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

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1 Overview

In this case study, we examine the role of a platform in facilitating anticompetitive price signaling through an analysis of the *Informed Sources* matter,[1] from the Australian retail gasoline industry. 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. Informed Sources provides a platform that facilitates near real-time, station-level price sharing among major gasoline retailers. In 2014, the Australian Competition and Consumer Commission (ACCC) 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.

In the ACCC's words:

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[1]Australian Competition and Consumer Commission v. Informed Sources (Australia) Pty Ltd. was filed to the Federal Court of Australia on August 19, 2014, with the matter dating to January 1, 2011. The matter was resolved via settlement in December 2015 (ACCC 2015).

> "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, 2014a)

Through a narrative example, we frame the Informed Sources matter and the key economic issues at play. Then, 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. To do so, we employ rich publicly-available real-time pricing data from a separate Australian price transparency platform called FuelCheck, which shares essential features with the Informed Sources platform: the same set of major participants, comprehensive real-time price information available to all major participants, and similar pricing behavior, market structure and demographics.[2] 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.

Our narrative example and examination of the FuelCheck pricing data sheds light on how anticompetitive pricing can arise not through meetings in smoke-filled rooms but through platform-enabled *signaling*. In particular, FuelCheck allows coordinating retailers to observe each other's prices, station by station, and know that the others observed these prices at high frequency (e.g., every 15-30 minutes). In addition, FuelCheck allows retailers to *monitor* any deviations from their coordinated pricing strategies. Such signaling and monitoring enable companies to implement price cycles, whereby retailers: (1) infrequently signal and coordinate on large discrete price increases; with (2) frequent daily price undercutting between price jumps. Coordinated price jumps periodically restore profit margins, allowing firms to

[2] As we discuss below, real-time station-level pricing data from the Informed Sources platform are not publicly available. However, such data granularity is necessary for illustrating the nature of platform-enabled anticompetitive pricing from the Informed Sources matter. Fortunately, such information is available from the FuelCheck platform and illustrative of the key competition issues from the Informed Sources matter.

control overall average margin levels. As we detail below, all of these insights regarding signaling, monitoring, and coordinated price cycles that we derive from the FuelCheck platform were at the center of the matter involving the Informed Sources platform.

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.[3] In 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 complementary rich gasoline price data from the FuelCheck platform, 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.[4]

These insights from our case study add to a growing body of empirical work describing signaling and coordination practices in retail gasoline markets using station-level price data. Byrne and de Roos (2019) document evidence from Perth, Australia, that price leaders created focal points and used price signals from a small number of stations to coordinate rival prices and soften price competition over time.[5] 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.[6]

[3]In our setting of retail gasoline, an 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).

[4]Article 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.

[5]In earlier work, Atkinson (2009) finds some evidence of individual stations using brief price increases to signal the price level and timing for the next market-wide price increase in the small town of Guelph, Canada.

[6]Luco (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. Montag and Winter (2020) find, in Germany, that the introduction of a government-run price information platform leads to lower

We develop our case study of the Informed Sources matter in four 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. Section 5 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."[7] Informed Sources provides a price information sharing platform to subscribing retailers as part of its services.[8] Two key aspects of the platform are that subscribers: (1) provide their station-level price data every 15 minutes to the platform,[9] and (2) have access to all prices provided to the platform. 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.[10]

These services have been provided to gasoline retailers in Australia since at least 2000 (Wang, 2009a). Since this time, retail gasoline prices across all major Australian cities have exhibited asymmetric price cycles that involve two parts: (1) infrequent large discrete price jumps; with (2) regular price undercutting between jumps. Such jumps and cuts give rise to a "sawtooth" pattern in prices over time (see Figure 2). Byrne and de Roos (2019) document the history of retail price cycles in Australian cities from 2001 to 2014, illustrating a change in conduct in 2009 that persists through to the Informed Sources matter.[11] Before 2009, price cycle stability and retailers' ability to coordinate price jumps were sensitive to wholesale price volatility largely due to crude oil prices. For instance, price cycles became particularly unstable in 2008-2009 amid a significant global crude oil shock. In addition, before 2009,

margins, particularly in local markets where consumers more intensively engage with price information from the platform. That the effect may be ambiguous makes sense since price data is available to both the demand and supply sides of the market.

[7]https://informedsources.com/

[8]From their website, they also collect and provide pricing data and analytics to grocery retailers as well.

[9]The price-sharing interval for a limited number of subscribers was 30 minutes.

[10]Prior to the settlement of the Informed Sources matter, Informed Sources provided data for consumers only twice daily and with geographic restrictions. Their high-frequency station-level data was not available to the demand-side of the market, such as through third-party search apps for consumers, at any stage prior to the Informed Sources matter.

[11]In particular, see Appendix B of their paper for the history of retail pricing across Australian cities.

price jumps predictably occurred on Thursdays, with regular 7, 14, or 21-day cycle lengths between jumps.

