

Informed Sources and the Role of Platforms for Facilitating Anticompetitive Communication*

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September 2, 2022

Abstract

This chapter discusses the *Informed Sources* matter from the Australian retail gasoline industry. Informed Sources is a data and analytics platform that facilitates near real-time, station-level price sharing among major gasoline retailers. In 2014, the government initiated proceedings against Informed Sources and major gasoline retailers that subscribed to it, contending that the platform likely substantially lessened competition by enabling price signaling and monitoring. Through a narrative example, we frame the Informed Sources matter and the key economic issues at play. Then, using rich real-time pricing data from the industry, we provide evidence on how such information sharing platforms facilitate anticompetitive conduct by reducing the cost of price signaling and enhancing its effectiveness in coordinating prices. Lastly, we discuss the matter and our empirics in the context of emerging research and antitrust cases, focusing on how cartels operate and how price-sharing platforms can serve as facilitating devices. In contrast to the extensive literature focusing on the role of monitoring in sustaining collusion, our results expand our understanding of how platforms enable low-cost, effective price signaling, making prices a medium of communication.

*We are grateful to Xiaosong Wu for research support and for funding from the Australian Research Council (DP21010231 and DP200103574). Simon Loertscher and seminar participants at Monash University provided helpful comments and suggestions. Disclosures: David P. Byrne, A. Rachel Grinberg, and Leslie M. Marx were retained by the Australian Competition and Consumer Commission for the Informed Sources matter, while Nicolas de Roos was retained by 7-Eleven. Disclaimers: Everywhere collusion is mentioned in this document, it is meant in the economic and not the legal sense. The interpretations of all results are those of the authors and do not necessarily represent those of the Australian Competition and Consumer Commission.

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1 Chapter overview

In this chapter, we examine the role of a platform in facilitating anticompetitive price signaling through a case study based on the *Informed Sources* matter.¹ The matter involves price coordination among retail gasoline stations in Melbourne, Australia, facilitated by a price information sharing platform from a retail data and analytics company called Informed Sources. The case was brought by the Australian Competition and Consumer Commission (ACCC), centering on Informed Sources and its arrangements with gasoline retailers in Melbourne. In the ACCC’s words:

“The ACCC alleges that the arrangements were likely to increase retail petrol price coordination and cooperation, and were likely to decrease competitive rivalry”

...

“The ACCC alleges that fuel retailers can use, and have used, the Informed Sources service as a near real time communication device in relation to petrol pricing. In particular, it is alleged that retailers can propose a price increase to their competitors and monitor the response to it. If, for example, the response is not sufficient, they can quickly withdraw the proposal and may punish competitors that have not accepted the proposed increased price”

– Rod Sims, ACCC Chair, August 20, 2014 (ACCC, 2014)

As we discuss, the gasoline retailers coordinated anticompetitive pricing not through meetings in smoke-filled rooms but through *signaling* using Informed Sources’ platform. In particular, the price information sharing service allowed the coordinating retailers to observe each other’s prices, station by station, and know that these prices were observed by the others, at a frequency of approximately 15-30 minutes. In addition, the real-time price information provided by the platform allowed retailers to *monitor* any deviations from their coordinated pricing strategies.

Because the economics literature has already given much attention to the role of monitoring in facilitating collusion, this case study focuses on the signaling role of the platform.² In

¹Australian Competition and Consumer Commission v. Informed Sources (Australia) Pty Ltd.

²An extensive literature studies collusion under imperfect monitoring. In particular, if colluding firms monitor each other by observing their own sales, and if they can commit to sufficiently harsh punishments for cheating on a collusive agreement, collusion is sustainable (Friedman, 1971; Green and Porter, 1984; Harrington, 2006; Ivaldi et al., 2007). In our setting of retail gasoline, another imperfect monitoring mechanism that is potentially available to retailers is employing price spotters (such as taxi drivers) to phone in their observations on rivals’ prices. Real-time price information sharing platforms move firms toward perfect monitoring. In doing so, they allow firms to more easily and quickly detect secret price cutting and enact punishments, which facilitates collusion (Harrington, 2011; Luco, 2019).

particular, we examine how a price information sharing platform enables firms to overcome otherwise significant challenges in coordinating their conduct in the face of imperfect signaling and the absence of explicit direct communication. Combining insights from the Informed Sources matter with rich gasoline price data, we illustrate how a platform facilitates anticompetitive coordination by reducing the risks and costs associated with price leadership and consensus building. In light of our results, we discuss how the signaling aspect of platforms such as Informed Sources raises particular challenges for antitrust authorities. Specifically, they allow prices to become a medium of communication, and there are difficulties associated with enjoining firms from changing their own prices.³

We develop our case study of the Informed Sources matter in five parts. We start by further describing the matter in Section 2. In Section 3, we provide a motivating narrative to illustrate the potential role of a platform such as Informed Sources in supporting elevated prices. In Section 4, we empirically describe and illustrate competitive effects of the Informed Sources platform, focusing on platform-enabled price signaling. In Section 5, we discuss related literature and the evolution of views on information sharing in antitrust cases. Section 6 concludes the case study.

2 The Informed Sources matter

Informed Sources is a global retail data and analytics company that provides gasoline retailers with “accurate, reliable, timely data” enabling them “to make decisions with confidence” with “a complete view of the market.”⁴ Informed Sources provides a price information sharing platform to subscribing retailers as part of their services. Two key aspects of the platform are that subscribers: (1) provide their station-level price data every 15 minutes to the platform,⁵ and (2) have access to all prices provided to the platform at all times. Importantly, prior to the Informed Sources matter, the platform enabled information sharing only on the *supply-side* of the market. It did not provide consumers or search apps on the *demand-side* of the market with complete, high-frequency price data to enable price search.⁶

Around the time of the Informed Sources matter in 2014, subscribers to Informed Sources’ information sharing service included all five major Australian gasoline retailers: BP Australia Pty Ltd (BP), Caltex Australia Petroleum Pty Ltd (Caltex), Woolworths Ltd (Woolworths),

³Article 101 of the Treaty on the Functioning of the European Union has policies prohibiting information exchange. In Australia, restrictions on concerted practices provided by Subsection 45(1)(c) of the Competition and Consumer Act 2010 might be relevant.

⁴<https://informedsources.com/>

⁵The price sharing interval for a limited number of subscribers was 30 minutes.

⁶Prior to the Informed Sources matter, Informed Sources provided data for consumers only twice daily and with geographic restrictions.

Eureka Operations Pty Ltd (trading as Coles Express), and 7-Eleven Stores Pty Ltd (7-Eleven) (ACCC, 2015). The ACCC alleged that “the price information exchange service allowed those retailers to communicate with each other about their prices, and had the effect or likely effect of substantially lessening competition for the sale of petrol in Melbourne” (ACCC, 2015). In addition, the ACCC noted the overall effect of the conduct on consumers was potentially large: “even a small increase in petrol pricing can have a significant impact on consumers overall. For example, if net petrol prices increase by 1c per litre over a year, the loss to Australian consumers would be around \$190 million for the year” (ACCC, 2014).

Outcome of the matter

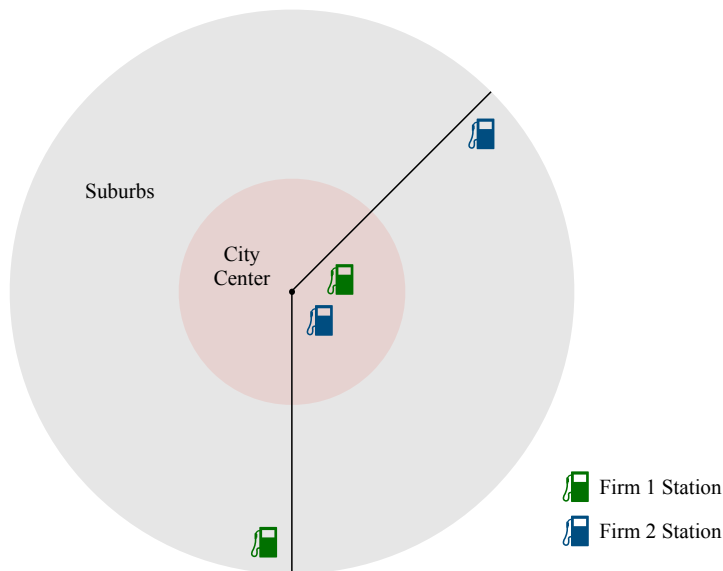
The ACCC instituted proceedings against Informed Sources and the five major gasoline retailers in August 2014, alleging that they violated Section 45 of the Competition and Consumer Act 2010, which prohibits “contracts, arrangements or understandings that have the purpose, effect or likely effect of substantially lessening competition” (ACCC, 2015). A settlement emerged 16 months later in December 2015, which saw one of the five major retailers, Coles Express, agree to withdraw from the Informed Sources information sharing agreement. Moreover, Informed Sources agreed to make the same high-frequency station-level price data used on its platform available to third-party consumer search apps.⁷

The case’s outcomes promoted competition through supply-side and demand-side forces. On the supply side, limiting coverage of Informed Sources from five to four major gasoline retailers could be expected to limit the platform’s role in facilitating price signaling and coordination. On the demand side, making the platform’s data available to third-party providers potentially allowed price comparison apps to enter. Through such apps, consumers could better compare prices across stations, increasing consumers’ sensitivity to price differences across stations, thereby building competitive pressure for stations to undercut each other.⁸

⁷“BP, Caltex, Woolworths, and 7-Eleven have agreed that they will not enter into or give effect to any price information exchange service unless the information each receives is made available to consumers and third party organisations at the same time. Informed Sources has agreed that it will not supply the information exchange service unless the pricing information it provides to petrol retailers is made available to consumers for free and to third parties on reasonable commercial terms at the same time” (ACCC, 2015). For a general discussion on this approach to remedying platform-based coordination, see Gal (forth.).

