Online Appendix:

Learning to Coordinate: A Study in Retail Gasoline

By: David P. Byrne and Nicolas de Roos

August 16, 2018

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A Institutional details

Our study focuses on BP price leadership, the creation of focal pricing strategies and margin enhancement between 2009 and 2014. However, other shocks may explain the transitions that we found in retail pricing and profit margins.

This Appendix considers other shocks to market structure between 2009 and 2014. We exploit two key sources of information for our investigation: our dataset and industry reports from the national competition authority, the Australian Competition and Consumer Commission (ACCC). Regarding the latter, the ACCC produces publicly available annual gasoline industry monitoring reports from 2007 to 2014.[1] Collectively, these reports provide exhaustive, in-depth analyses of demand, supply and regulation in gasoline refining, wholesaling and retailing. Using these reports, we retrace the history of shocks to market structure.

A.1 Supply

Refining and wholesaling. The oil majors, BP, Caltex, Shell and Mobil, dominate the refining and wholesale market over our sample period.[2] In 2002, there were 8 refineries in Australia, with at most two refineries in a single state. By 2015, there were only 4 remaining refineries in Australia. As a result, most retailers do not have access to a refinery in the same state carrying their brand. A retailer thus has three possible sources for refined petroleum: purchase from a refinery within its state; ship fuel from another state's refinery; or import fuel. Of these sources, the majority of fuel is obtained from a local refinery.

Wholesale contracts between competing retailers are a common feature of the market to ensure supply for retailers without a local refinery. Contracts between refiners are known as "buy-sell" arrangements. A typical contract lasts six months and specifies a price for a petroleum product based on a standardised "import parity price" (IPP) formula. The IPP formula incorporates a benchmark Singapore refined petroleum price, a quality premium, shipping costs, wharfage,

[1] These reports become quarterly starting in 2015.

[2] Prior to March 2015, Chevron has a 50% ownership stake in Caltex. Additional details regarding the structure of the wholesale supply chain are contained in ACCC (2007) and subsequent annual ACCC reports.

insurance and loss. Independent retailers that are not vertically integrated into refining tend to pay higher prices to obtain refined fuel.

BP operates the only refinery in Western Australia, which is just outside Perth in Kwinana. BP, Caltex, and Mobil operate petroleum terminals that receive shipments of both unrefined petroleum and of refined unleaded petrol from overseas, primarily from Singapore. BP, Caltex, and Mobil therefore are the local wholesale suppliers of gasoline in Perth who contract with retailers.

Supermarkets. The supermarket Woolworths and the oil major Caltex formed a partial joint venture in 2004. The joint venture includes an exclusive wholesale supply arrangement of Caltex gasoline at Woolworths stations. It also involves co-branding of Caltex-Woolworths stations and joint ownership of a subset of stations. Woolworths makes daily pricing decisions at all Caltex-Woolworths stations. This joint venture terminates in November 2014.

The supermarket Coles maintains an exclusive supply arrangement with the oil major Shell throughout our sample period. This joint venture also involves co-branding of stations by the companies and leaves retail pricing at Coles's discretion. The ACCC reports do not reveal any other major changes to contractual relationships between wholesalers and retailers between 2007 and 2014.

