Asymmetric Information Sharing in Oligopoly: A Natural Experiment in Retail Gasoline[*]

David P. Byrne[†] Nicolas de Roos[‡] Matthew S. Lewis[§]
Leslie M. Marx[¶] Xiaosong Wu[‖]

August 1, 2023

Abstract

Using a natural experiment from a retail gasoline antitrust case, we study how asymmetric information sharing affects oligopoly pricing. Empirically, price competition softens when, following case settlement, information sharing shifts from symmetric to asymmetric, with one firm losing access to high-frequency, granular rival price data. We provide theory and empirics illustrating how strategic ignorance creates price commitment, leading to higher price-cost margins. Using a structural model, we quantify the impact of asymmetric information sharing on firms' profits, finding substantial profit-enhancing effects. These results provide a cautionary tale for antitrust agencies regarding the potential unintended consequences of limiting price information sharing.

JEL Classification: D22, D43, D83, L13

Keywords: Information Sharing; Strategic Ignorance; Commitment; Retail Gasoline

[*]We thank John Asker, Aaron Barkley, Simon Loertscher, Leslie A. Martin, Nathan H. Miller, Carol Propper, Hsin-Tien Tsai, Eddie Watkins, and Tom Wilkening as well as seminar participants at APIOC 2022, SEA 2022, WEAI 2023, IIOC 2023, Deakin, NUS, Melbourne, Mannheim, Monash, UQ, UWA for helpful comments and suggestions. Funding from the Australian Research Council (DP200103574 and DP210102321) and the Samuel and June Hordern Endowment is gratefully acknowledged. We especially thank Brenda Mainland, Mark McKenzie, and David Prentice for facilitating consumer and transportation data access. Disclosures: David P. Byrne and Leslie M. Marx were retained by the Australian Competition and Consumer Commission for the Informed Sources matter, while 7-Eleven retained Nicolas de Roos. Disclaimers: The interpretations of all results are those of the authors and do not necessarily represent those of the Australian Competition and Consumer Commission, Australian Government, or any parties involved with the Informed Sources matter. Any references to collusion in the paper are strictly in the economic and not legal sense.

[†]Department of Economics, University of Melbourne, byrned@unimelb.edu.au.
[‡]School of Management, University of Liverpool, nicderoos@gmail.com.
[§]John E. Walker Department of Economics, Clemson University, mslewis@clemson.edu.
[¶]Fuqua School of Business, Duke University, marx@duke.edu.
[‖]Department of Economics, University of Melbourne, andy.wu1@unimelb.edu.au.

1 Introduction

What are the market impacts of information sharing among oligopolists? At least since Stigler (1964), research on this age-old question has focused on the effects of *symmetric* information sharing. Historically, the focus on symmetry is natural: it yields tractable models and applies to cartels and trade associations dating to the 1800s that centralize information sharing among firms (Kuhn and Vives, 1995). Moreover, empirical research has provided little guidance for extending theory and policymaking to consider the effects of *asymmetric* information sharing as the structure of firms' information sharing is typically unobserved.

Yet, decentralized information sharing is prevalent in many markets, particularly as industries digitize and firms share information on prices, products, and services offline and online. To the extent that firms differ in their ability to collect and process data on each other, asymmetric information sharing will be widespread. This begs the question: what are the competitive effects of asymmetric information sharing in oligopoly?

This paper informs this question using a natural experiment from the *Informed Sources* antitrust case in retail gasoline. The case outcome allows us to examine the competitive effects of a transition from symmetric to asymmetric information sharing among oligopolists. Under the latter structure, some firms access rival price information more frequently and granularly than others. We argue that such a change empowers a relatively uninformed firm with price commitment and show that this leads to higher equilibrium prices and profits. Notably, these effects were the opposite of what the antitrust agency expected in pursuing and settling the case. Against this backdrop, we view this first study of asymmetric information sharing in oligopoly as producing important new insights for agencies going forward.

Section 2 describes the *Informed Sources* case. The case centers on a price-sharing platform run by an international retail data and analytics company called Informed Sources. Before the case, all five major gasoline retailers in the industry subscribe to the platform and share complete station-level price information across their station networks every 15 or 30 minutes. Crucially, this information sharing occurs among subscribing firms only; consumers cannot access these data. As a result of the case settlement, one of the major retailers exits the platform. In doing so, it stops digitally uploading its data to the platform and loses the ability to observe granular rival price information at high frequency. Informed Sources responds to this turn of events by manually collecting high-frequency station-level price data from the exiting retailer and uploading them to its platform for its existing subscribers. As a result, the four remaining major retailers on the platform maintain complete data visibility after the case.

In effect, the *Informed Sources* case changes the price information sharing structure among the firms from symmetric to asymmetric. After the case, the firm that exits the platform becomes relatively uninformed and can no longer quickly observe and react to rival price changes. We suggest that this ignorance leads to price commitment, and illustrate the role of price commitment in a simple theoretical framework which connects to extensive literature on strategic moves in oligopoly pricing. The central prediction from our model and this literature is that higher equilibrium prices and profits emerge under strategic complementarity when strategic ignorance leads one firm to remain committed to a price for longer (or to set prices less frequently) than its rivals. Moreover, when changing from symmetric to asymmetric information sharing, compared to its informed rivals, the uninformed firm charges higher prices, loses market share, and realizes a smaller profit increase.

The discrete and asymmetric shock to information sharing created by the Informed Sources case settlement provides a unique opportunity to test these predictions empirically. Leveraging the complete, daily, station-level pricing data from the Informed Sources platform, we employ a high-frequency event study design to estimate the effects of the case on firms' pricing. Section 3 describes the station price data in detail. Having such rich data yields numerous advantages. Daily price observations allow us to evaluate case impacts within days of the market transitioning to asymmetric information sharing. Station-specific prices allow us to estimate these effects separately by firm, offering a clearer characterization of how the competitive equilibrium changes with a case-induced shift from symmetric to asymmetric information sharing. Observing a long sample period means we can focus our main analysis on a three-year window surrounding the case but use additional years to confirm the stability of the equilibrium under symmetric information sharing before the case and establish a persistent change in equilibrium under asymmetric information sharing for years after the case.

We present estimates of price effects of the case in Section 4. Here, we focus on changes in price-cost margins that account for cost fluctuations over time. We find substantial price effects for the uninformed firm and its rivals, with the uniformed firm increasing its prices the most. After the case, we estimate that price-cost margins increase by 5.9 and 3.4 cents per liter for the uninformed and informed firms. Compared to baseline levels, these are on the order of 50% margin increases. Exploiting the richness of our data, we further show that the uninformed firm begins adjusting its prices less frequently than its rivals after the case. Overall, these case-induced changes in price levels and adjustment frequencies directly align with theory regarding the price effects of asymmetric information sharing.

Section 5 examines market share and profit effects from the case. We obtain auxiliary market share data from an industry consumer panel and find, as predicted by theory, a 33% decrease in the uninformed firm's share and an average 45% increase in its (informed) rivals' share. These substantial changes in market shares stem from the case's large price effects and a high station-level gasoline price elasticity of demand that previous studies estimate range from -10 to -30

(Houde, 2012; Clark and Houde, 2014; Wu et al., forth.).

Lastly, we quantify case impacts on profits in two steps. First, we combine our price, cost, and retailer-level market share data with data on household commuting flows and auxiliary estimates of the value of time (Goldszmidt et al., 2020) to calibrate a station-level demand model from Houde (2012) that accounts for spatial frictions in consumers' station choice. With this model, we predict daily (inside good) market shares at the station level. Second, we measure and predict total daily fuel consumption at the market level using auxiliary information from the federal government. Then, combining our estimates of daily station-level market shares and market-level fuel consumption, we compute profit changes before and after the case.

We find that the uninformed firm experiences a 4% increase in average daily profits, weighted by stations' shares and daily fuel consumption, resulting from the case. Quantitatively, the firm's relative price increase and associated market share decrease from the case roughly offset in shaping the case's profit impacts. In stark contrast, its rivals experience a substantial 38–77% case-induced increase in average daily profits, reflecting their large increases in prices *and* market shares. Again, our profits results align with our theoretical predictions and reveal substantial quantitative effects of asymmetric information sharing in our setting. Annually, our estimates imply a $33 million (AUD) increase in annual profits due to the *Informed Sources* case settlement, which was intended to promote competition.

We summarize and conclude in Section 6, discussing policy implications from our study and avenues for future research. As part of our discussion, we address the question as to why the antitrust agency pursued and settled the *Informed Sources* case when, ultimately, it increased market power. We argue that the agency's decisions reflected the understanding of information sharing in oligopoly from the literature at the time of the case (Green and Porter, 1984; Kuhn, 2001; Vives, 2007). Policy discourse—informed by theory and empirics assuming symmetric information sharing—was aligned on the idea that restricting the sharing of granular, high-frequency price data within a tight oligopoly was procompetitive (OECD, 2011; European Commission, 2011; Federal Trade Commission, 2014).

What was not well understood, and which our study sheds light on, is that restricting information sharing in ways that create asymmetries can endow firms with price commitment, which can have the unintended consequence of bolstering market power. This insight is relevant for agencies in structuring and implementing antitrust laws, particularly in creating "safe harbours" for information sharing that might promote efficiency while still limiting tacit collusion (OECD, 2011), and in negotiating price-fixing case settlements that involve information sharing agreements. In this policy context, our study provides a cautionary tale about the challenges of regulating information sharing structures between firms, which we anticipate will be at the forefront of policymaking with increasingly digitized and data-driven industries.

Related literature

This article contributes to extensive theoretical and empirical research on the economics of information sharing in oligopoly that, as mentioned, focuses on symmetric information sharing.[1] Empirical studies have examined information sharing in various industries through trade associations (Christensen and Caves, 1997; Doyle and Snyder, 1999; Marshall et al., 2008), public earnings announcements (Aryal et al., 2022), price information-sharing platforms from private companies (Borenstein, 2004; Miller, 2010) and governments (Albaek et al., 1997; Rossi and Chintagunta, 2016; Luco, 2019; Ater and Rigbi, 2023; Montag et al., 2023). These studies yield mixed evidence of efficiency effects predicted by competitive theories of information sharing,[2] and also signalling, coordination, monitoring, and punishments that facilitate collusive conduct (Green and Porter, 1984; Scherer and Ross, 1990). None examine how the structure of information sharing arrangements affects market outcomes.

In contrast to previous research, we examine the competitive effects of asymmetric information sharing. We illustrate how such asymmetries can create price commitment and enhance market power. In this way, we connect the industrial organization (IO) literature on information sharing to a separate body of economic research on information avoidance,[3] which, among other phenomena, emphasizes the value of ignorance as a commitment device in strategic games. Indeed, this idea dates to theories of strategic moves from Schelling (1960) at the foundation of applied IO theory. To our knowledge, we provide some of the first evidence on this phenomenon from the field in an otherwise theoretical area of research.[4]

[1] This body of research complements extensive literature in antitrust law on the legality of information sharing. See Kuhn and Vives (1995) for an overview of the history of antitrust law on information sharing in the United States and the EU, which dates to the 1880s and the origins of the Sherman Act (1890). Tensions exist in the legal treatment of oligopolistic information sharing. For example, in the United States, it is not per se illegal. The FTC/DOJ apply a rule of reason approach to assessing its legality (FTC, 2000). In contrast, in the EU, some information sharing is per se illegal; in particular, sharing information about future prices is a restriction of competition by object (European Commission, 2011).

[2] Kuhn and Vives (1995) review static models of competition studying firms' incentives to share information and the impact of information sharing on welfare. This body of research establishes that welfare effects depend on the nature of competition (Bertrand versus Cournot competition) and of the private information shared (demand versus cost data). Recent dynamic models of information sharing also find mixed results regarding the welfare-enhancing (Asker et al., 2020) and anticompetitive effects (Kubitz and Woodward, 2020) of information sharing, depending on the underlying structure of competition (dynamic auctions or price posting) and the private information being shared (inventory of a firm's current projects or its marginal cost). Luco (2019), building on Varian (1980), illustrates the potential efficiency effects of public information sharing on the demand side of the market (e.g., through a government-provided price transparency website). Publicly providing such information can reduce consumers' search costs if their engagement with information from the website promotes price competition.

[3] See Golman et al. (2017) for an overview of this extensive literature.

[4] The value of ignorance in inter-personal games has been explored in bargaining and hold-up problems (Tirole, 1986; Rogerson, 1992; Gul, 2001), principal-agent contracting (Cremer, 1995; Dewatripont and Maskin, 1995; Aghion and Tirole, 1997), and sequential procurement (Krasteva and Yildirim, 2019). Carrillo and Mariotti (2000) examines strategic ignorance for commitment in intra-personal games with time-inconsistent decision-making.

Our study also connects to burgeoning IO research on the competitive effects of algorithmic pricing. We most closely relate to Brown and MacKay (2023), who examine the competitive impacts of firms employing heterogeneous pricing algorithms.[5] They document the existence of heterogeneous online pricing algorithms that adjust prices at different frequencies and theoretically show how such asymmetry increases prices and profits compared to a setting with symmetric pricing frequencies. We provide novel empirical results that (strongly) confirm their predictions and establish asymmetric information sharing as a microfoundation.

The context for our study—a federal antitrust case—further connects our analysis to cartel case studies in IO. These studies combine detailed information on the inner workings of cartels and market data (e.g., firms' prices and quantities) to reveal underlying sources of market power and quantify their impacts (e.g., Genesove and Mullin, 2001; Borenstein, 2004; Röller and Steen, 2006; Marshall et al., 2008; Asker, 2010; Marshall and Marx, 2012; Clark and Houde, 2013; Igami and Sugaya, 2022). We similarly use documentary evidence and rich data from an antitrust investigation into price fixing to provide a unique study on the internal (re)-organization of information sharing among oligopolists and its market power impacts. As with previous cartel cases, having a research design and results derived from an antitrust case gives our analysis weight in informing antitrust policy.

Finally, our study adds to a large body of research on market power in retail gasoline. It is particularly related to empirical studies of price leadership (e.g., Lewis, 2012; Lemus and Luco, 2021) and collusion, both tacit and explicit (e.g., Borenstein and Shepard, 1996; Wang, 2009; Erutku and Hildebrand, 2010; Clark and Houde, 2013, 2014; Lewis, 2015; Byrne and de Roos, 2019; Luco, 2019; Assad et al., forth), and associated market power effects. Our focus on asymmetric information sharing and commitment as a driver of market power distinguishes our study from this prior work.

2 Informed Sources case

Our study centres on Informed Sources (https://informedsources.com/), an international data and analytics company in the retail gasoline sector emphasizing:

[5] Other recent work on firm heterogeneity and price algorithms examines tacit collusion and vertical relations. Assad et al. (forth), Musolff (2022), and Leisten (2022) study price competition between algorithms and between algorithms and humans. This work sheds light on where algorithmic price-setting can lead to tacit collusion, informing broader policy debate on the issue (Ezrachi and Stucke, 2017). Chen and Tsai (2023) show how Amazon exploits its vertical information advantage on quantity data (in addition to price, demand and cost data) over third-party sellers on its platform to rapidly adjust its prices based on the sellers' sales in downstream retail markets where Amazon also sells products. Their study of informational asymmetry and fee setting on a platform complements our study of horizontal asymmetry, which addresses the different issue of commitment and more closely connects to theory and empirics on information sharing as overviewed by Kuhn (2001) and Vives (2007).

"Accurate, reliable, timely data ... To make decisions with confidence, you need a complete view of the market."

The company has been in operation for more than 30 years. It started out by manually collecting and sharing gasoline stations' prices using human price spotters. At least since the 2010s, it runs a digital platform that enables information sharing among gasoline retailers. Specifically, subscribers to the Informed Sources platform: (1) digitally provide their station-level price data every 15 or 30 minutes; and (2) gain access to all prices provided to the platform at all times. Informed Sources complements this information with non-subscriber station-level price data that the company collects manually at daily, weekly, or other frequencies.

An important feature of the Informed Sources platform is that, historically, it is available to the supply side of the market, but *not* the demand side. In the words of European Commission (2011) (Sec. 2.2.3), Informed Sources facilitates non-public information sharing that risks having a restrictive effect on competition.

2.1 ACCC case

In August 2014, the Australian Competition and Consumer Commission (ACCC) alleged that Informed Sources and Australia's five major gasoline retailers, BP, Caltex, Woolworths, Coles, and 7-Eleven,[6] violated section 45 of the Competition and Consumer Act of 2010, which makes illegal "contracts, arrangements or understandings that have the purpose, effect, or likely effect of substantially lessening competition." At the time, all five major retailers subscribed to the platform, and they operated and set prices for more than two-thirds of the stations nationwide (ACCC, 2018). These retailers' dominance and degree of information sharing underpinned the government's concerns about anticompetitive behavior. In the words of ACCC Chair Rod Sims from the agency's press release (ACCC, 2014) for the case:

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

[6]Formally, the retailers involved were BP Australia Pty Ltd, Caltex Australia Petroleum Pty Ltd, Woolworths Ltd, Eureka Operations Pty Ltd, and 7-Eleven Stores Pty Ltd. Both Woolworths and Coles also operated supermarket chains and offered gasoline price discounts if consumers' supermarket purchases on a given visit to the supermarket were sufficiently large. These fuel discounts were offered under Woolworths' and Coles' customer loyalty programs, which also offered points that could be redeemed for other retail rewards (e.g., appliances, travel). Caltex accepted discount vouchers from Woolworths' grocery stores throughout our sample period. BP's fuel customers could earn discounts for purchases within BP convenience stores and could earn Qantas frequent flyer points.

Since 2013, the federal government has regulated the tied discounts for all four major retailers to a maximum of 4 cents per litre (cpl) (ACCC, 2013). In effect, fuel purchases from BP, Coles, Caltex, and Woolworths were connected to retail loyalty schemes with national supermarket chains or airlines and offered 4 cpl discounts. In contrast, 7-Eleven, which primarily operated convenience stores, both with and without associated gasoline stations, offered 2 cpl discounts for in-store purchases but not a broader points program.

...

"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."

The case was alleged in the retail gasoline market of Melbourne, a major metropolitan area with 4.4 million people in 2014. In its press release, the ACCC went on to allege 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." The agency further emphasized potential consumer harm, noting that "even a small increase in petrol pricing can have a significant impact on consumers overall. For example, if net petrol prices increase by 1 cent per litre over a year, the loss to Australian consumers would be around $190 million for the year."

2.2 Case settlement

The case lasted 16 months, ending with a settlement in December 2015. Two key outcomes emerged, as summarized in press releases associated with the settlement ACCC (2015a,b):

#1 Informed Sources would make its data available "on reasonable commercial terms" to third parties, including third-party consumer search app developers and research organizations.

#2 Coles would withdraw from the Informed Sources platform when their contract expired four months later in April 2016. At this point, Coles would lose access to high-frequency station-level price data on its four major rivals, BP, Caltex, Woolworths, and 7-Eleven, which all remained on the platform.

Statements by ACCC Chair Rod Sims in the agency's press releases for the case settlement illustrated a belief by the agency that these case outcomes would be pro-competitive:

"Making [Informed Sources] pricing information available to consumers will allow consumers to make better informed purchasing decisions and therefore create greater competition in petrol pricing." (ACCC, 2015b)

> *"I welcome and appreciate the decision of Coles Express to cease using the Informed Sources information sharing service at the earliest available opportunity .... The ACCC considers this to be an extremely positive step towards increasing competition in the petrol market ...."* (ACCC, 2015a)

These beliefs were supported by existing research into the competitive effects of information sharing. Outcome #1 would make Informed Sources' data publicly available and reduce consumer search costs, thereby enhancing firms' incentives to undercut rivals' prices to steal business. In addition, having more price-attentive consumers would make price signaling and leadership more costly for firms looking to coordinate marketwide price increases (described in detail below). Outcome #2 would limit the sharing of high-frequency and granular strategic price data in a tight oligopoly, especially since Coles had a relatively more extensive station network widely distributed across the market (detailed below). Given Coles' station network, outcome #2 was expected to limit firms' ability to signal and coordinate price adjustments and monitor and punish secret price cutting by rivals through the Informed Sources platform.[7]

Existing research on (symmetric) information sharing in oligopoly at the time of the case (e.g., Green and Porter, 1984; Scherer and Ross, 1990; Kuhn, 2001; Vives, 2005) aligned antitrust agencies worldwide on the idea that making information public to firms *and* consumers (outcome #1) and limiting sharing of rich strategic data among firms (outcome #2) would help destabilize tacit collusion (OECD, 2011; European Commission, 2011; Federal Trade Commission, 2014). As the quotes from ACCC (2014) above make clear, in pursuing the case, the ACCC believed that Informed Sources' platform was indeed facilitating tacit collusion. The agency's outcomes in settling the case thus reflected the research frontier and best policy practice in attempting to regulate information sharing to promote competition.

2.3 Realized case outcomes

In practice, however, realized changes to the informational environment on the demand and supply side of the market departed in important ways from the ACCC's expectations.

On the demand side, there was virtually no change in third-party consumer app availability in the years after the Informed Sources case. Appendix A provides details on the history of consumer search apps in Australia, their (lack of) popularity, and lack of change in their availability before and after the case. In this sense, case outcome #1 did not significantly change

[7]While we are not privy to the details of Coles' case-induced platform exit, its station network size, and thus its potential importance for price information sharing among the firms, is one potential explanation for Coles' agreement to exit the platform. Another potential explanation is that its contract with Informed Sources was due to expire in April 2016, which was just four months after the case settlement.

app-enabled consumer search.[8]

On the supply side, all firms' information over rival prices worsened after Coles exited the Informed Sources platform, with an asymmetric impact on Coles. Our data from the platform, described in Section 3, allow us to track rival price information for BP, Caltex, Woolworths, and 7-Eleven over time. These four firms observed the universe of each other's station-level prices within a given market (city) every 15 or 30 minutes both before and after the case.

As we show below, despite Coles' exit from the platform, the remaining four Informed Sources subscribers still observed Coles' prices *after* Coles exited the platform. What made this possible was a strategic response by Informed Sources: the company began manually collecting Coles' stations' prices using human price spotters immediately after Coles exited the platform. As shown in Section 3, these spotters collected one price observation per station daily for approximately three-quarters of Coles' stations, with the focus being on stations in the urban core rather than the outer suburbs.

Notably, Informed Sources' strategic response worked against case outcome #2 in limiting information sharing across firms. To our knowledge, no such response by an information-sharing technology (e.g., trade journal, digital platform) to a government regulating information sharing had been previously documented in economic research or antitrust case law. Given the unprecedented nature of Informed Sources' strategic response, the ACCC possibly did not anticipate the evolution in information sharing among Informed Sources' four remaining subscribers after the case when forming its beliefs about case outcome #2's impact.

Coles likewise observed rivals' station-level prices every 15 or 30 minutes while on the platform. After leaving the platform, the extent to which Coles could observe rivals' prices becomes unknown. Given the speed and coverage of Informed Sources in generating 15 or 30-minute station-level data for the four remaining subscribers after the case, plus Informed Sources' intensive daily price spotting of Coles stations, Coles was almost surely at an informational disadvantage compared to its rivals in terms of rival station price data frequency and coverage after it exited the platform.[9] As we will see, stations adjust prices daily, and station-level price

[8] Various factors might explain why no third-party apps entered the market through an Informed Sources data purchasing agreement. First, competition existed from an incumbent private third-party app (PetrolSpy) that relied on consumers uploading prices to their platform at $0 cost and earned revenue through in-app advertising (see Appendix A for details). Second, PetrolSpy had low adoption rates, consistent with findings from Byrne and de Roos (2022) that consumers face large up-front search app adoption costs. Therefore, the expected app demand may have been low. Finally, most Australian state governments had implemented or were in the process of introducing mandatory price disclosure laws. These laws require gasoline retailers to upload real-time price data to government-run platforms or central databases for consumer access. The limited market size and the expectation of policy rollouts would further dampen incentives for third-party apps to enter the market. Victoria remains the only state to never enacted such a law, leading to the absence of a government-run platform in Melbourne.

[9] More precisely, we assume that Coles does not replicate the data generated by Informed Sources through 15 or 30-minute digital uploads. Coles could have their employees engage in price spotting of nearby competitors and upload the data to Coles' central database. However, this price collection lacks the complete market cover-

elasticities are large, underlining the value of granular and high-frequency rival price data in price-setting and Coles' informational disadvantage.

2.4 Asymmetric information sharing and price commitment

Using a simple conceptual framework, we elucidate the economic effects of transitioning from symmetric to asymmetric information sharing among Coles and its rivals due to the Informed Sources case settlement. Below, we discuss the robustness of our model predictions to various modeling assumptions.

Consider a Hotelling (1929) model of differentiation with two firms, 1 and 2, competing in prices along a linear city of length 1. Firm 1 is at location $y_1 = 0$ and charges price p_1 and Firm 2 is at the other extremity $y_2 = 1$ charging p_2. Each firm has a constant marginal cost of c and no fixed costs.

Consumers are indexed by i, have unit demand, and are uniformly distributed along the city. If consumer i, located at $x_i \in [0,1]$, purchases from Firm j, then consumer i obtains indirect utility

$$u(p_j, x_i) = \bar{u} - t|y_j - x_i| - p_j,$$

where $\bar{u}$ is the intrinsic value of purchasing and $t > 0$ is the transportation cost. Consumer i purchases from the firm that maximizes their utility, and we assume $\bar{u}$ is sufficiently large to ensure full market coverage. Given this setup, the share of consumers purchasing from firm $j \in \{1,2\}$ is

$$s_j = \frac{1}{2} + \frac{p_{-j} - p_j}{2t},$$

where the subscript $-j$ denotes j's rival. We can use this model to predict the impacts of a case-induced shift from symmetric to asymmetric information sharing on firms' prices, market shares, and profits.

Before the case: simultaneous pricing

Before the case, retailers symmetrically shared station-level price information every 15 or 30 minutes and commonly understood that they could quickly observe and react to each other's prices. Any firm contemplating a price change would understand that their rivals would also have an opportunity to adjust prices based on the same information, before the next infor-

age offered by Informed Sources data. In addition, while gasoline price reporting platforms such as MotorMouth (website) and PetrolSpy (search app), established in July 2013 and September 2014, respectively, could have been monitored by Coles, they provide incomplete coverage of stations day-to-day, often with multiple-day lags in price data; see Appendix A for details. These auxiliary data contrast with Coles' rivals' complete, 15–30 minute-level or daily price data on each other's stations, including Coles stations (via price spotters), after the case.

mation update. Through the lens of the model, we interpret this baseline scenario as corresponding to simultaneous (Bertrand) price competition. In this case, the Nash equilibrium is determined by the following reaction functions for firms $j \in \{1,2\}$

$$p_j = \frac{p_{-j} + t + c}{2}.$$

The equilibrium is unique, with Bertrand prices $p_1^B = p_2^B = t + c$ and profits $\pi_1^B = \pi_2^B = \frac{1}{2}t$.

After the case: sequential pricing

After the case, Coles was 'unplugged' from the Informed Sources platform and was at an informational disadvantage. Coles' rivals continued to observe each others' stations every 15 or 30 minutes and observed Informed Sources' manually collected prices for most of Coles' stations every day. Coles, in contrast, lost access to such high-frequency rival price data with marketwide coverage and the ability to observe and quickly react to rivals' prices. All retailers were commonly aware of this asymmetry in the retailers' information on rival prices.[10]

We interpret this case-induced change to information sharing as introducing sequential pricing day-to-day between Coles and its rivals. After the case, Coles became strategically ignorant and could credibly commit to prices over short time horizons each day because it was less able to observe and respond to rival price changes quickly. In contrast, Coles' rivals could observe and quickly react to Coles' and each other's price adjustments. Interpreting these changes with our model, suppose that Firm 1 (Coles) chooses its price first and then Firm 2 (Coles' rival) chooses its price after observing Coles via Informed Sources. In this sequential-move environment, the subgame perfect Nash equilibrium prices and profits are $p_1^S = \frac{3}{2}t + c$ and $p_2^S = \frac{5}{4}t + c$ and $\pi_1^S = \frac{9}{16}t$ and $\pi_2^S = \frac{25}{32}t$.

Hypotheses

We compare equilibrium under simultaneous and sequential pricing to develop three main hypotheses regarding the price, market share, and profit effects from the Informed Sources case:

Hypothesis 1 (Price effects). *Prices increase for Coles and its rivals after Coles exits the Informed*

[10]We assume that Coles was aware of Informed Sources' manual price spotters and its activity in monitoring and uploading Coles' stations' prices after the case. We show in Section 3 that, before the case, Informed Sources had a long history of using price spotters to manually upload non-subscribing retailers' stations' prices (e.g., smaller retail chains and independent stations) to the platform. These manually collected data, in turn, allowed Informed Sources' subscribers to monitor and adjust to non-subscribing retailers' prices. Given these institutional features, Coles was likely aware of Informed Sources' price-spotting workforce and that, as a non-subscribing retailer, its stations' prices would have been monitored and uploaded to the platform after the case.

Sources platform, with the increase in Coles' prices being the largest.

$$p_1^S > p_1^B, \qquad p_2^S > p_2^B, \qquad p_1^S - p_1^B > p_2^S - p_2^B.$$

Hypothesis 2 (Market shares). *Coles' market shares decrease after exiting the platform while its rivals' shares increase.*

$$s_1^S - s_1^B < 0, \qquad s_2^S - s_2^B > 0.$$

Hypothesis 3 (Profit impacts). *Profits increase for Coles and its rivals after Coles exits the platform, with the increase in rivals' profits being the largest.*

$$\pi_1^S > \pi_1^B, \qquad \pi_2^S > p_2^B, \qquad \pi_2^S - \pi_2^B > \pi_1^S - \pi_1^B.$$

While these hypotheses come from a highly simplified model, extensive work in applied theory (e.g., Gal-Or, 1985; Hamilton and Slutsky, 1990; Amir et al., 1999) on static and sequential pricing games establishes **Hypotheses 1-3** in more general settings as long as prices are strategic complements, allowing for market structures with one leader and multiple followers. In Appendix B, we further show that under strategic complementarity, **Hypotheses 1-3** emerge from: (1) repeated games models of collusion with perfect monitoring and/or imperfect coordination; and (2) dynamic oligopoly models with strategic complementarity whereby continuation payoffs are increasing in rivals' prices.

Brown and MacKay (2023) obtain similar insights from a dynamic continuous-time pricing game where duopolists can differ in (algorithmic) pricing frequency. Compared to a baseline scenario with symmetric pricing frequencies, prices and profits increase when the firms have asymmetric pricing frequencies. Moreover, the firm that adjusts its prices less frequently (i.e., Coles) has higher prices and lower profits than its rival, echoing predictions from static and sequential pricing models. Our empirical setting provides a unique opportunity to directly test their mechanism and explore asymmetric information sharing as a microfoundation.

In summary, theory predicts that the shift from symmetric to asymmetric information sharing following the Informed Sources case will lead to higher prices and profits for all firms, with Coles' prices rising the most and profits rising the least. In addition, Coles should lose market share while its rivals should gain. We now use a rich dataset from the Informed Sources platform to test these hypotheses and quantify the case's price, market share, and profit impacts.[11]

[11]Why do we not see a retailer exit the Informed Sources platform sometime *before* the case if, by gaining commitment power from strategic ignorance, it is profitable to do so? While addressing this question is outside the scope of our analysis, we can use our model to shed some light on it. The model predicts that the change in profits when going from simultaneous to sequential pricing for the first and second moving firm is $\frac{1}{16}t$ and $\frac{9}{32}t$, respectively. Retailers would thus face a coordination problem in determining who should exit the platform: each retailer would want to stay on the platform if a rival exited (to gain a second-mover advantage), but a given retailer would

3 Data

For our analysis, we obtained Informed Sources data on daily station-level prices for Melbourne (4.7 million people in 2017), where the case was alleged. We focus on prices for regular unleaded 91 petroleum as this accounts for the vast majority of fuel sales. We also obtained data from Sydney (5.1 million people) for comparison. While the case was not alleged there, we can validate in Sydney whether similar conduct changes occur after Coles exits the Informed Sources platform.