After global crude oil prices settled in 2009, the pricing structure evolved to what exists during the Informed Sources matter. Under this new pricing structure, the price jumps unpredictably occur on all days of the week. In addition, the cycle length becomes noisier and grows to 30 to 35 days. Yet despite less predictable jump timing and irregular cycle lengths, price cycles and jumps remain tightly coordinated throughout 2010-2014 and are robust to wholesale price volatility. Byrne and de Roos (2019) illustrates that BP (a major retailer) used price experimentation, signaling, and leadership in 2009 to coordinate a profit-enhancing equilibrium transition to a new, robust cyclical pricing structure in Perth. To our knowledge, there are no studies on why or how coinciding equilibrium transitions occurred in other major cities like Melbourne or Sydney. But Byrne and de Roos (2019) confirm that such transitions indeed occur and that this is the pricing structure that exists throughout 2009-2014, leading into the Informed Sources matter.

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), 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, 2014a).

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.[12]

The ACCC viewed the settlement as promoting competition through supply-side and demand-side forces.[13] 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.

3 Anticompetitive potential of information sharing platforms

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.

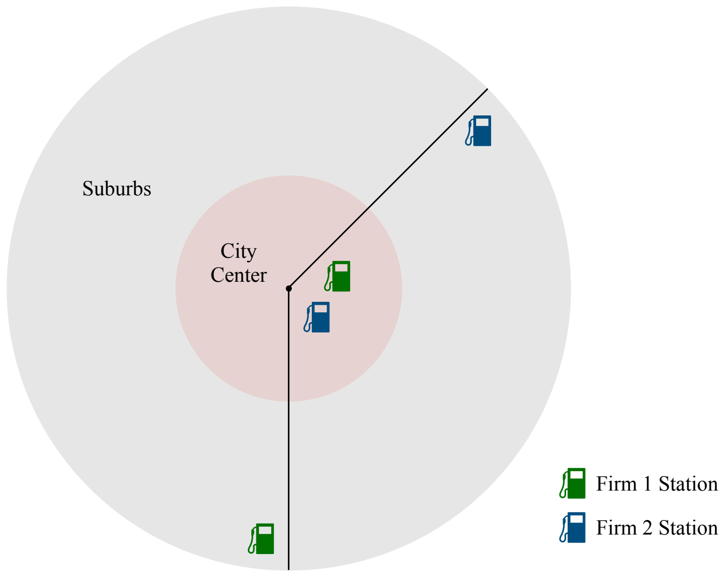
In our narrative, there is a city consisting of a city center and outlying areas (e.g., suburbs), which we visualize in Figure 1. Two firms operate retail gasoline stations. Each firm has two stations, one in the city center and the other in an outer suburb. Let us imagine that the two stations in the city center are within sight of each other and in locations that allow consumers in the city center to straightforwardly compare their prices before choosing whether and where to purchase gasoline. 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 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

[12]"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.).

[13]"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



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 is apparent to these firms, they face challenges in accomplishing such price increases.

Explicit communication

Suppose 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 position price spotters near their rivals' stations to confirm their opening prices. In this way, the coordinated price increase, which we refer to as a *price restoration*, is launched.[14] 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

[14]As discussed in Section 4.2, the retail gasoline markets we study exhibit regular asymmetric price cycles. A *restoration* refers to the phase of a price cycle in which prices are "restored" to the cycle peak.

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 (e.g., it sends a price spotter back out to check) 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 suppose that to avoid running afoul of antitrust laws, the firms refrain from direct communication. In this case, the firms face the task of signaling using prices alone. Starting from prices of $2.00, suppose that firm 1 tries to signal a price restoration by increasing its price in the city center to $2.20. Doing so makes it easy for firm 2 to observe firm 1's signal because firm 2, with its nearby city center station, can simply observe firm 1's price board. This quick and reliable observability is a benefit of city center signaling. However, consumers traveling in the city center, of which there are many, can also observe the price differential between the two stations and can, at little cost, divert their purchases to the lower-priced one. As a result, firm 1 risks substantial profit losses in its effort to signal a price restoration from its station in the city center.

Alternatively, firm 1 could try to signal only with its suburban station in a part of the city with fewer people. This risks firm 2 not recognizing the signal for a substantial amount of time and, with that delay, creates a risk of lost profits for firm 1. As time passes, consumers are increasingly likely to recognize the price differential with the distant stations and take advantage of it by purchasing at those other stations. These effects are exacerbated because firm 2, which benefits from the price differential, can credibly feign ignorance of the rival's signal for some time. Eventually, firm 2 might respond with a price increase of its own, but perhaps only moving its prices to its preferred $2.18, thereby initiating rounds of price undercutting.

In summary, signaling either with the city center or suburban station is costly, and the outcome is uncertain. But, if the signal at the suburban station were sure to be recognized quickly by firm 2, then suburban signaling would have the advantage that suburban consumers do not immediately see the price differential created by the signal, and they may face incremental travel costs to take advantage of that differential. Further, if the total volume of sales is lower in the suburbs than in the city center, then this would also mitigate profit loses from suburban signaling.[15] Thus, a technology that ensures that rivals promptly and reliably observe suburban signals limits the costs associated with the signaling process. A price information sharing platform enables precisely these properties.