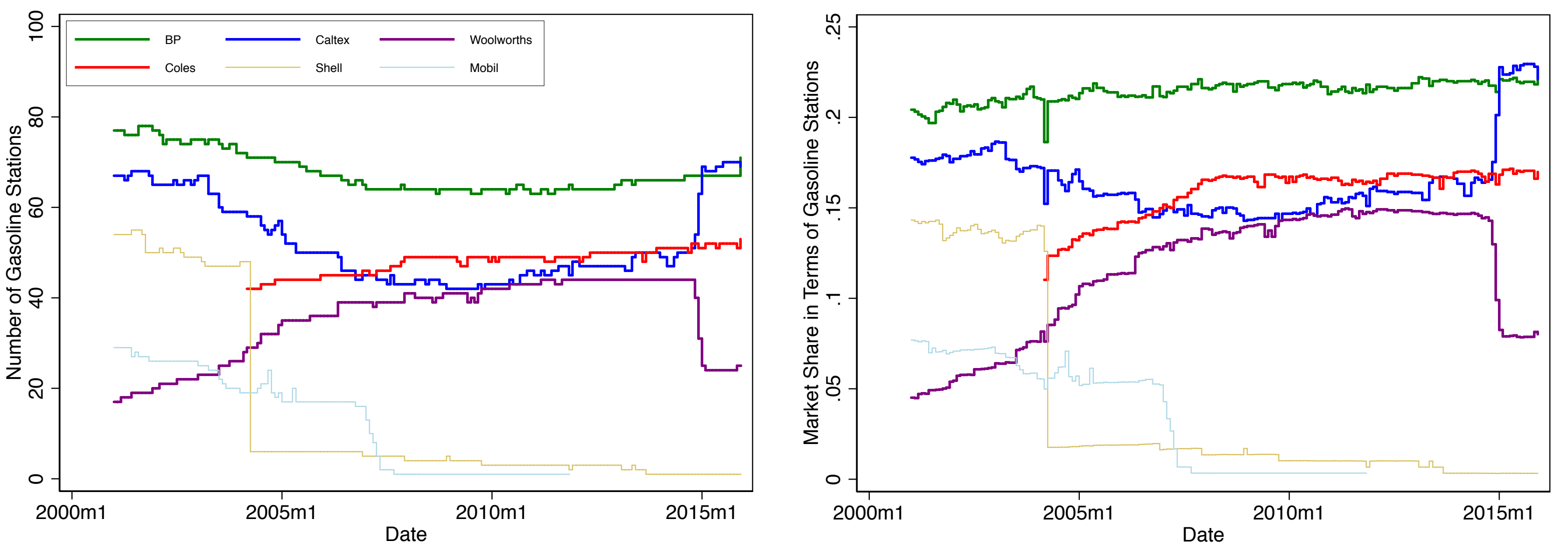
Both Woolworths and Coles offer "shopper dockets" that provide retail gasoline price discounts to customers who spend more than $30 on a single grocery store trip.[3] The minimum $30 amount is constant over our sample period (ACCC 2004, 2014). The gasoline price discount is 4 cpl for both Woolworths and Coles between 2004 and 2010 (ACCC 2004, 2014). ACCC (2011) first reports discounts greater than 4 cpl. By 2013, ACCC (2013) reports discounts of up to 45 cpl. Moreover, ACCC (2013) contains commentary regarding the potential anti-competitive effects of such aggressive discounts.[4] These concerns eventually lead to an intervention by the ACCC. Specifically, in January 2014 the ACCC sets a maximum allowable discount of 4 cpl (ACCC 2014).

[3]Other retailers, including BP and Caltex, do not offer shopper docket programs between 2007 and 2014 (ACCC 2007, 2014).

[4]For example, the supermarkets' gasoline price discounting could have a predatory effect that causes small independent retailers to exit in the long-run.

Figure A.1: Station Counts and Shares by Brand and Month

(i) Station Counts (ii) Shares of Stations in the Market



Retail market shares. Figure A.1 plots retailers' size in terms of station counts (panel (i) and shares of stations in the market (panel (ii)). From 2001-2004, BP, Caltex, Shell and Mobil dominate the market, operating 65% of stations. In March 2004, the distribution of market shares changes as Caltex, Shell and Mobil sell off their stations to the supermarkets, Coles and Woolworths. As the figures show, Coles is a new entrant in 2004.

However, from 2005 onwards, market shares are stable with BP emerging as the largest firm (22% share of stations), followed by Caltex, Woolworths, and Coles (16%, 14% and 16% shares, respectively). Importantly, the figure highlights the stability of supply-side market structure throughout our main sample period of interest, 2009-2014.[5]

[5] Figure A.1 also highlights the impact of Caltex and Woolworths ending their joint venture in November 2014. As the figure shows, one outcome of this transaction is an exchange of 20 stations from Woolworths to Caltex.