We have access to 15 years of station-level price data from Informed Sources, spanning 2005 to 2019. For studying the impacts of the Informed Sources case, we narrow our primary sample period to May 1, 2015, to December 31, 2017 (32 months). Coles exits the Informed Sources platform 11 months into the sample in April 2016. Aside from Coles' platform exit, the market does not experience major shocks to demand, costs, or industry structure over this period.[12] While our data allow us to identify case impacts at high frequency (e.g., within days of when Coles stops uploading data to the Informed Sources platform), the stability of the market environment allows us to examine changes in equilibrium associated with asymmetric information sharing arising from Coles' platform exit over a two-year horizon.[13]

We further obtain daily data on wholesale terminal gate prices (TGPs) for Melbourne and Sydney from the Australian Institute of Petroleum (https://www.aip.com.au/). TGPs are the main time-varying component of stations' daily marginal cost of unleaded 91 gasoline, reflecting changes in the Singapore MOGAS 95/92 crude oil price index and regional refining market conditions. Therefore, retailer margins (price−TGP) can be directly observed with high frequency to reveal any changes occurring before and after Coles exits the platform.

Table 1 presents summary statistics for our main Melbourne-based sample, while Appendix

want to unilaterally exit if its rivals remained on the platform (to gain commitment power). This tension in firms' incentives complicates tacitly coordinating *who* exits. Further, the profit increase from unilaterally exiting the platform is likely small given that station-level demand elasticity estimates range from −10 to −30 (Houde, 2012; Clark and Houde, 2014; Wu et al., forth.), implying a small transportation cost t. This small potential gain from unilaterally exiting the platform may also help explain why a retailer did not exit the platform before the case.

[12] In particular, there are no mergers between gasoline retailers or wholesalers, station entry and exit is minimal, supermarket-related fuel discounts for Coles and Woolworths are fixed by government regulation, and global crude oil prices are stable (e.g., no major international demand or supply shocks). We confirm these facts from a series of in-depth annual gasoline industry monitoring reports from the ACCC available at https://www.accc.gov.au/by-industry/petrol-and-fuel/fuel-and-petrol-monitoring (accessed August 2, 2023).

[13] Appendix C.1 describes our primary sample in the context of a larger Informed Sources dataset spanning 2014-2019. Our sample start date stems from a global crude oil price shock between October 2014 and January 2015, affecting retailers' wholesale costs and pricing structures. By May 1, 2015, the pricing structures stabilize and remain stable through 2017, save for when Coles exits the Informed Sources platform. Our sample end date (December 31, 2017) corresponds to a year where we can access consumer choice data over gasoline retailers to analyse the case's market share and profit impacts. We describe these auxiliary data in Section 5. Nevertheless, we discuss the robustness of our estimates of the case's price effects to using 2016 or 2018 sample end dates. In February 2019, there are two significant firm ownership changes (EG Group purchases Woolworths and a Viva Energy – Coles strategic alliance), effectively ending the 2015-18 window where the market environment is stable.

Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Max
Prices (cpl)				
Price	124.2	11.6	92.1	151.9
Terminal Gate Price	113.0	8.2	95.2	131.9
Margin	11.2	8.4	-12.2	47.3
Panel Dimensions (cpl)				
Dates		976		
Stations				
BP		127	(19%)	
Caltex		92	(13%)	
Coles		147	(22%)	
Woolworths		93	(14%)	
7-Eleven		148	(22%)	
Other		75	(11%)	
Total		682	(100%)	
Observations				
Electronically collected		438048	(81%)	
Manually collected		99829	(19%)	
Total		537877	(100%)	

Notes: Sample period is May 1, 2015, to December 1, 2017. Retail prices are at the station-date level. Wholesale Terminal Gate Prices (TGPs) are at the daily level from Melbourne's gasoline terminal gate. Margin is a station's retail price less Melbourne's TGP on a given date.

C.2 presents analogous statistics for Sydney. The top panel summarizes station-level retail prices, wholesale costs, and margins (measured in cents per liter, or cpl). On average, margins represent a 10–11% markup over the wholesale TGP.

The middle panel of Table 1 describes our panel's structure. Like many urban retail gasoline markets worldwide (Eckert, 2013), Melbourne has an asymmetric market structure, with five major retailers operating the majority of stations and a competitive fringe of smaller retail chains and independents ("Other" stations in the table). The largest retailers in terms of station counts are 7-Eleven and Coles, both operating 22% of the stations in the data.[14]

[14]These market structure figures only include stations for which Informed Sources electronically or manually collects prices. While the data include all stations operated by the five major retailers in the market, Informed Sources may not find it worthwhile to manually collect prices for some smaller retail chains and independent

3.1 Electronic and manual data collection

The bottom panel of Table 1 tabulates *how* Informed Sources collects each daily station-level observation. Most (81%) observations are electronically collected from the five major retailers who, as Informed Sources subscribers, upload price data to the company's information-sharing platform. However, Informed Sources manually collects a non-negligible share (19%) of daily station-level prices from price spotters driving around the market day-to-day.

Figure 1 illustrates how Informed Sources' electronic and manual data collection evolves six months before and after April 2016, when Coles' contract with Informed Sources expires. Various patterns of interest emerge.[15] Panel (a) shows a sudden and complete elimination of digital price uploads for Coles stations on April 15, 2016. Panel (b) illustrates a simultaneous jump to 75 Coles stations per day with manual price uploads (63% of Coles' stations) on April 15. A second jump in manual data collection for Coles stations occurred on June 14, 2016, rising to 98 stations per day (82% of Coles' stations). In sum, Informed Sources immediately starts manually collecting Coles' stations' prices with price spotters and uploading them to its platform when Coles stops electronically uploading its price data.

Panel (b) also shows how Informed Sources reallocates its price spotter workforce after Coles exits the platform. Before April 15, 2016, Informed Sources would manually collect price data from subscribers and non-subscribers (e.g., smaller retail chains and independents).[16] Collecting such information is consistent with Informed Sources validating electronically-uploaded price data from the five major subscribing retailers. However, after Coles stops uploading prices to the platform, panel (b) shows that Informed Sources reallocates all of its manual price collection efforts to collecting price data on Coles stations only.[17] This shift in behavior reveals, from Informed Sources' perspective, the importance of maintaining observability of Coles' stations'

stations. The latter source of sample selection is not problematic for our analysis of case-induced changes to major retailers' pricing structures in Section 4. However, as we discuss and address in Section 5, small retailer and independent station selection matter for estimating profit impacts from the case.

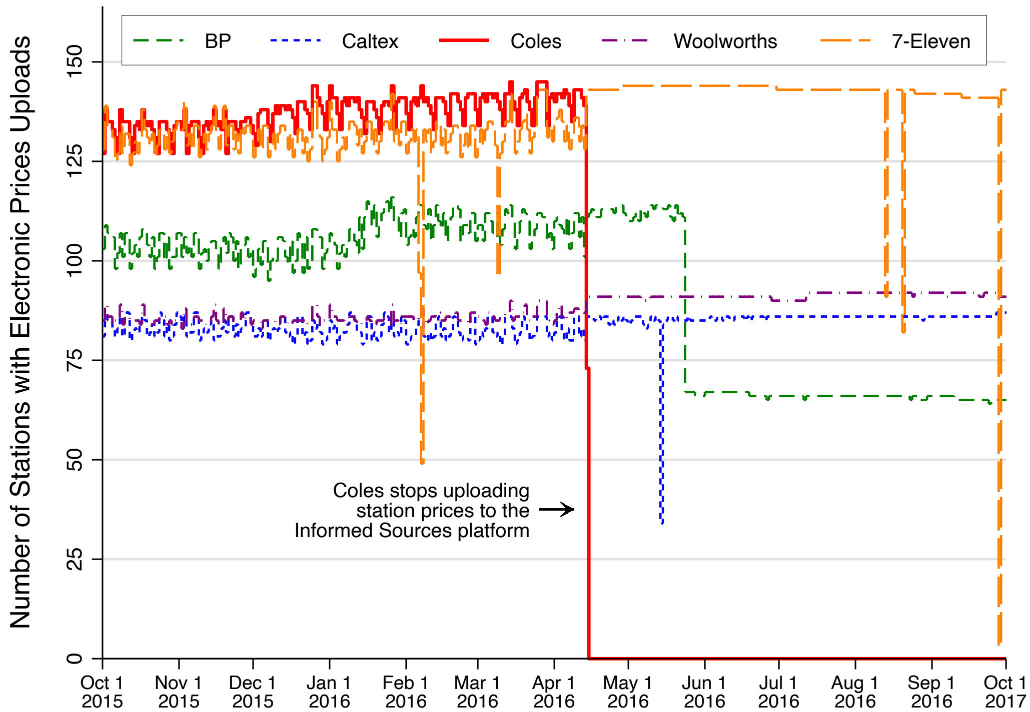
[15]Appendix C.2 contains parallel results for Sydney that mirror our findings in this section. These auxiliary results validate Coles' exit from the Informed Sources platform nationwide, as reported in ACCC (2015b). They also confirm similar price effects from Coles' platform exit in both Melbourne and Sydney, which we discuss below.

[16]Figure 1(b) indicates that some subscriber stations' prices are collected manually on certain days, leading to cycles in price uploads. These manual upload cycles align with the cycles observed in electronic data collection in panel (a). The manual price uploads for subscribers before Coles stops digital uploads seem to be an artifact of the dataset provided by Informed Sources. While subscriber stations' prices are uploaded electronically, the platform may manually spot-check their prices on certain days. In these cases, a station may have price observations with "Manual" and "Electronic" labels on a day. Informed Sources likely assigned a unique label to each station day when providing us with the daily station-level price data.

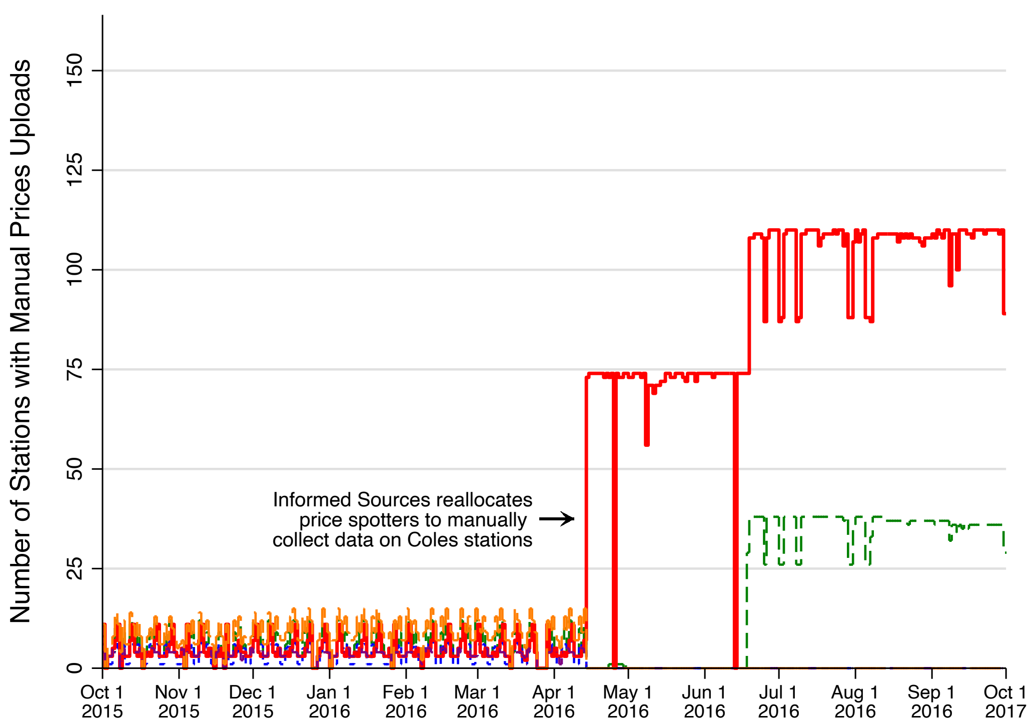
[17]By reallocating the price spotter workforce toward Coles stations, Informed Sources stops validating subscribers' prices through manual data collection after Coles exits the platform. Given evidence of tacit coordination in the industry (Byrne et al., forth.), to the extent that this change results in a deterioration in monitoring, we would expect this to make it more difficult to sustain supra-competitive margins (Green and Porter, 1984).

Figure 1: Daily Station-Level Price Uploads to the Informed Sources Platform

(a) **Electronic** Uploads



(b) **Manual** Uploads



Notes: Number of stations with electronic or manual uploads by data for Melbourne. Manual uploads drop to zero in April and June on ANZAC Day (April 26) and Queen's Birthday (June 13) public holidays.

prices for its remaining subscribers (BP, Caltex, Woolworths, 7-Eleven) after the case.[18]

Lastly, Appendix C.3 shows that Informed Sources manually collects data from Coles stations in the urban core, not the city's outer suburbs. The initial 75 Coles stations with manual data collection in April 2016 are in the middle of the city. The company then moves to the city's next suburban "ring" in June 2016 with an additional 23 stations, stopping before the more remote suburbs. Such an inside-out data collection approach likely reflects differences in the value of information for retail price-setting between stations in the urban core with high population density and more local competitors versus more isolated stations in less-dense outer suburbs. Moreover, the platform can minimize its per-station manual data collection cost by collecting data for clustered Coles stations along main roads in the urban core and not driving to outer suburbs to collect data from more sparsely distributed stations.

We emphasize the importance of Informed Sources' manual collection of Coles' price data for our study. Without it, we could not examine how Coles' loss of platform access affects the retailer's pricing behavior. In our analysis of price effects of asymmetric information sharing, we only use data for the 98 Coles stations for which Informed Sources collects data before *and* after the retailer exits the platform. Such issues do not arise for the other four major retailers with digital data uploads to the platform before and after Coles exits. Our results are, however, unaffected by simply including all prices for all Coles stations in our primary sample.

3.2 Price cycles

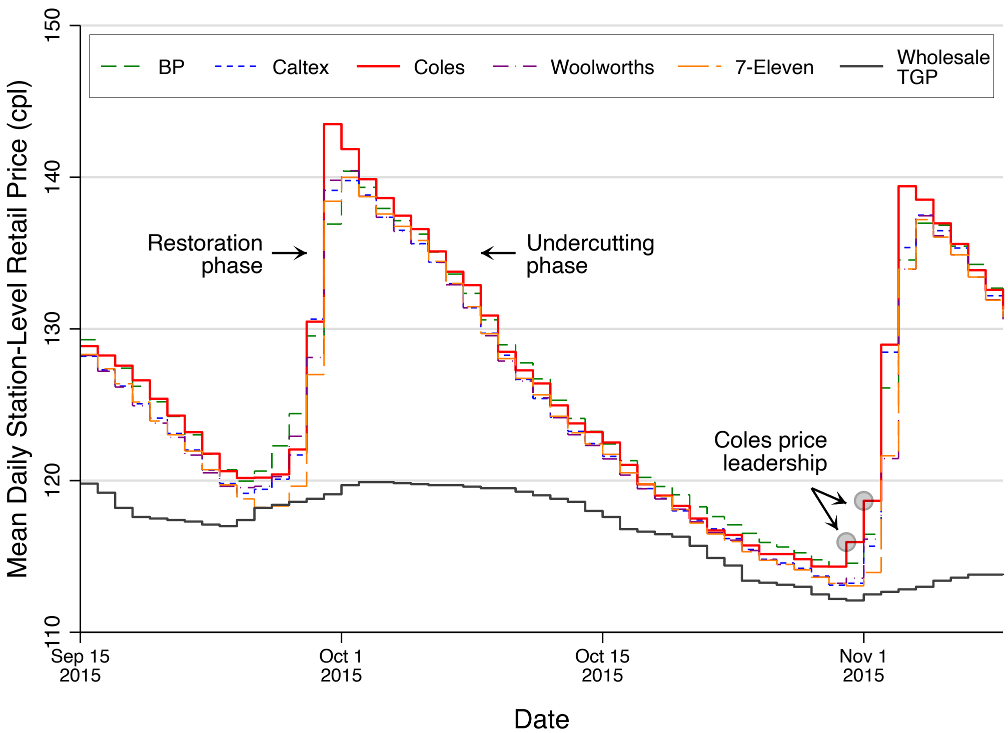
Turning to our price data, a key feature is that retail prices in Melbourne exhibit an asymmetric cycle.[19] Figure 2 illustrates this by way of example, plotting average daily retail prices by retailer between September 15 and November 7, 2015. Prices infrequently exhibit large jumps which restore profit margins (the *restoration* phase) with regular daily price undercutting in between the jumps (the *undercutting* phase). While Figure 2 shows retailer-level cycles, analogous cycles exist at the individual station level.

Figure 2 further illustrates two key aspects of price restorations. First, restorations occur when retail prices approach the wholesale TGP and margins go to zero. Second, retail chains

[18]There are two other features of the price collection data in Figure 1. First, we find three one-day drops in digital price reporting (2 for 7-Eleven and 1 for Caltex) in panel (a), likely reflecting technical issues. Second, we find a simultaneous shift in electronic and manual price uploads for BP stations in mid-June 2016. There are no public announcements during this period that help explain this shift. It possibly reflects a set of BP-branded independent licensee stations in Melbourne that no longer digitally upload their prices to the platform (ACCC, 2018). Informed Sources subsequently monitors their prices through manual data collection. Importantly, these licensee stations still receive recommended prices from BP, implying they still receive daily price recommendations that reflect BP's access to data from the Informed Sources platform.

[19]Gasoline price cycles exist worldwide, e.g., in the United States, Europe, and Canada (Eckert, 2013). In Australia, all major cities exhibit price cycles (Byrne and de Roos, 2019). High-frequency price cycles have also recently been found in digital marketplaces (Musolff, 2022).

Figure 2: Retailer-Level Price Cycles



Notes: The figure shows mean daily station-level retail prices for each major retailer between September 15 and November 7, 2015, computed from daily-station level prices from Informed Sources. The wholesale Terminal Gate Price (TGP) corresponds to the daily wholesale price for unleaded 91 gasoline from Melbourne's local terminal gate from the Australian Institute of Petroleum.

often exhibit small average price jumps in the days just before all retailers restore their margins. Figure 2 highlights this with Coles before a marketwide price restoration in November 2015 in Melbourne. These small average price jumps reflect a subset of a given retailer's stations restoring their prices a few days before the restorations of the remaining stations in their network. In this way, individual retailers, with relatively larger shares of stations within a market, tend to engage in station-level price leadership to coordinate marketwide price restorations, consistent with findings from, for example, Lewis (2012) and Byrne and de Roos (2019). Moreover, these small jumps highlight within-retailer price dispersion across stations that are not perfectly synchronized across a retailer's station network (despite the major retailers centrally setting station-level prices).

For our analysis of the price effects of asymmetric information sharing, it is useful to classify station-level price restorations and undercutting phases. We use the following classification:

Definition 1.

(i) *A station-level price restoration* occurs on date t if three conditions hold:

#1 $p_{it} > p_{it-1}$

#2 $p_{it} = \max\{p_{it-5}, \ldots, p_{it+5}\}$

#3 $p_{it} - \min\{p_{it-3}, \ldots, p_{it}\} \geq 10$.

(ii) *A station-level price cycle* begins with a station-level price restoration. We enumerate this as "Day 0" of a station's cycle. Cycle days $1, 2, \ldots$ follow as the undercutting phase until the next station-level price restoration occurs.

(iii) *Station-level cycle length* is the number of days between station-level price restorations.

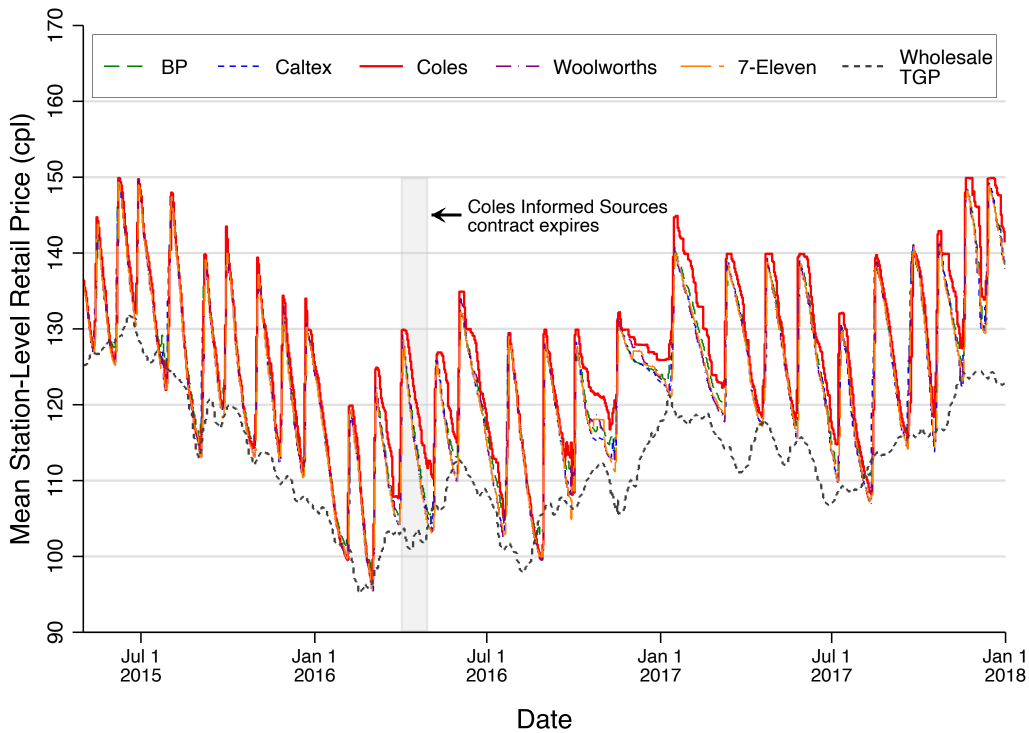
In words, a *station-level price restoration* from Definition 1(i) occurs when the station increases its price to a local maximum. Part #1 identifies dates when a station's prices rise. Part #2 creates a moving window that identifies a local maximum in a station's price within a 10-day window around each date. Part #3 requires a price restoration involving a sufficiently large price increase (at least 10 cpl) from its recent lowest price at the bottom of the previous cycle. Several validation checks confirm that our classification accurately identifies station-level price restorations.[20] The accuracy of our classification scheme reflects the stability of price cycles throughout our sample period. Holt et al. (2022) illustrate the effectiveness of threshold-based rules, like those used in Definition 1, for price cycle classification when cycles are stable.

4 Price effects of asymmetric information sharing

Using the shock to Coles' platform access, the Informed Sources case allows us to study how asymmetric information sharing affects oligopoly pricing. Figure 3 provides preliminary graphical evidence of the price effects. The figure shows each retailer's average daily retail price over our primary sample period. It shows that Coles' retail price decouples from its rivals' in March 2016. Visually, Coles' change in pricing is particularly evident during the undercutting phase of the cycle, where it starts pricing at a higher overall level and undercuts less aggressively, particularly immediately after a price restoration. Appendix C.1 shows Coles' decoupling persists

[20] Note that the daily station-level prices provided by Informed Sources are the daily average of the 15-minute level prices uploaded to the platform. In the data, a price restoration on date t is represented as two consecutive price jumps, one on date t and the other one on date $t+1$, with the price reaching the restoration level on date $t+1$. Consequently, the commonly used threshold-based rule on price jump magnitude cannot accurately identify price restorations. This is because a price restoration that happens early (or late) in the day on date t can result in a large (small) price jump on date t and a small (large) price jump on date $t+1$. Depending on the time of day a price restoration occurs, the jump magnitude rule may identify either date t or $t+1$ as the restoration date, potentially yielding an incorrect restoration level. In contrast, our Definition 1(i) reliably identifies date $t+1$, corresponding to the day when the price peaks in a station-level cycle. Thus, the method accurately captures the restoration level, regardless of the restoration timing on date t.

Figure 3: Retail Pricing with Coles On and Off the Informed Sources Platform



Notes: The figure shows mean daily station-level retail prices for each major retailer between May 1, 2015, and December 31, 2017 (our main sample period), computed from daily-station level prices from Informed Sources. The wholesale Terminal Gate Price (TGP) corresponds to the daily wholesale price for unleaded 91 gasoline from Melbourne's local terminal gate from the Australian Institute of Petroleum.

through 2018 until major retailer ownership changes occur in early 2019. Appendix C.2 shows similar patterns emerge around Coles' platform exit in Sydney, pointing to nationwide impacts.

Interestingly, Coles' March 2016 change in pricing does not perfectly align with its April 2016 Informed Sources contract expiration.[21] While we are not privy to details regarding the contract, the timing of the shift in pricing could reflect, for example, a sunset provision whereby Coles loses access to price data on the Informed Sources platform while still having to upload its data to the platform within a window before contract expiry. In evaluating the price effects of asymmetric information below, we abstract from these other aspects of equilibrium transition and omit the transition period—March 1 to April 30, 2016—from our estimation sample.

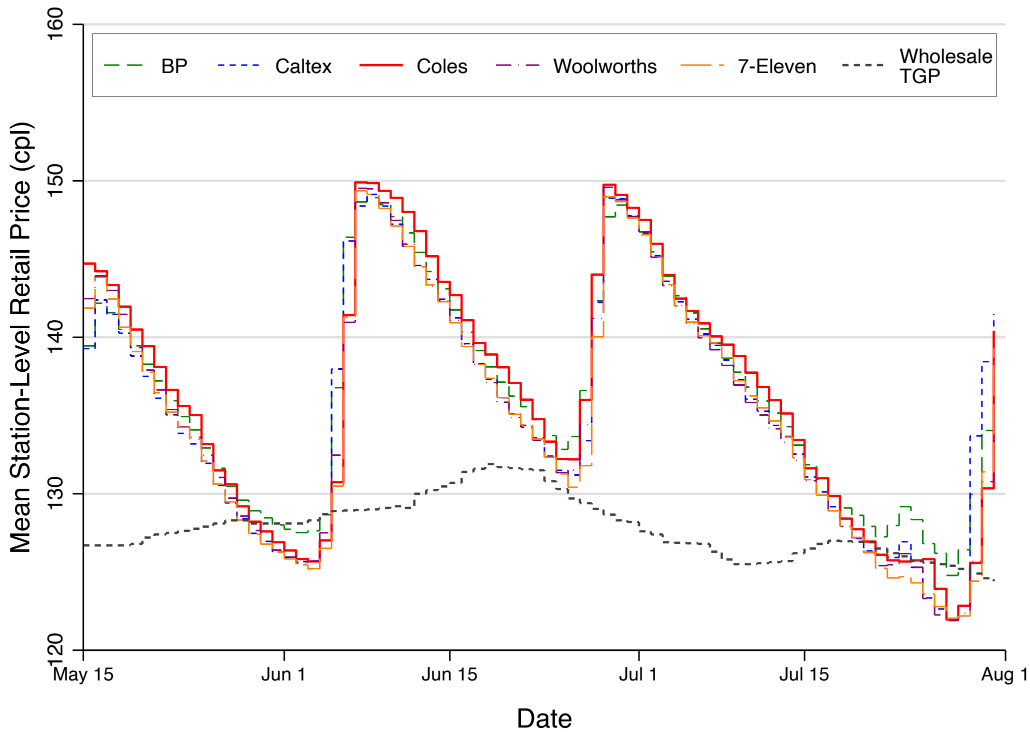
Figure 4 "zooms in" to show daily average retail prices for May 15–August 1 in 2015 and 2017. These figures allow us to see better how pricing evolves under symmetric and asymmetric infor-

[21] Appendix C.4 statistically confirms a decoupling of Coles' prices from its rivals in March 2016 using the Andrews (1993) test for a structural break with an unknown break point. Appendix C.1 further explores announcement effects around December 14, 2014, when the *Informed Sources* case was originally announced. There is little evidence of an immediate announcement effect.

Figure 4: Retail Pricing under Symmetric and Asymmetric Information Sharing

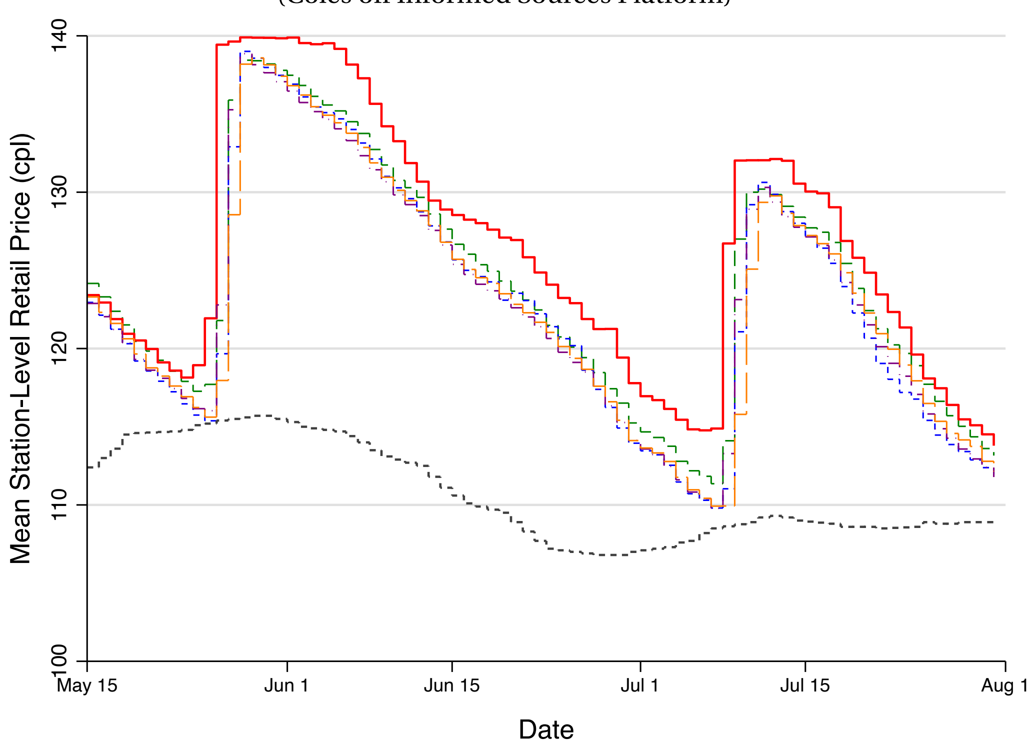
(a) May-July 2015: **Symmetric** Information Sharing

(Coles on Informed Sources Platform)



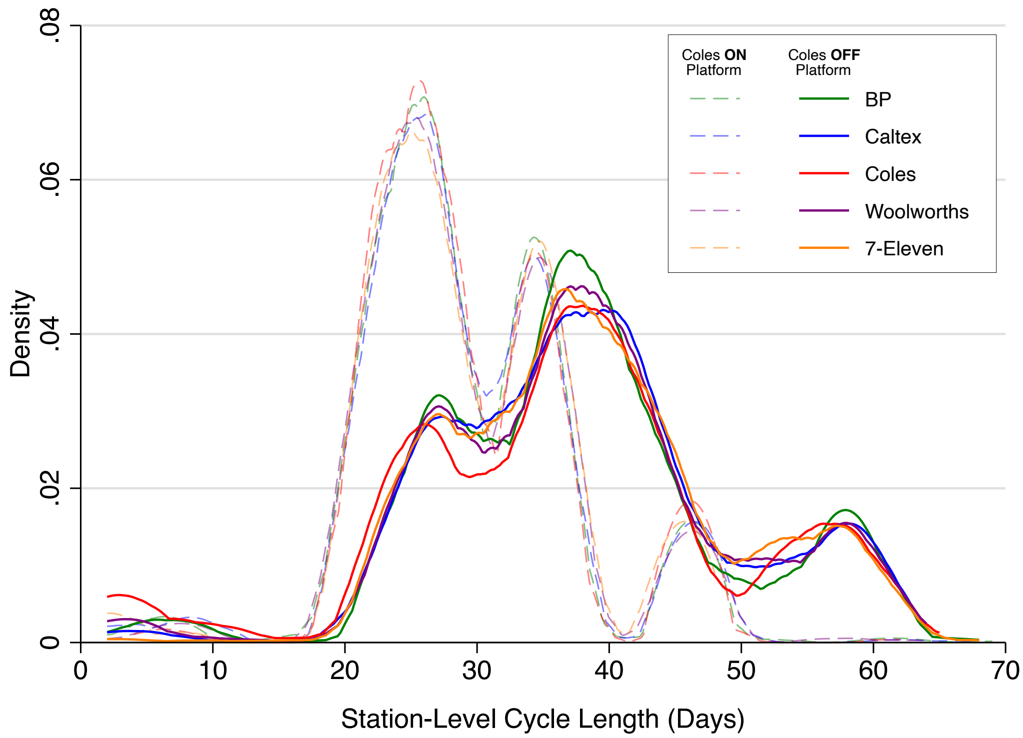
(b) May-July 2017: **Asymmetric** Information Sharing

(Coles off Informed Sources Platform)



Notes: The figure shows mean daily station-level retail prices for each major retailer for May 15, 2015–July 31, 2015 (panel (a)) and May 15, 2017–July 31, 2017 (panel (b)), computed from daily-station level prices from Informed Sources. The wholesale Terminal Gate Price (TGP) corresponds to the daily wholesale price for unleaded 91 gasoline from Melbourne's local terminal gate from the Australian Institute of Petroleum.