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 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. After a period without further flares, the pricing intentions of each firm have been communicated.

The platform then also facilitates the timing of the price restoration. Either firm can initiate the restoration by raising its price to the first proposed price or one of the counterproposals, confident that its rival will quickly be aware of its move. This time, the price increase will not be retracted. Their rival will follow with an equivalent price increase of their own, and a coordinated restoration will have been achieved.[16] Further, the platform enables reliable, prompt monitoring at a low cost because it provides searchable and sortable pricing data, making it easy for subscribers to verify compliance. 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.

[15]Retailers may have the incentive to vary which station is used for signaling to avoid having a station develop a reputation for being relatively high-priced because this could induce consumers to avoid that station or make more significant efforts to price compare before purchasing from that station.

[16]As we document below, in the second phase of a coordinated restoration, in which prices are increased without retraction, each firm may choose to raise prices gradually across their network to further confirm their rivals are also raising prices across their networks. Byrne and de Roos (2019) similarly document gradualism as a key feature of coordinated price increases.

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 can 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 gasoline price data from a separate platform called FuelCheck can shed light on the Informed Sources matter from Melbourne. 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 FuelCheck dataset to empirically document a price signaling process that parallels that from the Informed Sources matter, and we discuss the crucial role of platform-enabled price information sharing in facilitating such signaling. All of the data used in Section 4 is from FuelCheck for the Sydney market.

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.[17] 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.[18] Smaller retail chains and independent stations operated the remaining 246 (35%) 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, in particular price cycles (described momentarily). Thus, in Sydney, we observe the same players implementing similar

[17] Sydney 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, and each city had an area of approximately 2,000 square kilometers that contained more than 500 people per square kilometer (Australian Bureau of Statistics, 2016 Census QuickStats, https://www.abs.gov.au/).

[18] All major Australian cities have asymmetric market shares similar to Sydney, with the five major retailers operating approximately two-thirds of all stations in a given market (Byrne and de Roos, 2019; Byrne et al., 2023). These shares are stable around the Informed Sources matter, with little station entry or exit at that time (ACCC, 2014b, pp. 24–26).

coordinating pricing structures in a similar market setting as in the Informed Sources matter from Melbourne.

Second, in the period that we consider, August 1, 2016, to December 31, 2017, Sydney-based retailers and consumers had access to a platform called FuelCheck,[19] which provided (and continues to provide) real-time information on station-level prices.[20] The New South Wales government launched the platform in August 2016, eight months after the resolution of the Informed Sources matter.[21] In the period that we consider and the data that we analyze below, 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 to analyze 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.

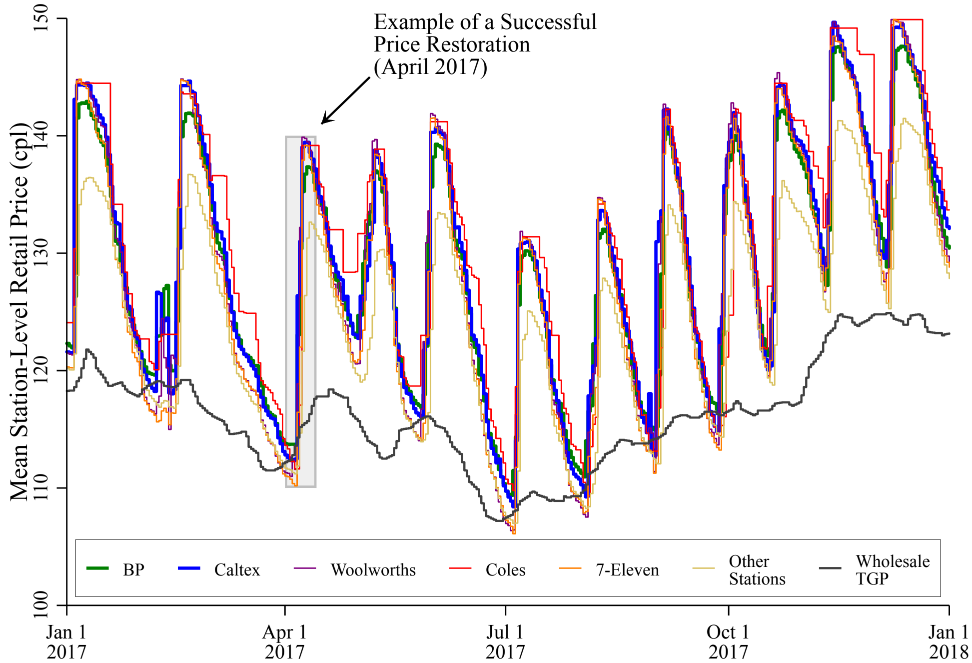
Given similar market structures and conduct, and sufficiently rich data for our case study, we describe pricing conduct from FuelCheck in Sydney to illustrate key issues from the Informed Sources matter in Melbourne. In doing so, we effectively presume that: (1) the Informed Sources platform could be effective for price signaling and coordinated increases; and (2) given it is the same retailers in Sydney and Melbourne, the Informed Sources platform is likely to have been used for that purpose.