⁸“Another key outcome is the availability of the retail price information to third-party service providers. This will promote innovation in the provision of petrol price information, to the benefit of consumers. . . . The ACCC believes that this will facilitate improved competition amongst petrol retailers” (ACCC, 2015, quoting ACCC Chairman Rod Sims).

Figure 1: Visual representation of suburban and city center stations



3 A motivating narrative

Before delving into the complexities of platform-enabled price signaling in practice, we develop a simplified narrative to highlight the potential role of a platform like Informed Sources in supporting the signaling of coordinated price increases.

In our narrative, there is a city consisting of a city center and outlying areas, which we visualize in Figure 1. Two firms operate retail gasoline stations. Each firm has two stations, one in the city center and the other in an outer suburb. Let us imagine that the two stations in the city center are close to each other and in locations that allow consumers to straightforwardly compare their prices before choosing whether and where to purchase gasoline in the city center. The suburban stations are far apart in separate suburbs, so comparisons with other stations are less straightforward. The firms have similar input costs for the gasoline that they sell to consumers.

Suppose both firms charge a price of \$2.00 per gallon at their stations, which is close to the firms' input cost. Given the information available to firm 1, its target is for both firms to increase their stations' prices to \$2.20 on the following day. In contrast, firm 2 considers a price of \$2.18 to be the best target. In this situation, a coordinated price increase is profitable to both firms (but harms consumers). However, suppose only one firm increases its price. In that case, that firm will lose substantial business at its city center location, where consumers can readily observe the price differential between the two city center stations. In addition, the firm will likely lose business at its suburban location as consumers choose to delay purchasing in response to the higher price and perhaps become aware of its rival's

lower prices in the city center and the other suburb. Thus, while the potential profitability of price increases are apparent to these firms, there are challenges for them to accomplish such price increases.

Explicit communication

Let us set aside antitrust laws for a moment and consider the possibility that the firms' managers talk on the phone and agree that each will open its stations at a compromise price of \$2.19 the next day. Then, when the stations open the next day, the managers both position price spotters near their rivals' stations to confirm their rivals' opening prices. In this way, the coordinated price increase, which we will refer to as a *price restoration*, is launched. Crucial to the success of the restoration is the managers' ability to communicate about which restoration price to set and when to implement the restoration price, and their ability to confirm that their rival stuck to their promises.

At prices above competitive levels, a firm has an incentive to undercut the price of its rival later in the day (when the price spotters have gone home), thereby increasing its market share significantly but only decreasing its (above-competitive level) margin slightly. Thus, after starting the day with a price of \$2.19, a firm might consider reducing its price at one or both stations to capture market share from the rival. Consumers would shift their purchasing toward lower-priced stations as they recognize the price differential. At some point, the firm with the higher price would realize that something had changed, either because it directly monitors the price of the other station or because it recognizes that the change in consumers' purchasing patterns must be due to a decrease in its rival's price. The firm may respond by cutting its price, which may lead to further discounting that reduces the profits of both firms.

Imperfect signaling

Now let us reimpose the antitrust laws and suppose that the firms refrain from direct communication. The firms now face the task of signaling using prices alone. Starting from prices of \$2.00, suppose firm 1 tries to signal a price restoration by increasing its city center station price to \$2.20. Doing so makes it easy for firm 2 to observe firm 1's signal because it has a nearby city center station. However, consumers also easily observe the substantial price differential between the city center stations. As a result, a significant number of consumers will shift to purchasing away from firm 1's city center station. As a result, firm 1 bears a substantial cost of lost profits in its effort to signal a price restoration.

Firm 1 could alternatively try to signal only with its suburban station to avoid rapidly

losing market share to its rival. Doing so, however, would risk firm 2 not recognizing the signal for a substantial amount of time, and eventually consumer recognition of the price differential would result in reduced sales at the suburban station.⁹ At some point, the manager of the lower-priced station will become aware of its rival's price increase. But, of course, the manager need not be in a rush to respond because that manager's lower-price stations enjoy an advantage from the price differential, and the manager might credibly feign ignorance of the rival's signal for some time. Eventually, the low-priced station might respond with a price increase of its own, but perhaps only moving its prices to its preferred \$2.18, thereby initiating rounds of undercutting prices.

In summary, signaling either with the city center or suburban station is costly and uncertain. A signal using city center stations is quickly and reliably observed, but it fairly immediately results in the loss of sales. Signaling using suburban stations is not reliably observed in a short time frame, and so a price differential may need to remain in place for a longer time to ensure that the rival observes it. Initially, the consumer response to the higher price at a suburban station may be limited, but eventually one expects reduced sales as consumers recognize and adjust to the differential. The ideal as far as the firms' profits are concerned is for signaling using the suburban stations to be promptly and reliably observed by rivals so that costs associated with the signaling process are limited. A price information sharing platform enables precisely this.

Platform-enabled signaling

Let us insert a near real-time information sharing platform like Informed Sources into our story. Once the platform is in place, firm 1 briefly increases its price to \$2.20, which we refer to as a "flare," at its suburban station. Because the flare is brief and at a remote station, it limits firm 1's signaling cost in terms of lost sales. Moreover, via the platform, the flare provides a reliable and immediately identifiable signal regarding the restoration price level. A brief flare from firm 2 at its suburban station hitting the same price can confirm that the signal was received and seconded; flares at different price levels can function as counterproposals of the restoration price level. Once flares and counter flares establish a target price, the resulting "meeting of the minds" allows the firms to coordinate a restoration at the agreed-upon price level.

In addition, the platform also facilitates the timing of the price restoration. Either firm can initiate the restoration by raising its price to the agreed level, confident that its rival

⁹Retailers may also want to avoid having a station develop a reputation for being relatively high-priced because this could induce consumers to either avoid that station or make more significant efforts to price compare before purchasing from that station.

will quickly be aware of its move. Further, with the platform, reliable, prompt monitoring is available at a low cost. The realization that undercutting will be detected essentially immediately acts as a deterrent for such undercutting in the first place.

Thus, the insertion of the platform into our narrative permits low-cost signaling using prices as a means of communication, facilitates monitoring, and ultimately promotes more frequent and prolonged episodes of elevated prices. In what follows, we show that the key elements of this narrative are apparent in the data.

4 Effects of Informed Sources

The Informed Sources matter highlights critical aspects of collusive, platform-enabled signaling as discussed in our narrative, which we empirically illustrate in this section. Although the Melbourne data used in the Informed Sources matter are confidential, we are able to illustrate the main effects using publicly available data sources from nearby Sydney. The effects seen in the public data illustrate well the effects at issue in the Informed Sources matter.

Our analysis proceeds in four parts. First, in Section 4.1, we explain why Sydney and our publicly available data shed light on the Informed Sources matter. In Section 4.2, we describe key features of gasoline price dynamics in the markets in which Informed Sources operated. We then develop an illustrative empirical example of platform-enabled price signaling in Section 4.3. Motivated by our example, in Section 4.4 we leverage our rich dataset to empirically document the price signaling process that arose in the Informed Sources matter, and we discuss the crucial role of platform-enabled price information sharing in facilitating such signaling.

4.1 Sydney and FuelCheck

Sydney has three relevant features for the Informed Sources matter. First, it is the closest comparison city to Melbourne worldwide in terms of size, demographics, consumer behavior, and market structure.¹⁰ In the 2016-17 sample period that we consider, Sydney's market, like Melbourne's, was dominated by the same five retailers that subscribed to Informed Sources before December 2015: BP, Caltex, Coles, Woolworths, and 7-Eleven. In total, these retailers operated 448 of 694 (65%) of all stations in the greater Sydney metropolitan area and set prices centrally across their station networks. Smaller retail chains and independent

¹⁰Sydney and Melbourne are both on the east coast of Australia, separated by 500 miles. In 2016, the population of Sydney was 4,446,805, and the population of Melbourne was 4,485,211 (Australian Bureau of Statistics, 2016 Census QuickStats, <https://www.abs.gov.au/>).

stations operated the remaining 246 (35%) of stations. Further, as shown in Byrne and de Roos (2019, Online Appendix), retailers in Sydney and Melbourne, as well as in Brisbane and Adelaide, have a history of employing similar pricing strategies. Thus, in Sydney, we observe the same players implementing similar coordinating pricing structures in a similar market setting as in the Informed Sources matter from Melbourne.