A.2 Demand

Australia exhibits stable economic growth through the 2008 global financial crisis (Reserve Bank of Australia, 2014). Locally, Perth exhibits persistent growth in its primary employment sector – mining – between 2005 and 2014. These macroeconomic facts do not suggest an aggregate demand shock occurs in Perth between 2009 and 2014.

There is an established literature that finds gasoline demand is highly inelastic at the country level. Highly cited price elasticity of demand estimates based on US price and quantity data include: -0.31 to -0.34 (Hughes, Knittel, Sperling 2008; monthly data, 1974-2006), -0.43 (Small and Van Dender 2007; annual data, 1966-2001) and -0.25 (Park and Zhao 2010; annual data, 1976-2008). Davis and Kilian (2011) estimate demand elasticity of -0.46 using monthly, U.S. state-level data. Using quarterly price and quantity data for Australia, Breunig and Gisz (2009) obtain a similar range of elasticity estimates between -0.2 and -0.3.

More relevant for our study is daily market-level demand elasticity. In a recent study, Levin, Lewis and Wolak (2017) have, for the first time, estimated daily price elasticity of demand for gasoline at the market level. Their analysis is based on daily price and quantity data for 243 metropolitan markets in the U.S. from February 2006 to December 2009. These unique data yield elasticity estimates that similarly range from -0.27 to -0.35.[6]

Daily data on sales volumes at the station or market level are, unfortunately, not available for Australia. Given this data limitation, we rely on evidence on daily demand from ACCC (2007) and (2014). In these industry reports, the ACCC presents average daily retail gasoline sales volumes by day of the week and capi-

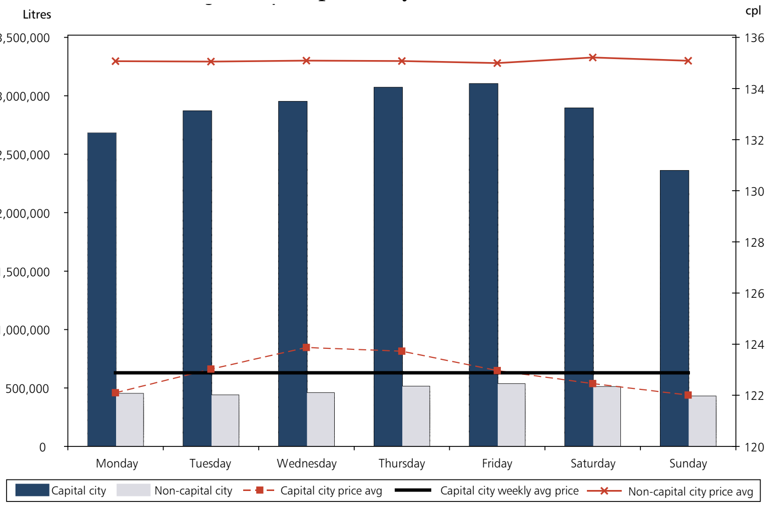
[6]There are related studies that estimate station-level demand elasticities. These studies typically use price and quantity data available for a handful of stations in particular markets. Typically, such data yield relatively larger elasticity estimates at the station level: -0.4 to -7.7 (Slade 1986, daily data from 13 stations in Vancouver from 1983), -4.5 to -18.8 (Wang 2009, daily data from 8 stations in Perth from 2001-2003), -10 to -15 (Houde 2012, Quebec City, bi-monthly data from stations in Quebec City from 1991-2001), -30 (Clark and Houde 2013, quarterly data for stations in Victoriaville Quebec from 2001-2007). Therefore, while country- and market-level elasticities are relatively small (everyone needs gasoline for travel and other reasons), local, within-market station-level elasticities are large, likely because gasoline is a homogeneous product and stations' prices are clearly displayed on large signs.

tal city for 2006-07 and 2013-14. We reproduce the daily sales volumes from the reports for Perth, Adelaide, Melbourne and Sydney in Figures A.2 and A.3 below.

Figure A.2 highlights daily demand cycles for Adelaide, Melbourne and Sydney in 2006-07. In these markets, the average share of weekly gasoline sales spikes on Tuesdays at 24%, 22%, and 21%, respectively. These shares bottom out at 11% on Thursday in each market. In contrast, the daily share of volumes sold is relatively uniform across the week in Perth: the maximum share is 16% on Fridays and the minimum share is 12% on Sundays.