[19] https://www.fuelcheck.nsw.gov.au/

[20] Although FuelCheck was (and still is) available to consumers, we would not expect this to interfere with the gasoline retailers' use of FuelCheck for price signaling because consumers generally do not engage in data aggregation and analysis of fuel prices, and therefore are unlikely to observe flares and understand their information content. Moreover, successful signaling in FuelCheck (to which consumers had access) indicates that signaling was viable in the Informed Sources platform (to which they did not).

[21] FuelCheck differs from Informed Sources in that FuelCheck provides prices to both retailers and consumers, whereas Informed Sources before December 2015 only provided prices to retailers. As we show, this difference does not prevent Sydney retailers during our 2017 case study period from engaging in signaling similar to that of Melbourne retailers during the period at issue in the ACCC's proceedings.

Figure 2: Daily price cycles



4.2 Price cycles

Price cycles characterize retail gasoline pricing in urban markets worldwide.[22] In Australia, gasoline prices in Melbourne, Sydney, and many urban markets exhibit price cycles.[23] 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."[24]

[22] 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). See Eckert (2013) for a survey. 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.

[23] See, for example, ACCC, "Petrol Price Cycles", https://www.accc.gov.au/consumers/petrol-diesel-lpg/petrol-price-cycles.

[24] ACCC, "Petrol Price Cycles", https://www.accc.gov.au/consumers/petrol-diesel-lpg/petrol-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).[25] The size of the price increase in a given cycle's restoration is thus central to determining retailers' average margins.[26]

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,

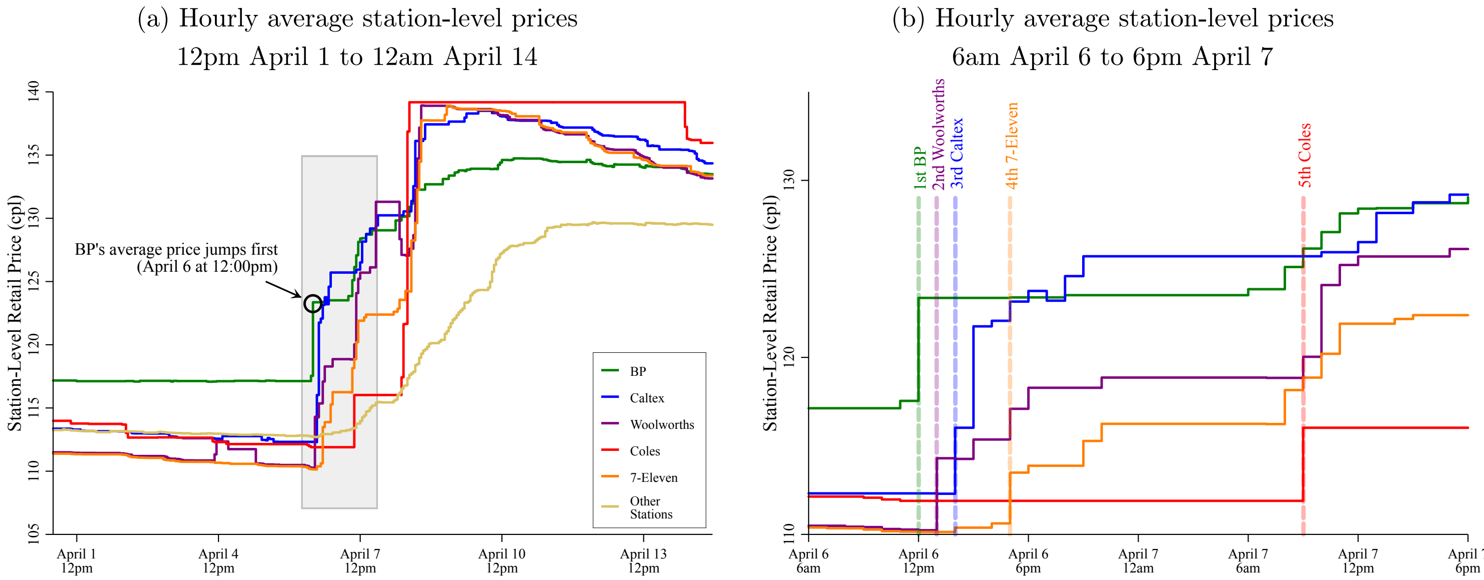
[25] From ACCC (2014b, p. 44): "TGPs are the spot prices at which petrol can be bought from a refinery or terminal. ... TGPs are calculated with reference to the IPP [Input Parity Price] and by adding excise and GST, other operating costs incurred in the wholesale sector (including storage and local transportation) and a wholesale margin. ...

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

As stated on p. 39 of the same report, "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." And, from p. 41, the relevant international price for computing the IPP is the price of Singapore Mogas 95 Unleaded.

[26] Given 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 other words, we focus on stations that exhibit monthly price cycles in Sydney. We classify 420 of 694 stations in the greater Sydney 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. Our results are robust to variations in identifying station-level price cycles and classifying cycling versus non-cycling stations.