Second, in the time period that we consider, August 1, 2016, to December 31, 2017, Sydney-based retailers and consumers had access to a platform called FuelCheck,¹¹ which provided (and continues to provide) real-time information on station-level prices. The platform was launched by the New South Wales government in August 2016, eight months after the resolution of the Informed Sources matter.¹² In the period that we consider, retailers in Sydney used FuelCheck to coordinate price increases in similar ways to how they used the Informed Sources platform in the period prior to the ACCC’s proceedings against Informed Sources. Thus, FuelCheck in Sydney provides a comparable technological and competitive setting to Informed Sources in Melbourne for the analysis of platform-enabled price signaling.

Finally, FuelCheck provides access to comprehensive historical real-time station-level gasoline prices. These data allow us to undertake a forensic analysis of retail pricing, ranging from daily prices at the retailer level to hourly prices at the station level. The richness of the data proves critical because key aspects of platform-based price signaling, as employed in the Informed Sources matter, are only observable at high frequencies at individual stations.

4.2 Price cycles

Price cycles characterize retail gasoline pricing in urban markets worldwide (Eckert, 2013). In Australia, gasoline prices in Melbourne, Sydney, and all other major cities exhibit price cycles.¹³ The ACCC describes gasoline (petrol) price cycles as follows:

“A petrol price cycle is a movement in retail price from a low point (or trough) to a high point (or peak) to a subsequent low point. In these cycles, prices steadily go down for a period followed by a sharp increase. Price cycles result from deliberate pricing policies of petrol retailers and are not directly related to changes in wholesale costs.”¹⁴

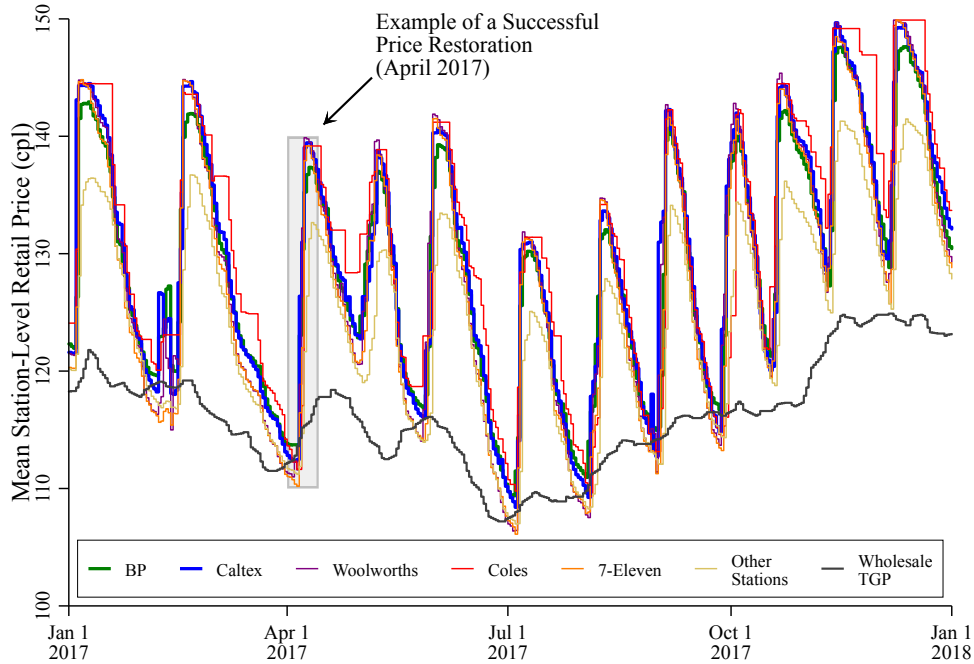
¹¹<https://www.fuelcheck.nsw.gov.au/>

¹²FuelCheck differs from Informed Sources in that FuelCheck provides prices to both retailers and consumers, whereas Informed Sources prior to December 2015 only provided prices to retailers. As we show, this difference does not prevent Sydney retailers during our time period from engaging in signaling similar to that of Melbourne retailers during the period at issue in the ACCC’s proceedings.

¹³See, for example, ACCC, “Petrol Price Cycles”, <https://www.accc.gov.au/consumers/petrol-diesel-lpg/petrol-price-cycles>.

¹⁴ACCC, “Petrol Price Cycles”, <https://www.accc.gov.au/consumers/petrol-diesel-lpg/petrol-price-cycle> s.

Figure 2: Daily price cycles



In the Informed Sources matter, the overarching price dynamics involved price cycles, which we illustrate with Figure 2. The figure plots daily average prices for the five major retailers and all other (smaller) retailers for all of 2017. With roughly monthly frequency, prices exhibit discrete jumps (*price restorations*) with gradual price undercutting in between the jumps (*undercutting phase*). Price restorations become more likely as retail prices approach the main time-varying component of stations’ marginal cost, the wholesale terminal gate price (TGP).¹⁵ The size of a given cycle’s price restoration is thus central to determining retailers’ average margins.¹⁶

¹⁵From ACCC (2014): “TGP’s are the spot prices at which petrol can be bought from a refinery or terminal. . . . TGP’s are calculated with reference to the Input Parity Price (IPP) and by adding excise and GST, other operating costs incurred in the wholesale sector (including storage and local transportation) and a wholesale margin: . . .

$$\text{TGP} = \text{IPP} + \text{excise} + \text{GST} + \text{wholesale operating costs} + \text{wholesale margin}”.$$

The IPP “is based on the international price of refined petrol plus other import costs and is an indicator of the notional average cost of importing refined petrol into Australia. . . . In 2013-14 the international price of refined petrol accounted for over 95 percent of the IPP.” The Singapore Mogas 95/92 is the relevant international price for computing the IPP.

¹⁶Given the central role of cycles in shaping the market’s price dynamics, we restrict our attention to stations that regularly engage in price cycles. Specifically, we focus on stations with 18 or more dates with daily margin jumps greater than 5 cpl, identifying station-level price restorations. In words, we focus on stations that exhibit monthly price cycles in Sydney. We classify 420 of 694 stations in the greater Sydney

Figure 3: Price restoration in April 2017

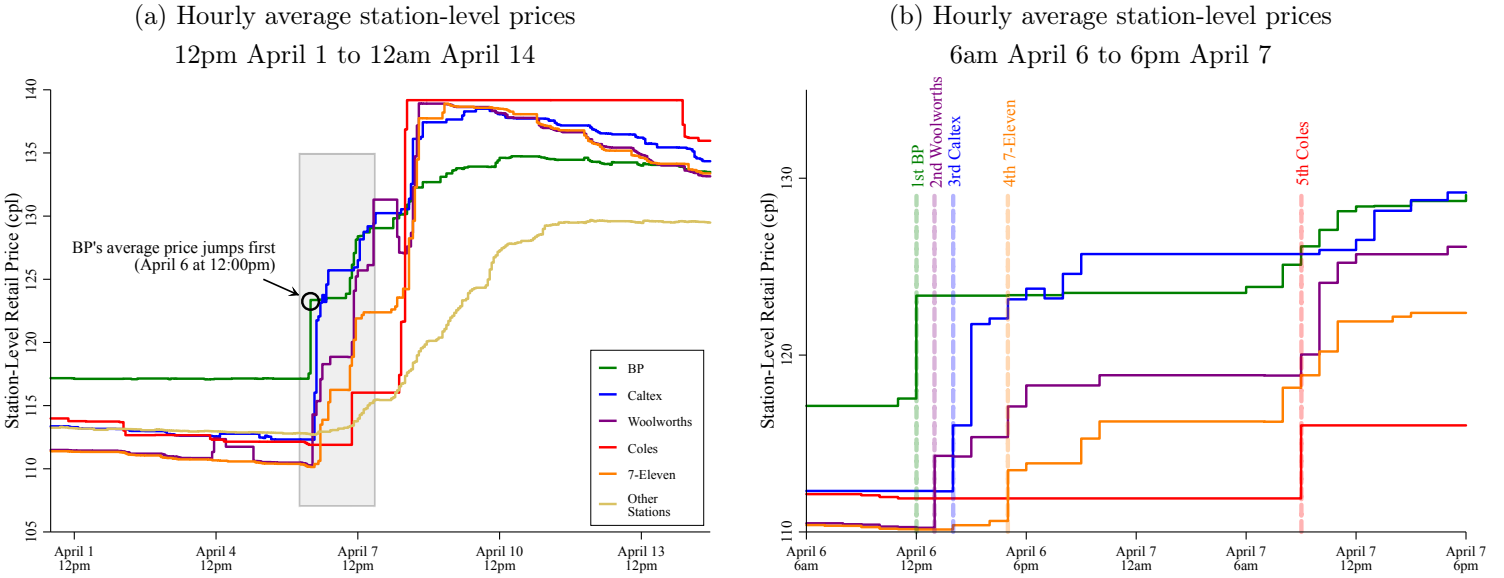


Figure 2 further reveals cross-sectional and inter-temporal price dispersion across retailers, with smaller retailers’ prices tracking with the major retailers’ prices but staying below and following them. Thus, the major retailers’ price leadership and ability to coordinate price restorations is central to determining both their own *and* rival price levels.