Figure 5: Price Cycle Length with Coles On and Off the Informed Sources Platform



Notes: The figure shows the station-level price cycle length distribution by retailer with Coles on and off the Informed Sources platform from our primary sample period (May 1, 2015 – December 31, 2017). See Definition 1 for the definition of station-level cycle length.

mation sharing. Panel (a) illustrates highly coordinated prices with daily price adjustments by all retailers while Coles is on the platform, with Coles regularly pricing around 1 cpl higher than its rivals. In contrast, Coles' prices become far less coordinated with its rivals' prices in panel (b) when off the platform. The lack of coordination is evident during the restoration and undercutting phases of the cycle. Moreover, unlike in panel (a), Coles' daily prices exhibit multi-day runs without price adjustments in panel (b), while its rivals adjust prices daily. These preliminary patterns are consistent with Coles' committing to higher prices and making less frequent price adjustments under asymmetric information sharing arising from the Informed Sources case settlement.

4.1 Softer price undercutting and cycle length

It appears from Figures 3 and 4 that undercutting progresses more slowly during the cycles that follow Coles' exit from the platform. Because restorations tend to occur only after prices have fallen close to cost, cycles should take longer to complete with Coles off the platform.

To illustrate a change in cycle length, we plot in Figure 5 a kernel density of station-level cycle length (in days) in Melbourne before and after Coles exits the platform. These distributions confirm our visual inspection of Figures 3 and 4: price cycle length significantly increases after Coles exits the platform, consistent with a softening of price undercutting. Simple t-tests, by retailer confirm statistically significant changes ($p < 0.01$) in retailers' mean station-level cycle length under asymmetric information sharing.

4.2 Estimating price effects of asymmetric information sharing

In light of the initial evidence, we now conduct a more formal analysis of how prices change under asymmetric information sharing. While Figures 3-5 suggest that undercutting becomes more sluggish after Coles' platform exit, the overall impact on stations' margins is unclear. Margins could be affected by a uniform shift in daily price levels or by a change in shares of days with relatively high or low margins. Therefore, to assess price effects, we specify a model of the typical evolution of margins within a price cycle and identify whether margins evolve differently after Coles exits the platform. Given that we are studying a change in equilibrium, we examine changes in pricing and margins separately for each retailer.

We define margin_{it} as the difference between station i's retail price on date t, p_{it}, and the wholesale TGP, c_t. We then estimate regressions of the following form

$$\begin{aligned}\text{margin}_{it} = \alpha_0 &+ \sum_{k=0}^{10}\left[\beta_k \text{CycPct}_{it}^k + \gamma_k \text{ColesOff}_t \times \text{CycPct}_{it}^k\right] \\ &+ \sum_{\ell=0}^{7}\left[\delta_\ell^+ \Delta^+ c_{t-\ell} + \delta_\ell^- \Delta^- c_{t-\ell}\right] + \eta_i + \nu_d + \lambda_m + \epsilon_{it}, \qquad (1)\end{aligned}$$

where CycPct_{it}^0 is a dummy variable equaling one if station i has a station-level price restoration on date t ($k = 0$), and CycPct_{it}^k, for $k = 1, \ldots, 10$ equals one if station i's cycle day falls within the k^{th} decile of its current station-level cycle length.[22] ColesOff_t is a dummy equaling one if date t is after April 1, 2015 (e.g., the month when Coles' Informed Sources contract expires).[23] Variables η_i, ν_d, and λ_m are station, day of week, and month of year fixed effects.

We also account for the influence of lagged cost fluctuations on margins in (1). Prices in gasoline markets, with and without cycles, have been shown to pass through cost changes with a lag, with negative changes passing through more slowly than positive changes (Lewis and

[22]To take a concrete example, suppose that station i on date t has a station-level price restoration (as classified per Definition 1 and that there are 20 days until its next restoration. In this case, we would have CycPct_{it}^0=1 and 0 otherwise, CycPct_{it+1}^1=1 and CycPct_{it+2}^1=1 (and 0 otherwise for both), CycPct_{it+3}^2=1 and CycPct_{it+4}^2=1 (and 0 otherwise for both), and so on. Additionally, our analysis excludes the last day of each station-level cycle. As discussed in footnote 20, a price restoration is represented by two consecutive price increases in our data. The final day of a cycle corresponds to the initial phase of the price restoration in the subsequent cycle.

[23]Recall that we omit the March 1–April 30, 2015, equilibrium transition period from our estimation sample.

Noel, 2011). Therefore, the model also incorporates the potential influence of cost fluctuations on margins by including lagged positive and negative cost changes, $\Delta^+ c_{t-\ell} = \max\{0, \Delta c_{t-\ell}\}$ and $\Delta^- c_{t-\ell} = \min\{0, \Delta c_{t-\ell}\}$. The β_k and γ_k coefficients thus quantify margin levels immediately following the restoration ($k = 0$) and during the undercutting phase ($k = 1, \ldots, 10$) while flexibly accounting for recent cost changes. The cycle decile dummies, CycPct_{it}^k, allow us to compare the within-cycle evolution of margins across cycles with different lengths before and after Coles exits the platform.

Lastly, the econometric error ϵ_{it} is two-way clustered by station and date to account for unmodeled correlation in margins within a station over time and across stations on a given date. Appendix C.5 provides extensive robustness checks on clustering and inference, validating two-way clustering by station and date.[24]

Results

Figure 6 presents station-level margin estimates from (1) for each part of the cycle with Coles on and off the Informed Sources platform. More precisely, we plot $\hat{\alpha}_0 + \hat{\beta}_k$ and $\hat{\alpha}_0 + \hat{\beta}_k + \hat{\gamma}_k$ for $k = 0, \ldots, 10$. Panel (a) presents estimates for Coles, while panel (b) presents pooled estimates for Coles' rivals (BP, Caltex, Woolworths, 7-Eleven).[25] Figure 7 complements these graphs by plotting the *change* in margins for Coles and its rivals under asymmetric information sharing (i.e., $\hat{\gamma}_k$ from (1) for $k = 0, \ldots, 10$). Four key results emerge, which we highlight in Figure 6. First, restoration margin levels increase for both Coles and its rivals after Coles exits the platform. Coles' restoration margin rises from 24 to 27 cpl, while its rivals' restoration margin rises from 21 to 24 cpl. There is, however, no statistical difference Coles' and its rivals' increase in restoration margins.[26] In other words, Coles and its rivals coordinate on the same higher restoration margin level after Coles exits the platform.

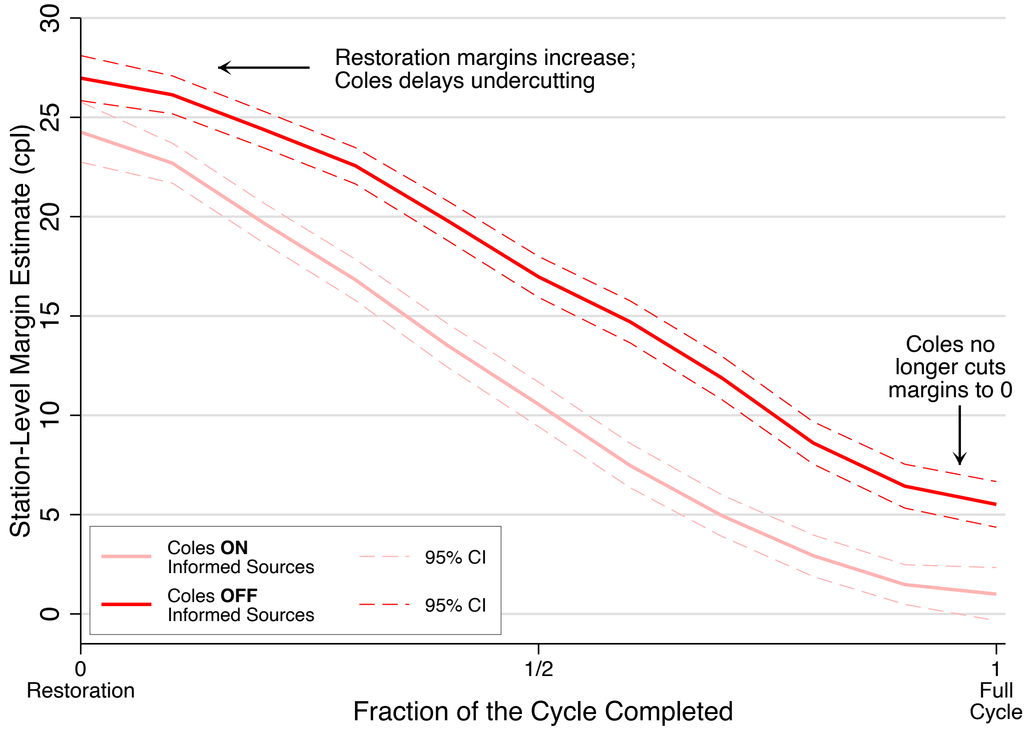
[24] More specifically, Appendix C.5 considers combinations of two-way and one-way clustering by station, station-cycle day, station-cycle length decile, retailer, retailer-cycle day, and retailer-cycle length decile, where cycle days are defined per Definition 1 and cycle length decile corresponds to CycPct_{it}^k. All of the clustering combinations that we consider using margin regressions at either the station level (as in (1)) or retailer level (in terms of mean daily retailer margins as in Figure 3) yield the same inferences regarding the price effects of asymmetric information sharing. Newey and West (1987) standard errors in retailer-level margin regressions that explicitly model temporal dependence in ϵ_{it} also yield the same inferences. In line with recommendations from MacKinnon et al. (2023), our main results report two-way clustered standard errors by station and date because they tend to be more conservative than those obtained under other plausible clusters and Newey and West (1987) standard errors.

[25] Appendix C.6 reports the full set of coefficient estimates and standard errors from our baseline regression in equation (1). We jointly estimate $\alpha_0 + \beta_k$ and $\alpha_0 + \beta_k + \gamma_k$ from (1) using an appropriate set of interactions between dummy variables for Coles and rival stations and CycPct_{it}^k, $\text{ColesOff}_t \times \text{CycPct}_{it}^k$ (for $k = 0, \ldots, 10$) and $\Delta^+ c_{t-\ell}$ and $\Delta^- c_{t-\ell}$ (for $\ell = 0, \ldots, 7$). Appendix C.7 presents analogous results to those in Figure 6 for each of the four rivals. Each rival exhibits similar changes in pricing as those in Figure 6(b), justifying pooling data for BP, Caltex, Woolworths, and 7-Eleven. For this same reason, for the remainder of Section 4, we present pooled results for Coles' rivals and provide retailer-specific results for BP, Caltex, Woolworths, and 7-Eleven in Appendix C.7.

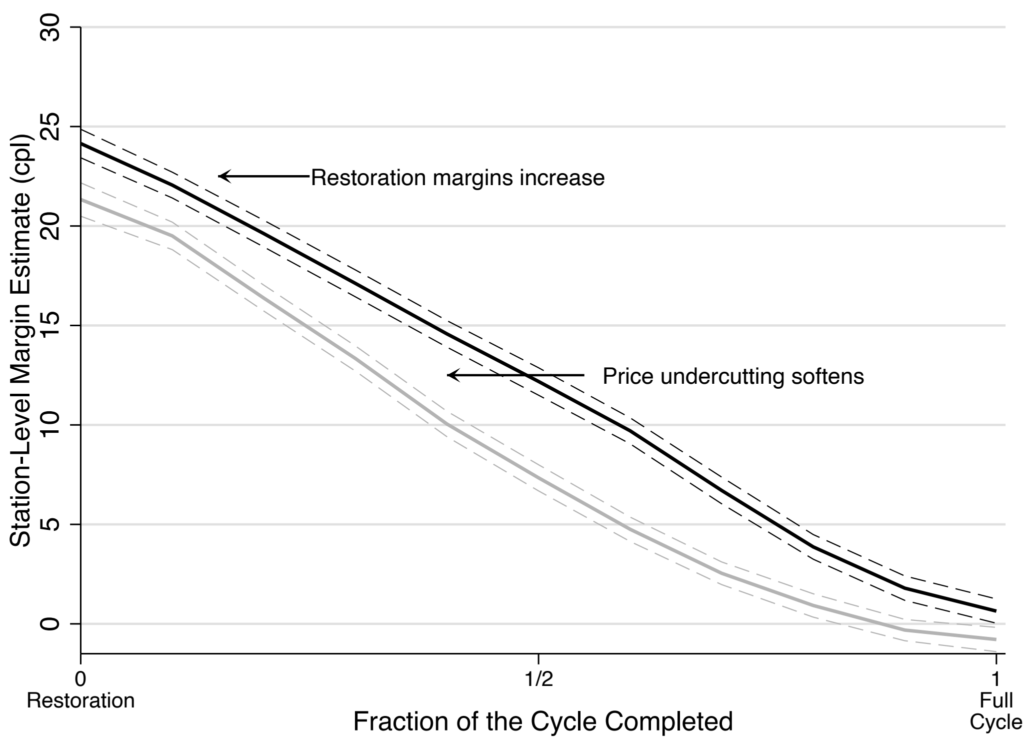
[26] Formally, a test of equality of γ_0 from equation (1) for Coles and its rivals has a p-value of 0.09.

Figure 6: How Margins Change After Coles Exits the Informed Sources Platform

(a) Coles

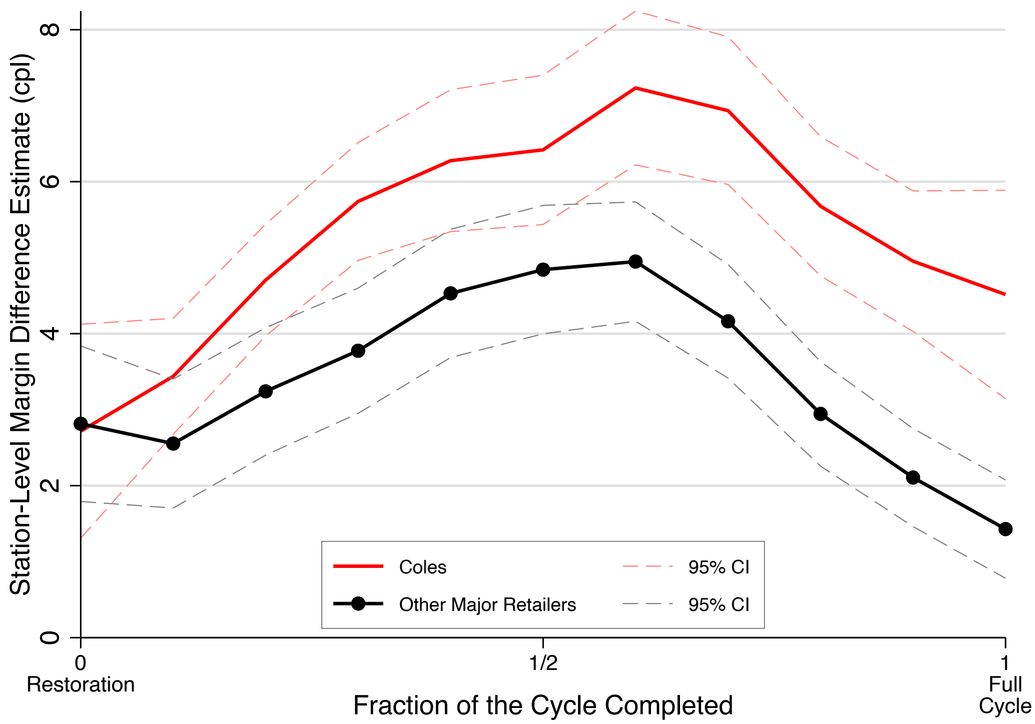


(b) Other major retailers



Notes: The figures contain $\alpha_0 + \beta_k$ (light shade) and $\alpha_0 + \beta_k + \gamma_k$ (dark share) estimates and their 95% confidence intervals from equation (1). Standard errors are two-way clustered by station and date. Panels (a) and (b), respectively, contain estimates for Coles' stations and pooled estimates for other major retailers' stations (BP, Caltex, Woolworths, and 7-Eleven).

Figure 7: Change in Margins when Coles Exits the Informed Sources Platform



Notes: The figures contain γ_k estimates and their 95% confidence intervals from equation (1) for Coles and other major retailers (pooling BP, Caltex, Woolworths, and 7-Eleven). Standard errors are two-way clustered by station and date.

Second, panel (a) shows that, after exiting the platform, Coles takes longer to begin undercutting after each restoration. For instance, between 0% and 20% through the cycle, we see a divergence in Coles' margins. While on the platform, Coles undercuts its restoration margin by 4.52 cpl 20% through the undercutting phase. This figure's magnitude drops to 2.59 cpl, a large and statistically significant reduction in price undercutting.[27]

Third, following Coles' delay in undercutting, at every point throughout the undercutting phase, Coles' margins are statistically significantly above their baseline level after it exits the platform. Moreover, the margin differences are large. Relative to when Coles is on the platform, its margins increase by 5.7 cpl 30% of the way through the cycle, 7.2 cpl at 60%, and 4.9 cpl at 90%. Respectfully, these margin increases represent 34%, 96%, and 345% increases relative to baseline levels when Coles is on the platform.

Coles' rivals likewise increase their price-cost margins in Figure 6(b) when Coles exits the platform. This finding is consistent with strategic complementarity. The price increases are

[27]More precisely, from (1), the test of H_0: $(\gamma_0 - \gamma_2) = 0$ vs. H_1: $(\gamma_0 - \gamma_2) \neq 0$ has $p = 0.017$. The difference $(\gamma_0 - \gamma_k)$ is statistically significantly different from 0 for $k = 2, \ldots, 10$, implying that Coles softens undercutting between the 20% and 100% cycle deciles after exiting the Informed Sources platform.

comparatively smaller than Coles', but economically significant. For example, there are statistically significant margin increases of 3.8 cpl 30% of the way through the cycle, 4.9 cpl at 60%, and 2.1 cpl at 90%, which all represent substantial percentage increases in rivals' margins. These margin increases are, however, statistically significantly different from Coles' margin increases after its platform exit at all points of the undercutting phase.[28] In sum, our estimates imply statistically and economically significant price increases for all firms, with larger price increases for Coles. Figure 7 further illustrates this key empirical result.

Lastly, Coles' pricing behavior at the bottom of the cycle changes substantially after exiting the platform. Panels (a) and (b) show that Coles and its rivals cut prices until margins reach 0 cpl before restoring prices with Coles on the platform. However, after Coles exits, it cuts prices until margins reach 5.5 cpl on average. The rivals likewise soften price undercutting, but less so compared to Coles, with a 1.8 cpl margin at the bottom of the cycle after Coles is off the platform. Again, these represent substantial price increases for all firms, but with Coles increasing its prices the most.[29]

Further underlining the size of these price effects, Byrne and de Roos (2019) estimate an (unweighted) 3.5 cpl daily price-cost margin increase from the same retailers tacitly coordinating a transition to a new pricing structure between 2010 and 2015 in Perth, Australia (pop. ≈ 2 million). Averaging across cycle length deciles, we obtain (unweighted) price-cost margin increases of 5.9 cpl and 3.4 cpl for Coles and its rivals. Thus, the margin increases in Melbourne stemming from Coles' settlement-enforced strategic ignorance and commitment power are of similar magnitude as those arising from a voluntary transition in a similar market around a similar period.

Overall, our pricing results suggest that the equilibrium shifts to one with higher price levels after Coles exits the Informed Sources platform. Our finding of such price effects for all firms, with Coles having the largest price increase, directly aligns with the predicted price effects of asymmetric information sharing, per **Hypothesis 1**. A question remains about the associated market share and profit impacts from these large price increases. We test and quantify these impacts in Section 5 below.

[28] Formally, pairwise tests of equality for γ_k from (1) for Coles and its rivals reject the null with $p < 0.01$ for each $k = 1, \ldots, 10$.

[29] Appendix C.8 shows that the four key results from Figures 6 and 7, which are based on a 2015–2017 subsample also hold over shorter and longer horizons. In particular, we re-estimate (1) using samples that end, respectively, on December 31, 2016, and December 31, 2018, and find statistically and economically similar price effects from Coles' exit from the platform. The transition to a new equilibrium under asymmetric information sharing occurs relatively quickly in 2016 and persists through 2018.

4.3 Asymmetric pricing frequency

The richness of our data allows us to examine whether the sluggish price adjustments in Figure 6 after Coles exits the platform reflect less frequent price adjustments or price cuts of smaller magnitude.[30] As above, we estimate how each brand's pricing structure changes before and after Coles exits the platform. This time, however, we compute the average *frequency* and *magnitude* of daily price cuts by decile of a station's current cycle length (i.e., from above, CycPct_{it}^{k} for $k = 1, \ldots, 10$).

Following the motivation provided in Section 2.4, and in particular the theoretical predictions from Brown and MacKay (2023), we might expect the case-induced reduction in the frequency with which Coles observes rival prices to generate asymmetry in the frequency of price adjustments between Coles and its rivals. In this case, Coles should exhibit a comparatively large drop in price adjustment frequency after it exits the Informed Sources platform due to asymmetric information sharing. Figure 4 foreshadowed these patterns as Coles exhibited multi-day runs with 0 price changes after exiting its platform, while its rivals adjusted prices daily.

Figure 8 shows that, indeed, the frequency of Coles' price adjustments plummets after exiting the platform. For example, in panel (a), Coles stations go from making 1.7 price changes on average in the first decile of the cycle while on the platform to making just 0.5 changes while off. This substantial reduction in pricing frequency persists throughout the entire cycle for Coles. In stark contrast, panel (b) reveals that the number of price changes per cycle made by Coles' rivals does not change when Coles exits the platform. Together, these findings align with Coles making less frequent price adjustments due to observing rival price data less frequently after the case.

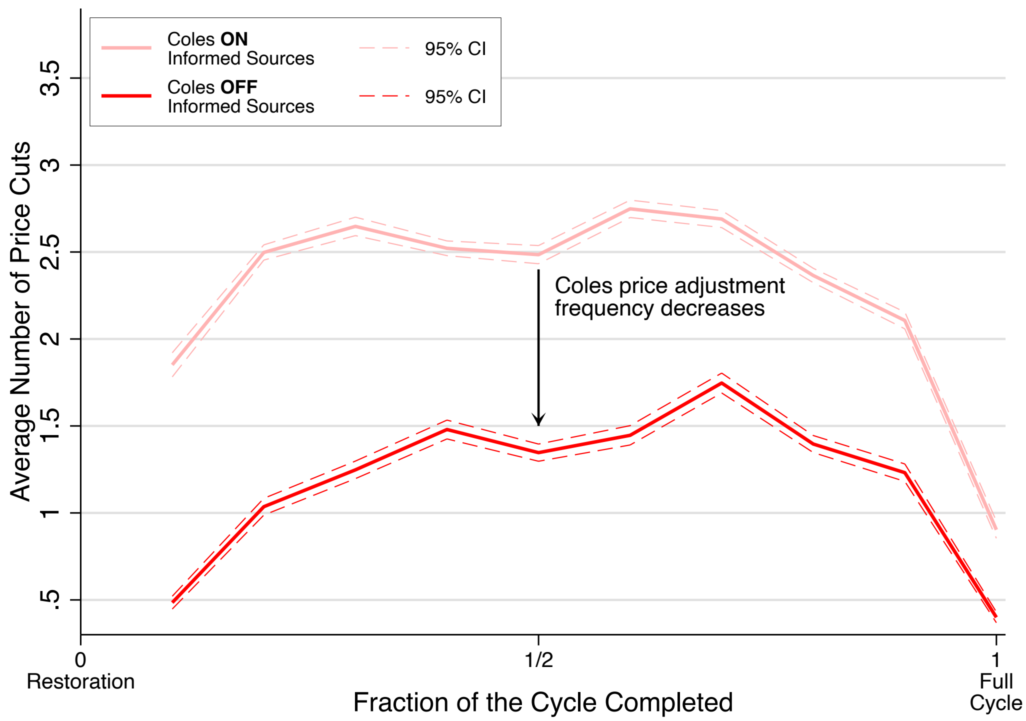
Panel (a) of Figure 9 shows that Coles simultaneously starts making larger price adjustments (conditional on adjusting a price) after exiting the platform. For instance, in the first decile of a station's cycle, average price cuts go from 1.5 cpl to 2.6 cpl after Coles exits the platform. We find similarly large-magnitude changes in price adjustments on all days of the cycle in panel (a). On the other hand, in panel (b), the size of price cuts made by Coles' rivals does not change as much when Coles exits the platform, perhaps even becoming somewhat smaller in the first three-quarters of the cycle.

In sum, Figures 8 and 9 reveal that the additional sluggishness of Coles' price reductions in Figure 6 after exiting the platform is driven entirely by a substantial decline in the frequency of price adjustments, whereas the additional sluggishness of price reductions by Coles' rivals

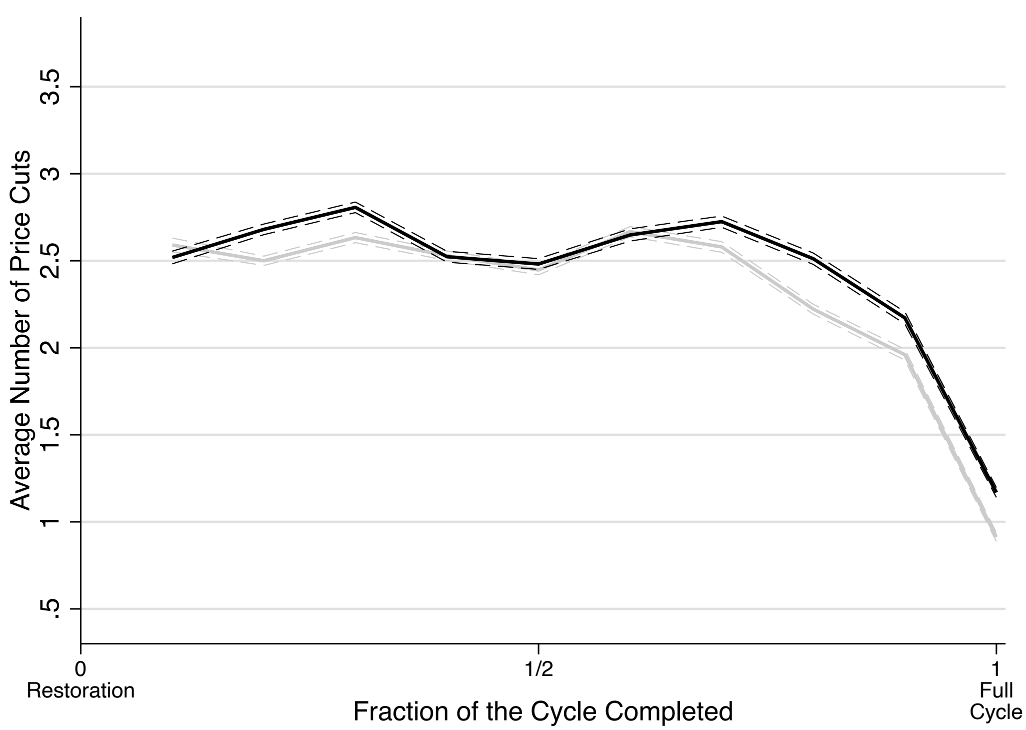
[30] ACCC (2011) uses 30-minute station-level pricing data from Informed Sources to confirm that stations in Melbourne mainly adjust prices once per day. We also have examined auxiliary 30-minute level pricing data from Informed Sources to confirm this using a three-month sample in 2015. Therefore, examining non-zero price changes between days before and after Coles exits the platform captures the relevant price adjustment frequency (daily).

Figure 8: How Price Cut **Frequency** Changes After Coles Exits the Informed Sources Platform

(a) Coles



(b) Other major retailers

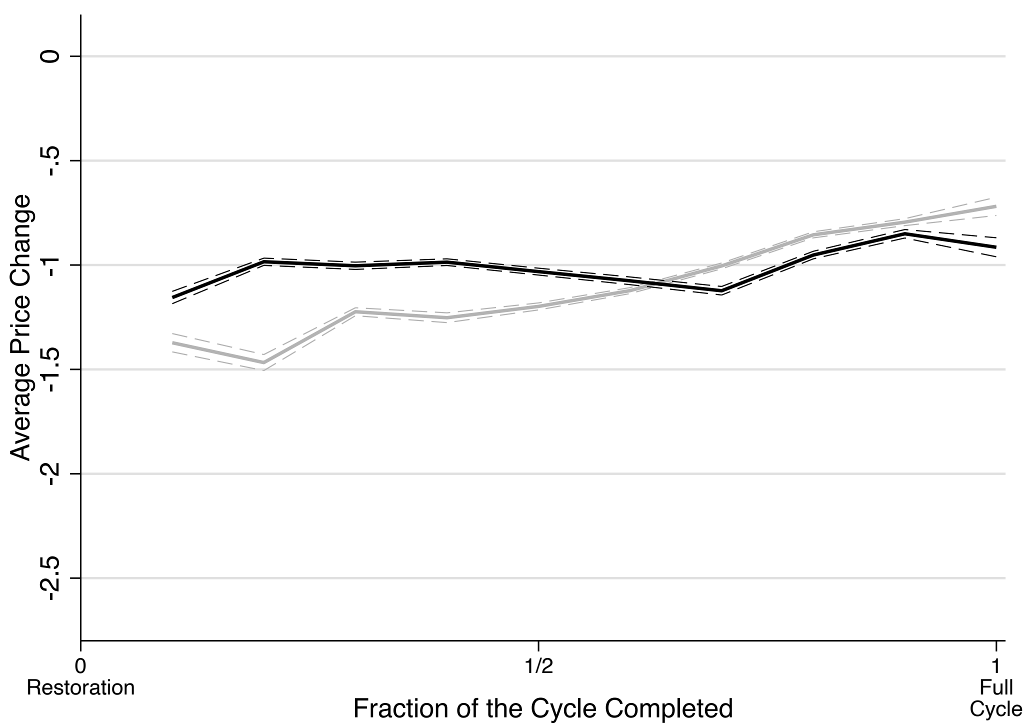


Notes: The figures show the average number of changes within a station's cycle length decile, CycPct_{it}^{k} for $k = 1, \ldots, 10$. Panel (b) pools data for other major retailers' stations (BP, Caltex, Woolworths, and 7-Eleven).

Figure 9: How Price Cut **Magnitude** Changes After Coles Exits the Informed Sources Platform

(a) Coles

(b) Other major retailers



Notes: The figures show the average price change (conditional on making a price change) within a station's cycle length decile, CycPct_{it}^{k} for $k = 1, \ldots, 10$. Panel (b) pools data for other major retailers' stations (BP, Caltex, Woolworths, and 7-Eleven).

(following Coles' exit from the platform) occurs because they begin adjusting prices in smaller increments. These results illustrate how asymmetric information sharing can give rise to asymmetric pricing frequency and associated price commitment for Coles.

5 Market shares and profits impacts

In this section, we quantify the case's market share and profit impacts and investigate **Hypotheses 2** and **3**—namely whether asymmetric information sharing leads to (1) lower market shares for Coles and higher shares for its rivals and (2) higher profits for all firms with a comparatively larger profit increase for Coles' rivals.

5.1 Market shares

We assess firm-level market share impacts using auxiliary data from the Australasian Convenience and Petroleum Marketers Association (ACAPMA), a national industry group. ACAPMA runs a biennial consumer panel, asking a nationally-representative sample of 1000 households questions about their residence, demographics, and gasoline shopping behaviors. For our study, ACAPMA provided us with complete raw data underlying their 2015, 2017, and 2019 national *Monitor of Fuel Consumer Attitudes*.