Figure 3: Price restoration in April 2017



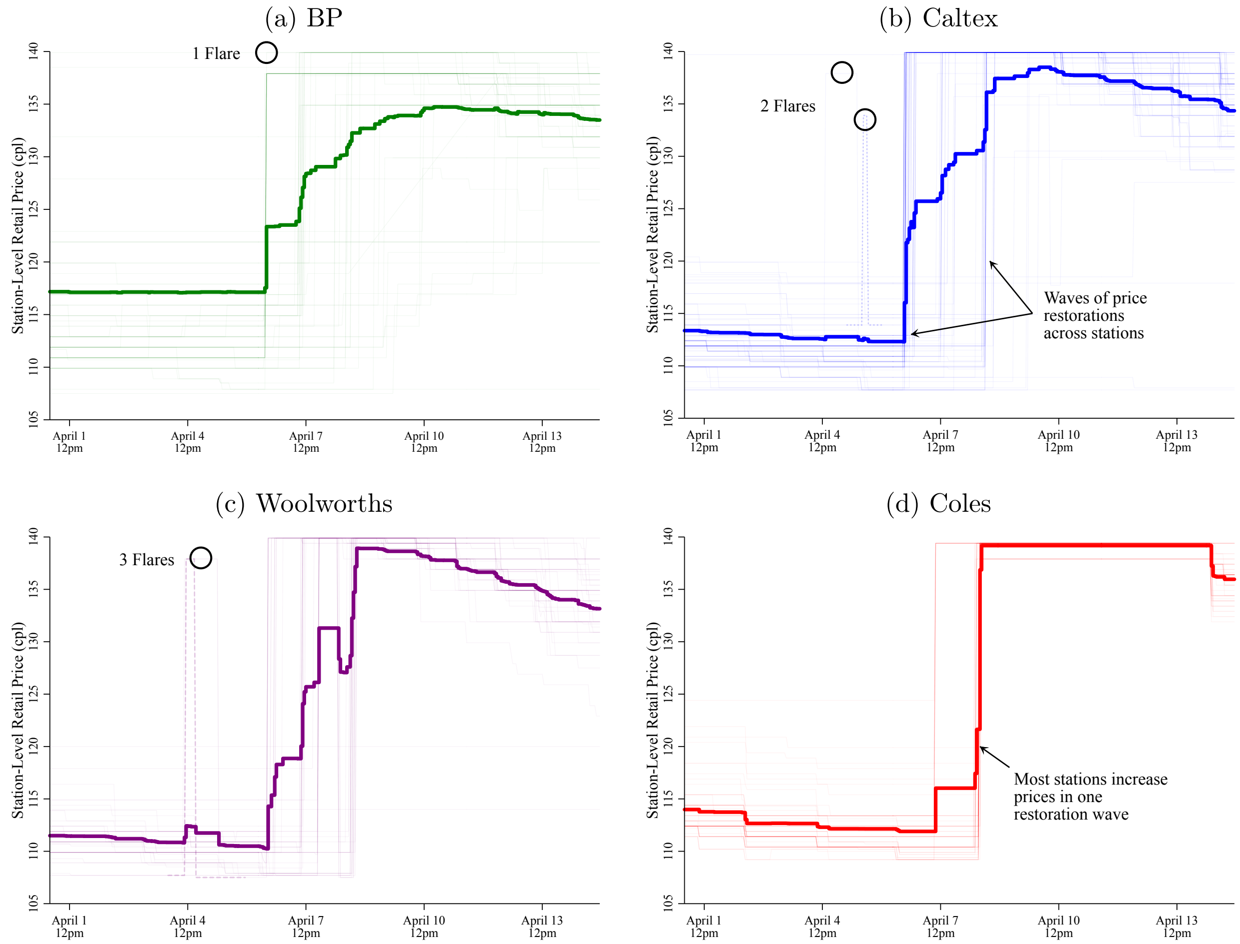
7-Eleven's average price jumps at 5pm. Finally, Coles' average price is the last to jump, at 9am on April 7 (the following day).

While Figure 3 focuses on average retailer-level prices, the FuelCheck (and, by analogy, the Informed Sources) platform 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 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 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

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.

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.

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**.

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 because of their participation in a price-sharing platform and the associated ability to sort, average, and analyze real-time price data.