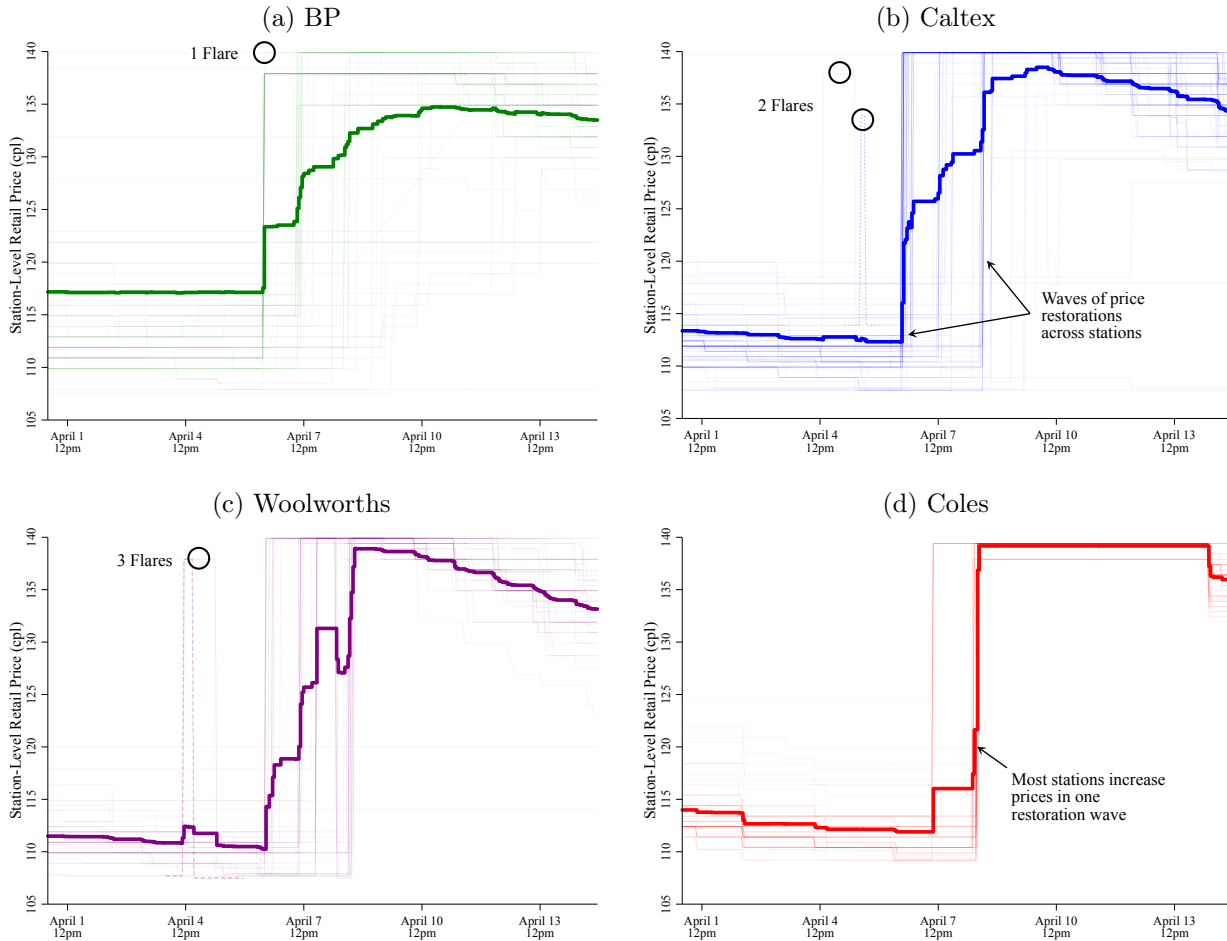
4.3 Price signaling and coordination: an illustrative example

The shaded box in Figure 2 carves out a particular price restoration from April 2017 that serves as our working example for highlighting platform-enabled signaling. We zoom in around this event in panel (a) of Figure 3, which plots *hourly* prices by retailer between April 1 and April 14. At this frequency and level of aggregation, BP emerges as the retailer whose prices jump first in initiating a marketwide price restoration. Panel (b) further zooms into hourly-level pricing on April 6 and 7 (as indicated by the shaded box in panel (a)), which more clearly illustrates the exact order in which retailer-level price jumps occur. BP’s average price is the first to exhibit a significant jump at 12pm on April 6. Woolworths and Caltex follow with significant jumps at 1pm and 2pm, respectively. Later in the same day, 7-Eleven’s average price jumps at 5pm. Finally, Coles’ average price is the last to jump, at 9am the following day on April 7.

While Figure 3 focuses on average retailer-level prices, the Informed Sources platform

region as engaging in monthly cycles. The five major retailers operate 319 (76%) of these stations. Smaller retail chains and independent retailers operate the remaining 101 (24%) stations. All of our results are robust to variations in identifying station-level price cycles and classifying cycling versus non-cycling stations.

Figure 4: Station-level price cycles and restorations at hourly frequencies



Notes: Faint thin solid lines plot station-level hourly prices for a given retailer. Faint thin dashed lines plot station-level hourly prices for selected stations whose prices temporarily jump (“flares”) in advance of the marketwide price restoration. Dark thick solid lines plot average hourly prices across stations.

allows effective signaling and confirmatory reply signaling by a retailer using the prices at individual gasoline stations. To see this, we need to unpack Figure 3 even further and move from the retailer level to the individual station level. Doing so, we show in Figure 4 that in the days leading up to the restoration on April 6, the retailers used prices at individual stations to communicate regarding the target price level for the restoration.

In particular, Figure 4 plots hourly station-level prices with thin lines and average retailer prices (as in panel (a) of Figure 3) in thick lines. Panels (a)–(d) provide these plots for BP, Caltex, Woolworths, and Coles, respectively, from April 1 at 12am to April 14 at 12am. The dashed lines and circles in the panels highlight the flares. As shown in panel (c), Woolworths is the first to flare, with one station jumping to 137.9 cents per liter (cpl) at 10am on April

Table 1: Timeline for price signaling and restoration in April 2017

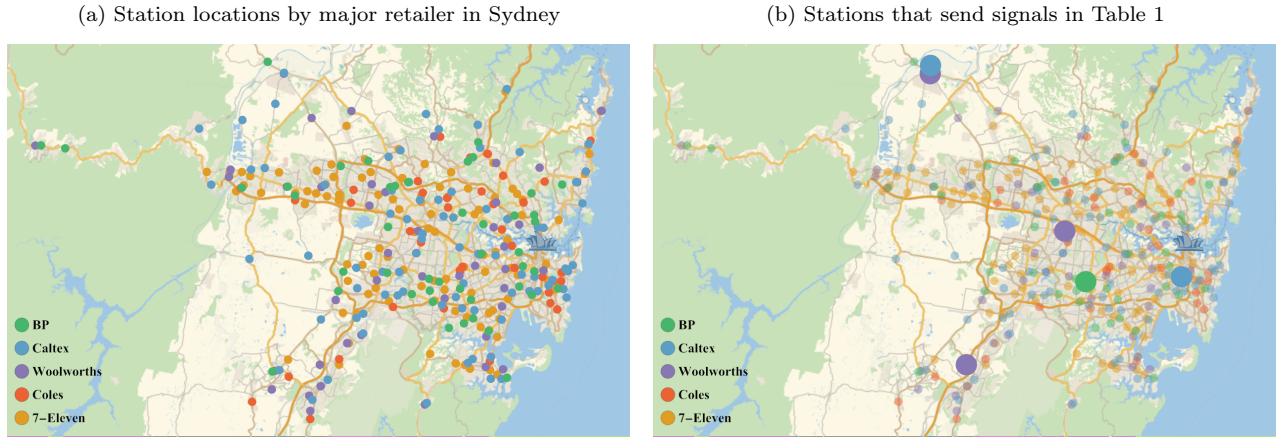
Date	Time	Retailer	Action
April 4	10am	Woolworths	1 station jumps to 137.9 → flare stays up until April 5 at 6am (station open the next day)
	11am	Woolworths	2 stations jump to 137.9 → flare 1 stays up until April 4 at 5pm (6 hours) → flare 2 stays up until April 5 at 6am (station open the next day)
	2pm	Caltex	1 stations jumps to 137.9 → flare stays up until April 5 at 10am (station open the next day)
April 5	1pm	Caltex	1 station jumps to 133.9 → flare stays up until April 5 at 4pm (3 hours)
April 6	11am	BP	1 station jumps to 137.9
	12pm	BP	16 stations jump to 137.9 1 station jumps to 139.9 → flare embedded within the 16 stations jumping to 137.9
	1pm	Woolworths	7 stations jump to 139.9
	2pm	Caltex	8 stations jump to 139.9

For the remainder of the cycle, the focal point for price restoration is **139.9**.