Importantly, the consumer panel asks, "*From which of the following fuel retailers do you most regularly purchase fuel?*" Consumers then choose just one retailer from an exhaustive list of retailers, including the five major retailers, smaller retail chains, and independent stations (as a single group). Table 2 presents the corresponding choice probabilities by retailer and year among the subset of surveyed consumers living in Melbourne. Taking a discrete choice demand perspective (e.g., Berry, 1994; Berry et al., 1995), we interpret these choice probabilities as retailer market shares.[31]

[31] Volume-based market shares at the station or retailer level for a given market are proprietary, highly sensitive, and thus unavailable. Reassuringly, the relative rank and magnitudes of 2017 shares in Table 2 align with (proprietary) volume-based national market shares by brand in 2017, as reported in the ACCC's industry monitoring reports, specifically ACCC (2018), which is based on station-level volume data that the government obtained from retailers through its regulatory powers. Moreover, in line with the station shares and consumer choice probabilities in Tables 1 and 2, ACCC (2018) finds that: (1) Coles stands out with a large volume-based market share relative to the share of stations that it operates; and (2) 7-Eleven's volume-based shares are smaller relative to its share of stations. Indeed, the ACCC identifies 7-Eleven as an 'Other' (minor) retail chain because of its smaller volume-based market share (7-Eleven stores typically focus more on convenience store operations than gasoline sales). From our discussion in Section 2.1, especially footnote 6, the relatively small 7-Eleven shares may reflect their offering 2 cpl discounts tied to in-store purchases with no further loyalty scheme, whereas BP, Caltex, Coles, and Woolworths offer 4 cpl discounts and have broader customer loyalty programs with national supermarket chains (Caltex, Coles, Woolworths) and airlines (BP).

Table 2: Consumers' Retailer Choice Probabilities by Year

	Information Sharing		
	Symmetric	Asymmetric	
	2015	2017	2019
BP	0.117	0.133	0.190
Caltex	0.150	0.145	0.104
Coles	0.444	0.297	0.288
Woolworths	0.183	0.212	0.184
7-Eleven	0.039	0.079	0.074
Other	0.067	0.133	0.160
Number of responses	180	165	163

Notes: Data from the Australasian Convenience and Petroleum Marketers Association (ACAPMA) 2015, 2017, 2019 *Monitor of Fuel Consumer Attitudes*. The 'Other' category consists of smaller retail chains and independent stations.

The data reveal a substantial 14.7 percentage point (pp) reduction in Coles' choice probability between 2015 and 2017 (i.e., before and after the *Informed Sources* case) that is statistically different from 0 ($p < 0.05$). This diversion of customers from Coles to its rivals in 2017 parallels the predicted market share impacts of asymmetric information sharing expressed in **Hypothesis 2**. Quantitatively, the large market share loss for Coles and gain for its rivals reflects: (1) our estimates of Coles' comparatively large price increase under asymmetric information sharing in Section 4; and (2) highly price elastic station-level demand.

Lastly, while the 2019 data in Table 2 fall outside our sample window, they illustrate the persistence of the decline in Coles' choice probability and the diversion of consumer choices to its rivals. This finding further underlines the stability of the shift in the retailers' pricing structures under asymmetric information sharing, as we observed in Figure 3 above, which persists through 2018 before major ownership changes in 2019 (see Appendix C.1).[32]

[32] The drop in Caltex's choice probability in 2019 potentially reflects a change in the retailer's re-branding to "Ampol" as part of the retailer's corporate sale to Chevron in 2019. See https://www.afr.com/companies/energy/caltex-to-rebrand-itself-as-ampol-20191223-p53mdd (accessed August 2, 2023). In addition, the rebranding of Woolworths following its March 2019 sale to EG Group also potentially affects the 2019 choice probabilities.

5.2 Profits

We now investigate how retailers' profits change under a case-induced shift to asymmetric information sharing. While we have information on retailers' prices, wholesale TGPs, and market shares, simple aggregate calculations based on changes in average prices and retailer-level market shares are likely insufficient for quantifying case impacts. This is because prices and sales volumes vary considerably across stations, even within the same brand. Some stations may increase margins substantially when Coles exits the platform, but if these stations have low sales volumes, the impact on firm profits may be minimal. To account for station-level differences in price-cost margins and volumes sold in our profit calculations, as well as differences in volumes sold across different parts of the price cycle, we calibrate a station-level demand model.

Our approach involves specifying the daily profits for each station j on each date t as

$$\pi_{jt} = Q_t \times s_{jt} \times (p_{jt} - c_t). \tag{2}$$

This equation has three key objects to compute: station j's price-cost margin $p_{jt} - c_t$, its (inside good) market share s_{jt} on date t, and total fuel sold in the market Q_t on date t. From our discussion in Section 3 above, we can compute $p_{jt} - c_t$ directly using our price data from Informed Sources and the wholesale TGP from the Australian Institute of Petroleum. What remains is computing station j's market share and total fuel sold in the market on date t. As we do not directly observe these objects, we estimate them using auxiliary data and models.[33]

Provided that we can estimate Q_t and s_{jt}, and hence π_{jt}, we can use our high-frequency event study design to quantify the impact of asymmetric information sharing on retailers' profits. In particular, we compare each retailer's total profit with Coles on and off the platform. Crucial to our approach is: (1) a stable economic environment throughout the evaluation period (except for Coles' exit from the platform); and (2) having information on all objects in equation (2) before and after Coles' platform exit.

Notably, these features of our data and environment allow us to quantify the profit impacts of asymmetric information sharing without specifying a (potentially intractable) supply-side model of dynamic retail pricing with arbitrary information sharing structures among retailers. Pricing under symmetric information sharing just before Coles' platform exit provides the counterfactual to pricing under asymmetric information sharing just after its platform exit. And we do not need a model to recover firms' (typically unobserved) marginal costs to quan-

[33]The multiplicative specification of total fuel volume sold and market shares in (2) aligns with the demand structure of Hendel and Nevo (2006). In particular, they assume consumers' brand choice is conditionally independent of purchase size, allowing them to estimate static and dynamic parameters associated with these respective decisions separately. We likewise estimate separate empirical demand models for retailer choice and total fuel consumption.

tify changes in profit under asymmetric information sharing because the main time-varying component of marginal cost is directly observable through the wholesale TGP.

We now describe the specifics of these calculations. First, we describe how we estimate station-level market shares (s_{jt}). We then detail how we estimate market-level fuel quantities sold (Q_t). Finally, using these estimates and stations' price-cost margins, we quantify the profit impacts of asymmetric information sharing, as induced by the *Informed Sources* case.

Estimating station-level market shares

To predict station j's market share on date t, s_{jt}, we calibrate a spatial demand model in the spirit of Houde (2012). The model specifies the indirect utility of consumer i travelling from location o_i (origin, e.g., "home") to d_i (destination, e.g., "work") purchasing from station j at location l_j as

$$u_{ijt} = X_j\beta + p_{jt}\alpha - \lambda T(o_i, d_i, l_j) + \epsilon_{ijt}, \tag{3}$$

where X_j and p_{jt} are, respectively, a vector of station characteristics and the price of a unit of gasoline purchased at station j on date t.[34] Spatial frictions affect demand through $T(o_i, d_i, l_j)$, which is the *additional* travel time household i expends departing from the driving route between o_i and d_i to purchase gasoline at station j. Formally, $T(o_i, d_i, l_j) \equiv t(o_i, l_j) + t(l_j, d_i) - t(o_i, d_i)$, where $t(x, y)$ is the driving time between points x and y along the fastest path given the market's road network. The idiosyncratic shock ϵ_{ijt} is independently and identically distributed according to a Type-1 Extreme Value distribution.[35]

Let $\delta_{jt} \equiv X_j\beta + p_{jt}\alpha$. Given our logit assumption for ϵ_{ijt}, the probability consumer i travelling from o_i to d_i chooses station j among J potential stations along their travel route is

$$P_{ij}(\boldsymbol{\delta}_t) = \frac{\exp\{\delta_{jt} - \lambda T(o_i, d_i, l_j)\}}{\sum_{j'}^{J_i} \exp\{\delta_{j't} - \lambda T(o_i, d_i, l_{j'})\}}, \tag{4}$$

where $\boldsymbol{\delta}_t$ is a $J_i \times 1$ vector stacking the δ_{jt}'s on date t.[36] Given $P_{ij}(\boldsymbol{\delta}_t)$, we can compute station

[34] Per Houde (2012), we need to calibrate a unit of gasoline purchased to implement the model empirically. We assume p_{jt} corresponds to the purchase price of a consumer buying 35 liters of gasoline. This figure corresponds to the mean estimate for Melbourne from Budget Direct (2022)'s consumer fuel consumption survey. All of our quantitative results below are robust to this assumption.

[35] Notice that our model does not include daily station-level heterogeneity through the usual "ξ_{jt}" shock within the Berry et al. (1995) discrete choice demand framework. Because we calibrate the model based on retailer and not station-level market shares (discussed momentarily), we cannot recover such ξ_{jt} shocks.

[36] In calibrating the model, we assume that consumer i's J_i-station consideration set includes all stations that involve less than five additional minutes of travel time in departing from the fast path between o_i to d_i. Notice that consumer i is assumed to have complete information over the J_i stations in its choice set on date t. Wu, Lewis, and Wolak (forth.) consider a dynamic demand model with search and learning whereby an individual learns about prices as they drive past stations along their route on a given day, updating their belief about that day's price distribution across stations as they do so.

j's market share by summing choice probabilities across all routes, i.e., origin-destination pairs:

$$s_j(\boldsymbol{\delta}_t, \mathbf{f}) = \sum_o \sum_d P_{ij}(\boldsymbol{\delta}_t) \times f_{od}, \tag{5}$$

where f_{od} is the fraction of drivers in the market that travel along route od, and $\mathbf{f}$ is a vector that stacks f_{od} for all (o, d) pairs in the market.[37]

Model calibration. If we can calibrate the model parameters with $\hat{\alpha}, \hat{\beta}, \hat{\lambda}$, then we can use data $(\{X_j, p_{jt}, o_i, d_i, l_j, \mathbf{f}\})$ and the model to infer station j's market share on date t from (5) by $\hat{s}_{jt} = s_j(\hat{\boldsymbol{\delta}}_t, \mathbf{f})$. To this end, we pursue a three-step calibration strategy.

We first recover all stations in the market *not* in the Informed Sources data. These consist of stations run by smaller retail chains and independent owners. We summarize our approach here and provide details in Appendix D.1. Effectively, we scrape the identity and location of all operational stations in Melbourne in February 2023 from PetrolSpy (https://petrolspy.com.au/). This information, combined with the minimal station-level entry and exit between 2015 and the present-day, allows us to recover all stations in the market during our sample period.[38]

Our second step combines our station identity data with price data from Informed Sources to impute daily station-level prices for instances where the platform does not collect prices between 2015 and 2017, including the non-subscribing stations recovered from the first step. We summarize our imputation here and provide details in Appendix D.2. Using Informed Sources price data for the five major retailers and non-subscribing small retail chains and independents that Informed Sources manually collects, we build machine learning models that accurately predict daily station-level prices as a function of local rival stations' prices, wholesale cost, local market structure, and other variables. We use these models to impute daily station-level prices for all instances where prices are not available in the Informed Sources dataset. Combining these imputed prices with our Informed Sources price data, we obtain a distribution of prices across all stations in the market on each day of the 2015–2017 sample period that we use to evaluate the profit effects of the case.

Finally, after imputing missing prices, we calibrate the model. We begin with λ, which, recall, governs a consumer's cost of travel time. Goldszmidt et al. (2020) estimates the value of

[37]Notice that equation (4) only considers choice probabilities among inside goods (e.g., gasoline retailers). Focusing on inside good choices and market shares is sufficient for estimating profits per equation (2) provided that we can estimate total market fuel consumption on date t, Q_t.

[38]PetrolSpy is a consumer search platform that launched in 2014 and infrequently updates station-level prices (see Appendix A). Using auxiliary data from FUELTrac (http://fueltrac.com.au/) on annual station counts by all retailer types (including smaller retail chains and independents), we confirm minimal station-level entry and exit since 2015. Annual ACCC industry reports from https://www.accc.gov.au/by-industry/petrol-and-fuel/fuel-and-petrol-monitoring (accessed August 2, 2023) further validate a lack of station-level entry and exit since 2015.

time to be \$19.38/hour (USD) using Lyft ride-hail data and field experiments across 13 large U.S. cities in 2015.[39] We convert this estimate to 0.43 AUD/minute in 2015 and set $\lambda = 0.43 \times \alpha$.

We then calibrate α and β by finding the values that most closely align the model's predicted retailer-level market shares in 2015 and 2017 to those reported in Table 2.[40] For our calibration, we specify X_j to contain 5 dummy variables corresponding to the 5 major retailers in Table 2. The omitted independent stations serve as the base group. Therefore, β_j captures the features of retailer j's stations unrelated to price or location that affect demand (e.g., convenience store, number of pumps or service bays, loyalty programs, or brand value).[41]

Appendix D.3 provides numerical details on how we obtain $\hat{\alpha}, \hat{\beta}, \hat{\lambda}$ and presents our calibration results.[42] Our predicted retailer market shares align with their empirical analogues in Table 2. The mean station-level (inside good) price elasticity from the calibrated model is −44, which is higher than previous estimates ranging from −10 to −30 (Houde, 2012; Clark and Houde, 2014; Wu, Lewis, and Wolak, forth.), reflecting that we quantify elasticities for a more dense urban market compared to markets in previous studies. With the calibrated model in hand, we use the model and our data to estimate stations' daily market shares, $\hat{s}_{jt}$, from equation (5).

Estimating daily market-level fuel consumption

The second object to estimate in equation (2) is Q_t, the total daily fuel sold in the market on date t. Figure 10 presents the two data sets we use to estimate this object. Panel (a) is extracted from ACCC (2018) and shows the share of gasoline volume sold in Melbourne by date over three months, specifically July 1–October 1, 2016 (i.e., three months after Coles exits the Informed Sources platform) out of total volume sold over the three-month period.[43] For comparison, we

[39] Buchholz et al. (2022) obtain a \$13.47/hour estimate from a structural model and ride-hail data from Liftago from Prague in 2016-18. Given closer market size and period similarity with our sample, we calibrate λ based on Goldszmidt et al. (2020).

[40] In particular, we calibrate α and β by aligning the predicted average daily retailer-level market shares between May 1 and July 31 in both 2015 and 2017 with the retailer-level choice probabilities in the ACAPMA surveys in those years. These time frames correspond to the months just before the surveys in August each year.

[41] The large market share for Coles in Table 2, a major supermarket retailer, partly reflects a loyalty scheme that provides 4 cpl discounts at gasoline stations for spending \$30 or more at one of its supermarkets. Indeed, from the 2015 and 2017 ACAPMA surveys, many consumers whose main retailer is Coles indicate that loyalty schemes drive their choice. As noted in Section 3, the government has regulated these discounts to be 4 cpl since 2014.

[42] We note two key auxiliary information sources for calibration here and provide further discussion in Appendix D.3. First, $\mathbf{f}$ contains traffic flows in the 2018 Origin-Destination matrix for Melbourne from the Victoria State Government Department of Transportation and Planning (2018). The Origin-Destination matrix contains daily traffic flows between 2975 unique travel zones in Victoria. We collect the daily count of drivers traveling from various origins to destinations within Melbourne to construct $\mathbf{f}$. Second, for each trip from x to y, we obtain the fastest travel route along the street network and the associated travel times $t(x, y)$ in equation (3) from OpenStreetMap (https://www.openstreetmap.org/). We generate a total of 1.15 million unique fastest routes.

[43] ACCC (2018) obtained this sensitive information directly from all gasoline retailers as part of their federal investigation into retail gasoline market shares. Given the sensitivity of the data, the report does not report daily or total volume sold over the three-month period.

also plot daily average station prices for Melbourne.

Figure 10(a) highlights two patterns of note. First, there are weekly cycles in gasoline purchases that arise from higher purchasing levels on weekends. Second, daily fuel volume sold drops sharply during price restoration episodes, reflecting demand anticipation and accumulation in the spirit of Hendel and Nevo (2006). These patterns also align with findings of consumer search cycles in retail gasoline markets with price cycles from Byrne and de Roos (2017, 2022), where consumer search intensity rises in anticipation of price restorations.

Panel (b) of Figure 10 shows the average daily volume of gasoline sold by month in Victoria from the Australian Government Department of Environment and Energy (2018). The figure indicates stable total fuel sales over our sample period, with seasonal summer purchasing peaks. We convert this state-level daily metric to volumes for Melbourne by scaling the volume of gasoline sold by the fraction of the total distance driven in Melbourne relative to the entire state as measured by the Origin-Destination tables from Victoria State Government Department of Transportation and Planning (2018).

We estimate Q_t using the information in Figure 10 in two steps. First, using the data in panel (a), we estimate a logit model for the daily shares of volume sold within a quarter

$$\ln(w_t) = \sum_{k=-4}^{2} \gamma_k^+ \Delta p_{t+k}^+ + \gamma_k^- \Delta p_{t+k}^- + \tau_d + \epsilon_t, \tag{6}$$

where w_t is the share of gasoline sold on date t out of total sales between July 1 and October 1, 2016, $\Delta p_{t+k}^+ = \max\{\Delta p_{t+k}, 0\}$, $\Delta p_{t+k}^- = \min\{\Delta p_{t+k}, 0\}$ and τ_d is a day-of-week fixed effect. Using (6), we predict the share of volume sold within a quarter on date t, $\hat{w}_t$, accounting for day-of-week effects and leading and lagged positive and negative price changes, which may affect consumers' purchasing decisions, per Hendel and Nevo (2006).

Second, we convert state-level monthly sales volumes in Figure 10(b) to quarterly volumes in Melbourne and compute Q_q, the total volume of fuel consumption for Melbourne in quarter q. Combining $\hat{w}_t$ and Q_q, we predict total fuel consumption in Melbourne on date t to be

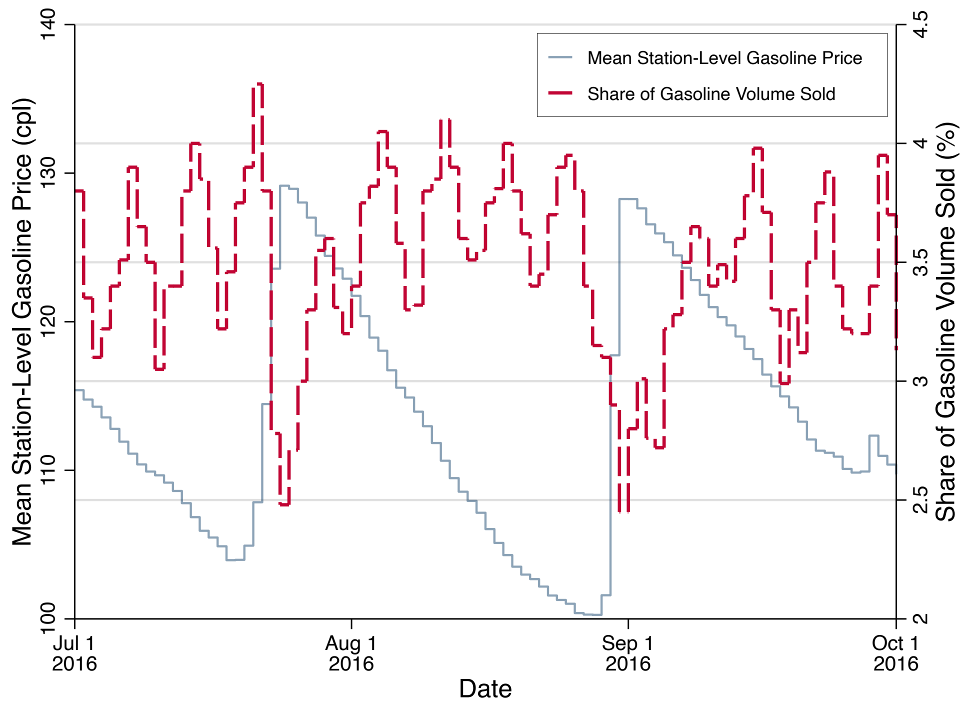
$$\hat{Q}_t = \hat{w}_t \times Q_{q[t]}, \tag{7}$$

where $q[t]$ indicates that date t falls within quarter of sample q.

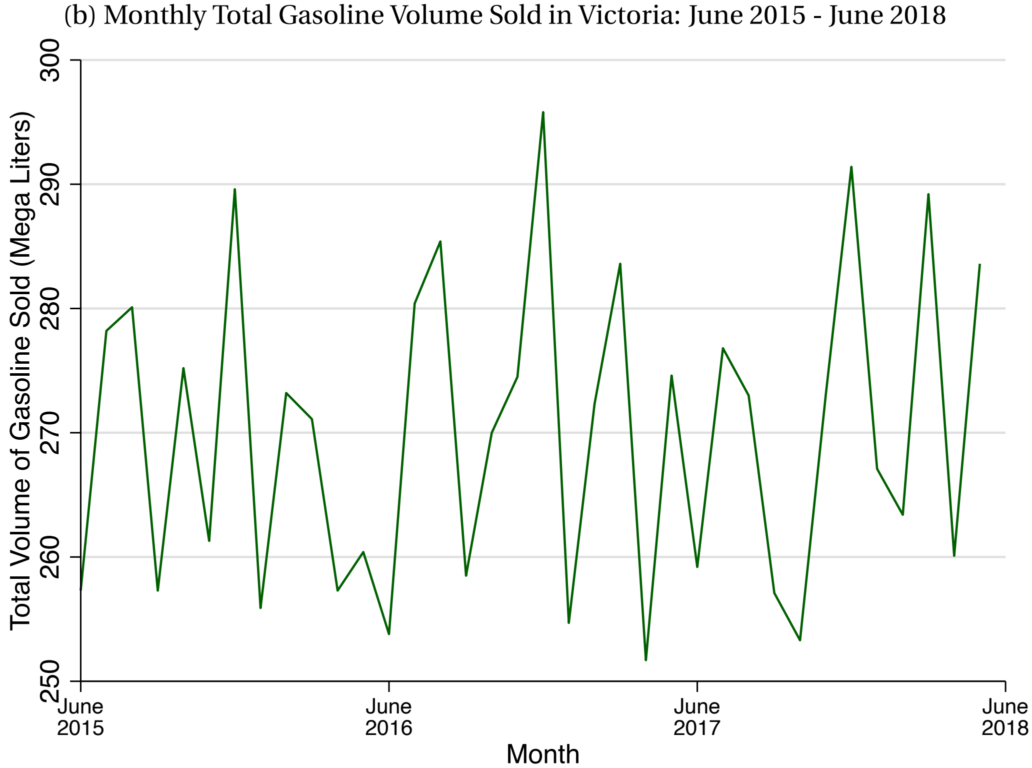
Appendix D.4 provides step-by-step details on how we convert state-level fuel volume sold to volume sold in Melbourne, model selection and estimation results for (6), and minor adjustments to $\hat{w}_t$ to ensure that they sum to one quarter-by-quarter.

Figure 10: Daily and Monthly Gasoline Expenditures

(a) Daily Share of Gasoline Sold of Total Quarterly Sales in Melbourne: July 1 - October 1 2016



(b) Monthly Total Gasoline Volume Sold in Victoria: June 2015 - June 2018



Notes: Shares of volume sold by date in Melbourne between July 1 and October 1, 2016, in panel (a) are extracted from ACCC (2018). For each date, we plot the share of fuel volume sold on that date relative to the total volume sold between July 1 and October 1, 2016. The mean daily station-level retail price in panel (a) is computed from the daily station-level price data from Informed Sources. The monthly volume of gasoline sold in Victoria in panel (b) is from Australian Government Department of Environment and Energy (2018).

Profit impacts

With data on station-level price-cost margins $p_{jt} - c_t$, estimates of station-level market shares $\hat{s}_{jt}$ and market-level fuel purchases $\hat{Q}_t$, we can quantify retailer b's total profit on date t by

$$\hat{\pi}_{bt} = \hat{Q}_t \times \sum_{j \in \mathbf{j}_b} \hat{s}_{jt} \times (p_{jt} - c_t), \tag{8}$$

where $\mathbf{j}_b$ is the set of stations in retailer b's network. Using our daily profit estimates from (8), we compute the change in retailers' daily profits between May 1, 2015, and February 28, 2016 (symmetric information sharing), and May 1, 2016, and February 28, 2017 (asymmetric information sharing). These periods fall within our estimation sample for the price effects of asymmetric information sharing from Section 4 above, and abstract from the March 1–April 30, 2016, equilibrium transition period. Per our arguments at the start of this section, computing the change in profits within retailers across these periods enables us to quantify the profit impacts of asymmetric information sharing through our event study research design.[44]

Table 3 presents our results. The first two panels illustrate the importance of weighting stations' price-cost margins in computing profits. The first panel simply computes retailers' margin by averaging across all stations and dates in the symmetric and asymmetric information sharing periods. The second panel weights stations' margins by their market share on a given date *and* total market-level fuel sales across dates. We find weighted margins are much lower than unweighted margins, reflecting consumers' substitution toward lower-priced stations within days and substitution across days toward days with lower overall price levels (e.g., away from price restorations).

Focusing on weighted margins in the middle panel of the table, we find that Coles exhibits a large 51% increase in its margin while other major retailers experience smaller but significant increases in margin. This reflects our finding from Section 4 that Coles' prices increase by more than its rivals' under asymmetric information sharing. We also find a large 52% increase in the weighted margins of smaller chains and independents (in the 'Other' category), rising from 2.99 to 4.55 cpl. Smaller retailers' prices follow the major five retailers' prices (due to strategic complementarity) but remain at a lower price level. Under asymmetric information sharing, the overall price increase by the five major retailers enables smaller retail chains and independents to increase their prices and bolster their price-cost margin.

[44] Our $\hat{w}_t$ estimate used in computing $\hat{Q}_t$ assumes a stable relationship between fuel expenditures and leading and lagging price changes, per equation (6). Byrne and de Roos (2017, 2022) document stable consumer search responses to price cycles using similar empirical models to (6) in multi-year periods with stable price cycles. And, as shown in Figure 3 above, price cycles are stable throughout our three-year sample period. Thus, previous research on consumer search in retail gasoline and the stability of our market environment supports our use of $\hat{w}_t$ in computing $\hat{Q}_t$ between 2015 and 2017.

Table 3: Retailer Profits Under Symmetric and Asymmetric Information Sharing

	Unweighted Margin (cpl)			Weighted Margin(cpl)			Mean Daily Profit ($)		
	Sym	Asym	%Δ	Sym	Asym	%Δ	Sym	Asym	%Δ
BP	9.57	11.22	17%	8.13	10.05	24%	$44.36K	$66.78K	51%
Caltex	8.89	10.28	16%	7.09	8.14	15%	$41.88K	$64.56K	54%
Coles	9.90	13.37	35%	7.80	11.77	51%	$153.69K	$159.92K	4%
Woolworths	8.57	10.33	21%	7.06	7.97	13%	$56.14K	$77.69K	38%
7-Eleven	8.58	10.13	18%	6.96	7.81	12%	$13.96K	$20.78K	49%
Other	6.80	8.19	20%	2.99	4.55	52%	$13.21K	$23.42K	77%

Notes: Daily station-level margins are computed as the difference between a station's price and the wholesale terminal gate price on a given date. 'Sym' indicates the symmetric information sharing period of May 1, 2015, to February 28, 2016, before Coles exits the Informed Sources platform. 'Aym' indicates the asymmetric information sharing period of May 1, 2016, to February 28, 2017, after Coles exits the Informed Sources platform. Daily total volume sold in the market is computed per equation (7). Mean daily profit is computed as the average of predicted station-level profits per equation (8), averaged over the symmetric and asymmetric information sharing periods.

The third panel of Table 3 puts together the price-cost margin and market share effects of asymmetric information to finally arrive at profit impacts. Our findings align with **Hypothesis 3**: all firms' profits rise under asymmetric information sharing with the strategically ignorant firm (Coles), which temporarily commits to prices, doing worse than its rivals that undercut. Quantitatively, we find a large discrepancy in profit impacts. Whereas Coles realizes just a 4% daily average profit increase, its rivals' profits rise between 38–77%. The figures underline how the uninformed firm gains comparatively little from price commitment in a market with high demand elasticity across firms. In contrast, informed firms gain substantially from their ability to price undercut while pricing at a higher overall price level *and* increasing their market shares.

Over a year, the nominal change in average daily profits between symmetric and asymmetric information sharing in Table 3 implies an annual industry profit increase of $32.82 million. This figure implies an additional fuel cost of $23.66 per year for each vehicle-driving household, which is about half the cost a typical household incurs from visiting a station and purchasing gasoline.[45] These additional fuel costs for consumers were, of course, unexpected. While the

[45] From the 2016 Census, there are 1.39 million households in Melbourne with at least one car; see https://www.abs.gov.au/census/find-census-data/quickstats/2016/2GMEL (accessed August 2, 2023). Thus, the figures in the far right panel of Table 3 imply a $32.82/1.39 = $23.66 increase in retailers' profit per-driving household. From Table 1, our sample's average retail gasoline price is 124.2 cpl. Given a typical household purchases 35L each time they visit a gasoline station (Budget Direct, 2022), this implies a 1.242 × 35 = $43.47 purchase cost.

government had hoped to encourage competition by reducing participation in the Informed Sources platform, the case settlement has, according to our analysis, had the opposite effect.

6 Conclusion

Prevailing wisdom suggests that competition is likely to soften when competing firms share price information, particularly when that information sharing allows them to easily and rapidly monitor each other's prices. This wisdom is grounded in a rich body of theoretical and empirical economic research that, to date, has assumed that firms are symmetric in their ability to share and monitor information. Leveraging a unique natural experiment and rich data from an antitrust case in retail gasoline, we have examined the competitive effects of asymmetric information sharing in an oligopoly. Our findings illustrate how such asymmetry can empower firms with price commitment and create market power. Quantitatively, we show that such market power effects can be large in practice.

The rise in market power induced by the *Informed Sources* settlement was unanticipated by the antitrust authority, which believed that limiting information sharing by one major firm would be "an extremely positive step towards increasing competition" (ACCC, 2015a). In fact, the authority's expectations largely aligned with the prevailing wisdom regarding the procompetitive effects of limiting price information sharing. Asymmetric information sharing had yet to be directly considered in IO research or antitrust policy, leaving a conceptual gap for the agency in negotiating the case settlement, which ultimately led to asymmetric information sharing and increased market power. In this way, our analysis provides an important cautionary tale for antitrust agencies regarding the challenges of creating "safe harbors" for information sharing (OECD, 2011) and pursuing cases involving anticompetitive information sharing. With many industries rapidly digitizing and decentralizing information sharing among firms, we expect more such cases in the future.

A final takeaway is that the structure of information sharing among oligopolists shapes market power. Our novel study of a particular structure highlights how strategic ignorance can facilitate credible commitment and generate market power. This, however, raises additional questions about the competitive effects of other potential information-sharing structures that could have emerged from the case settlement. For example, suppose the settlement had removed not one but *two* firms from the platform. Rather than having a single uninformed "price leader" with commitment power, this information-sharing structure results in competing uninformed and informed firms. In follow-up work, we explore the competitive effects of a more general set of asymmetric information-sharing structures that could arise in oligopoly markets.

References

ACCC (2011): "Monitoring of the Australian Petroleum Industry: Report of the ACCC into the Prices, Costs and Profits of Unleaded Petrol in Australia," December.

——— (2013): "Coles and Woolworths Undertake to Cease Supermarket Subsidised Fuel Discounts," Press Release, December 6, 2013.

——— (2014): "ACCC Takes Action Against Informed Sources and Petrol Retailers for Price Information Sharing," Press Release, August 20, 2014.

——— (2015a): "ACCC and Coles Express Resolve Petrol Price Information Sharing Proceedings," Press Release, December 16, 2015.

——— (2015b): "Petrol Price Information Sharing Proceedings Resolved," Press Release, December 23, 2015.

——— (2018): "Retail and Wholesale Petrol Market Shares in Australia," September 2018.

AGHION, P. AND J. TIROLE (1997): "Formal and Real Authority in Organizations," *Journal of Political Economy*, 105, 1–29.

ALBAEK, S., P. MOLLGAARD, AND P. B. OVERGAARD (1997): "Government-Assisted Oligopoly Coordination? A Concrete Case," *Journal of Industrial Economics*, 45, 429–443.

AMIR, R., I. GRILO, AND J. JIN (1999): "Demand-Induced Endogenous Price Leadership," *International Game Theory Review*, 1, 219–240.

ANDREWS, D. W. K. (1993): "Tests for Parameter Instability and Structural Change with Unknown Change Point," *Econometrica*, 61, 821–856.

ARYAL, G., F. CILIBERTO, AND B. T. LEYDEN (2022): "Coordinated Capacity Reductions and Public Communication in the Airline Industry," *Review of Economic Studies*, 89, 3055–3084.

ASKER, J. (2010): "A Study of the Internal Organization of a Bidding Cartel," *American Economic Review*, 100, 724–762.