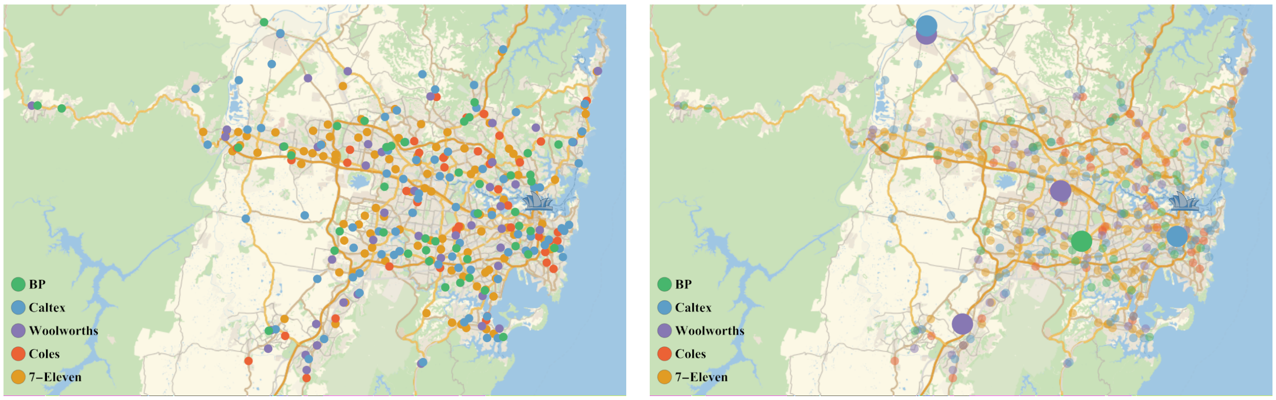
Location of signaling stations

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

Figure 5: Signaling propensity and precision across retailers

(a) Station locations by major retailer in Sydney

(b) Highlighting stations that send signals in Table 1



price increases from relatively remote stations to help reduce the cost of signaling due to lost market share.

4.4 Sparsity, precision, and seclusion in price signaling

Building from our illustrative example, we now use our entire August 2016 to December 2017 sample to characterize three key aspects of platform-enabled signaling: sparsity, precision, 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.[27]

[27] Visually, 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

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 $p_{i\tau}^{rest} = \max(\{p_{i\tau-7}, \ldots, p_{i\tau+7}\})$. 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.[28]
   We identify retailer r's restoration price among its n_r stations in a market-level price restoration starting on date τ as $p_{r\tau}^{rest} = \text{mode}\{p_{1\tau}^{rest}, \ldots, p_{n_r\tau}^{rest}\}$. In words, retailer r's 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.[29] 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.[30]

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. Our results are robust to varying the margin threshold from 1 cpl to 10 cpl.

[28] Recall 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.

[29] Like 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.

[30] For 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

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. This sparsity is valuable to gasoline retailers because it reduces the cost of signaling.

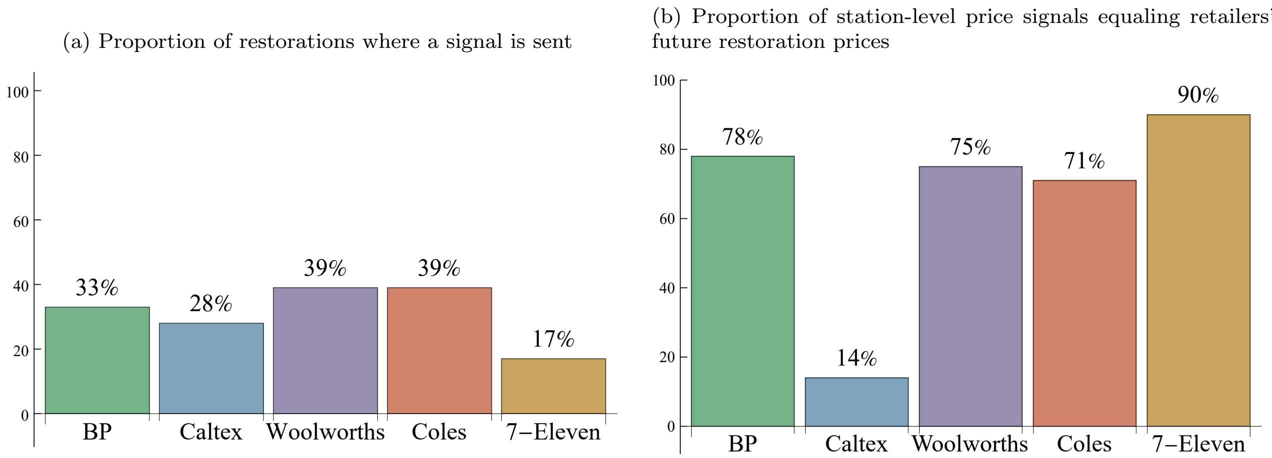
Precision

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 $e_{it} = p_{it} - p^{rest}_{r\tau}$, 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, $p^{rest}_{r\tau}$. If, for example, $e_{it} = 0$, then station i's signal on date t corresponds exactly 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 $\bar{e}_{it} = 1.2$, 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

Figure 6: Signaling propensity and precision across retailers



signals in 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 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, although 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 just a 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 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.[31]

[31]There is a precedent for these results from Perth, Australia, which also has regular price cycles and a platform that makes real-time price data available. Byrne and de Roos (2019) show that in Perth, BP,

Seclusion

Our discussion so far raises the question of whether the major retailers account for stations' proximity to competitor stations in determining from which stations to send signals.

The data show that signaling and non-signaling stations are similar in terms of their geographic proximity to the city's center; however, there are 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 (see Appendix A for details). Signaling stations tend to have fewer local rival stations, suggesting they are more secluded from competition.[32]

Further, we estimate an econometric model (see Appendix A) to formally characterize factors that influence whether a station ever sends a signal in our sample. Results show that 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.