4. Woolworths reinforces this signal by increasing its price at two more stations to 137.9 cpl at 11am the same day. Panel (b) reveals two subsequent flares from Caltex in response to Woolworths. The first occurs three hours after the Woolworth flares, with Caltex increasing its price at one station to 137.9 cpl at 2pm and returning the station’s price to its previous level at the station’s opening the next day. Caltex sends a second flare at 133.9 cpl for three hours on April 5 from 1pm to 4pm, proposing another potential restoration price.

Having observed four flares at 137.9 cpl and one flare at 133.9 cpl, at 11am on April 6, BP increases its price at one station to 137.9 cpl, signaling the imminent launch of the price restoration. An hour later at 12pm, BP increases its price at 16 stations to the same level and, interestingly, increases its price at one station to 139.9 cpl. We interpret this latter increase as a flare embedded within BP’s restoration-initiating increases to 137.9 at the other 16 stations. BP’s flare proves crucial as Woolworths and Caltex follow with price increases within two hours at numerous stations, all of which target 139.9 cpl. Indeed, the focal point for the remainder of the cycle’s price restoration is 139.9 cpl at hundreds of stations across the market. A flare by just one BP station appears to have set this off. Table 1 summarizes the timeline of price signaling and coordination from our example.

Figure 5: Signaling propensity and precision across retailers



Signals in executing the price restoration

An additional feature in Panel(a) of Figure 3 is the dip in Woolworths' average price midway between April 7 and April 10. Woolworths' price dip occurs just before the increase in Coles' average price through its largely marketwide increase in prices across its stations. While Coles increases prices at many of its stations in the signaling window highlighted in Figure 3(a), its more significant marketwide price increases did not occur until *after* Woolworths' price decrease, which may have served as a prompt. All of this would have been clear to the stations involved due to their participation in a price sharing platform and the associated ability to sort, average, and analyze real-time price data.

Location of signaling stations

Table 1 contains 6 stations that send signals before retailers begin restoring price levels. Given our motivating narrative above, it is natural to ask about these stations' locations. Panel (a) of Figure 5 plots the station locations for all major retailers in Sydney, while panel (b) highlights the location of the 6 signaling stations from Table 1 with enlarged station markers. Relative to the city center, marked by the Sydney Opera House in the center-right of both panels, we find that 5 signaling stations are in remote suburbs. This pattern aligns with our narrative discussion above and how platforms make it possible to effectively signal price increases from relatively remote stations to help reduce the cost of signaling due to lost market share.

4.4 Sparsity, speed, and seclusion in price signaling

Building from our illustrative example, we now use our entire August 2016 to December 2017 sample to characterize the three S’s of platform-enabled signaling: sparsity, speed, and seclusion. Our results from this analysis confirm the insights from our illustrative example and offer new ones.

Classifying price restorations and signals

For our empirical analysis, it is necessary to classify price restorations at various levels of aggregation and signals at the station-level. We do so in the following four steps (price measures are in terms of cents per liter):

1. Identify the start of *market-level price restorations*.

Let \bar{m}_t be the market-level average daily retail price – TGP margin across stations (in cpl) with $\Delta\bar{m}_t = \bar{m}_t - \bar{m}_{t-1}$. We identify the start of a marketwide price restoration on date t if $\Delta\bar{m}_t > 2$ and $\Delta\bar{m}_{t-k} < 2$ for $k = 1, 2, 3$. In words, date t is the start of a market level price restoration if: (1) enough stations begin restoring their prices such that the marketwide average margin grows by more than 2 cpl; and (2) such market level average margin increases are not observed in the dates just before t .¹⁷

2. Identify *station-level price restorations* within a market-level restoration window.

Let p_{it} be station i ’s price on date t , and let τ be a date when a market-level price restoration begins (as identified in step 1). Station i ’s restoration price within a 14-day market-level restoration window around τ is computed as $p_{i\tau}^{rest} = \max(\{p_{i\tau-7}, \dots, p_{i\tau+7}\})$. In words, a station’s restoration price is the highest price that it charges within a 14-day window around the start of a market-level price restoration.

3. Identify *retailer-level price restorations* within a market-level restoration window.¹⁸

We identify retailer r ’s restoration price among its n_r stations in a market-level price restoration starting on date τ as $p_{r\tau}^{rest} = \text{mode}\{p_{1\tau}^{rest}, \dots, p_{n_r\tau}^{rest}\}$. In words, retailer r ’s

¹⁷Visually, Figure 2 shows that marketwide restorations eventually yield average daily margin increases of more than 20 cpl. However, this restoration-driven margin increase occurs once all retailers, including smaller independents, begin restoring margins, which is later in the market-level restoration phase. Using a 2 cpl margin increase threshold allows us to identify the *beginning* of market-level restorations phases, typically when major retailers restore margins at multiple stations but before the entire market starts doing so. For instance, April 6, in our example above, is classified as the beginning of a restoration phase. All of our results are robust to variations on the margin threshold.

¹⁸Recall from our discussion in Section 4.2 above that cycles occur roughly once per month. Using a 14-day market-level restoration window ensures that no such windows overlap across restorations and yields a sufficiently large window to capture all early and late station-level restorations around a market-level restoration.

restoration price is the modal station-level restoration price within a 14-day market-level price restoration window around τ .

4. Identify *signaling dates* and *signals* just before market-level price restorations.

Let $\Delta p_{it} = p_{it} - p_{it-1}$ be station i 's daily price change. Date t is classified as a signaling date if: (1) it is within 7 days before the start of a market-level price restoration (as identified in step 1); and (2) $\Delta p_{it} > 5$ at less than 15 stations.¹⁹ In other words, signaling dates are just before the start of market-level price restorations when a small group of stations engages in price jumps. We classify station-level price jumps where $\Delta p_{it} > 5$ as station-level price signals on these dates. Notably, such signals do not necessarily correspond to a station's restoration price within a given market-level restoration window.²⁰

Sparsity

Our classification scheme identifies 18 market-level price restorations within our August 1, 2016, to December 1, 2017, sample from Sydney. As alluded to above, market-level restorations occur about once per month. Across the 18 restorations, we identify 132 station-level price signals, which implies 7.3 station-level price signals per market-level restoration. Table 2 summarizes the average number of station-level signals by retailer and compares this to the size of each retailer's station network. Retailers tend to send signals from 1 or 2 stations, yet they have station networks with 40 to 101 stations, which underlines the sparsity of station-level price signaling.

Precision

In our illustrative example, the 137.9 price signals from Caltex and Woolworths precipitate their 139.9 restoration prices. Their station-level signals do not perfectly correspond to the retailer-level restoration prices. To systematically investigate such signaling error, we compute a *signal error* as $e_{it} = p_{it} - p_{r\tau}^{rest}$, which is the difference between a given station-level signal p_{it} and station i 's subsequent retailer-level restoration price within restoration window τ , $p_{r\tau}^{rest}$. If, for example, $e_{it} = 0$, then station i 's signal on date t corresponds exactly

¹⁹Like our simple threshold rule for classifying the start of marketwide price restorations, this simple rule is effective in classifying periods involving pre-restoration price signaling. Our results are robust to variations on the 5 cpl and 15 station thresholds. The threshold rule that we employ is one of several methods used in the literature to classify cyclical pricing. See Holt et al. (2022) for a discussion of the performance of a range of related methods.

²⁰For instance, recall from our example above that Woolworths and Caltex had pre-restoration signals of 137.9, but their restoration price was subsequently 139.9.

Table 2: Sparsity in station-level restoration price signaling by retailer

Retailer	Station-level signals per restoration	Number of stations
BP	1.28	45
Caltex	1.22	80
Woolworths	1.56	48
Coles	1.94	40
7-Eleven	0.56	106

to its corresponding retailer’s subsequent restoration price within the marketwide restoration window that t sits within.

Empirically, we find that signals are precise and informative about retailers’ restoration prices. For instance, the average signal error is $\bar{\epsilon}_{it} = 1.2$, which is small relative to a mean station-level restoration price of 137.5, and an average restoration price jump of 21.2. Of the 132 signals that we identify, 78 (59%) are exactly 0 cpl, with 90% being 4 cpl or less.