ASKER, J., C. FERSHTMAN, J. JEON, AND A. PAKES (2020): "A Computational Framework for Analyzing Dynamic Auctions: The Market Impact of Information Sharing," *RAND Journal of Economics*, 51, 805–839.

ASSAD, S., R. CLARK, D. ERSHOV, AND X. LEI (forth): "Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market," *Journal of Political Economy*.

ATER, I. AND O. RIGBI (2023): "Price Transparency, Media and Informative Advertising," *American Economic Journal: Microeconomics*, 15, 1–29.

AUSTRALASIAN CONVENIENCE AND PETROLEUM MARKETERS ASSOCIATION (2015): "Monitor of Fuel Consumer Attitudes," Compiled by Survey Matters.

——— (2017): "Monitor of Fuel Consumer Attitudes," Compiled by Survey Matters.

——— (2019): "Monitor of Fuel Consumer Attitudes," Compiled by Survey Matters.

AUSTRALIAN GOVERNMENT DEPARTMENT OF ENVIRONMENT AND ENERGY (2018): "Australian Petroleum Statistics," Issue 262, May.

BAUMEISTER, C. AND L. KILIAN (2016): "Understanding the Decline in the Price of Oil since June 2014," *Journal of the Association of Environmental and Resource Economists*, 3, 131–158.

BERRY, S. (1994): "Estimating Discrete-Choice Models of Product Differentiation," *RAND Journal of Economics*, 25, 242–262.

BERRY, S., J. LEVINSOHN, AND A. PAKES (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63, 841–890.

BORENSTEIN, S. (2004): "Rapid Price Communication and Coordination: The Airline Tariff Publishing Case (1994)," in *The Antitrust Revolution: Economics, Competition and Policy*, ed. by J. Kwoka Jr. and L. White, Oxford University Press, 233–251.

BORENSTEIN, S. AND A. SHEPARD (1996): "Dynamic Pricing in Retail Gasoline Markets," *RAND Journal of Economics*, 27, 429–451.

BROWN, Z. Y. AND A. MACKAY (2023): "Competition in Pricing Algorithms," *American Economic Journal: Microeconomics*, 15, 109–156.

BUCHHOLZ, N., L. DOVAL, J. KASTL, F. MATEJKA, AND T. SALZK (2022): "The Value of Time: Evidence from Auctioned Cab Rides," NBER Working Paper 27087.

BUDGET DIRECT (2022): "Car Running Costs in Australia 2022," Available at https://www.budgetdirect.com.au/car-insurance/research/average-fuel-consumption-australia.html (accessed 14 July 2023).

BYRNE, D. P. AND N. DE ROOS (2017): "Consumer Search in Retail Gasoline Markets," *Journal of Industrial Economics*, 65, 183–193.

——— (2019): "Learning to Coordinate: A Study in Retail Gasoline," *American Economic Review*, 109, 591–619.

——— (2022): "Startup Search Costs," *American Economic Journal: Microeconomics*, 14, 81–112.

BYRNE, D. P., N. DE ROOS, A. R. GRINBERG, AND L. M. MARX (forth.): "Informed Sources and the Role of Platforms for Facilitating Anticompetitive Communication," in *Cartels Diagnosed: New Insight on Collusion*, ed. by J. E. Harrington and M. P. Schinkel, Cambridge.

CARRILLO, J. D. AND T. MARIOTTI (2000): "Strategic Ignorance as a Self-Disciplining Device," *Review of Economic Studies*, 67, 529–544.

CHEN, N. AND H.-T. TSAI (2023): "Price Competition Under Information (Dis)advantage," Working Paper, National University of Singapore.

CHRISTENSEN, L. R. AND R. E. CAVES (1997): "Cheap Talk and Investment Rivalry in the Pulp and Paper Industry," *Journal of Industrial Economics*, 45, 47–73.

CLARK, R. AND J.-F. HOUDE (2013): "Collusion with Asymmetric Retailers: Evidence from a Gasoline Price-Fixing Case," *American Economic Journal: Microeconomics*, 5, 97–123.

——— (2014): "The Impact of Explicit Communication on Pricing: Evidence from the Collapse of a Gasoline Cartel," *Journal of Industrial Economics*, 62, 191–228.

CREMER, J. (1995): "Arm's Length Relationships," *Quarterly Journal of Economics*, 110, 275–295.

DE ROOS, N. (2012): "Static Models of the Edgeworth Cycle," *Economics Letters*, 117, 881–882.

DE ROOS, N. AND V. SMIRNOV (2020): "Collusion with Intertemporal Price Dispersion," *The RAND Journal of Economics*, 51, 158–188.

DEWATRIPONT, M. AND E. MASKIN (1995): "Contractual Contingencies and Renegotiation," *RAND Journal of Economics*, 26, 704–719.

DOYLE, M. P. AND C. M. SNYDER (1999): "Information Sharing and Competition in the Motor Vehicle Industry," *Journal of Political Economy*, 107, 1326–1364.

ECKERT, A. (2013): "Empirical Studies of Gasoline Retailing: A Guide to the Literature," *Journal of Economic Surveys*, 27, 140–166.

EDGEWORTH, F. Y. (1925): *Papers Relating to Political Economy. Volume I, The Pure Theory of Monopoly*, Macmillan, London.

ERUTKU, C. AND V. A. HILDEBRAND (2010): "Conspiracy at the Pump," *Journal of Law and Economics*, 53, 223–237.

EUROPEAN COMMISSION (2011): "Guidelines on the Applicability of Article 101 of the Treaty on the Functioning of the European Union to Horizontal Co-operation Agreements," Document 52011XC0114(04).

EZRACHI, A. AND M. E. STUCKE (2017): "Algorithmic Collusion: Problems and Counter-Measures," Roundtable on Algorithms and Collusion at the OECD Competition Committee.

FEDERAL TRADE COMMISSION (2014): "Information Exchange: Be Reasonable," *Competition Matters*.

FTC (2000): "Antitrust Guidelines for Collaborations Among Competitors," Issued by the Federal Trade Commission and the U.S. Department of Justice.

GAL-OR, E. (1985): "First Mover and Second Mover Advantages," *International Economic Review*, 26, 649–653.

GENESOVE, D. AND W. MULLIN (2001): "Rules, Communication, and Collusion: Narrative Evidence from the Sugar Institute Case," *American Economic Review*, 91, 379–398.

GOLDSZMIDT, A., J. A. LIST, I. M. ROBERT D. METCALFE, V. K. SMITH, AND J. WANG (2020): "The Value of Time in the United States: Estimates from Nationwide Natural Field Experiments," NBER Working Paper 28208.

GOLMAN, R., D. HAGMANN, AND G. LOEWENSTEIN (2017): "Information Avoidance," *Journal of Economic Literature*, 55, 96–135.

GREEN, E. J. AND R. H. PORTER (1984): "Noncooperative Collusion under Imperfect Price Information," *Econometrica*, 52, 87–100.

GUL, F. (2001): "Unobservable Investment and the Hold-Up Problem," *Econometrica*, 69, 343–376.

HAMILTON, J. H. AND S. M. SLUTSKY (1990): "Endogenous Timing in Duopoly Games: Stackelberg or Cournot Equilibria," *Games and Economic Behavior*, 2, 29–46.

HENDEL, I. AND A. NEVO (2006): "Measuring the Implications of Sales and Consumer Inventory Behavior," *Econometrica*, 74, 1637–1673.

HOLT, T., M. IGAMI, AND S. SCHEIDEGGER (2022): "Detecting Edgeworth Cycles," Working Paper, Yale University.

HOTELLING, H. (1929): "Stability in Competition," *Economic Journal*, 39, 41–57.

HOUDE, J.-F. (2012): "Spatial Differentiation and Vertical Mergers in Retail Markets for Gasoline," *American Economic Review*, 105, 2147–2182.

IGAMI, M. AND T. SUGAYA (2022): "Measuring the Incentive to Collude: The Vitamins Cartels, 1990-1999," *Review of Economic Studies*, 89, 1460–1494.

KRASTEVA, S. AND H. YILDIRIM (2019): "Strategic Ignorance in Sequential Procurement," *American Economic Journal: Microeconomics*, 11, 131–172.

KUBITZ, G. AND K. WOODWARD (2020): "Sharing Cost Information in Dynamic Oligopoly," Working paper.

KUHN, K.-U. (2001): "Fighting Collusion by Regulating Communication between Firms," *Economic Policy*, 16, 169–204.

KUHN, K.-U. AND X. VIVES (1995): "Information Exchanges Among Firms and Their Impact on Competition," European Commission Document, Luxembourg: Office for Official Publications of the European Communities.

LEISTEN, M. (2022): "Algorithmic Competition, With Humans," Working Paper, U.S. Federal Trade Commission.

LEMUS, J. AND F. LUCO (2021): "Price Leadership and Uncertainty about Future Costs," *Journal of Industrial Economics*, 69, 305–337.

LEWIS, M. AND M. NOEL (2011): "The Speed of Gasoline Price Response in Markets with and without Edgeworth Cycles," *The Review of Economics and Statistics*, 93, 672–682.

LEWIS, M. S. (2012): "Price Leadership and Coordination in Retail Gasoline Markets with Price Cycles," *International Journal of Industrial Organization*, 30, 342–351.

——— (2015): "Odd Prices at Retail Gasoline Stations: Focal Point Pricing and Tacit Collusion," *Journal of Economics and Management Strategy*, 24, 664–685.

LUCO, F. (2019): "Who Benefits from Information Disclosure? The Case of Retail Gasoline," *American Economic Journal: Microeconomics*, 11, 277–305.

MACKINNON, J. G., M. Ø. NIELSEN, AND M. D. WEBB (2023): "Testing for the Appropriate Level of Clustering in Linear Regression Models," *Journal of Econometrics*, 232, 272–299.

MARSHALL, R. C. AND L. M. MARX (2012): *The Economics of Collusion: Cartels and Bidding Rings*, MIT Press.

MARSHALL, R. C., L. M. MARX, AND M. E. RAIFF (2008): "Cartel Price Announcements: The Vitamins Industry," *International Journal of Industrial Organization*, 26, 762–802.

MASKIN, E. AND J. TIROLE (1988): "A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles," *Econometrica*, 56, 571–99.

MILLER, A. R. (2010): "Did the Airline Tariff Publishing Case Reduce Collusion?" *Journal of Law and Economics*, 53, 569–586.

MONTAG, F., A. SAGIMULDINA, AND C. WINTER (2023): "Whom To Inform About Prices? Evidence from the German Fuel Market," Working Paper, Dartmouth.

MUSOLFF, L. (2022): "Algorithmic Pricing Facilitates Tacit Collusion: Evidence from E-Commerce," Working Paper, Microsoft Research.

NEWEY, W. K. AND K. D. WEST (1987): "A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703–708.

OECD (2011): "Information Exchanges Between Competitors under Competition Law," *OECD Policy Roundtables*, Directorate for Financial and Enterprise Affairs Competition Committee, DAF/COMP(2010)37.

ROGERSON, W. P. (1992): "Contractual Solutions to the Hold-Up Problem," *Review of Economic Studies*, 59, 777–793.

RÖLLER, L.-H. AND F. STEEN (2006): "On the Workings of a Cartel: Evidence from the Norwegian Cement Industry," *American Economic Review*, 96, 321–338.

ROSSI, F. AND P. K. CHINTAGUNTA (2016): "Price Transparency and Retail Prices: Evidence from Fuel Price Signs in the Italian Highway System," *Journal of Marketing Research*, 53, 407–423.

SCHELLING, T. C. (1960): *The Strategy of Conflict*, Harvard University Press.

SCHERER, F. M. AND D. R. ROSS (1990): *Industrial Market Structure and Economic Performance*, Houghton Mifflin.

STIGLER, G. J. (1964): "A Theory of Oligopoly," *Journal of Political Economy*, 72, 44–61.

TIROLE, J. (1986): "Procurement and Renegotiation," *Journal of Political Economy*, 94, 235–259.

——— (1988): *The theory of industrial organization*, MIT Press, Cambridge, Massachusetts.

VARIAN, H. (1980): "A Model of Sales," *American Economic Review*, 70, 651–659.

VICTORIA STATE GOVERNMENT DEPARTMENT OF TRANSPORTATION AND PLANNING (2018): "Origin Destination Gasoline Demand Matrices," Report.

VIVES, X. (2005): "Complementarities and Games: New Developments," *Journal of Economic Literature*, XLIII, 437–79.

——— (2007): "Information Sharing: Economics and Antitrust," IESE Business School Occasional Paper 07/11, University of Navarra.

WANG, Z. (2009): "(Mixed) Strategy in Oligopoly Pricing: Evidence from Gasoline Price Cycles Before and Under a Timing Regulation," *Journal of Political Economy*, 117, 987–1030.

WU, X., M. S. LEWIS, AND F. A. WOLAK (forth.): "Search with Learning in the Retail Gasoline Market," *RAND Journal of Economics*.

Appendix

A Consumer search apps

Three gasoline price comparator platforms operated in Melbourne during our May 1, 2014 - December 31, 2017, main sample period: MotorMouth, Petrol Spy, and GasBuddy. Industry reports from the ACCC over this period, and internet archives indicate that these platforms provide users with time-delayed price information from a subset of stations in a given market.

MotorMouth

MotorMouth, owned by Informed Sources, started its price monitoring service in Melbourne in 2001. It created a mobile phone app in mid-2013. Price data on the app primarily come from electronically uploaded prices from the major retailers and manually collected data from price spotters employed by the company. In February 2016, the MotorMouth app started allowing users to collect and upload prices in February 2016.

Since its inception, Motormouth limited gasoline station monitoring on the app. For instance, users can only see prices at 2 user-specified "Favorite Stations" on the app. If a user wants to see prices at an additional station, they have to earn “app credits” from manually uploading stations’ prices to Motormouth to unlock an additional station on the app for a limited time period. Lastly, Motormouth price data is not real-time and is provided with a daily lag.

Informed Sources changed price data availability (but not frequency) on the MotorMouth app in May 2016. At this time, the app introduced a “price reveal” function where a consumer had to manually click a station to see its (lagged) price. At the start of each week, app users get 30 “price reveal points.” If these points run out during the week, users can top up their quote by entering an SMS code into the app.

The incomplete, lagged, and difficult-to-access price data on Motormouth makes it unpopular among the public. For instance, as of October 2022, the MotorMouth app (version 4) was rated 1.9 out of 5 by 134 reviewers in the Apple store. User comments on the Apple store explicitly state the challenge of viewing stations’ prices on the app as one of its disappointing features. In contrast, the state government-run FuelCheck app in New South Wales, with real-time, complete, and easy-to-access station-level price data, was rated 4.7 out of 5 by 67,000 reviewers on the Apple store. As discussed in the paper, no such app exists in Victoria, and thus Melbourne.

PetrolSpy

PetrolSpy was launched in 2014 and is Australia’s most popular third-party gasoline price search platform. The app relies on crowdsourcing for its price data. In particular, app users can manually upload and update price changes to earn points to enter into a $25 Fuel Card draw every two weeks. According to the company, it had over 25,000 active users, and 2,500 daily price updates daily across all states and territories in Australia in March 2016. The app has coverage of all stations in Melbourne, but the frequency of price uploads varies widely across stations. A back-of-the-envelope calculation using a sample of 2022 price data scraped from the app suggests that the given station's prices are updated with a one-day lag on the app, with more frequent uploads at stations on major roadways.

GasBuddy

GasBuddy, a North America-based third-party gasoline price app provider, launched in Australia in March 2016. However, it never gained popularity and exited the market. The last Twitter post from its official account, GasBuddy Australia, was from April 2017. The app's lack of success may reflect that it relies on a similar crowdsourcing model as PetrolSpy. PetrolSpy's two-year headstart on GasBuddy and network effects in crowdsource-based search may have limited GasBuddy's ability to penetrate the market as a competing search platform.

B Asymmetric information sharing in dynamic environments

In this section, we illustrate the role of asymmetric information sharing in several stylized dynamic environments. In Section B.1, we consider a price-fixing cartel with impatient firms and perfect monitoring. In Section B.2, we consider a price-fixing cartel with patient firms subject to imperfect coordination. Finally, in Section B.3, we consider a range of dynamic environments that satisfy a simple property of strategic complementarity.

B.1 A cartel with perfect monitoring

In this section, we amend the simple framework considered in Section 2.4 to examine the impact of a transition to asymmetric information sharing for a price-setting, differentiated-product cartel with perfect monitoring. Consider a setup in which $n = 3$ firms are evenly spaced along a circular city of circumference 3. Each firm has constant marginal costs of c and no fixed costs. A measure 3 of consumers, indexed by i, are located uniformly along the city. Each consumer chooses exactly one product. If consumer i, located x_i units from Firm j, purchases product j, consumer i obtains indirect utility

$$u(p_j, x_i) = \overline{u} - t|x_i| - p_j,$$

where $\overline{u}$ indicates a consumer's intrinsic value of buying, t indicates travel costs, and p_j is the price of Firm j.

Given the price vector $\mathbf{p} = (p_1, p_2, p_3)$, the demand for each Firm j is given by:

$$q_j = 1 + \frac{\sum_{k \neq j} p_k - 2p_j}{2t}.$$

Before the case: simultaneous pricing

As in the body of the paper, we interpret the pre-case symmetric information-sharing environment as one of simultaneous price setting. Suppose then that each Firm j simultaneously chooses a price $p_j \in \mathbb{R}_+$ in a single period. The reaction function for Firm j is given by

$$p_j = \frac{\sum_{k \neq j} p_k}{4} + \frac{t + c}{2}.$$

In the symmetric Nash equilibrium, each firm sets the price $p^n = t + c$ and earns profits of $\pi^n = t$.

Next, suppose firms simultaneously choose prices over an infinite horizon. Firms play grim-trigger strategies that involve setting the price $p > p^n$ on the equilibrium path, and the price p^n following any deviation. Suppose that the cartel's internal incentive constraints bind so that p is lower than the joint profit-maximising price of the cartel, $p^m = \frac{\overline{u}+c}{2}$. Let $m = p - c$ be the margin earned by cartel members. On the equilibrium path, firms earn profits of $\pi^c = m$. The optimal deviation, on the reaction function, yields profits of $\pi^d = \frac{(m+t)^2}{4t}$. The above grim-trigger strategies are sustainable if cartel members are sufficiently patient. In particular, the cartel's critical discount factor is given by:

$$\delta^* = \frac{(m + t)^2 - 4tm}{(m + t)^2 - 4t^2}. \tag{B.1}$$

After the case: sequential pricing

As before, we consider the post-case asymmetric information sharing environment to be one of sequential price setting. Suppose first that, in a single period, Firm 1 chooses price first, followed simultaneously by Firms 2 and 3. In the subgame perfect Nash equilibrium, Firm 1 chooses price $p_1 = c + \frac{5}{4}t$ and earns profits $\pi_1 = \frac{25}{24}t$; and Firms 2 and 3 set price $p_2 = c + \frac{13}{12}t$ and earn profits $\pi_2 = \frac{169}{144}t$.[46]

Next, suppose that, over an infinite horizon, Firm 1 chooses price first in each period, followed simultaneously by Firms 2 and 3. Firms play grim-trigger strategies that involve Firm 1 setting price $p_a > p_1$ and Firms 2 and 3 setting price $p_b > p_2$ on the equilibrium path, and the prices p_1 and p_2, respectively, following any deviation. Let $m_x = p_x - c$ for $x \in \{1, 2, a, b\}$ be the margin associated with each price.

On the equilibrium path, profits are given by $\pi_a = \frac{m_a}{t}(p_b - p_a + t)$ for Firm 1 and $\pi_b = \frac{m_b}{2t}(p_a - p_b + 2t)$ for Firms 2 and 3. Firm 1 is unable to profitably deviate because Firms 2 and 3 can retalliate immediately within the same period. For Firms 2 and 3, the optimal deviation yields profits of $\pi^d = \frac{(\overline{m}+t)^2}{4t}$, where $\overline{m} = (m_a + m_b)/2$. The critical discount factor for Firms 2 and 3 is given by

$$\delta^{**} = \frac{(\overline{m} + t)^2 - 4tm_b(1 + 2(p_a - p_b))}{(\overline{m} + t)^2 - (169/36)t^2}. \tag{B.2}$$

In the special case in which firms set the same prices as in the simultaneous move case, $p_a = p_b = p$, the critical discount factor simplifies to

$$\delta^{**} = \frac{(m + t)^2 - 4tm}{(m + t)^2 - (169/36)t^2}. \tag{B.3}$$

Implications of the move to asymmetric information sharing

This simple model of a differentiated-products cartel with perfect monitoring leads to the following implications. First, if firms coordinate on the same prices in the simultaneous and sequential moves games, then the cartel is more difficult to sustain in the sequential moves game. This is because punishment profits are higher for the followers in the sequential moves game. Second, by (B.2), starting from the prices $p_a = p_b = p$, the cartel's incentive constraints can be relaxed by either raising the leader's price (p_a) or lowering the price of the followers (p_b). Further, a given change in the leader's price has a greater impact on the incentive constraints than an opposite change of the same magnitude in the price set by the followers.

Loosely speaking, in order to satisfy the cartel's incentive constraints when moving to a sequential moves environment, we might therefore expect the leader to raise its price, and for the followers to raise their prices by a smaller amount.[47] Thus, our analysis of a differentiated products cartel leads to qualified predictions for pricing that are in line with the static analysis in Section 2.4.

[46] This single-period pricing game leads to the same qualitative conclusions as the two-firm Hotelling model studied in Section 2.4, summarized by Hypotheses 1, 2, and 3.

[47] It is also possible for the incentive constraints (B.2) to be satisfied following a decrease in prices by the leader, in conjunction with a sufficiently large decrease in prices by the followers. However, this would result in lower profits for all firms.

B.2 A cartel with imperfect coordination

In the standard model of collusion, supra-competitive prices are sustainable as long as cartel members are sufficiently patient to resist the short-term benefits of deviating from cartel prices in favour of the elevated future payoffs of the cartel. A feature of the market that we study is high-frequency, observable pricing. In such an environment, it is likely that the time scales involved in detecting and responding to deviations are sufficiently short to render this calculus somewhat moot. In this section, we consider a stylized model in which the principal challenge of a price-fixing cartel relates to coordination rather than internal cartel incentive constraints. Cartel members may seek to maximize joint payoffs, but due to imperfect coordination, each firm may fail to completely account for the interests of their rivals when setting its price.

Consider a market with n firms. Let $\mathbf{p} = (p_1, \ldots, p_n)$ and $\pi = (\pi_1, \ldots, \pi_n)$ be the vectors of market prices and profits, respectively. Each Firm j earns profits which depend on the vector of prices, $\pi_j(\mathbf{p})$, and seeks to maximise an objective function based on the vector of profits:

$$g_j(\pi) = \sum_k \alpha_{jk}\pi_k, \qquad \alpha_{jk} \in [0,1], \qquad \sum_k \alpha_{jk} = 1.$$

The specification of the objective function depends on the nature of interaction between firms. Static profit maximisation corresponds to $g_j(\pi) = \pi_j$. We could think of a Firm j in a perfect cartel maximising $g_j(\pi) = \sum_k \pi_k / n$, and a Firm j operating in an imperfectly coordinated cartel having profit weights with $\alpha_{jj} > \alpha_{jk}$ for $k \neq j$.[48] Consistent with our earlier analysis, we consider two variations on the timing of play. Under *simultaneous play*, all firms simultaneously set prices. Under *sequential play*, Firm 1 sets price first, and then all remaining firms set prices simultaneously.

Assumption 1. For all j and $k \neq j$, $\frac{\partial g_j(\pi)}{\partial p_k} > 0$.

We maintain Assumption 1. In the case of static profit maximisation, this follows if products are substitutes. In the case of a perfect cartel, this follows if cartel members face other constraints that prevent pricing at the monopoly level. The proof of the proposition below is based on Brown and MacKay (2023), Proposition 2.

Proposition 1. Suppose prices are strategic complements. Then, all prices are higher under sequential play than simultaneous play.

Proof. Firm 1 solves the first order conditions:

$$\frac{dg_1(\pi)}{dp_1} = \frac{\partial g_1(\pi)}{\partial p_1} + \sum_{j\neq 1} \frac{\partial g_1(\pi)}{\partial p_j}\frac{\partial p_j}{\partial p_1} = 0.$$

Under simultaneous play, Firm 1 takes all rival prices as given, and $\frac{\partial p_j}{\partial p_1} = 0$ for all $j \neq 1$. Under sequential play, at the simultaneous play equilibrium price vector, by strategic complementarity and Assumption 1, $\frac{dg_1(\pi)}{dp_1} > 0$. Firm 1 therefore sets a strictly higher price under sequential play. By strategic complementarity, so do the other firms. $\square$

[48]One interpretation of a constrained cartel is that, absent direct communication, cartel members are unable to perfectly coordinate on pricing. To the extent that prices cannot be perfectly coordinated, firms are likely to give greater weight to their own profits in their objective function.

Implications of the move to asymmetric information sharing

As before, we interpret the transition to asymmetric information sharing as a move from simultaneous to sequential price setting. The simple stylized model introduced in this section nests the case of single-period price competition. As in the simple model introduced in Section 2.4 and the more general formulation of Brown and MacKay (2023), the combination of strategic complementarity and the information sharing transition leads to an increase in the price of both the information-constrained committed player and the unconstrained players. The same logic applies in the event that firms imperfectly coordinate by partially considering the payoffs of their competitors.

B.3 Other dynamic environments

In the simple analytic framework that we introduced in Section 2.4, firms compete by setting prices in a single period. As described in Byrne and de Roos (2019) and Byrne et al. (forth.), tacit coordination is a feature of retail gasoline markets in Australia. Further, the dynamic pricing patterns that we observe in the market for retail gasoline (see, for example, Figure 2) have led to a number of alternative explanations including price commitment (Maskin and Tirole, 1988), obfuscation through intertemporal price variation (de Roos and Smirnov, 2020), capacity constraints (Edgeworth, 1925), and other discontinuities in residual demand (de Roos, 2012). In this section, we introduce a simple stylized model that allows for market dynamics by decomposing payoffs into current and continuation payoffs.

Consider a market with n firms. Given price vector $\mathbf{p}$, Firm j receives payoffs of

$$V^j(\mathbf{p}) = \pi^j(\mathbf{p}) + W^j(\mathbf{p}),$$

where π describes instantaneous profits, and W indicates the continuation value if prices $\mathbf{p}$ are set in the current period. Given the frequency with which prices are set, we do not incorporate discounting.

Assumption 2. For all j and $k \neq j$, $\frac{\partial V^j(\mathbf{p})}{\partial p_k} > 0$.

Assumption 2 will be satisfied if products are substitutes and the continuation value of a firm is increasing in the prices of its rivals. If firms engage in tacit coordination, then we might expect continuation values to increase in rival prices. Similarly, in the price commitment model of Maskin and Tirole (1988), commonly discussed as a potential explanation for asymmetric price cycles, continuation values are increasing in rival prices.

Proposition 2. If prices are strategic complements with respect to the objective $V(\mathbf{p})$, then all prices are higher under sequential play than simultaneous play.

The proof follows that of Proposition 1. Let $V^j_{jk}(\mathbf{p})$ refer to the cross partial derivative of Firm j's objective function with respect to the prices of Firm j and Firm k. Reaction functions will slope up and strategic complementarity will be satisfied if $V^j_{jk}(\mathbf{p})/V^j_{jj}(\mathbf{p}) < 0$.[49] The second order conditions for an optimum require that $V^j_{jj}(\mathbf{p}) < 0$. Strategic complementarity will be satisfied if $V^j_{jk}(\mathbf{p}) = \pi^j_{jk}(\mathbf{p}) + W^j_{jk}(\mathbf{p}) >$

[49] See Tirole (1988) for a discussion.

0. Thus, if the static profit function exhibits strategic complementarity, $\pi^j_{jk}(\mathbf{p}) > 0$, then a sufficient condition is that the continuation value exhibits the same property in weak form, $W^j_{jk}(\mathbf{p}) \geq 0$. In words, continuation payoffs provide a weak incentive to set higher prices when rivals set higher prices. For example, we might expect this property to be satisfied if firms seek to tacitly coordinate on focal prices as in Byrne and de Roos (2019).

Implications of the shift to asymmetric information sharing

In sum, the simple framework introduced in this section suggests that the move to asymmetric information sharing will lead to higher prices in the presence of strategic complementarity.

C Supplemental empirics

C.1 Sample dates

Figure C.1 shows daily average retail prices and the wholesale terminal gate price (TGP) for 2014–2019. The grey shaded area highlights our May 1, 2015–December 31, 2017 primary estimation sample.

Sample start date. Panels (a) and (b) illustrate a major world oil price shock that defines the start of our sample. In particular, the wholesale TGP drops from 140 to 100 cpl between October 1, 2014, and January 15, 2015.[50] During this period, there is no regular price cycle as retailers continually cut their prices to pass through falling wholesale prices while maintaining a margin. It is not until the wholesale TGP starts rising in panel (b) that regular price cycles return. Our May 1, 2015 start date allows a four-cycle "burn-in" period as retailers re-establish the cycle and restoration price-TGP margins stabilize.

Separately, panel (a) also highlights when the ACCC publicly announces the Informed Sources case on August 14, 2014. Visually, there is no evidence of an immediate announcement effect on retailers' pricing. Formally testing for a break is complicated by the global oil demand shock between October 2014 and February 2015, which causes regular price cycles to stop shortly after the Informed Sources case announcement. In this sense, the oil price shock dwarfs any announcement effects in retail pricing that might have subsequently emerged. Ultimately, our May 1, 2015 sample start date, after regular cycles are re-established following the world oil price shock, combined with our high-frequency event study design leaves little scope for case announcement effects to contaminate our estimates of the price effects of asymmetric information sharing.

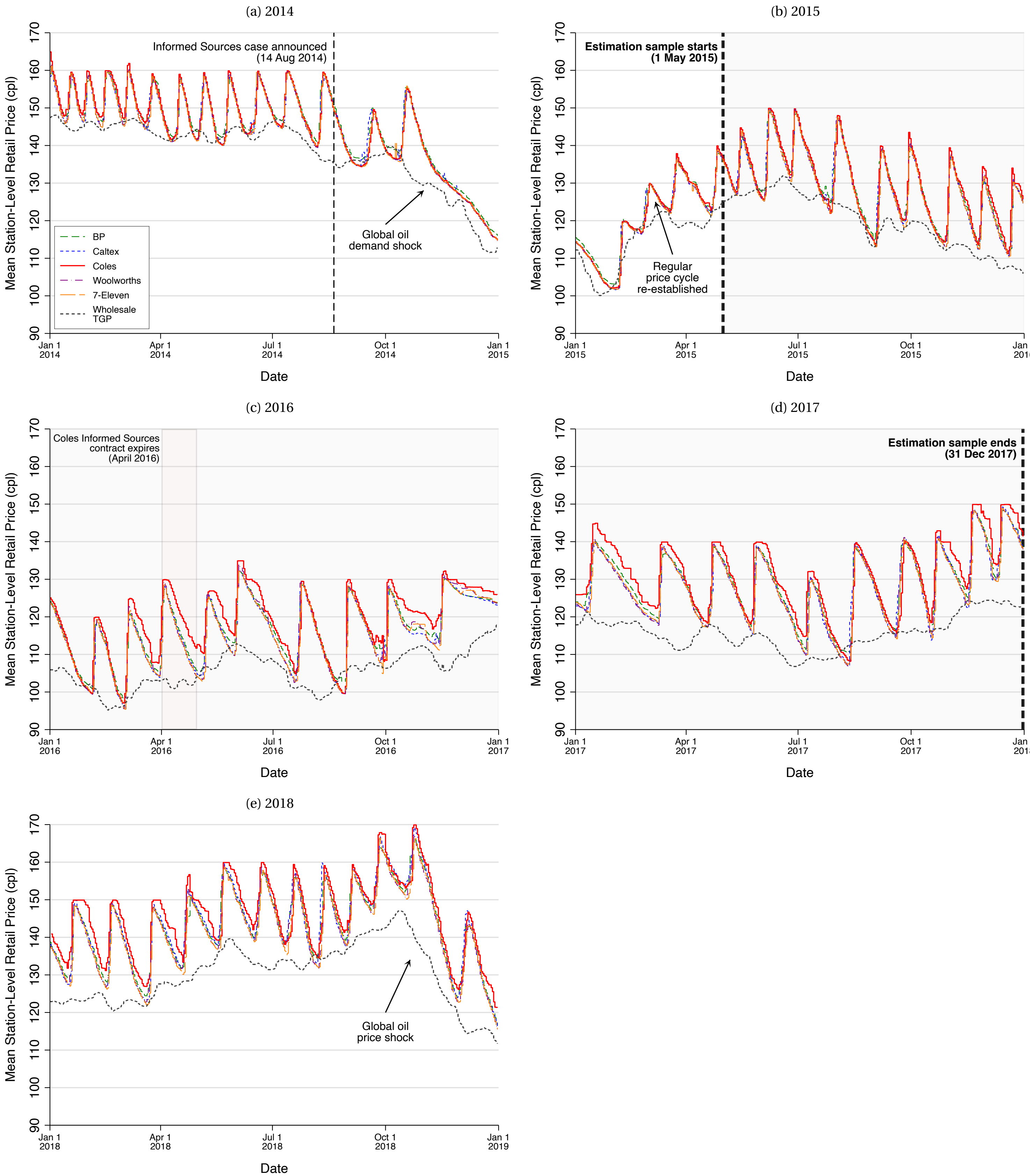
Sample end date. Our sample end date is defined by the Australasian Convenience and Petroleum Marketers Association (2017) consumer panel, which provides information on consumers' choice of gasoline retailer. We use this information to evaluate the market share and profit impacts of asymmetric information sharing created by the Informed Sources case settlement.

