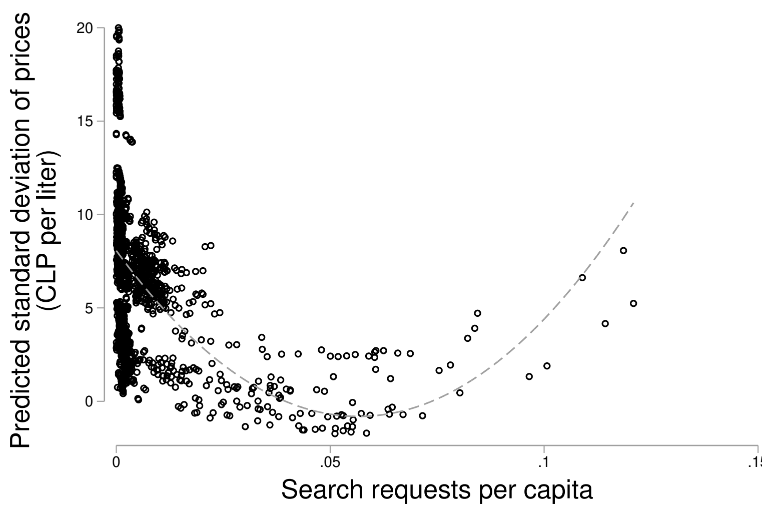
(b) 5 kilometers

Figure D.6a reports predicted margins and (cleaned) price dispersion for markets defined using a 1-kilometer radius around gas stations. Figure D.6b present the same predicted outcomes using markets defined using a 5-kilometer radius. The underlying regressions for the predicted margins are columns (2) and (6) of Table 5. The underlying regressions for predicted price dispersion correspond to those in Table 6.

Figure D.7: Predicted range and standard deviation of prices as a function of local search intensity



(a) Range of prices



(b) Standard deviation of prices

The upper panel plots the predicted range of prices for markets defined using a 3-kilometer radius around gas stations. The lower panel repeats the analysis using the predicted standard deviation of prices for the same market definition. The figures are similar for markets defined using a 1- and 5-kilometer radius around gas stations. The underlying regressions for predicted price dispersion correspond to those in Table 6.