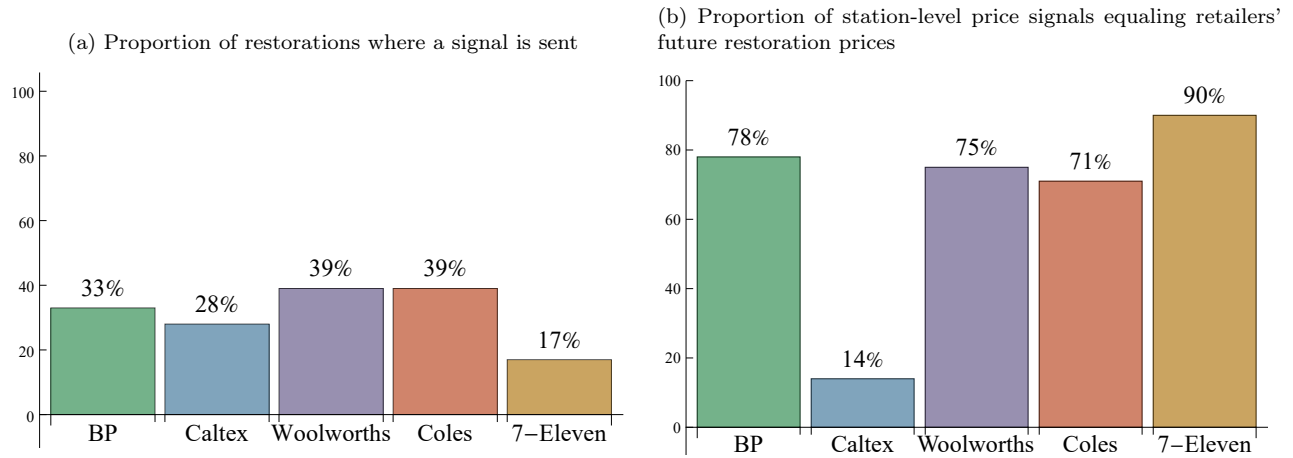
Figure 6 documents retailers’ propensity to engage in price signaling and the precision of their signals. Panel (a) shows that retailers signal at similar rates. For instance, BP sends signals before 6 of 18 (33%) market-level restorations, whereas 7-Eleven is the least likely to send signals, with signals in 3 of 18 (17%) restorations.

Panel (b) shows that retailers send highly informative signals about future restoration prices. Except for Caltex, retailers’ signals correspond *exactly* to their restoration price levels between 71% and 90% of the time. Furthermore, statistical tests confirm at the 1% significance level that the proportion of signals that exactly equal a given station’s retailer’s restoration price level is statistically significantly different from 0. Price signals are, statistically, informative about retailers’ future restoration prices.

Caltex stands out in not sending signals that exactly correspond to its restoration prices. However, in additional calculations, we find that more than 80% of Caltex’s station-level price signals are within 3 cpl of their future retailer-level restoration prices. So while their signals are relatively less precise, they are informative within a 3 cpl bandwidth of future restoration prices.

In sum, the results from Table 2 and Figure 6 imply that stations send precise signals about restoration prices from few stations. Moreover, retailers vary their participation in sending signals across price restorations, suggesting that they share signaling costs associated with lost market share. In a market with more than 600 stations, quickly identifying precise signals about rivals’ prices from a handful of station-level price jumps would be difficult

Figure 6: Signaling propensity and precision across retailers



without a platform. Platform-generated real-time price data and the ability to sort rivals' station-level price distributions make monitoring sparse price signals straightforward.²¹

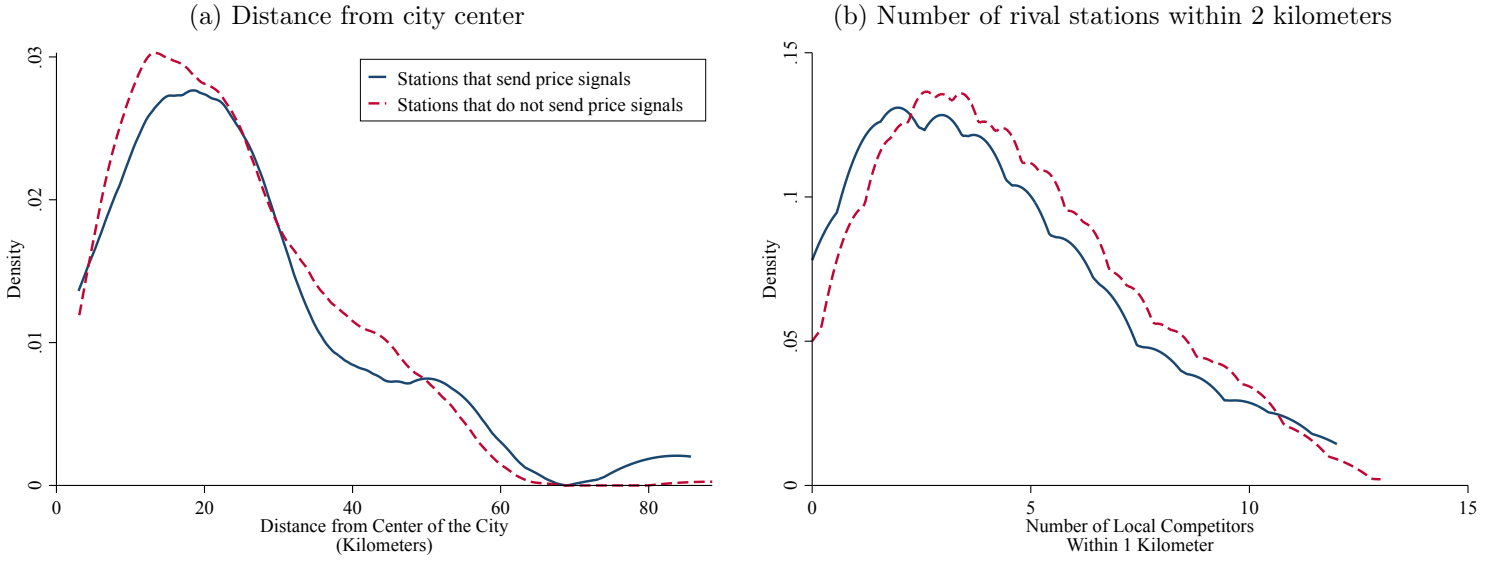
Seclusion

Our discussion so far raises the question whether the major retailers account for stations' local market structures in determining from which stations to send signals. The panels in Figure 7 provide visual evidence related to this question. To construct the figures, we classify a station as a *signaling station* if it sends at least 1 signal across any of the 18 market-level restorations that we examine. Of the major retailers' 319 stations, 89 (28%) send at least one signal. Figure 7(a), which plots a station's distance from the center of the city (the Sydney Opera House), indicates that signaling and non-signaling stations are similar in terms of their geographic proximity to the city's center. Figure 7(b), in contrast, visually reveals differences between signaling and non-signaling stations in terms of local competition as measured by the number of rival stations within a 1-kilometer radius. Signaling stations tend to have fewer local rival stations, suggesting they are more secluded from competition.²²

²¹There is precedent from Perth, Australia, which also has regular price cycles and a platform that makes real-time price data available, for these results. Byrne and de Roos (2019) show that in Perth, BP, the market price leader between 2009-2013, was able to signal future price restorations and coordinate rival prices with a small number (< 5) of stations. Wang (2009a) documents that retailers employ mixed strategies in leading price restorations, thereby enabling the sharing of costs (due to lost market share) among price leaders.

²²Previous empirical retail gasoline studies find that competition is highly localized. See, for example, Verlinda (2008), Hastings (2004), Chandra and Tappata (2011), and Luco (2019). Our radius-based approach to defining localized markets around individual stations is consistent with the approach used in previous studies.

Figure 7: Characteristics of stations that price signals



We use a linear probability model (LPM) to formally characterize factors that influence whether station i ever sends a signal in our sample:

$$1\{\text{signals}\}_i = \alpha_0 + \alpha_1 \text{Nrival}_i^k + \alpha_2 \text{Dist}_i + X_i \beta + \rho_r + \epsilon_i$$

where $1\{\text{signals}\}_i$ is a dummy equaling 1 if station i ever sends a signal before a restoration, Nrival_i^k is the number of rival stations within distance k of station i , Dist_i is the distance of station i from the city center (the Sydney Opera House), X_i is a vector of demographic variables for population, density, income, age, education, and language in station i 's census block,²³ ρ_r is a fixed effect for retailer r operating station i , and ϵ_i is an econometric error that we allow to be heteroskedastic.

Table 3 contains our LPM results. The coefficient estimates for our local market structure variables correspond to the visual evidence from Figure 7: local competition is a key determinant of whether a station sends signals, while the distance from the center of the city is not. The influence of competition is particularly localized, as one additional rival station within 500 meters yields a 5.6 percentage point drop in the probability that a station sends signals. This influence is quantitatively large, as it implies a 20% reduction in the probability a station ever engages in signaling relative to the sample mean probability of 28 percentage points.

²³We use Statistical Area 2 (SA2) census blocks from the Australian Bureau of Statistics. SA2's correspond to well-defined suburbs across Sydney.