The market's structure is, however, stable through 2018. Therefore, we can evaluate the price effects of asymmetric information sharing using a sample that includes 2018. Panel (e) of Figure C.1 illustrates a major crude oil price shock between November and January 2019, causing wholesale TGPs to fall from 150 to 110 cpl in just two months. Despite this shock, however, gasoline price cycles remain stable.

Our case evaluation window closes in February 2019 with two major ownership changes. On February 2, EG Group purchases Woolworths and on February 9 Coles and Viva Energy enter into a strategic alliance. With the latter ownership change, Viva takes over price setting across Coles' station network.

[50] This substantial drop corresponds to a global oil supply glut for crude oil arising from unexpectedly weak demand in the face of stable oil production levels from OPEC and the emergence of alternative oil sources. See Baumeister and Kilian (2016) for an analysis of the 2014–2015 collapse in world oil prices.

Figure C.1: Average Daily Retail Prices by Retailer: 2014-2018



Notes: Average daily prices across stations plotted for each retailer. The shaded area in panels (b)-(d) highlights our primary estimation sample for our empirical analysis in the paper. The boxed shaded area on panel (c) highlights the month Coles' contract with Informed Sources expires.

C.2 Sydney summary statistics, price uploads, and pricing

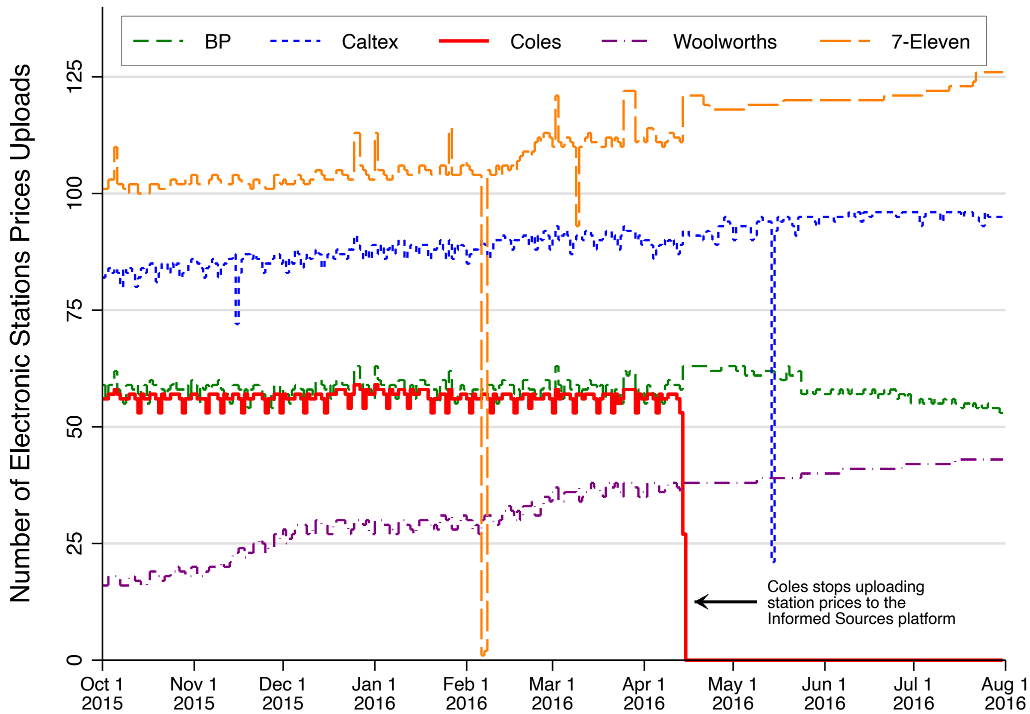
Table C.1: Summary Statistics for the Sydney Sample

	Mean	Std. Dev.	Min	Max
Prices (cpl)				
Price	120.2	12.8	88.9	156.9
Terminal Gate Price	109.1	7.2	95.7	124.9
Margin	11.4	9.8	-13.1	43.0
Panel Dimensions (cpl)				
Dates		366		
Stations				
BP		66	(13%)	
Caltex		100	(19%)	
Coles		59	(11%)	
Woolworths		45	(9%)	
7-Eleven		128	(25%)	
Other		116	(23%)	
Total		514	(100%)	
Observations				
Electronically collected		165542	(88%)	
Manually collected		22216	(12%)	
Total		187758	(100%)	

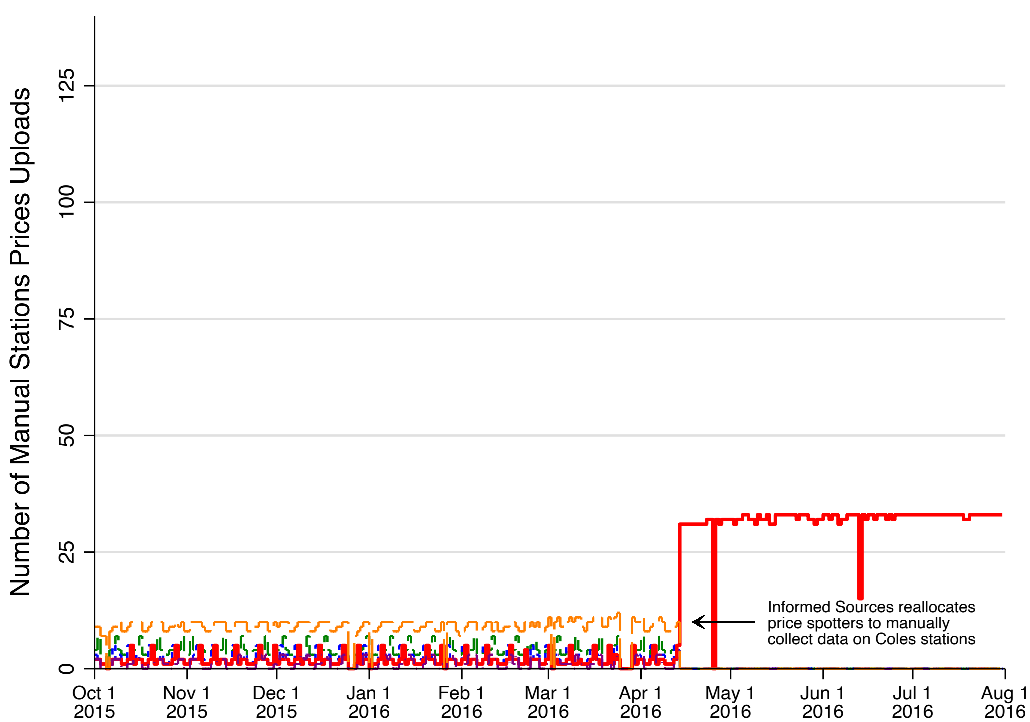
Notes: Sample period is May 1, 2015, to July 31, 2016. Retail prices are at the station-date level. Wholesale Terminal Gate Prices (TGPs) are at the daily level from Sydneys's gasoline terminal gate. Margin is a station's retail price less Melbourne's TGP on a given date.

Figure C.2: Daily Station-Level Price Uploads to the Informed Sources Platform in Sydney

(a) Sydney **Electronic** Uploads

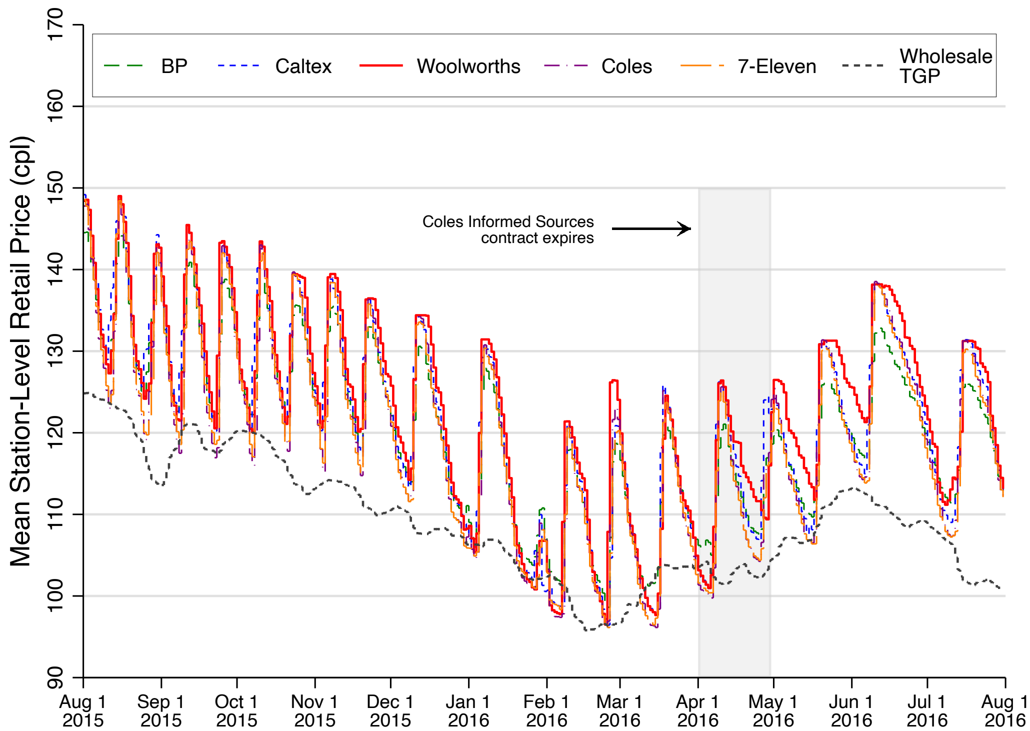


(b) Sydney **Manual** Uploads



Notes: Manual uploads in panel (b) drop to zero on ANZAC Day (April 26) and Queen's Birthday (June 13) public holidays.

Figure C.3: Retail Pricing Before and After the Informed Sources Case in Sydney

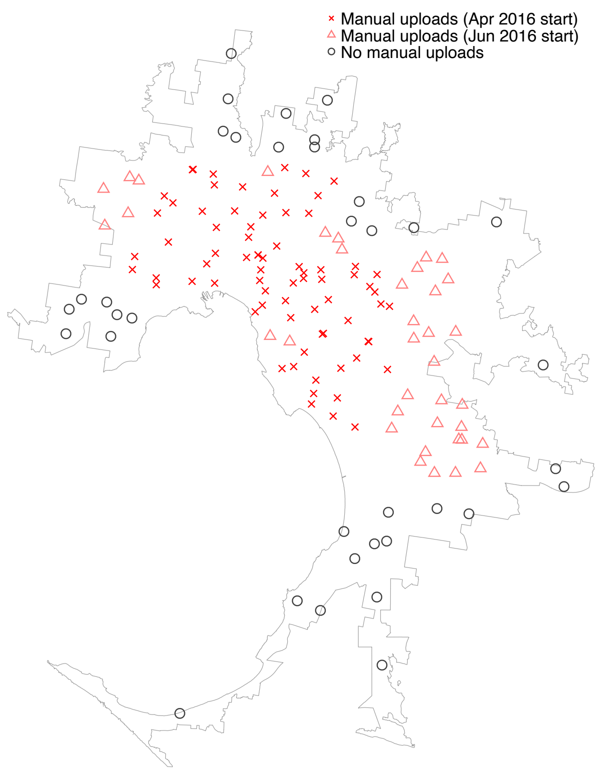


Notes: The figure shows daily average retail prices for each major retailer in Sydney. The wholesale Terminal Gate Prices (TGP) correspond to daily wholesale prices from Sydney's local terminal gate.

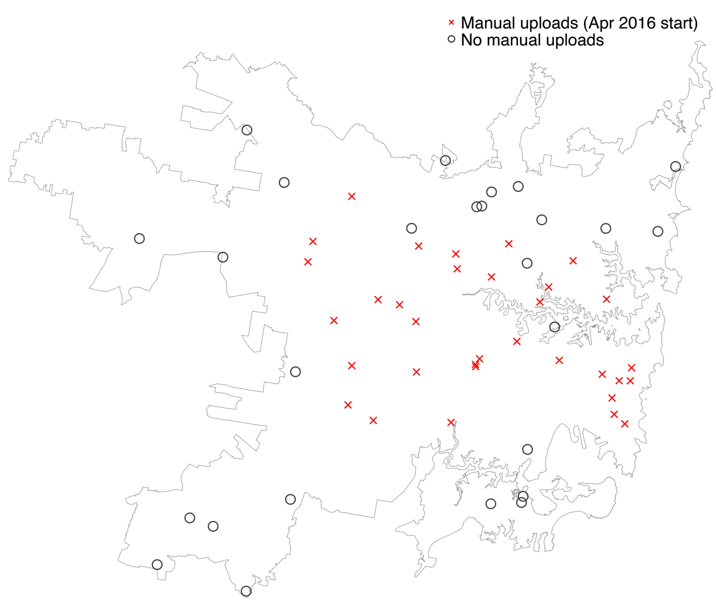
C.3 Coles stations with manual data collection

Figure C.4: Coles Stations that Informed Sources Electronically and Manually Collect On
(Manual Data Collection Begins After April 15, 2016)

(a) Melbourne



(b) Sydney



C.4 Structural break tests for change in Coles' pricing

This section tests for a structural break in Coles' pricing relative to its rivals' prices. Specifically, we use the supF test from Andrews (1993), which tests for a structural break with an unknown break point. To this end, we estimate regressions of the following form

$$\text{margin}_{jt} = \beta_0 + \beta_{1,\tau}\left(\text{Coles}_j \times \{\text{Break } \tau\}_t\right) + \eta_j + \lambda_m + \epsilon_{jt}, \tag{C.1}$$

where margin_{jt} is the average daily station-level margin of retailer j on date t, Coles_j is a dummy equalling one if retailer j is Coles, $\{\text{Break } \tau\}$ is a dummy equalling one if $t \geq \tau$, η_j is a retailer j fixed effect, λ_m is a month of sample m dummy, and ϵ_{jt} is the error term. The coefficient of interest with the test is $\beta_{1,\tau}$ as it measures a break in Coles' margin relative to the other retailers after a candidate structural break point τ. The test involves (1) estimating (C.1) for multiple candidate values for τ in the sample; (2) testing H_0: $\beta_{1,\tau} = 0$ vs H_1: $\beta_1 \neq 0$ for each τ value; and (3) finding the τ value that yields the largest F-statistic from the test.

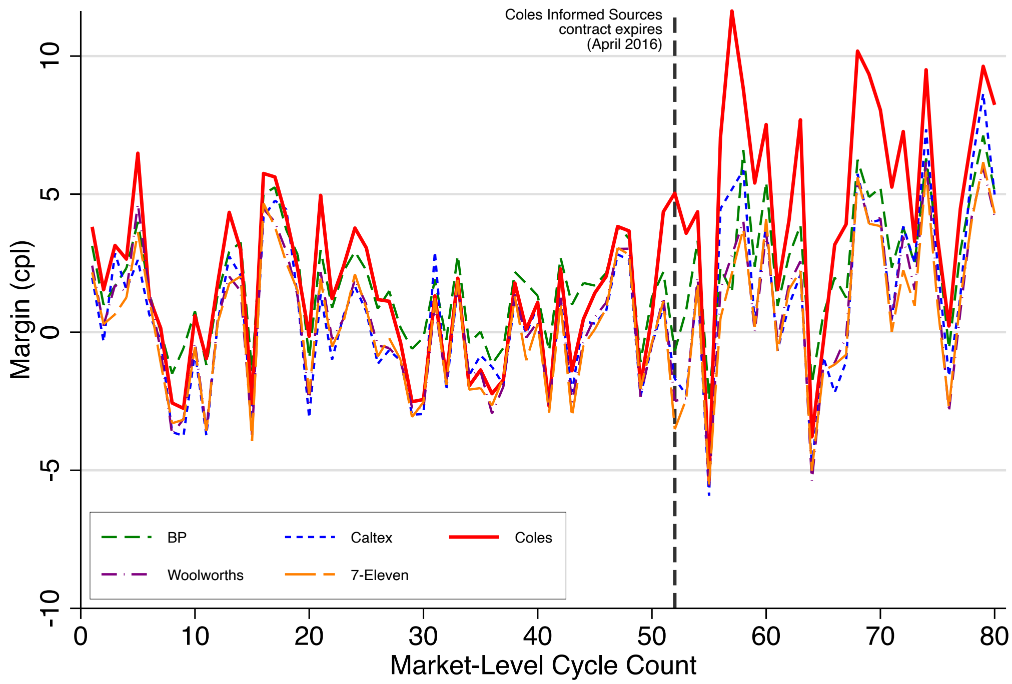
From Figures 3-6 in the paper, recall Coles' break in pricing involves decoupling its prices from its rivals at: (1) the *top of the cycle* just after restorations with a delay in price undercutting; and (2) the *bottom of the cycle* with not undercutting prices until they reach wholesale TGP (i.e. before the next restoration occurs). Thus, to test for structural breaks in Coles' pricing, it makes sense to estimate (C.1) on two sub-samples that "carve out" the top and bottom of stations' cycles, thereby allowing us to test for breaks in Coles' pricing relative to its rivals.

We proceed in three steps in implementing these tests. First, we compute daily average prices across all stations in the market. Using these average market prices, we classify market-level *price restorations*, *price cycles*, and *cycle days* precisely as in Definition 1, where we replace station-level prices with market-level average prices. For our supF tests, we consider all market-level cycles between January 1, 2014, and December 31, 2018. Our cycle classification identifies 82 market-level cycles over this period.

Second, within each market-level cycle, we identify two sets of stations and dates: (1) stations-dates within cycle days 1-5 of a station's cycle (per Definition 1); and (2) station-dates within 5 days before a station-level restoration. The former station-dates correspond to the *top* of station-level cycles and the latter correspond to the *bottom*.

Finally, we compute average price-cost margins for station-dates in the *top* and *bottom* sub-samples by retailer and market-level cycle. With these average margins, we can plot retailers' average prices at the top and bottom of the cycle across the 82 market cycles in our sample and test for breaks in Coles' pricing behavior relative to its rivals. For example, Figure C.5 shows the average margin at the bottom of the cycle by retailer across the 82 market-level cycles between January 1, 2014, and December 31, 2018. The figure visually illustrates how Coles' margins at the bottom of the cycle depart from its rivals around market-level cycle #50. In addition, the figure shows how retailers' margins at the bottom of the cycle center on 0 cpl before Coles exits the Informed Sources platform and shift to a higher level after, led by Coles' change in pricing. This sharp shift in margins by each part of the cycle after Coles exits the platform is precisely what our high-frequency event study design in Section 4.2 exploits in identifying price effects of asymmetric sharing. Our supF test takes a data-driven approach to identify when the

Figure C.5: Price-Cost Margins at the Bottom of the Cycle by Retailer and Market Cycle



Notes: The figure shows mean daily price-cost margins by retailer and market-level cycle among stations within 5 days of a station-level price restoration.

shift occurs.

Using the *bottom* of cycle time series in market-level "cycle time" from Figure C.5 (and similarly for the *top* of cycle time series), we implement the supF using equation (C.1) as described above, except that t indexes the market-level cycle as in Figure C.5 and not date-time. The regression equation and tests for implementing the supF test are otherwise identical. Following Andrews (1993), we test for structural breaks starting 20% into the sample and ending 80% into the sample. This implies testing for structural breaks in market-level cycles $\tau = 16, \dots, 65$.

The results of the supF test yield a structural break at the *top* of the cycle in market-level cycle #50 (March 2016) with $F(1,466) = 2.95$ and $p = 0.082$ and a break at the *bottom* of the cycle in market-level cycle #51 (April 2016) with $F = (1,466) = 17.29$ and $p < 0.01$. These test results confirm our claim in Section 4.2 that Coles' prices decouple from its rivals' between March and April 2016. This finding motivates us to drop observations between March 1 and April 30, 2016 for our main analysis of the price effects of asymmetric information sharing.

C.5 Clustering robustness checks

This appendix checks the robustness of how we account for unmodeled correlation of our margin results, which are based on equation (1). For reference, we reproduce the regression equation here

$$\begin{aligned}\text{margin}_{it} = \alpha_0 + \sum_{k=0}^{10}\left[\beta_k \text{CycPct}_{it}^k + \gamma_k \text{ColesOff}_t \times \text{CycPct}_{it}^k\right] \\ + \sum_{\ell=0}^{7}\left[\delta_\ell^+ \Delta^+ c_{t-\ell} + \delta_\ell^- \Delta^- c_{t-\ell}\right] + \eta_i + \nu_d + \lambda_m + \epsilon_{it}.\end{aligned} \tag{C.2}$$

The γ_k coefficient quantifies how margin levels change at cycle decile k after Coles exits the platform, controlling for lagged wholesale cost changes and fixed effects for station i, day of the week d, and month of the year m. For inference, it is important to account for unmodeled correlation in ϵ_{it}, potentially within and across stations, retailers, dates, and days of the cycle.

Our robustness checks consider one-way and two-way clustering based on the clusters in Table C.2. The variables used to construct the clusters are station, date, station-level cycle day, and station-level cycle length decile, CycPct_{it}^k. From Definition 1(ii) in the paper, recall station-level cycle days enumerate starting from a station's price restoration: a restoration date is "Day 0" of a station's cycle, and cycle days $1, 2, \ldots$ follow until a station's next price restoration event. CycPct_{it}^k is from our baseline margins regression in (1) and enumerates the deciles of a station's current cycle.[51]

Table C.2: Clusters

Cluster	Persistence accounted for in ϵ_{it}
Station	Between dates t and $t+j$ for station i
Station-Cycle Day	Between dates t and $t+j$ for station i where station i is at cycle day k on t and $t+j$
Station-Cycle Decile	Between dates t and $t+j$ for station i where station i is at cycle decile k on t and $t+j$
Retailer	Across stations i and $i+\ell$ on date t and within and across stations i and $i+\ell$ between dates t and $t+j$ where stations i and $i+\ell$ belong to the same retailer
Retailer-Cycle Day	Within and across stations i and $i+\ell$ between dates t and $t+j$ where stations i and $i+\ell$ belong to the same retailer, and where stations i and $i+\ell$ are at cycle day k on t and $t+j$
Retailer-Cycle Decile	Within and across stations i and $i+\ell$ between dates t and $t+j$ where stations i and $i+\ell$ belong to the same retailer, and where stations i and $i+\ell$ are at cycle decile k on t and $t+j$
Cycle Day	Within and across stations i and $i+\ell$ on dates t and $t+j$ where stations i and $i+\ell$ are at cycle day k on t and $t+j$
Cycle Decile	Within and across stations i and $i+\ell$ on dates t and $t+j$ where stations i and $i+\ell$ are at cycle decile k on t and $t+j$
Date	Across all stations on date t

The second column of Table C.2 summarizes the persistence in ϵ_{it} accounted for with these different clusters. Our analysis has two potentially important sources of temporal persistence in margins:

[51] Reiterating our illustrative example for CycPct_{it}^k from the paper here, suppose station i on date t has a station-level price restoration, and it is 20 days until its next restoration. In this case, we would have CycPct_{it}^0=1 and 0 otherwise, CycPct_{it+1}^1=1 and CycPct_{it+2}^1=1 (and 0 otherwise for both), CycPct_{it+3}^2=1 and CycPct_{it+4}^2=1 (and 0 otherwise for both), and so on.

across dates and cycles. For instance, ϵ_{it} may persist daily due to daily gasoline demand or wholesale cost shocks. Likewise, there may also be temporal persistence across cycles if, for example, there is a correlation in demand shocks across different parts of the cycle, such as around restoration events.

It is unclear, *a priori*, the impact of modeling temporal persistence across dates or cycles at the station or retailer level. Given this ambiguity, particularly in a setting with multiple potential clustering dimensions, we follow guidance from MacKinnon et al. (2023) and report confidence intervals for $\hat{\gamma}_k$ for various levels of clustering.[52]

A *station* cluster allows day-to-day persistence in station i's margins. *Station-cycle day* and *station-cycle decile* clusters allow for persistence across different parts of the cycle (e.g., restoration events, early/late in the undercutting phase) for a given station but potentially ignore day-to-day persistence in margins. Clustering instead at a (higher) retailer level (*retailer*, *retailer-cycle day*, *retailer-cycle decile*) allows for persistence in margins across stations belonging to the same retailer on a given date, across dates, or across cycles (e.g., possibly due to brand-level pricing over the cycle, demand shocks, or cost shocks).

Cycle day and *cycle decile* clusters allow for persistence in margins across all stations (irrespective of retailer) at different parts of the cycle across price cycles, which again can be driven by unmodeled demand or cost shocks that persistently affect stations' margins across price cycles.

Lastly, clustering by *date* allows for persistence in margins across all stations on a given date. From our margin regression, it is an empirical question as to how these different clusters affect the standard errors and confidence intervals $\hat{\gamma}_k$.

Station-level regressions

Tables C.3 and C.4, respectively, present two-way clustering robustness checks for our $\hat{\gamma}_k$ estimates from station-level regressions per equation (1) for Coles and other major retailers (BP, Caltex, Woolworths, 7-Eleven).[53] We present these checks through the confidence intervals we obtain for γ_k for $k = 0, \ldots, 10$ for Coles and its rivals. The tables' top panel shows station-level clustering results, and the bottom panel shows analogous retailer-level clustering results.

Overall, none of our statistical inferences from Section 4 regarding the change in the margins of Coles and its rivals after Coles exits the Informed Sources platform changes under the various two-way clustering combinations in Tables C.3 and C.4. Quantitatively, the confidence intervals are similar across all combinations, though clustering by date or cycle day tends to yield more conservative intervals than clustering by cycle decile. As expected, clustering at the retailer level (bottom panel) yields wider inter-

[52]We note here a nuanced aspect of clusters involving a cycle decile. Suppose t and $t+1$ belong to the same cycle decile within a given cycle for station i. In this case, a station-cycle decile cluster allows for persistence in margins between dates t and $t+1$ for station i. However, a station-cycle decile cluster does not allow for persistence across dates t and $t+1$ if they lie within the same station-level cycle but fall within different cycle deciles. Likewise, a retailer-cycle decile cluster allows for persistence in margins within and across stations for stations i and dates t at the same cycle decile in our sample, irrespective of which particular station-level cycle they sit within.

[53]As in Section 4, we jointly estimate $\hat{\gamma}_k$ for $k = 0, \ldots, 10$ for Coles and its rivals, where we pool station-level price data for BP, Caltex, Woolworths, and 7-Eleven stations. Thus, the confidence intervals in a given panel and column in Tables C.3 and C.4 are obtained jointly.

vals than at the station level (top panel). However, differences in interval widths are small in magnutude.

As a further check, we present one-way clustering robustness checks in Table C.5 for Coles (top panel) and other major retailers (bottom panel). Here, we focus on clustering at the station or retailer level and ignore clustering by date (which recall from Tables C.3 and C.4 matters). We obtain far less conservative confidence intervals under one-way clustering than two-way clustering, where we also cluster by date. The large difference in the intervals under one-way and two-way clustering underlines the importance of clustering by date to account for correlation in ϵ_{it} across stations on a given date.

Retailer-level regressions

An alternative to accounting for correlation in unobservables across stations is aggregating prices to the retailer level. Let p_{rt} be the average price across retailer r's stations on date t. We can estimate retailer-level regressions of the following form to identify case impacts

$$\begin{aligned}\text{margin}_{rt} = \alpha_0 + \sum_{k=0}^{10}\left[\beta_k \text{CycPct}^k_{rt} + \gamma_k \text{ColesOff}_t \times \text{CycPct}^k_{rt}\right] \\ + \sum_{\ell=0}^{7}\left[\delta^+_\ell \Delta^+ c_{t-\ell} + \delta^-_\ell \Delta^- c_{t-\ell}\right] + \eta_r + \nu_d + \lambda_m + \epsilon_{rt}.\end{aligned} \quad \text{(C.3)}$$

All variables derived are constructed exactly as we did at the *station* level, except now they are based on *retailer* level price cycles. These variable constructions include an analogous use of Definition 1 for identifying retailer-level restorations and undercutting phases, exactly as we did with individual stations. Indeed, these aggregate retailer-level cycles correspond precisely to what we plot in Figure 3 in the paper. Our inferences about Informed Sources case impacts at the retailer level directly correspond to the decoupling of Coles' prices from its rivals around the time of its platform exit in Figure 3.

Valid inferences about γ_k require us to account for temporal persistence in ϵ_{rt}, possibly across dates or cycle days. In addition, correlation in unobservables across retailers on a given date also potentially matters. As with the station-level regressions, we consider two-way and one-way clustering combinations and check how confidence intervals for γ_k differ per MacKinnon et al. (2023).

Table C.6 presents our two-way and one-way clustering results for γ_k for $k = 0, \dots, 10$ for Coles (top panel) and other major retailers (bottom panel). Overall, the takeaways are the same as those from our station-level regressions. In particular, we do not find large differences in confidence intervals that change our inferences about case impacts under the different clustering approaches. Two-way clustering that accounts for persistence within retailers over time yields more conservative intervals.

As a final robustness check, we compute Newey and West (1987) standard errors, assuming different lag lengths for persistence in ϵ_{rt} across t. Table C.7 presents our corresponding confidence intervals for γ_k for $k = 0, \dots, 10$ for Coles (top panel) and other major retailers (bottom panel).[54] Again, none of our inferences about the price effects of asymmetric information sharing change. Moreover, we obtain confidence intervals for $\hat{\gamma}$ for Coles and its rivals of similar widths as those in Table C.6.

[54] In computing Newey and West (1987) standard errors, we cannot drop the transition period Coles exits the platform (March 15 to April 15 2016). Doing so would introduce gaps in our time series. We thus obtain slightly different γ_k estimates in Table C.7 compared to those in the paper and reported in Tables C.3-C.6 above.