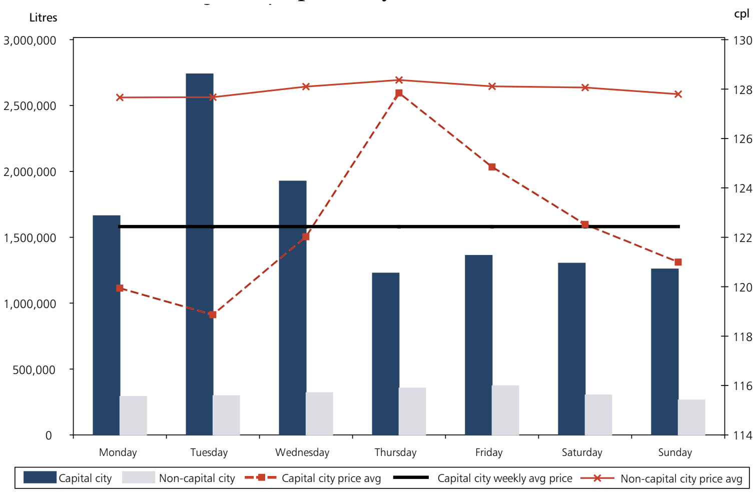
Figure A.2: Average Retail Prices and Volumes by State and Capital City, 2006-07

(i) Western Australia
(capital city: Perth)



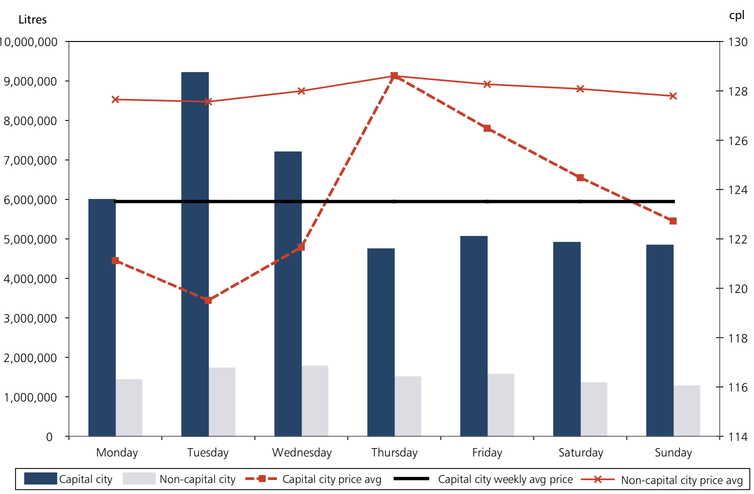
Source: ACCC from data supplied under s. 95ZK of the Act and Informed Sources.

(ii) South Australia
(capital city: Adelaide)



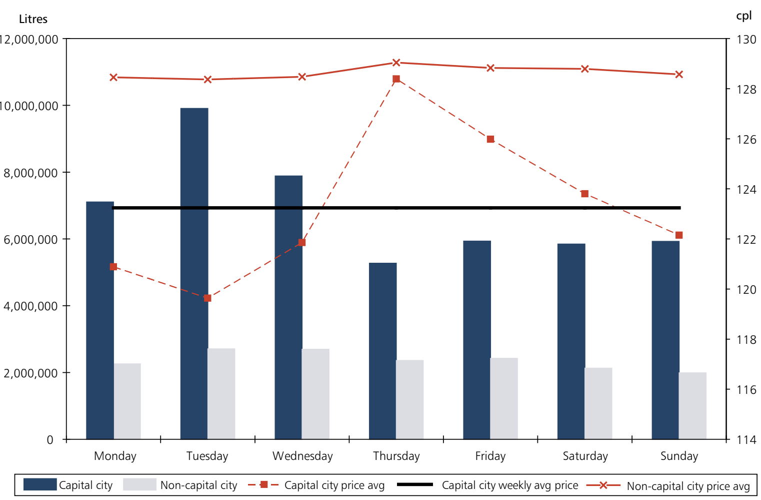
Source: ACCC from data supplied under s. 95ZK of the Act and Informed Sources.