Table 3: Characteristics of stations that send price signals

	(1)	(2)	(3)	(4)
<i>Local market structure</i>				
Number of rival stations within ...				
500 meters	-0.056** (0.028)			
1 kilometer		-0.032* (0.017)		
2 kilometers			-0.013 (0.009)	
3 kilometers				-0.008 (0.005)
Distance from city center (km)	0.003 (0.002)	0.003 (0.002)	0.002 (0.002)	0.002 (0.002)
Population (100,000's)	-0.188 (0.291)	-0.175 (0.291)	-0.187 (0.292)	-0.185 (0.293)
Population density (100,000's)	-1.169 (1.308)	-0.841 (1.299)	-0.584 (1.330)	-0.548 (1.341)
Median income (100,000's)	-0.632 (0.480)	-0.695 (0.480)	-0.759 (0.501)	-0.761 (0.514)
Average Age	0.005 (0.008)	0.005 (0.008)	0.004 (0.008)	0.004 (0.008)
Share of people with Bachelor's degree	0.828*** (0.292)	0.809*** (0.294)	0.810*** (0.294)	0.804*** (0.294)
Share of people English speaking	0.046 (0.441)	0.015 (0.440)	0.028 (0.447)	-0.070 (0.440)
R-Squared	0.113	0.113	0.110	0.110
Observations	420	420	420	420

Notes: The dependent variable is a dummy variable equaling one if a station ever engages in price signaling between August 1, 2016, and December 31, 2017. The mean of the dependent variable is 0.22. Local demographics are measured at the Australian Bureau of Statistics “Statistical Area 2” (SA2) level and correspond to the SA2 in which a given station is located. All regressions include retailer fixed effects. Robust standard errors are in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We can also estimate the cost of price signaling in the presence of local rival stations that rationalizes retailers’ decision to send signals from stations secluded from local competition. Using unique daily station-level sales data, Wang (2009b) estimates a local cross-price demand elasticity of -18 between neighboring stations in Australian retail gasoline markets with price cycles.²⁴ The average station-level restoration price jump, corresponding to price jumps from precise signals, is 21.2. Given an average restoration price of 137.5, an average restoration price jump represents an 18% price increase ($21.2/(137.5-21.2)$). A back-of-the-envelope calculation based on these figures implies 0 sales for a station that sends signals in the presence of a nearby rival. Such a potential collapse in sales helps explain why having local rivals within 500 meters has such a large quantitative impact on whether a given station sends price signals.

Varying which stations send signals

Beyond secluding signaling stations from local competition, we also find that retailers vary which stations send signals over time. Specifically, among the 89 stations that sent at least one signal, 62 (70%) only sent one signal over our 18-month sample period. Overall, 96% of all signaling stations send three or fewer signals over this period, implying there do not exist “focal” stations from which retailers signal.

These findings further emphasize the importance of a platform for enabling price signaling. In particular, our market structure results highlight how platforms eliminate the role of geography with signaling. Consider a counterfactual scenario without a platform: retailers want to signal with stations with nearby rivals to ensure their price signals are received. Yet, we find the *exact opposite* of this, consistent with geography not determining whether rivals observe signals. Instead, through a platform, retailers can avoid high signaling costs while sending effective signals using stations that are secluded from nearby competitors.

To further reduce signaling costs, stations vary which isolated stations send signals, thereby limiting consumers’ ability to learn which stations are high-priced “signallers” and substitute away from them. At the same time, on the supply side, rivals do not require consistent “signaller” stations to monitor for signals. Instead, with access to real-time price data and a searchable platform that can quickly identify maximal prices and large price changes among rivals’ stations, the retailers can monitor price signals irrespective of the consistency of their geographic locations.

²⁴The estimate of Wang (2009b) sits between other estimates from Canada from Houde (2012) and Clark and Houde (2013) of -15 and -30 , respectively.

5 Discussion

In this section, we put the Informed Sources case and our empirics on platform-enabled price signaling in the context of related literature on collusion and the evolution of information sharing in antitrust cases.

5.1 Related literature

Information sharing and collusion

The economics literature on collusion in the tradition of Green and Porter (1984) provides models in which cooperation and punishment phases are supported through firms’ observation of their own sales or marketwide data. Thus, in certain settings, it is theoretically possible for cartel members to support elevated prices without sharing firm-specific information among the members. However, subsequent literature has established the value of information sharing in facilitating Green and Porter-style conduct. Indeed, in the context of the Dutch banking industry following the 2009 financial crisis, Dijkstra and Schinkel (2019) show how a reduction in the cost of signaling high prices due to a ban on price undercutting by banks receiving subsidies was a catalyst for a switch to coordinated price leadership at higher than competitive levels. High prices lingered for several years, even after the ban on price undercutting was lifted. Cramton and Schwartz (2000) document how the design of FCC spectrum auctions, specifically simultaneous open bidding, facilitated bid signaling, punishments, and coordination. Backus et al. (2022) show that introducing communication via text messages into eBay bargaining reduces bargaining breakdown, facilitating bilateral exchange among competitors.

Information sharing can also help firms to coordinate on the initiation of a cooperation phase and monitoring deviations. In addition, it can help firms to coordinate on the price to be charged in the cooperation phase and reduce the possibility of misinterpreting marketwide data. Chilet (2018) shows that colluding firms in Chilean pharmaceuticals gradually extended the reach of their agreement to additional products through price signaling. Notably, the cartel leader stated: “[W]e offered to be the chain that raised its prices first ([every week] on Monday or Tuesday) so that the other two chains would have three or four days to ‘detect’ these [price] increases and absorb them. ... Due to the good results, we hope to repeat the ‘procedure’ with more products and with more pharmaceuticals in the coming weeks” (Chilet, 2018, p. 11).²⁵

²⁵Further, “According to the NEP and declarations of Fasa’s executives, the procedure most used to increase prices was the following. Every time Salcobrand raised the price of a drug, the other two chains would wait a few days and then take turns as the second firm to raise the price. The remaining chain would

Recent papers by Awaya and Krishna (2016) and Spector (2022) show that information sharing among firms improves their ability to support elevated prices. Awaya and Krishna (2016) emphasize that information sharing improves monitoring, reduces uncertainty, and allows greater coordination profits, and Aryal et al. (forth.) build on this, tying communication in airline industry analyst calls to coordinate conduct. Spector (2022) illustrates how information sharing can allow firms to detect deviations more quickly, making deviations less profitable and so reducing the incentive for firms to deviate in the first place. Luco (2019) proposes a similar mechanism and finds evidence in support of it in the context of the Chilean retail gasoline industry following the roll-out of a government-run price comparison platform.²⁶

Harrington (2021) provides a model in which a private exchange of prices by competing duopolists results in higher consumer prices. Firms are assumed to exchange initial and final prices, where each firm incurs a positive adjustment cost if its final price differs from its initial price. “The private sharing of prices by competitors gives each firm an opportunity to lower its price should it learn that its rival’s price is relatively low. In anticipation of the information exchange and such a possible response by rival firms, a firm is incentivized to set and share a supracompetitive price, which could be in the form of a high list price or the addition of a surcharge. Notably, it is the information exchange agreement that creates harm, for it is the anticipation of sharing prices that induces firms to initially set higher prices. While there is no agreement on prices, there is an agreement to share prices and there lies the unlawful agreement” (Harrington, 2021, p. 21).

Retail gasoline

Regular asymmetric cycles in prices, sometimes referred to as Edgeworth cycles, have been observed in a variety of retail gasoline markets around the world, including in Australia (Wang, 2009a; Byrne and de Roos, 2019), Canada (Noel, 2007; Clark and Houde, 2013, 2014; Byrne et al., 2015), Europe (Foros and Steen, 2013; Linder, 2018), and the United States (Lewis, 2012; Zimmerman et al., 2013). In an Edgeworth cycle, price movements are sharply asymmetric over time and highly coordinated across firms. These features are evident in Figure 2, which shows that in each cycle, prices rise rapidly for all retailers and decline gradually until the next cycle begins.

Several alternative explanations for Edgeworth cycles exist. In the Edgeworth (1925) model, two capacity-constrained price-setting firms operate in a homogeneous product market. “... one firm will increase its price a few days afterward. Hence, in a period of one week, all three chains would have the same price” (Chilet, 2018, p. 11).

²⁶See also Harrington and Skrzypacz (2011), Chan and Zhang (2015), and Aoyagi (2002) on the importance of information sharing for cartel monitoring, enforcement, and stability.

ket. The reaction functions of the firms provide the intuition for price cycles. Because products are identical, firms have an incentive to undercut high prices set by their rival marginally. Because their rival is capacity constrained, firms have an incentive to raise their price if their rival sets a low price. In the Edgeworth model, capacity constraints are the source of residual demand for a high-priced firm. Absent capacity constraints, several alternative market features, including search or information frictions or consumer loyalty, could play a similar role (de Roos, 2012).

In the price commitment model of Maskin and Tirole (1988), two firms alternate in setting prices in a homogeneous product market. They show that there exists a Markov perfect equilibrium characterized by price cycles. In the equilibrium, firms undercut the committed price of their rival if that price is sufficiently high. When prices are sufficiently low, each firm would like its rival to raise its price. A war of attrition ensues, which is resolved by each firm playing randomized strategies over whether to increase its price.

Recently, theories and empirics have pointed to collusive explanations for price cycles. In the repeated game analyzed by de Roos and Smirnov (2020, 2021), firms set prices simultaneously over an infinite horizon in the market for a homogeneous product. Consumers are imperfectly attentive, paying more attention to unusually low prices relative to their recent experience. An Edgeworth cycle is the most robust pricing structure that emerges in terms of the sustainability of collusion.