Table C.3: 95% Confidence Intervals for γ_k from Equation (C.2) from Different **Two-Way** Error Clustering for the Change in **Coles' Station-Level** Margins by Cycle Length Decile After Exiting the Platform

		95% Confidence Intervals, **Station-Level Clusters**				
CycPct_{it}^{k}	$\hat{\gamma}_k$	#1 Station #2 Date	#1 Station #2 Cycle Day	#1 Station #2 Cycle Decile	#1 Station-Cycle Day #2 Date	#1 Station-Cycle Decile #2 Date
0	2.71	[1.30, 4.12]	[1.17, 4.25]	[2.36, 3.06]	[1.29, 4.13]	[1.30, 4.12]
1	3.33	[2.56, 4.11]	[2.83, 3.84]	[3.10, 3.56]	[2.57, 4.10]	[2.56, 4.11]
2	4.64	[3.90, 5.37]	[4.11, 5.16]	[4.39, 4.89]	[3.91, 5.36]	[3.91, 5.37]
3	5.67	[4.90, 6.44]	[4.84, 6.49]	[5.46, 5.87]	[4.90, 6.43]	[4.90, 6.43]
4	6.16	[5.25, 7.07]	[5.33, 7.00]	[5.90, 6.43]	[5.26, 7.07]	[5.26, 7.07]
5	6.43	[5.45, 7.41]	[5.64, 7.22]	[6.02, 6.84]	[5.46, 7.40]	[5.45, 7.41]
6	7.16	[6.15, 8.18]	[6.54, 7.79]	[6.71, 7.61]	[6.16, 8.16]	[6.15, 8.18]
7	6.94	[5.98, 7.91]	[6.41, 7.48]	[6.46, 7.43]	[6.00, 7.89]	[5.98, 7.91]
8	5.63	[4.72, 6.54]	[4.87, 6.39]	[5.12, 6.14]	[4.73, 6.53]	[4.72, 6.54]
9	4.94	[4.02, 5.87]	[4.10, 5.78]	[4.40, 5.49]	[4.03, 5.86]	[4.02, 5.87]
10	5.00	[3.87, 6.12]	[3.81, 6.18]	[4.51, 5.48]	[3.88, 6.12]	[3.88, 6.12]
No. Clusters #1		682	682	682	37794	7647
No. Clusters #2		907	60	12	907	907
		95% Confidence Intervals, **Retailer-Level Clusters**				
CycPct_{it}^{k}	$\hat{\gamma}_k$	#1 Retailer #2 Date	#1 Retailer #2 Cycle Day	#1 Retailer #2 Cycle Decile	#1 Retailer-Cycle Day #2 Date	#1 Retailer-Cycle Decile #2 Date
0	2.71	[1.62, 3.80]	[1.23, 4.19]	[2.28, 3.14]	[1.18, 4.24]	[1.90, 3.51]
1	3.33	[2.46, 4.21]	[2.78, 3.89]	[3.09, 3.58]	[2.64, 4.03]	[2.68, 3.99]
2	4.64	[3.82, 5.45]	[3.98, 5.29]	[4.44, 4.84]	[3.95, 5.32]	[4.06, 5.22]
3	5.67	[4.86, 6.47]	[4.67, 6.66]	[5.55, 5.78]	[4.76, 6.57]	[5.09, 6.24]
4	6.16	[5.22, 7.11]	[5.22, 7.11]	[5.93, 6.40]	[5.24, 7.09]	[5.49, 6.84]
5	6.43	[5.40, 7.46]	[5.58, 7.28]	[6.02, 6.85]	[5.51, 7.35]	[5.68, 7.18]
6	7.16	[6.16, 8.16]	[6.49, 7.84]	[6.71, 7.62]	[6.36, 7.97]	[6.43, 7.89]
7	6.94	[6.00, 7.89]	[6.36, 7.53]	[6.43, 7.45]	[6.22, 7.67]	[6.26, 7.63]
8	5.63	[4.74, 6.52]	[4.85, 6.41]	[5.10, 6.16]	[4.76, 6.50]	[4.98, 6.28]
9	4.94	[4.03, 5.85]	[4.11, 5.78]	[4.34, 5.55]	[4.02, 5.86]	[4.27, 5.62]
10	5.00	[4.04, 5.95]	[4.03, 5.97]	[4.43, 5.56]	[3.79, 6.21]	[4.32, 5.68]
No. Clusters #1		6	6	6	360	72
No. Clusters #2		907	60	12	907	907

Notes: Estimate for γ_k from equation (C.2) for $k = 0, \ldots, 10$ for **Coles** presented along with 95% confidence intervals for different clustering assumptions. The main results in the paper assume two-way clustering by station and date. The sample period is May 1, 2015 to December 31, 2017. Retail prices are at the station-date level. Wholesale Terminal Gate Prices (TGPs) are at the daily level from Melbourne's gasoline terminal gate. Margin is a station's retail price less Melbourne's TGP on a given date. Coles exits the Informed Sources platform in April 2016.

Table C.4: 95% Confidence Intervals for γ_k from Equation (C.2) from Different **Two-Way** Clustering for the Change in **Other Major Retailers' Station-Level** Margins by Cycle Length Decile After Exiting the Platform

		95% Confidence Intervals, **Station-Level Clusters**				
CycPct_{it}^{k}	$\hat{\gamma}_k$	#1 Station #2 Date	#1 Station #2 Cycle Day	#1 Station #2 Cycle Decile	#1 Station-Cycle Day #2 Date	#1 Station-Cycle Decile #2 Date
0	2.81	[1.79, 3.84]	[1.81, 3.81]	[2.52, 3.10]	[1.78, 3.84]	[1.79, 3.84]
1	2.54	[1.69, 3.39]	[2.07, 3.01]	[2.36, 2.72]	[1.69, 3.39]	[1.69, 3.39]
2	3.23	[2.40, 4.07]	[2.52, 3.95]	[3.06, 3.41]	[2.40, 4.07]	[2.40, 4.07]
3	3.76	[2.94, 4.59]	[2.78, 4.75]	[3.61, 3.92]	[2.95, 4.58]	[2.94, 4.59]
4	4.52	[3.68, 5.36]	[3.69, 5.35]	[4.26, 4.78]	[3.69, 5.36]	[3.68, 5.36]
5	4.84	[3.99, 5.68]	[4.07, 5.61]	[4.42, 5.25]	[4.00, 5.68]	[3.99, 5.68]
6	4.94	[4.15, 5.72]	[4.23, 5.65]	[4.50, 5.37]	[4.16, 5.71]	[4.15, 5.72]
7	4.15	[3.41, 4.90]	[3.47, 4.84]	[3.71, 4.60]	[3.42, 4.89]	[3.41, 4.90]
8	2.94	[2.25, 3.63]	[2.32, 3.56]	[2.44, 3.44]	[2.27, 3.62]	[2.26, 3.63]
9	2.11	[1.46, 2.75]	[1.50, 2.71]	[1.61, 2.60]	[1.47, 2.74]	[1.46, 2.75]
10	1.46	[0.81, 2.10]	[0.92, 2.00]	[1.06, 1.85]	[0.83, 2.09]	[0.81, 2.10]
No. Clusters #1		682	682	682	37794	7647
No. Clusters #2		907	60	12	907	907

		95% Confidence Intervals, **Retailer-Level Clusters**				
CycPct_{it}^{k}	$\hat{\gamma}_k$	#1 Retailer #2 Date	#1 Retailer #2 Cycle Day	#1 Retailer #2 Cycle Decile	#1 Retailer-Cycle Day #2 Date	#1 Retailer-Cycle Decile #2 Date
0	2.81	[1.37, 4.26]	[1.48, 4.14]	[2.32, 3.30]	[1.79, 3.83]	[1.82, 3.81]
1	2.54	[1.45, 3.63]	[1.83, 3.25]	[2.19, 2.89]	[1.77, 3.31]	[1.77, 3.31]
2	3.23	[2.15, 4.32]	[2.31, 4.16]	[2.89, 3.58]	[2.43, 4.04]	[2.46, 4.01]
3	3.76	[2.74, 4.79]	[2.55, 4.98]	[3.62, 3.91]	[2.90, 4.63]	[3.03, 4.50]
4	4.52	[3.45, 5.59]	[3.43, 5.62]	[4.23, 4.81]	[3.68, 5.36]	[3.75, 5.29]
5	4.84	[3.74, 5.94]	[3.81, 5.87]	[4.26, 5.42]	[4.00, 5.67]	[4.04, 5.64]
6	4.94	[3.88, 6.00]	[3.80, 6.08]	[4.17, 5.71]	[4.16, 5.71]	[4.18, 5.69]
7	4.15	[3.16, 5.15]	[3.21, 5.10]	[3.51, 4.80]	[3.43, 4.88]	[3.44, 4.87]
8	2.94	[2.00, 3.88]	[2.03, 3.86]	[2.27, 3.61]	[2.27, 3.61]	[2.26, 3.63]
9	2.11	[1.18, 3.03]	[1.14, 3.08]	[1.43, 2.79]	[1.48, 2.74]	[1.45, 2.77]
10	1.46	[0.45, 2.47]	[0.55, 2.36]	[0.62, 2.29]	[0.84, 2.07]	[0.76, 2.15]
No. Clusters #1		6	6	6	360	72
No. Clusters #2		907	60	12	907	907

Notes: Estimate for γ_k from equation (C.2) for $k = 0, \ldots, 10$ for **Coles** presented along with 95% confidence intervals for different clustering assumptions. The main results in the paper assume two-way clustering by station and date. The sample period is May 1, 2015 to December 31, 2017. Retail prices are at the station-date level. Wholesale Terminal Gate Prices (TGPs) are at the daily level from Melbourne's gasoline terminal gate. Margin is a station's retail price less Melbourne's TGP on a given date. Coles exits the Informed Sources platform in April 2016.

Table C.5: 95% Confidence Intervals for γ_k from Equation (C.2) from Different **One-Way** Clustering for the Change in Margins by Cycle Length Decile After Exiting the Platform

		95% Confidence Intervals, **Coles**					
CycPct_{it}^k	$\hat{\gamma}_k$	Station	Station-Cycle Day	Station-Cycle Decile	Retailer	Retailer-Cycle Day	Retailer-Cycle Decile
0	2.71	[2.60, 2.82]	[2.52, 2.90]	[2.61, 2.81]	[2.47, 2.95]	[1.21, 4.21]	[2.52, 2.90]
1	3.33	[3.21, 3.46]	[3.25, 3.42]	[3.22, 3.44]	[3.22, 3.45]	[2.87, 3.80]	[3.20, 3.47]
2	4.64	[4.48, 4.79]	[4.54, 4.73]	[4.49, 4.78]	[4.57, 4.71]	[4.13, 5.15]	[4.53, 4.75]
3	5.67	[5.51, 5.82]	[5.56, 5.77]	[5.53, 5.81]	[5.63, 5.70]	[4.86, 6.47]	[5.58, 5.75]
4	6.16	[6.00, 6.33]	[6.05, 6.28]	[6.02, 6.31]	[6.11, 6.21]	[5.38, 6.95]	[6.06, 6.27]
5	6.43	[6.26, 6.60]	[6.31, 6.55]	[6.27, 6.59]	[6.36, 6.50]	[5.71, 7.15]	[6.26, 6.60]
6	7.16	[6.96, 7.36]	[7.05, 7.27]	[6.98, 7.35]	[7.03, 7.29]	[6.61, 7.71]	[6.98, 7.35]
7	6.94	[6.73, 7.16]	[6.84, 7.05]	[6.74, 7.15]	[6.74, 7.14]	[6.46, 7.42]	[6.75, 7.14]
8	5.63	[5.41, 5.85]	[5.51, 5.75]	[5.43, 5.83]	[5.45, 5.81]	[4.91, 6.35]	[5.42, 5.84]
9	4.94	[4.75, 5.13]	[4.83, 5.06]	[4.77, 5.12]	[4.72, 5.16]	[4.13, 5.76]	[4.71, 5.18]
10	5.00	[4.82, 5.18]	[4.83, 5.16]	[4.83, 5.16]	[4.74, 5.25]	[3.84, 6.15]	[4.77, 5.23]
No. Clusters		682	37794	7647	6	360	72

		95% Confidence Intervals, **Other Major Retailers**					
CycPct_{it}^k	$\hat{\gamma}_k$	Station	Station-Cycle Day	Station-Cycle Decile	Retailer	Retailer-Cycle Day	Retailer-Cycle Decile
0	2.81	[2.72, 2.90]	[2.70, 2.93]	[2.73, 2.90]	[2.52, 3.10]	[2.26, 3.36]	[2.64, 2.98]
1	2.54	[2.44, 2.64]	[2.48, 2.60]	[2.44, 2.64]	[2.32, 2.76]	[2.30, 2.78]	[2.40, 2.68]
2	3.23	[3.11, 3.36]	[3.16, 3.31]	[3.11, 3.36]	[2.91, 3.56]	[2.86, 3.61]	[3.00, 3.47]
3	3.76	[3.63, 3.90]	[3.69, 3.84]	[3.64, 3.89]	[3.67, 3.86]	[3.27, 4.26]	[3.67, 3.86]
4	4.52	[4.39, 4.65]	[4.45, 4.59]	[4.39, 4.65]	[4.36, 4.69]	[4.10, 4.94]	[4.36, 4.68]
5	4.84	[4.71, 4.97]	[4.77, 4.91]	[4.71, 4.96]	[4.59, 5.09]	[4.45, 5.23]	[4.60, 5.08]
6	4.94	[4.80, 5.08]	[4.87, 5.00]	[4.81, 5.07]	[4.58, 5.30]	[4.57, 5.30]	[4.66, 5.21]
7	4.15	[4.01, 4.30]	[4.09, 4.22]	[4.02, 4.29]	[3.82, 4.49]	[3.81, 4.49]	[3.89, 4.42]
8	2.94	[2.80, 3.08]	[2.88, 3.00]	[2.81, 3.07]	[2.55, 3.33]	[2.62, 3.26]	[2.63, 3.25]
9	2.11	[1.98, 2.24]	[2.05, 2.17]	[1.99, 2.23]	[1.67, 2.55]	[1.80, 2.42]	[1.79, 2.43]
10	1.46	[1.30, 1.62]	[1.37, 1.54]	[1.31, 1.61]	[0.80, 2.11]	[1.12, 1.79]	[1.03, 1.88]
No. Clusters		682	37794	7647	6	360	72

Notes: Estimate for γ_k from equation (C.2) for $k = 0, \ldots, 10$ for **Coles** presented along with 95% confidence intervals for different clustering assumptions. The main results in the paper assume two-way clustering by station and date. The sample period is May 1, 2015 to December 31, 2017. Retail prices are at the station-date level. Wholesale Terminal Gate Prices (TGPs) are at the daily level from Melbourne's gasoline terminal gate. Margin is a station's retail price less Melbourne's TGP on a given date. Coles exits the Informed Sources platform in April 2016.

Table C.6: 95% Confidence Intervals for γ_k from Equation (C.3) from Different Clustering for the Change in **Retailer-Level** Margins by Cycle Length Decile After Exiting the Platform

95% Confidence Intervals, **Coles**

		Two-way Clusters					One-way Clusters		
CycPct_{it}^k	$\hat{\gamma}_k$	#1 Retailer #2 Date	#1 Retailer #2 Cycle Day	#1 Retailer #2 Cycle Decile	#1 Retailer-Cycle Day #2 Date	#1 Retailer-Cycle Decile #2 Date	Retailer	Retailer-Cycle Day	Retailer-Cycle Decile
0	1.91	[-0.75, 4.57]	[1.59, 2.24]	[1.54, 2.29]	[0.17, 3.65]	[0.13, 3.70]	[1.84, 1.99]	[1.78, 2.05]	[1.76, 2.07]
1	3.34	[2.09, 4.58]	[2.23, 4.44]	[3.10, 3.57]	[2.36, 4.31]	[2.53, 4.14]	[3.27, 3.40]	[2.51, 4.16]	[3.25, 3.42]
2	5.10	[3.92, 6.27]	[4.12, 6.07]	[4.76, 5.43]	[4.16, 6.04]	[4.28, 5.91]	[5.05, 5.15]	[4.40, 5.79]	[4.96, 5.23]
3	5.96	[4.93, 7.00]	[4.35, 7.57]	[5.77, 6.16]	[4.69, 7.24]	[5.24, 6.69]	[5.92, 6.01]	[4.74, 7.19]	[5.89, 6.04]
4	6.57	[5.34, 7.80]	[5.17, 7.97]	[6.14, 7.00]	[5.24, 7.90]	[5.81, 7.33]	[6.51, 6.63]	[5.41, 7.73]	[6.43, 6.71]
5	6.49	[5.04, 7.95]	[5.08, 7.91]	[6.04, 6.94]	[5.16, 7.82]	[5.52, 7.46]	[6.40, 6.58]	[5.35, 7.64]	[6.34, 6.65]
6	7.09	[5.78, 8.39]	[5.72, 8.46]	[6.42, 7.76]	[5.84, 8.34]	[6.30, 7.87]	[6.85, 7.33]	[5.95, 8.22]	[6.87, 7.30]
7	6.86	[5.68, 8.04]	[5.71, 8.01]	[6.20, 7.52]	[5.80, 7.92]	[6.19, 7.53]	[6.61, 7.10]	[5.95, 7.77]	[6.64, 7.08]
8	6.16	[4.96, 7.37]	[5.16, 7.17]	[5.48, 6.85]	[5.06, 7.26]	[5.47, 6.86]	[5.83, 6.49]	[5.23, 7.10]	[5.93, 6.40]
9	5.39	[3.98, 6.80]	[4.19, 6.59]	[4.81, 5.97]	[4.07, 6.71]	[4.50, 6.28]	[5.16, 5.62]	[4.25, 6.53]	[5.19, 5.59]
10	4.88	[3.56, 6.20]	[3.55, 6.21]	[4.38, 5.39]	[3.46, 6.30]	[4.03, 5.74]	[4.69, 5.07]	[3.55, 6.22]	[4.69, 5.07]
No. Clusters #1		6	6	6	354	72	6	354	72
No. Clusters #2		901	60	12	901	901	.	.	.

95% Confidence Intervals, **Other Major Retailers**

		Two-way Clusters					One-way Clusters		
CycPct_{it}^k	$\hat{\gamma}_k$	#1 Retailer #2 Date	#1 Retailer #2 Cycle Day	#1 Retailer #2 Cycle Decile	#1 Retailer-Cycle Day #2 Date	#1 Retailer-Cycle Decile #2 Date	Retailer	Retailer-Cycle Day	Retailer-Cycle Decile
0	2.70	[-1.36, 6.75]	[0.61, 4.79]	[0.51, 4.88]	[-0.13, 5.53]	[-0.19, 5.58]	[0.50, 4.89]	[1.16, 4.24]	[1.13, 4.27]
1	2.74	[0.59, 4.89]	[1.35, 4.13]	[1.38, 4.10]	[1.34, 4.14]	[1.22, 4.26]	[1.31, 4.18]	[1.89, 3.59]	[1.73, 3.75]
2	3.24	[1.66, 4.81]	[1.92, 4.56]	[2.47, 4.00]	[2.13, 4.34]	[2.11, 4.36]	[2.44, 4.03]	[2.65, 3.82]	[2.66, 3.81]
3	3.44	[2.06, 4.83]	[2.02, 4.86]	[2.86, 4.02]	[2.26, 4.63]	[2.47, 4.42]	[2.85, 4.03]	[2.63, 4.25]	[3.04, 3.84]
4	4.02	[2.16, 5.88]	[2.03, 6.02]	[2.65, 5.39]	[2.92, 5.13]	[2.73, 5.31]	[2.71, 5.34]	[3.39, 4.65]	[3.12, 4.92]
5	4.65	[2.93, 6.37]	[2.83, 6.46]	[3.46, 5.83]	[3.46, 5.84]	[3.44, 5.85]	[3.59, 5.71]	[3.90, 5.39]	[3.92, 5.38]
6	4.53	[2.39, 6.66]	[2.26, 6.79]	[2.81, 6.25]	[3.41, 5.64]	[3.09, 5.96]	[2.81, 6.24]	[3.82, 5.23]	[3.40, 5.66]
7	3.98	[1.73, 6.24]	[1.79, 6.18]	[2.19, 5.78]	[2.86, 5.11]	[2.42, 5.55]	[2.13, 5.84]	[3.30, 4.67]	[2.71, 5.26]
8	2.89	[0.38, 5.40]	[0.49, 5.29]	[0.92, 4.86]	[1.73, 4.05]	[1.15, 4.63]	[0.73, 5.05]	[2.14, 3.64]	[1.40, 4.38]
9	2.39	[0.23, 4.56]	[0.17, 4.61]	[0.76, 4.02]	[1.24, 3.54]	[0.90, 3.88]	[0.67, 4.11]	[1.68, 3.10]	[1.22, 3.56]
10	1.53	[-0.40, 3.46]	[-0.28, 3.35]	[0.06, 3.00]	[0.55, 2.51]	[0.16, 2.90]	[0.00, 3.06]	[0.97, 2.10]	[0.44, 2.62]
No. Clusters #1		6	6	6	354	72	6	354	72
No. Clusters #2		901	60	12	901	901	.	.	.

Notes: Estimate for γ_k from equation (C.3) for $k = 0,\ldots,10$ for **Coles** presented along with 95% confidence intervals for different clustering assumptions. The main results in the paper assume two-way clustering by station and date. The sample period is May 1, 2015 to December 31, 2017. Retail prices are at the station-date level. Wholesale Terminal Gate Prices (TGPs) are at the daily level from Melbourne's gasoline terminal gate. Margin is a station's retail price less Melbourne's TGP on a given date. Coles exits the Informed Sources platform in April 2016.

Table C.7: **Newey West** 95% Confidence Intervals for γ_k from Equation (C.3) Under Different Lag Lengths for the Change in **Retailer-Level** Margins by Cycle Length Decile After Exiting the Platform

		95% Confidence Intervals, Different Lag Lengths (7-49 days), **Coles**					
$CycPct_{it}^k$	$\hat{\gamma}_k$	7 days	14 days	21 days	28 days	35 days	42 days
0	1.32	[-1.49, 4.13]	[-1.53, 4.17]	[-1.55, 4.19]	[-1.62, 4.27]	[-1.71, 4.35]	[-1.79, 4.44]
1	2.83	[1.16, 4.51]	[1.09, 4.57]	[1.07, 4.60]	[1.03, 4.64]	[0.99, 4.67]	[0.96, 4.71]
2	4.89	[2.93, 6.86]	[2.87, 6.91]	[2.85, 6.93]	[2.90, 6.89]	[2.94, 6.84]	[2.95, 6.83]
3	6.00	[4.01, 7.99]	[3.95, 8.05]	[3.94, 8.07]	[3.94, 8.06]	[3.97, 8.03]	[3.96, 8.04]
4	6.68	[4.26, 9.11]	[4.19, 9.18]	[4.17, 9.20]	[4.14, 9.23]	[4.14, 9.23]	[4.10, 9.27]
5	6.89	[4.11, 9.66]	[4.04, 9.74]	[4.02, 9.76]	[3.97, 9.81]	[3.99, 9.78]	[3.96, 9.81]
6	7.33	[4.69, 9.97]	[4.63, 10.04]	[4.60, 10.06]	[4.54, 10.13]	[4.53, 10.14]	[4.47, 10.19]
7	7.00	[4.42, 9.58]	[4.35, 9.66]	[4.33, 9.68]	[4.30, 9.70]	[4.32, 9.68]	[4.31, 9.70]
8	6.55	[4.50, 8.61]	[4.44, 8.67]	[4.41, 8.69]	[4.40, 8.71]	[4.41, 8.69]	[4.40, 8.70]
9	5.53	[3.21, 7.86]	[3.14, 7.92]	[3.11, 7.96]	[3.07, 7.99]	[3.06, 8.01]	[3.03, 8.04]
10	4.94	[2.51, 7.37]	[2.44, 7.44]	[2.40, 7.48]	[2.37, 7.52]	[2.33, 7.55]	[2.27, 7.61]
		95% Confidence Intervals, Different Lag Lengths (7-49 days), **Other Major Retailers**					
$CycPct_{it}^k$	$\hat{\gamma}_k$	7 days	14 days	21 days	28 days	35 days	42 days
0	2.35	[0.69, 4.01]	[0.64, 4.06]	[0.60, 4.10]	[0.55, 4.15]	[0.49, 4.21]	[0.43, 4.27]
1	2.22	[1.18, 3.26]	[1.14, 3.31]	[1.11, 3.34]	[1.08, 3.37]	[1.03, 3.41]	[0.99, 3.46]
2	3.02	[2.07, 3.97]	[2.05, 3.99]	[2.04, 3.99]	[2.06, 3.98]	[2.07, 3.97]	[2.07, 3.97]
3	3.51	[2.42, 4.59]	[2.39, 4.62]	[2.38, 4.64]	[2.37, 4.65]	[2.36, 4.66]	[2.34, 4.68]
4	4.01	[2.98, 5.03]	[2.96, 5.06]	[2.95, 5.06]	[2.96, 5.06]	[2.97, 5.04]	[2.97, 5.05]
5	4.98	[3.85, 6.11]	[3.84, 6.11]	[3.85, 6.10]	[3.86, 6.09]	[3.88, 6.07]	[3.88, 6.07]
6	4.83	[3.76, 5.89]	[3.74, 5.91]	[3.74, 5.91]	[3.73, 5.92]	[3.74, 5.91]	[3.73, 5.92]
7	4.11	[3.07, 5.15]	[3.06, 5.16]	[3.05, 5.16]	[3.05, 5.17]	[3.07, 5.15]	[3.07, 5.15]
8	3.34	[2.32, 4.36]	[2.28, 4.40]	[2.26, 4.42]	[2.24, 4.44]	[2.24, 4.44]	[2.23, 4.45]
9	2.49	[1.53, 3.44]	[1.51, 3.46]	[1.49, 3.48]	[1.49, 3.48]	[1.49, 3.48]	[1.48, 3.49]
10	1.57	[0.68, 2.46]	[0.66, 2.48]	[0.65, 2.50]	[0.64, 2.50]	[0.64, 2.51]	[0.62, 2.52]

Notes: Estimate for γ_k from equation (C.3) for $k = 0, \ldots, 10$ presented along with 95% confidence intervals for different clustering assumptions. The top panel reports results for two-way clusters, and the bottom panel reports results for one-way clusters. The main results in the paper assume two-way clustering by station and date. The sample period is May 1, 2015 to December 31, 2017. Retail prices are at the station-date level. Wholesale Terminal Gate Prices (TGPs) are at the daily level from Melbourne's gasoline terminal gate. Margin is a station's retail price less Melbourne's TGP on a given date. Coles exits the Informed Sources platform in April 2016.

C.6 Baseline regression equation coefficient estimates

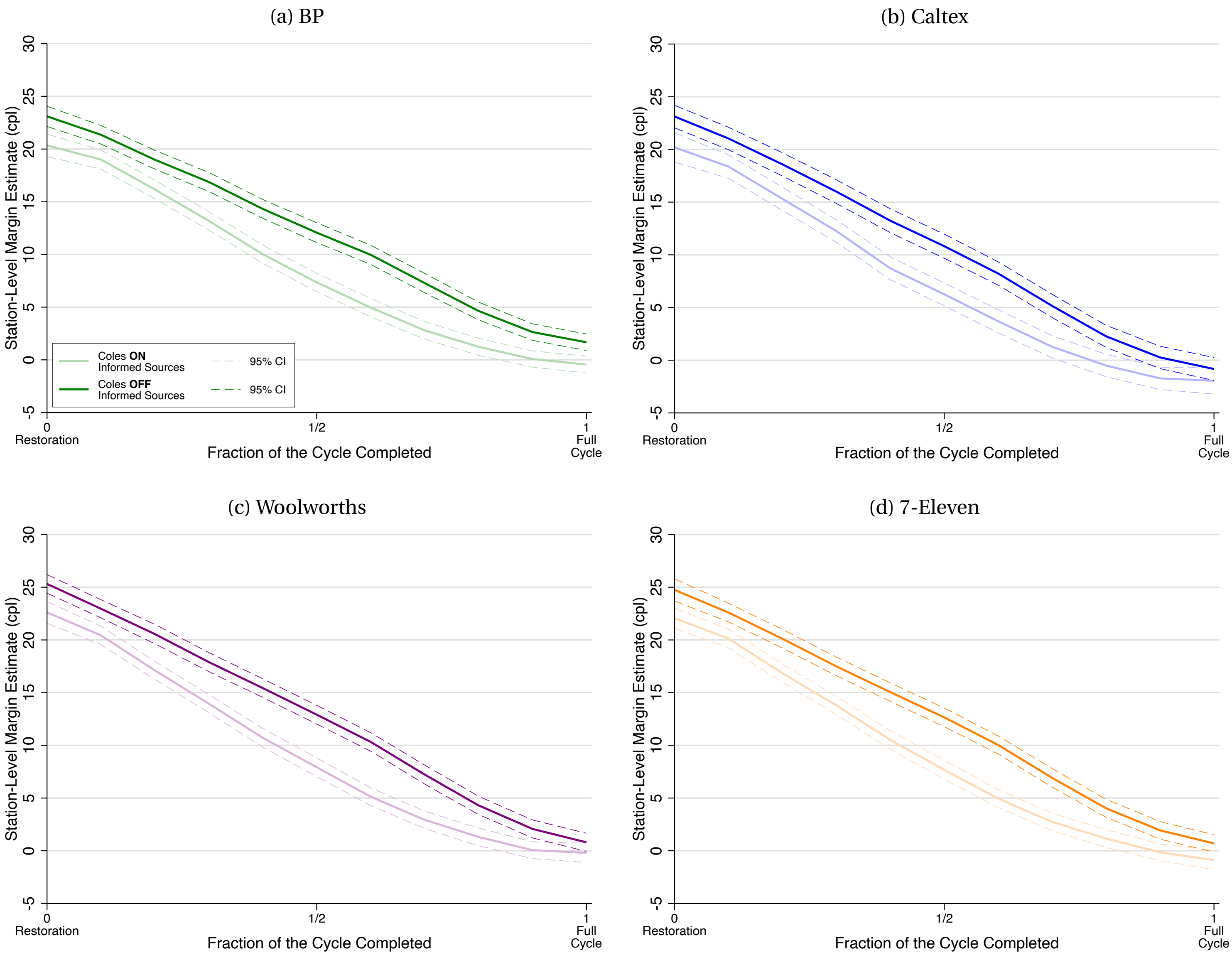
Table C.8: Baseline Regression Equation Coefficient Estimates

Coefficient	Estimate	Standard Error
$\hat{\beta}_0^{coles}$	15.17	(0.79)
$\hat{\gamma}_0^{coles}$	2.72	(0.72)
$\hat{\beta}_1^{coles}$	13.61	(0.57)
$\hat{\gamma}_1^{coles}$	3.44	(0.39)
$\hat{\beta}_2^{coles}$	10.59	(0.59)
$\hat{\gamma}_2^{coles}$	4.71	(0.37)
$\hat{\beta}_3^{coles}$	7.73	(0.60)
$\hat{\gamma}_3^{coles}$	5.74	(0.39)
$\hat{\beta}_4^{coles}$	4.45	(0.63)
$\hat{\gamma}_4^{coles}$	6.28	(0.48)
$\hat{\beta}_5^{coles}$	1.46	(0.63)
$\hat{\gamma}_5^{coles}$	6.42	(0.50)
$\hat{\beta}_6^{coles}$	-1.62	(0.63)
$\hat{\gamma}_6^{coles}$	7.23	(0.52)
$\hat{\beta}_7^{coles}$	-4.13	(0.59)
$\hat{\gamma}_7^{coles}$	6.93	(0.49)
$\hat{\beta}_8^{coles}$	-6.16	(0.59)
$\hat{\gamma}_8^{coles}$	5.68	(0.47)
$\hat{\beta}_9^{coles}$	-7.61	(0.57)
$\hat{\gamma}_9^{coles}$	4.95	(0.47)
$\hat{\beta}_{10}^{coles}$	-8.09	(0.72)
$\hat{\gamma}_{10}^{coles}$	4.52	(0.70)
$\hat{\beta}_0^{other}$	12.25	(0.43)
$\hat{\gamma}_0^{other}$	2.82	(0.52)
$\hat{\beta}_1^{other}$	10.42	(0.39)
$\hat{\gamma}_1^{other}$	2.55	(0.43)
$\hat{\beta}_2^{other}$	7.29	(0.38)
$\hat{\gamma}_2^{other}$	3.24	(0.43)
$\hat{\beta}_3^{other}$	4.25	(0.37)
$\hat{\gamma}_3^{other}$	3.78	(0.42)
$\hat{\beta}_4^{other}$	0.96	(0.38)
$\hat{\gamma}_4^{other}$	4.53	(0.43)
$\hat{\beta}_5^{other}$	-1.74	(0.38)
$\hat{\gamma}_5^{other}$	4.84	(0.43)
$\hat{\beta}_6^{other}$	-4.33	(0.36)
$\hat{\gamma}_6^{other}$	4.95	(0.40)
$\hat{\beta}_7^{other}$	-6.54	(0.33)
$\hat{\gamma}_7^{other}$	4.16	(0.38)
$\hat{\beta}_8^{other}$	-8.16	(0.33)
$\hat{\gamma}_8^{other}$	2.94	(0.35)
$\hat{\beta}_9^{other}$	-9.40	(0.31)
$\hat{\gamma}_9^{other}$	2.11	(0.33)
$\hat{\beta}_{10}^{other}$	-9.87	(0.33)
$\hat{\gamma}_{10}^{other}$	1.43	(0.33)
$\hat{\delta}_0^{+}$	-0.80	(0.45)
$\hat{\delta}_1^{+}$	-0.50	(0.47)
$\hat{\delta}_2^{+}$	-0.67	(0.44)
$\hat{\delta}_3^{+}$	-0.70	(0.43)
$\hat{\delta}_4^{+}$	-0.59	(0.43)
$\hat{\delta}_5^{+}$	-0.68	(0.42)
$\hat{\delta}_6^{+}$	-0.57	(0.41)
$\hat{\delta}_7^{+}$	-1.18	(0.37)
$\hat{\delta}_0^{-}$	0.11	(0.33)
$\hat{\delta}_1^{-}$	-0.20	(0.35)
$\hat{\delta}_2^{-}$	-0.41	(0.34)
$\hat{\delta}_3^{-}$	-0.44	(0.34)
$\hat{\delta}_4^{-}$	-0.53	(0.34)
$\hat{\delta}_5^{-}$	-0.52	(0.34)
$\hat{\delta}_6^{-}$	-0.68	(0.33)
$\hat{\delta}_7^{-}$	-1.06	(0.36)
$\hat{\alpha}_0$	9.09	(0.27)

Notes: The table reports coefficient estimates from equation (1). The regression includes station, day of week, and month of year fixed effects. Standard errors are in parentheses and are two-way clustered by station and date. The number of observations is $N = 497,568$, and the adjusted R-squared for the regression is 0.85. Other major retailers ("*other*") pool stations operated by BP, Caltex, Woolworths, and 7-Eleven.