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.[33] The average station-level restoration price jump, corresponding to price jumps from precise signals, is 21.2 cpl. Given an average restoration price of 137.5 cpl, 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.

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.

[32] Previous empirical retail gasoline studies find that competition is highly localized. See, for example, Verlinda (2008), Hastings (2004), Chandra and Tappata (2011), and Luco (2019).

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

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 sent 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 in which retailers want to signal with stations with nearby rivals to ensure their price signals are received. Yet, we find the *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.[34] 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, a searchable platform, and pricing algorithms (Assad et al., 2022) that can quickly identify maximal prices and large price changes among rivals' stations, retailers can monitor and respond to price signals irrespective of the consistency of their geographic locations.

5 Conclusion

Informed Sources provided a mechanism for subscribing gasoline retailers to communicate effectively regarding future prices (including proposals and responses). Although the retailers used their actual prices to communicate, they were able to limit the costs of doing so because, with the facilitation of the Informed Sources platform, they could effectively communicate with only brief price changes at a small number of sites. Even more, communication sites were varied over time and strategically chosen for their limited local competition. In contrast,

[34] Our demand-based argument for firms' incentives to vary the identities of signaling stations stems from recent empirical evidence from Wu et al. (2022). They find that gasoline consumers rapidly update their beliefs about stations' relative price levels within a given day along their commuting routes, substituting toward lower-priced stations. Given habitual commuting behavior in urban markets, like Melbourne and Sydney, we believe consumers would likewise update their beliefs about relatively "high" and "low" priced stations over time if a retailer designated a particular station to be a "signaller." Recall that such signals represent extreme, 20% to 30%, discrete price jumps relative to rival stations' prices when sent from the bottom of the cycle. Such price jumps are likely salient to consumers, particularly if a given station repeatedly sends them each month in coordinating restorations.

in other settings absent an information sharing platform, price-based communication could expose firms to potentially significant lost profits because a firm that signals using elevated prices risks losing substantial business to its lower-priced rivals. In sum, the Informed Sources platform facilitated anticompetitive effects by enabling the monitoring of current prices and the reliable, low-cost signaling of future prices.

It has long been recognized that price-sharing systems can serve as facilitating devices. For example, in the 1920s, the U.S. government prosecuted several trade association cases.[35] In these cases, competitors engaged in frequent (often daily or weekly) information reporting and dissemination via a centralized information exchange system. More recently, in the 1994 Airline Tariff Publishing Company case, the U.S. government investigated collusion in the Airline Industry.[36] 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, with the U.S. government contending that through the airline's information sharing system (ATP), firms engaged in an "electronic dialogue" that helped them to fix prices.[37] In the context of historical antitrust cases involving price-sharing systems, our case study of the Informed Sources matter provides a key takeaway: digital information sharing platforms provide a forum for an "electronic dialogue" that facilitates anticompetitive conduct.

For policymakers, our case study underlines competitive concerns associated with price-sharing platforms. In particular, the speed and reliability with which communication was possible through the Informed Source platform substantially removed the usual deterrents to firms' using prices for signaling. In resolving the Informed Sources matter, the ACCC attempted to reinsert such deterrents by requiring that the shared prices be made available to consumers and third parties for five years. Further, the ACCC's settlement with Informed Sources included that two retailers, Mobil and Coles Express, would not subscribe

[35] Cases 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).

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

[37] "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.

to Informed Sources or a similar service for five years. In concurrent research, Byrne et al. (2023) study the effectiveness of these remedies, finding that the removal of Coles from the platform was associated with an increase in prices. Intuitively, the more limited information flow to Coles slowed Coles' reaction time relative to its competitors, thereby slowing the rate of decline of prices in the undercutting phase of the price cycle.

Price-fixing conspiracies have historically created systems that share price data, making prices transparent to participating firms. The case history shows a progression from letters, telephone, fax, email, and text messages to digital platforms. Although the use of price-sharing devices is not new, the type of systems used have evolved with technological advancements. Thus, as technology advances, so do facilitating devices, and so must our appreciation for the possible anticompetitive effects of the latest advance.

How, then, might policy evolve with the rise of digital price-sharing technologies and associated signaling practices? Monitoring is a natural policy lever, particularly through the use of "big data" screens for anticompetitive conduct. Recent studies by Byrne and de Roos (2019), Assad et al. (2022), and Miller et al. (2021) leverage high-frequency panel data, like the data generated by the Informed Sources platform, to detect price signaling and transitions toward anticompetitive conduct. In principle, similar algorithms used by firms to detect and respond to rivals via platform-generated price data can also be used by antitrust authorities for monitoring conduct. Our case study underlines the importance of having high-frequency, disaggregated price data for such data driven monitoring.