Both the price commitment model of Maskin and Tirole (1988) and the repeated game of de Roos and Smirnov (2020) assume that firms perfectly observe the recent history of prices but do not otherwise require information sharing to coordinate price movements. In practice, however, prices may not be perfectly observed. Moreover, stations in markets with price cycles have engaged in illegal communication, establishing that the benefits of communication can be sufficiently high to outweigh the potential costs of illegal conduct. For example, as described in Wang (2009a), the effectiveness of the price cycles in Ballarat, Australia, in 1999–2000 was aided by direct communication, with multiple station managers admitting that they explicitly colluded via telephone to coordinate marketwide price jumps. Clark and Houde (2013, 2014) analyze a cartel in Quebec, Canada, involving around 130 stations, 60 firms, and 4 cycling markets, where explicit telephone communication facilitated collusion, which helped to coordinate the timing and magnitude of price increases and to limit undercutting.

Evidence of signaling and coordination through prices has emerged with the availability of richer daily, station-level price data. Lewis (2012) documents price leadership by major retailers in the United States as being a critical factor in coordinating price restorations, which departs from the randomization mechanism considered by Maskin and Tirole (1988).

Byrne and de Roos (2019) document evidence from Perth, Australia that price leaders created focal points and used price signals from sparse stations to coordinate rival prices and soften price competition over time.²⁷ Assad et al. (2022) document that the adoption of algorithmic pricing among German gasoline retailers led to elevated prices and margins similar to what Byrne and de Roos (2019) find. Notably, Byrne and de Roos (2019) and Assad et al. (2022) study markets with government-run price information platforms that provide real-time information to consumers and retailers. That both environments reveal an evolution toward higher, coordinated prices underlines the role of information sharing in facilitating anticompetitive conduct.²⁸

In sum, the literature explains how price cycles can arise without communication and information sharing. However, it also establishes that the profitability of such price cycles and the corresponding adverse effects for consumers increase as a result of shared firm-specific information on prices. Our case study of the Informed Sources matter adds to this growing body of evidence on coordination-facilitating and margin-enhancing information sharing in retail gasoline markets.

5.2 Evolution of information sharing in antitrust cases

It has long been recognized that price-sharing systems can serve as facilitating devices. For example, in the 1920s, the U.S. government prosecuted a number of trade association cases, which have been discussed in the literature.²⁹ In these cases, competitors engaged in frequent (often daily or weekly) information reporting and dissemination via a centralized information exchange system. To name a few other cases, the information sharing in the Sugar Institute case of 1936 involved public announcements by sugar refiners of price increases to be effective in the future.³⁰ At issue in GE and Westinghouse of 1962 were the firms' pricing policies: GE published a price book and a standard multiplier that made it straightforward to compute the prices of each model of its complex turbine generator.³¹ And in the 1994 Airline Tariff Publishing Company case, the U.S. government investigated collusion in the

²⁷In earlier work, Atkinson (2009) finds some evidence of individuals stations sending flares similar to those in our illustrative example to coordinate price restorations in the small town of Guelph, Canada.

²⁸Luco (2019) also finds elevated margins after the introduction of a government-run price information platform in Chile, particularly in markets where consumers fail to use the platform.

²⁹Cases include: *Am. Column & Lumber Co. v. United States*, 257 U.S. 377 (1921); *United States v. Am. Linseed Oil Co.*, 262 U.S. 371 (1923); *Maple Flooring Mfrs. Ass'n. v. United States*, 268 U.S. 563 (1925); *Cement Mfrs. Ass'n. v. United States*, 268 U.S. 588 (1925). See also, Whitney (1934), Alexander (1997), and Borenstein (2004).

³⁰*Sugar Inst., Inc. v. United States*, 297 U.S. 553, 597 (1936).

³¹*United States v. Gen. Elec. Co.*, 209 F.Supp. 197 (E.D. Pa. 1962).

Airline Industry.³² Although the case settled without a judicial ruling on defendants’ liability, it is regarded as a landmark case for competition policy toward treatment of information sharing via price announcements. The U.S. government contended that through the airline’s information sharing system (ATP), firms engaged in an “electronic dialogue” that helped them to fix prices.³³

In the Informed Sources matter, the Informed Sources platform gave gasoline retailers excellent visibility into their rivals’ prices while leaving consumers with limited ability to price compare. Various price-fixing conspiracies have created systems to share price data to make prices transparent to participating firms. Although the use of price-sharing devices is not new, the type of systems used have evolved with technological advancements. The case history shows a progression from letters, delivery mail, telephone, electronic systems to digital platforms. As technology advances, so do facilitating devices.

Price-sharing systems provide a mechanism for communication. In Table 4, we summarize attributes of communication and comment on the extent to which those attributes support coordinated conduct. To organize the discussion, we note that some legal scholars have found it helpful to identify three categories of collusion: conscious parallelism, concerted action, and explicit collusion.³⁴ While these are largely legal distinctions, economists have explored how they can be viewed in terms of the underlying economics,³⁵ and it is an economic interpretation that we apply in our case study. Of course, a spectrum of possibilities remain that do not fit cleanly into these categories, but we believe they provide a helpful framework for organizing broad forms of conduct.

Specifically, for the purposes of this case study, we view *conscious parallelism* as occurring when firms achieve elevated prices through recognizing their mutual interdependence but without communication or express agreement. We view *concerted actions* as firms’ achieving elevated prices through facilitating devices, including various types of communication, but without express agreement. And, we view *explicit collusion* as occurring when firms achieve elevated prices through an agreement to suppress rivalry reached through communication or

³²*United States v. Airline Tariff Publ’g Co.*, No. 92-cv-2854 SSH (D.D.C. 1994). See also Borenstein (2004) and Miller (2010).

³³“The ATP fare dissemination system provided a forum for the airline defendants to communicate about their prices. Using, among other things, first and last ticket dates and footnote designators, they exchanged clear and concise messages setting forth the fares each wanted the others to charge, and identifying fares each wanted the others to eliminate. Through this electronic dialogue, they conducted negotiations, offered explanations, traded concessions with one another, took actions against their independent self-interests, punished recalcitrant airlines that discounted fares, and exchanged commitments and assurances – all to the end of reaching agreements to increase fares, eliminate discounts and set fare restrictions.” Competitive Impact Statement, *United States v. Airline Tariff Publ’g Co.*, No. 92-cv-2854 SSH (D.D.C. Mar. 17, 1994), available at <http://www.justice.gov/file/483606/download>.

³⁴See, e.g., Kovacic et al. (2011) and Gavil et al. (2008, pp. 267–268).

³⁵See, e.g., Harrington (2013) and Green et al. (2015).

Table 4: Taxonomy of communication features

FEATURE OF COMMUNICATION	FORM OF CONDUCT		
	Conscious parallelism	Concerted action	Explicit collusion
Cost to propose an action	High because requires market-based signaling	Depends on facilitating devices used	Low because the proposal can be communicated directly
Speed and accuracy with which can discern that proposal was received	Low because relies on the collection and interpretation of market data	Depends on facilitating devices used	High because the proposal can be communicated directly
Speed and accuracy with which can discern a response	Low because relies on the collection and interpretation of market data	Depends on facilitating devices used	High because the proposal can be communicated directly
Face-to-face conversations	No	Depends on facilitating devices used	Yes
Formal agreement	No	No	Yes

involving transfers.

As displayed in Table 4, the cost to propose, say, a coordinated price increase is higher in a regime of conscious parallelism that lacks direct communication than under explicit collusion where communication can be direct. Once a proposal is made, the speed and accuracy with which the proposer can discern that its proposal was received and then discern rivals' responses is lower in a regime with conscious parallelism than under explicit collusion because, again, there is a lack of direct communication and so firms must rely on potentially more ambiguous market-based signals. Conscious parallelism, in our view of it, does not involve face-to-face conversations or formal agreement, while explicit collusion does. We place concerted action as an intermediate between conscious parallelism and explicit collusion, with the exact placement depending on the facilitating devices used.

Now consider the communication features provided by the Informed Sources platform. Informed Sources provides a mechanism for subscribing retailers to effectively and reliably communicate regarding future prices (including proposals and responses) using brief price changes at only a small number of sites chosen strategically for their limited local competition and varied over time, thereby reducing the cost to the proposer.³⁶ A station can discern that its proposal was received and discern a response quickly and accurately because of the high-frequency, reliable information exchange. And these effects occur even in the absence of face-to-face conversations and formal agreements. Thus, the Informed Sources platform

³⁶In contrast, in the economic models of coordinated action described above, price-based communication exposes firms to potentially significant lost profits.

moves the industry’s communication regime towards that available under explicit collusion and away from that under conscious parallelism. This supports the conclusion that the use of Informed Sources platform as a communication device can be viewed as facilitating economic outcomes that are more coordinated than without the service, although potentially not achieving the level that would be possible through direct, explicit communication and agreement among the firms.

6 Conclusion

The Informed Sources matter highlighted how a price information sharing platform could give rise to anticompetitive effects. The ACCC announced that they had resolved Federal Court proceedings against Informed Sources in December 2015 (ACCC 2015). The settlement included that Mobil and Coles Express would not subscribe to Informed Sources or a similar service for 5 years and that subscribers to the service would allow their prices to be made available to consumers and third parties for 5 years. We examine the impact of these remedies on signaling, coordination, and margins in concurrent research in Byrne et al. (2022).

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