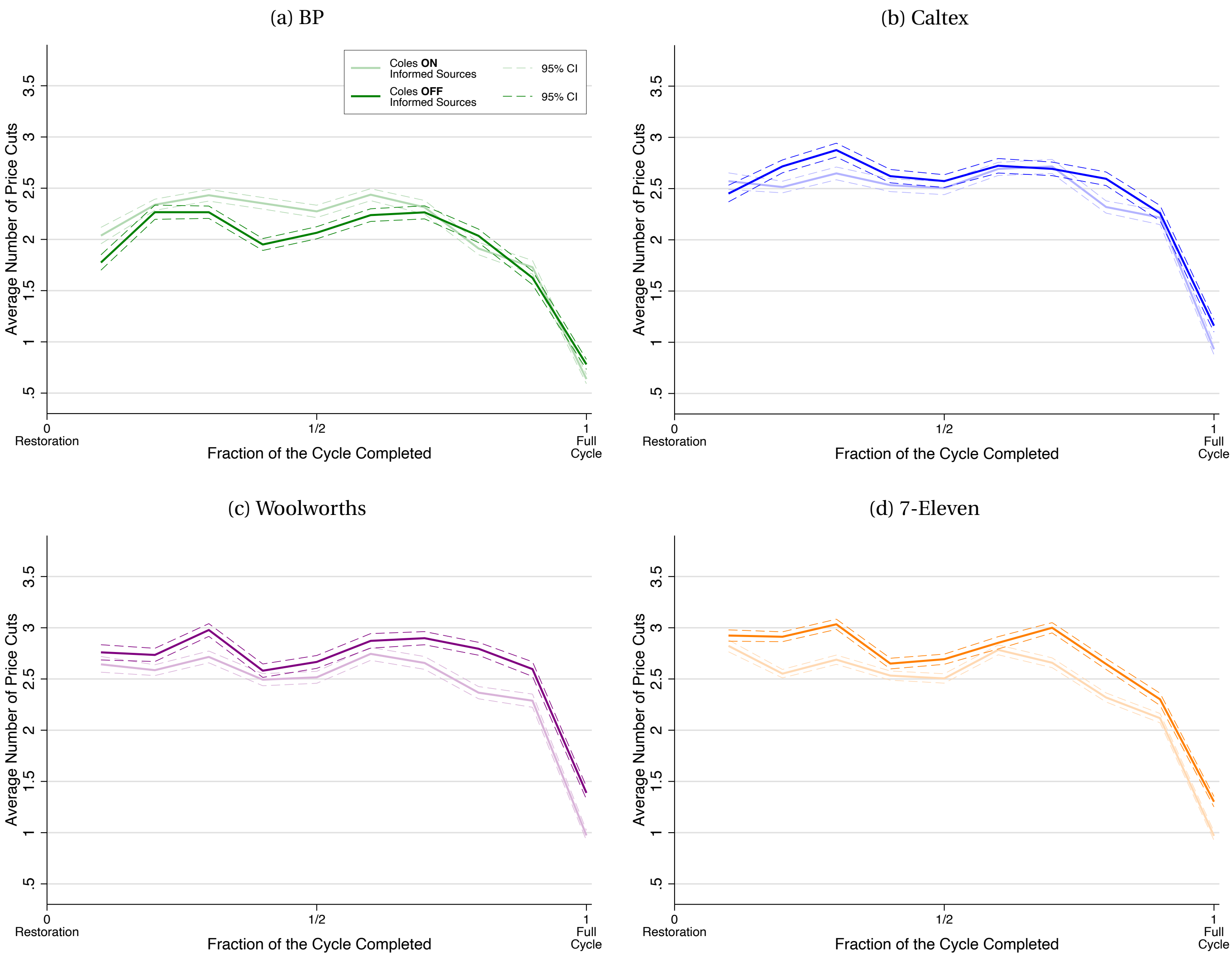
C.7 Margins, pricing frequency, and pricing magnitude effects by retailer

Figure C.6: How Margins Change when Coles Exits the Platform by Major Retailer



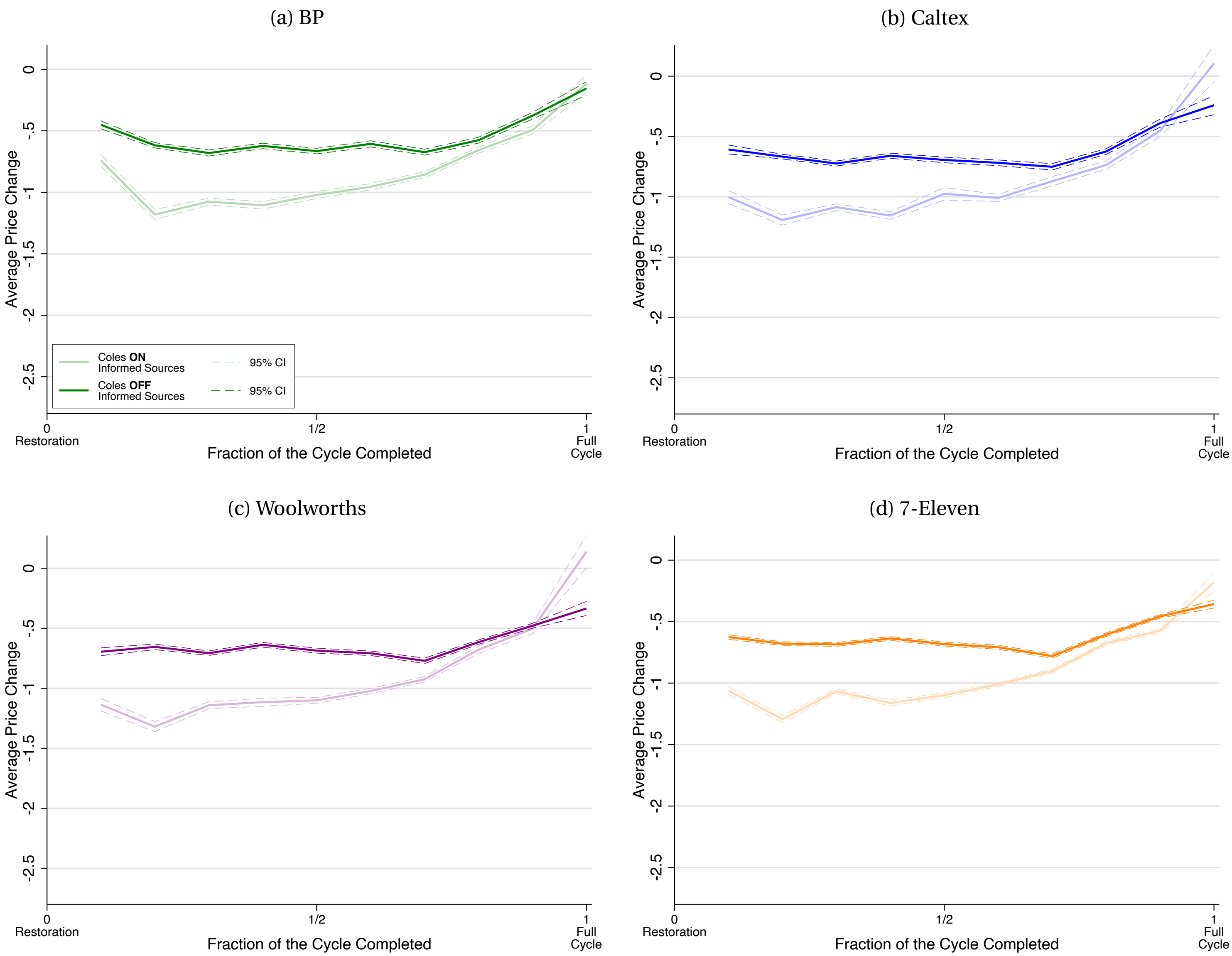
Notes: The figures contain $\alpha_0 + \beta_k$ (light shade) and $\alpha_0 + \beta_k + \gamma_k$ (dark share) estimates and their 95% confidence intervals from (1). Standard errors are two-way clustered by station and date. Panels (a)–(d), respectively, show results for BP, Caltex, Woolworths, and 7-Eleven stations.

Figure C.7: Price Cut **Frequency** Before and After Coles Exits the Platform



Notes: The figures contain the average number of daily station-level price changes by decile of a station's current cycle length.

Figure C.8: Price Cut **Magnitude** Before and After Coles Exits the Platform



Notes: The figures show the average magnitude of daily station-level price changes by decile of a station's current cycle length.

C.8 Robustness of price effects to sample window

In this Appendix, we re-estimate our baseline regression in (1) for Coles and other major retailers' (BP, Caltex, Woolworths, 7-Eleven) stations using the following three samples:

#1 May 1, 2015 - December 31, 2016

#2 May 1, 2015 - December 31, 2017

#3 May 1, 2015 - December 31, 2018

As in the paper, in each sample we omit the March 1, 2016 - April 30, 2016 equilibrium transition period after Coles' Informed Sources contract expires in April 2016. Sample #2, therefore, corresponds to the main sample we use in the paper, while samples #1 and #3 allow us to examine price effects from Coles' exit from the platform over shorter and longer horizons.

Table C.9 presents the corresponding $\hat{\gamma}_k$ estimates for $k = 0, \ldots, 10$. Recall these coefficient estimates from (1) quantify the difference in margins after Coles exits the platform for Coles and the other major retailers. Overall, the four major results from Section 4.2 emerge. In particular, after Coles exits the Informed Sources platform:

1. Restoration margins increase by 2-3 cpl when $CycPct_{it}^{k} = 0$ for Coles and the other major retailers
2. Margin increases occur throughout Coles' undercutting phase for $CycPct_{it}^{k} > 0$ as price cutting softens
3. Rivals' margins also increase for $CycPct_{it}^{k} > 0$, but not at the same level as Coles.
4. Coles no longer prices to wholesale terminal gate prices at the bottom of the cycle where $CycPct_{it}^{k} = 10$. In contrast, the other major retailers continue pricing closer to wholesale costs before restoring prices.

If anything, compared to the results presented in the paper for 2015-17, the results that include 2018 suggest even larger price-cost margins under asymmetric information sharing over longer horizons.

Table C.9: Price Effects of Asymmetric Information Sharing with Samples Ending in 2016, 2017, and 2018

	$\hat{\gamma}_k$ - Coles			$\hat{\gamma}_k$ - Other Major Retailers		
Sample Period	2015-16	2015-17	2015-18	2015-16	2015-17	2015-18
CycPct_{it}^{k}						
0	2.36	2.80	3.28	2.50	2.87	3.39
	(0.95)	(0.73)	(0.72)	(0.61)	(0.54)	(0.48)
1	2.92	3.45	4.02	2.14	2.53	3.19
	(0.47)	(0.40)	(0.39)	(0.52)	(0.44)	(0.41)
2	3.10	4.58	5.27	2.09	3.16	3.75
	(0.43)	(0.39)	(0.36)	(0.54)	(0.44)	(0.39)
3	4.22	5.63	6.20	2.37	3.72	4.21
	(0.41)	(0.40)	(0.36)	(0.57)	(0.43)	(0.37)
4	4.94	6.25	6.75	3.04	4.48	4.86
	(0.49)	(0.48)	(0.44)	(0.58)	(0.44)	(0.38)
5	5.00	6.29	6.87	3.34	4.78	5.05
	(0.48)	(0.51)	(0.47)	(0.48)	(0.44)	(0.38)
6	5.86	7.00	7.41	3.54	4.89	5.08
	(0.48)	(0.51)	(0.48)	(0.36)	(0.41)	(0.35)
7	5.12	6.69	7.19	2.54	4.16	4.43
	(0.58)	(0.49)	(0.45)	(0.43)	(0.39)	(0.32)
8	4.16	5.59	6.19	0.95	2.92	3.46
	(0.60)	(0.48)	(0.41)	(0.36)	(0.36)	(0.31)
9	3.84	4.81	5.86	0.98	2.02	2.86
	(0.73)	(0.48)	(0.39)	(0.38)	(0.34)	(0.28)
10	3.43	4.38	5.47	0.70	1.33	2.30
	(1.03)	(0.71)	(0.64)	(0.42)	(0.34)	(0.31)

Notes: The table reports estimates for γ_k from equation (1) for $k = 0, \ldots, 10$ for Coles and other major retailers (BP, Caltex, Woolworths, 7-Eleven) for three different sample periods: 2015-16, 2015-17, and 2015-18. As in the paper, each sample excludes the March 1, 2016 - April 30, 2016 equilibrium transition period around Coles' Informed Sources contract expiration. Standard errors are in parentheses and are two-way clustered by station and date.

D Demand model calibration details

D.1 Recovering all stations in the market

Informed Sources only manually collected prices for a subset of stations from smaller retail chains and independent stations. These "Other" stations were not included in the Informed Sources dataset if the company did not manually collect their prices at some stage.

To obtain data on the missing independent stations in the market, we compare the current distribution of stations with the Informed Sources dataset. In February 2023, we web-scraped PetrolSpy (https://petrolspy.com.au/) to gather information on prices, names, brands, addresses, and geographic coordinates for all gas stations in the Melbourne metropolitan area. Table D.1 compares the number of stations for each brand in our May 1, 2015 - January 31, 2017 primary sample with the 2023 numbers in Melbourne. The table reveals minimal changes for the 5 major retailers. This pattern is consistent with trends in station counts by retailers in annual and quarterly ACCC gasoline industry monitorying reports between 2015 and 2023, available at . We also consulted with another industry data collection entity called FUELTrac (https://fueltrac.com.au/) who have confirmed minimal station level entry/exit in Melbourne between 2015 and 2023. The discrepancy in the "Other" group illustrates the number of independent stations missing from the Informed Sources dataset.

To recover the missing independent stations, we assume that all independent stations today were also operational during our sample period. Given the industry facts regarding minimal station-level entry/exit just discussed, we consider this assumption reasonable. For each independent station in PetrolSpy, we check if it can match with any stations in Informed Sources by comparing the geographic coordinates. If an independent station in PetrolSpy is located within 50 meters of any station in Informed Sources, we regard this station as not recorded by the platform, and we add this station to our sample.[55] In total, we recover 126 additional independent stations not in the Informed Sources dataset.

Table D.1: Number of Stations by Brand: Informed Sources vs. PetrolSpy

	Informed Sources (2015-2017)	PetrolSpy (2023)
BP	127	142
Caltex	92	88
Coles	147	145
Woolworths	93	93
7-Eleven	148	151
Other	75	190

[55] A station may have slightly different geographic coordinates across the two datasets due to measurement error. If two sets of coordinates are less than 50 meters away, validation checks suggest they most likely belong to the same station.

D.2 Imputing missing prices

In our calibration exercise in Section 5.2, imputing missing prices for stations and dates where Informed Sources did not collect prices is necessary. These instances can be categorized as:

1. For the 75 independent stations Informed Sources collected data on, the manual collection was not daily (unlike the major 5 retailers on the platform). On average, a station's prices were collected every 2.6 days before Coles exited the platform. We need to predict prices for all stations and dates with missing information for these stations that Informed Sources collected data on at some stage.

2. For the 124 independent stations that we recovered from PetrolSpy, we likewise need to predict their prices.

3. Regarding Coles stations, the platform initially collected only 63% of their stations' prices daily immediately after the exit. Two months later, the manual price collection increased to 82% of the stations. See Figure 1 in the paper. From Appendix C.3, these Coles stations were on the periphery of the Melbourne greater metropolitan area. We need to predict prices for the stations when the platform did not collect their prices.

4. For BP stations, approximately 10% of them had their prices no longer collected by Informed Sources starting from June 2016, requiring price imputation for these stations as well. Again see Figure 1 in the paper. Regarding the remaining major retailers, Informed Sources electronically collected prices for all of their stations throughout the entire sample period. In rare cases where a price is missing, likely due to technical issues, we fill it with the last observed price.

In instances where prices were not collected by Informed Sources, we utilize Machine Learning to generate a model of pricing at the station level. Specifically, we train separate, brand-specific Least Absolute Shrinkage and Selection Operator (LASSO) models to predict daily prices for BP, Coles, and independent stations, respectively. LASSO is a well-known form of regularized regression. It includes a penalty term that shrinks some coefficients to zero, thereby effectively excluding irrelevant predictors. Thus, LASSO performs feature selection to identify the most important predictor variables for prices.

For each independent station, the predictor construction involves the following information:

1. Station-specific variables, including smaller retail brand dummy variables for United and Liberty stations (other smaller retail chains in the market).

2. The average price of the five closest stations recorded by the platform on date t and its lagged values for 1 to 7 days.

3. The current wholesale terminal gate price and its lagged values for 1 to 7 days

4. Additional variables describing the local market structure around a given station, including the Herfindahl-Hirschman Index (HHI), the number of stations, the share of independent stations

within a 5-kilometer radius, and a dummy variable indicating the presence of a competitor within 200 meters.

Additionally, we include interactions between all these variables, resulting in approximately 300 variables for predicting station-level prices. These variables collectively capture various aspects of pricing dynamics, market structure, and competition in the vicinity of each independent station.

In the BP and Coles models, we substitute the brand dummies mentioned earlier with the average prices of Coles and BP stations, along with their corresponding lagged prices for up to 3 days. The models also include interactions between these current and lagged brand-specific average prices and the other predictors, resulting in more than 700 predictors. Incorporating these brand-specific average prices allows for the consideration of price coordination within these prominent retail brands.

In total, have 112,441, 123,986, and 9,908 price observations for BP, Coles, and independent stations, respectively. We randomly split the price observations and corresponding predictor variables for each brand into 80% training and 20% test sets. The training set is used to fit the model, while the test set is held out for evaluating the model's out-of-sample performance.

We use a 5-fold cross-validation to find the optimal regularization parameter, which controls the penalty applied to the model. The estimated optimal regularization parameter for BP, Coles, and independents is 0.0001, 0.0001, and 0.0008, respectively. The algorithm selects 43, 43, and 38 predictors for the corresponding models.

The out-of-sample prediction accuracies measured by pseudo-R^2 on the testing dataset are 0.931, 0.945, and 0.901 for BP, Coles, and the independents, respectively. To demonstrate the model's performance, we compare the distribution of observed and predicted prices for independent stations across cycle deciles from May 2015 to May 2016. During this period, Informed Sources manually collected prices for 74 independent stations before shifting their focus to collecting Coles' prices. Figure D.1 depicts the 25th, 50th, and 75th percentile of observed and model-predicted prices for each local cycle decile. The figure demonstrates the model's ability to effectively capture the heterogeneity in pricing among different stations.

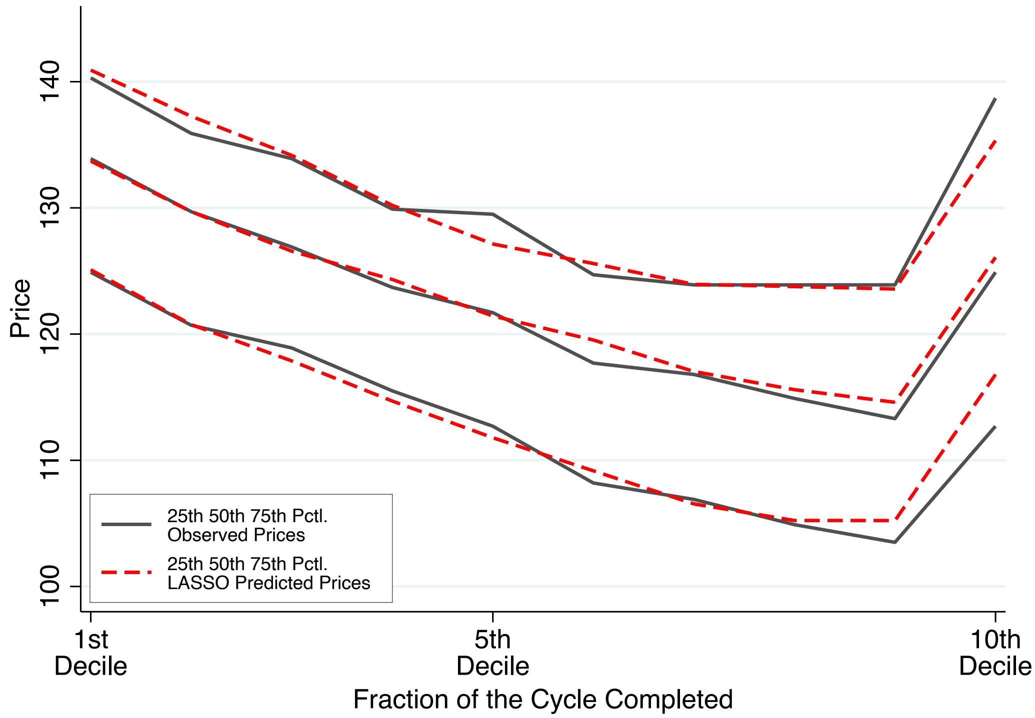
We use the trained and validated LASSO models to predict missing prices for BP, Coles, and independent stations in the dataset. After imputing missing prices, we calibrate the model per Section 5.2.

D.3 Matching moments and imputing market shares

Here, we detail how we calibrate α and β in the demand model. To estimate $s_{jt}(\boldsymbol{\delta}_t, \mathbf{f})$, we need to construct f_{od} and $T(o,d,l_j)$. The Origin-Destination (OD) matrix obtained from the Victoria State Government Department of Transportation and Planning (2018) provides information on the average daily number of drivers traveling between the 2975 traffic zones in Victoria. We restrict the traffic zones to the ones within the Melbourne metropolitan area. Then, f_{od} is calculated as the proportion of total drivers traveling within Melbourne who journey from the origin zone o to the destination zone d.

$T(o,d,l_j)$ represents the additional time required in minutes for household i to deviate from the

Figure D.1: Observed and Predicted Prices for Independent Stations by Cycle Deciles



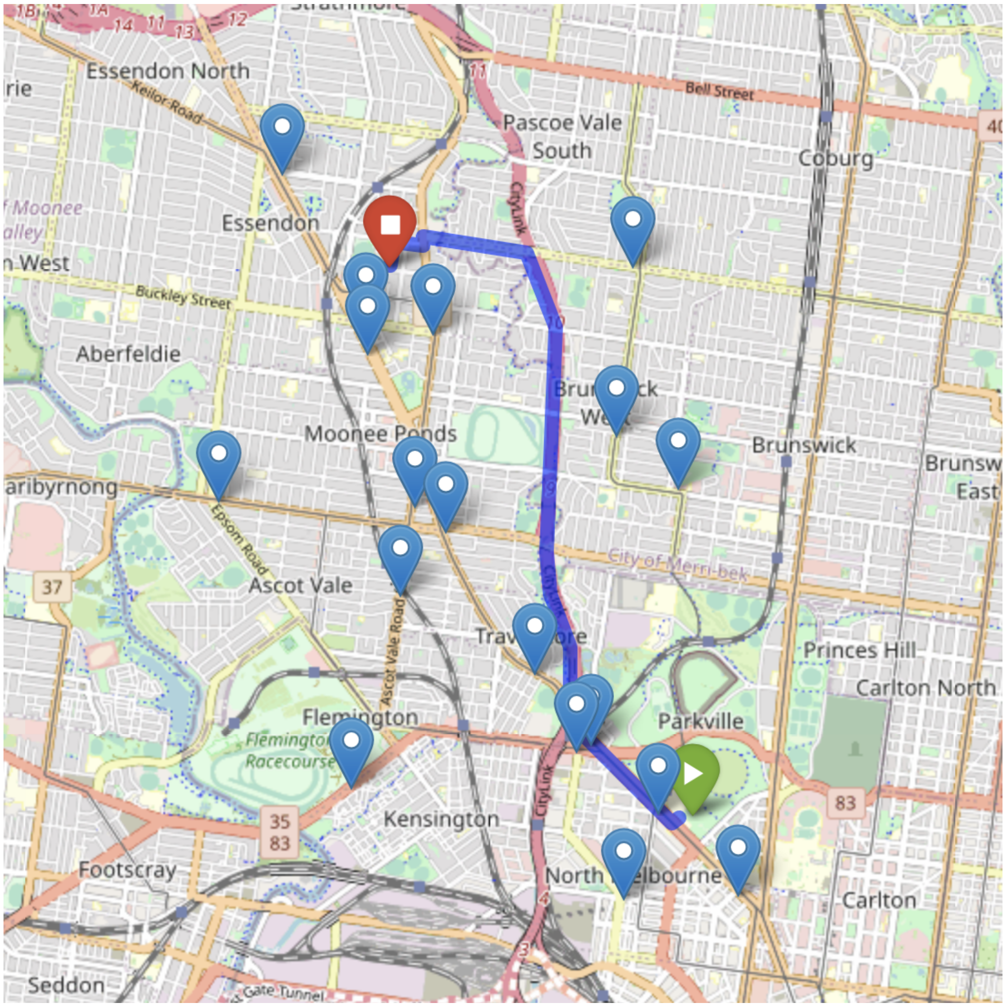
Notes: The cycle deciles are constructed based on the average prices of the five closest stations documented by the platform. We first identify the local market cycle peaks using the local maximum algorithm introduced in the main text. Then, we divide the days between each peak into ten deciles. Notably, the price increases observed in the 10th decile capture the restoration phase of the subsequent cycle.

fastest driving route between the origin o and destination d in order to visit gas station j. It is calculated as $t(o,l_j)+t(l_j,d)-t(o,d)$, where $t(x,y)$ represents the fastest driving time between points x and y following the street network in Melbourne. We leverage OpenStreetMap routing API (openstreetmap.org) to calculate the fastest driving time and distance between any two points.

We use the centroid of each traffic zone as drivers' origin o or destination d location and obtain the fastest driving time $t(o,d)$ for over 1.15 million od pairs in Melbourne. Then, for each od pair, we obtain the fastest driving time from o to l_j and from l_j to d, enabling us to obtain the departure time $t(o,l_j)+t(l_j,d)-t(o,d)$ for every gas station j. In the calibration, to reduce dimensionality for computation, we limit the consideration set for consumers driving from o to d to stations with less than 5 additional minutes of travel time when departing from the fastest route. Figure D.2 provides an example of an od travel route with the gas stations consumers consider on the route.

Given a set of α and β values and the constructed traffic data, we can calculate the model predicted $\hat{s}_{jt}$ following equations (4) and (5). We then aggregate the predicted daily station-level market shares to the average daily retailer-level market shares between May 1 and July 31 in both 2015 and 2017. In calibration, we select α and β values to minimize the squared distance between the model-predicted

Figure D.2: Example *od* Route with Stations



market shares and the observed choice probabilities for the 5 major retailers in 2015 and 2017. The share of the independents is excluded because the market shares across all brands inherently sum up to one.

The cross-sectional variation in the brand-level market shares identifies the brand valuation β conditional on the distribution of traffic flows. We identify α by exploring variations in price changes across brands and the corresponding shifts in consumers' brand choices from 2015 to 2017. This variation informs us of the substitution patterns across gasoline stations.

Table D.2 presents the estimated parameter values and the resulting brand valuations. According to our calibrated model, the mean estimated station-level price elasticity is -44. The estimated brand valuations suggest that, on average, consumers value gasoline at the five major retailers more highly than independent stations. For instance, consumers are willing to pay an additional 9.3 cents per liter to purchase gasoline at a Coles station than at an independent station.

Using the calibrated model, we obtain estimates of (inside good) station-level market shares, $\hat{s}_{jt}$, for each station and date in the sample from equation (5).

Table D.2: Parameter Values and Brand Valuations from Model Calibration

	Price	BP	Caltex	Coles	Woolworths	7-Eleven
Parameter estimates	-1.32	2.78	2.93	4.29	3.42	1.06
Brand valuation (cpl)		5.99	6.32	9.25	7.38	2.29

D.4 Estimating daily total quantity of fuel sold

We utilize two datasets to determine the daily total volume of gasoline sold in Melbourne. The first dataset, obtained from ACCC (2018), provides the daily share of gasoline volume sold in Melbourne in the third quarter of 2016. The second dataset, sourced from Australian Government Department of Environment and Energy (2018), provides data on monthly total gasoline consumption in Victoria.

We calculate the daily volume of gasoline sold in Melbourne throughout our entire sample period in two steps. First, using the ACCC (2018) data, we estimate the following logit model that predicts the share of gasoline sold in date t out of total sales within a quarter:

$$\ln(w_t) = \sum_{k=-L}^{F} \gamma_k^+ \Delta p_{t+k}^+ + \gamma_k^- \Delta p_{t+k}^- + \tau_d + \epsilon_t, \tag{D.1}$$

where w_t is the share of gasoline sold in date t out of total sales between July 1 and October 1, 2016, $\Delta p_{t+k}^+ = \max\{\Delta p_{t+k}, 0\}$, $\Delta p_{t+k}^- = \min\{\Delta p_{t+k}, 0\}$ and τ_d is a day-of-week fixed effect. We compare models with different numbers of lags, L, and leads, F, and find the model with $L = 4$ and $F = 2$ is preferred, yielding the lowest AIC value of -293.459 and an R-squared of 0.879.[56]

However, due to price-level fluctuations quarter-by-quarter, the predicted daily shares $\hat{w}_t$ from (D.1) may potentially not be stable over the entire sample. This possibility makes it necessary to re-scale these predicted daily shares so that the adjusted predicted shares in each quarter sum up to one. In particular, we define the adjusted daily volume share as $\tilde{w}_t = \frac{1}{\sum_{k \in q[t]} \hat{w}_k} \hat{w}_t$, where $\sum_{k \in q[t]} \hat{w}_k$ denotes the summation of the predicted shares for all days within the same quarter as t. In practice, this adjustment yields minimal changes to our predicted $\hat{w}_t$ values from (D.1), reflecting the stability of aggregate gasoline price and quantity levels over our primary May 1, 2015 - December 31, 2017 primary sample period.[57]

Second, we scale down the total monthly gasoline sales volume in the state of Victoria from Australian Government Department of Environment and Energy (2018) to measure the monthly volume for the city of Melbourne by utilizing the share of vehicle miles traveled in Victoria that occur within Melbourne. To determine this share, we utilize the state's Origin and Destination table, described in Section D.3 above, which provides data on the average daily number of drivers traveling between any two traffic zones in Victoria. By multiplying the number of drivers by the driving distance along the fastest travel route, we calculate the total daily mileage driven in Victoria. We obtain the driving distances us-

[56] We use AIC for model selection rather than cross-validation because of the limited number of observations.

[57] More specifically, we find that there are minimal changes in the sales volume during the 10 months preceding the case and the 10 months following it. Specifically, the average daily sales volume is 4.536 million liters (ML) in the pre-period and 4.566 ML in the post-period, indicating a 0.66% change.

ing OpenStreetMap optimal routing. We then calculate the total daily mileage driven overall in the state and within Melbourne and find it to be 51.3% of the overall daily mileage driven in Victoria. Therefore, we measure Melbourne's monthly gasoline sales volume as 51.3% of the state volume. This calculation assumes similar average fuel efficiency between the metropolitan and regional areas.

We convert monthly sales volume in Melbourne to quarterly volume and denote the measure by Q_q. Multiplying Q_q with the predicted daily share of fuel sold within a quarter $\hat{w}_t$ yields our predicted daily volume of fuel sold in Melbourne,

$$\hat{Q}_t = \tilde{w}_t \times Q_q[t], \tag{D.2}$$

where $Q_q[t]$ indicates that date t falls within quarter q. This corresponds to equation (7) in the paper.