In this case study, we have illustrated that a platform that provides high-frequency, marketwide price information facilitates low-cost signaling, aiding coordination. We might expect that regulating the scope or frequency of information provision could disrupt these signaling practices. However, there are trade-offs involved. In the Informed Sources matter, removing Coles from the platform as part of the settlement effectively reduced the frequency of information flows to Coles, potentially contributing to an increase in prices (Byrne et al., 2023). In the retail gasoline market in Perth studied by Byrne and de Roos (2019), regulators restricted firms to daily price changes. While this limited the scope for low-cost signaling, the data suggest that it simplified the problem of coordinating on focal points for pricing. Given such trade-offs, policy debates regarding the regulation of digital platforms and pricing algorithms are ongoing.[38]

[38] See Ezrachi and Stucke (2020) for an extensive discussion of public policy and regulatory debates over information sharing, pricing algorithms, and the impact of digital platforms on competitive conduct. Recent theoretical and empirical research in economics on these issues include Byrne and de Roos (2019), Luco (2019), Calvano et al. (2020), Montag and Winter (2020), Assad et al. (2022), Asker et al. (2022), Leisten (2022), Ater and Rigbi (2022), and Brown and MacKay (2023).

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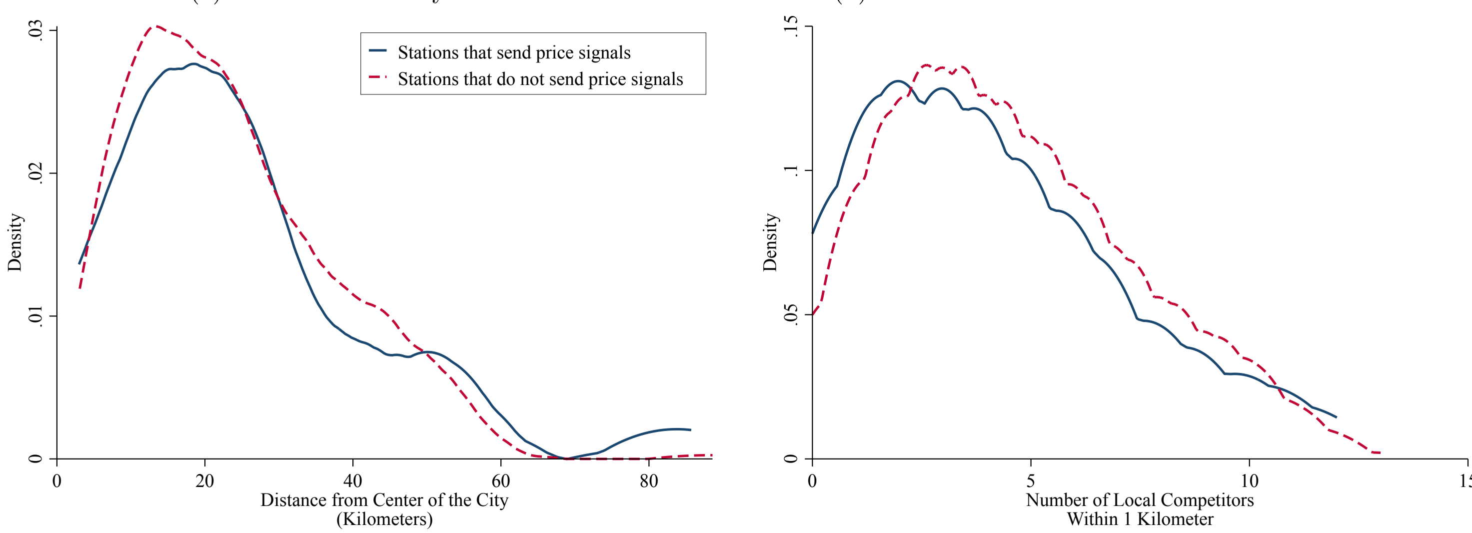
A Appendix: Details for analysis of seclusion

As mentioned in the body of the case study, our discussion raises the question whether the major retailers account for stations' proximity to competitor stations 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.[39]

Figure 7: Characteristics of stations that price signals

(a) Distance from city center

(b) Number of rival stations within 2 kilometers



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,

[39] Our radius-based approach to defining localized markets around individual stations is consistent with the approach used in previous studies (see, e.g., Verlinda, 2008; Hastings, 2004; Chandra and Tappata, 2011; Luco, 2019).

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,[40] 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 (see Table 3) 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.

[40] We 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)
Local market structure				
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	0.003	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Population (100,000's)	-0.188	-0.175	-0.187	-0.185
	(0.291)	(0.291)	(0.292)	(0.293)
Population density (100,000's)	-1.169	-0.841	-0.584	-0.548
	(1.308)	(1.299)	(1.330)	(1.341)
Median income (100,000's)	-0.632	-0.695	-0.759	-0.761
	(0.480)	(0.480)	(0.501)	(0.514)
Average Age	0.005	0.005	0.004	0.004
	(0.008)	(0.008)	(0.008)	(0.008)
Share of people with Bachelor's degree	0.828***	0.809***	0.810***	0.804***
	(0.292)	(0.294)	(0.294)	(0.294)
Share of people English speaking	0.046	0.015	0.028	-0.070
	(0.441)	(0.440)	(0.447)	(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: $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.