(iii) Victoria
(capital city: Melbourne)



Source: ACCC from data supplied under s. 95ZK of the Act and Informed Sources.

(iv) New South Wales
(capital city: Sydney)

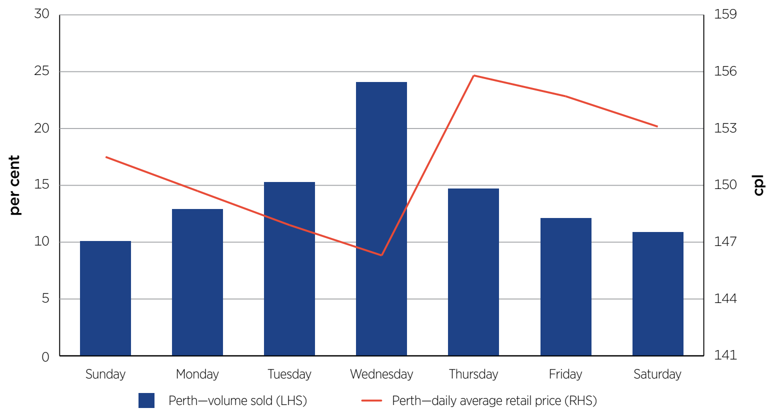


Source: ACCC from data supplied under s. 95ZK of the Act and Informed Sources.

Source: Petrol Prices and Australian Consumers, Report of the Australian Competition and Consumer Commission Inquiry into the Price of Unleaded Petrol. Figures P.1, P.2, P.4, P.5 from Appendix P reproduced.

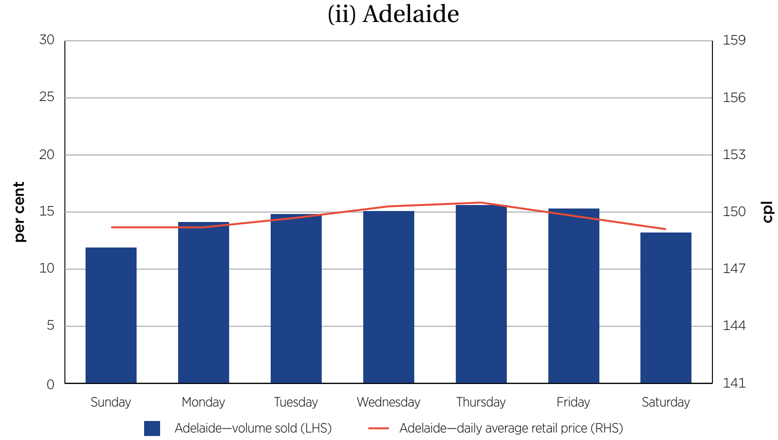
Figure A.3: Average Retail Prices and Volumes by Capital City, 2013-14

(i) Perth



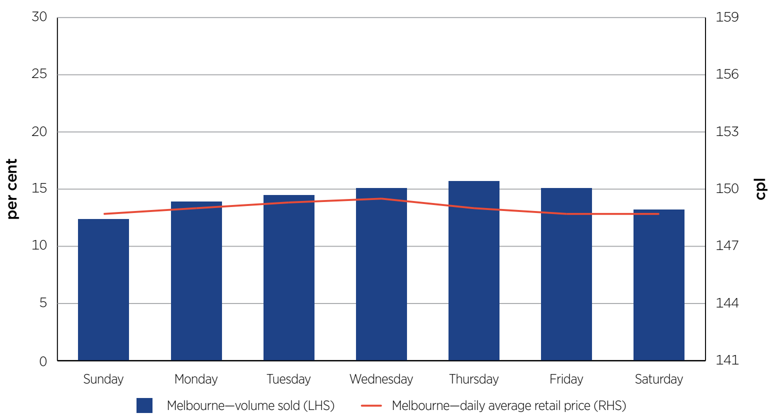
Source: ACCC analysis based on Informed Sources data, and information provided by the monitored companies.

(ii) Adelaide



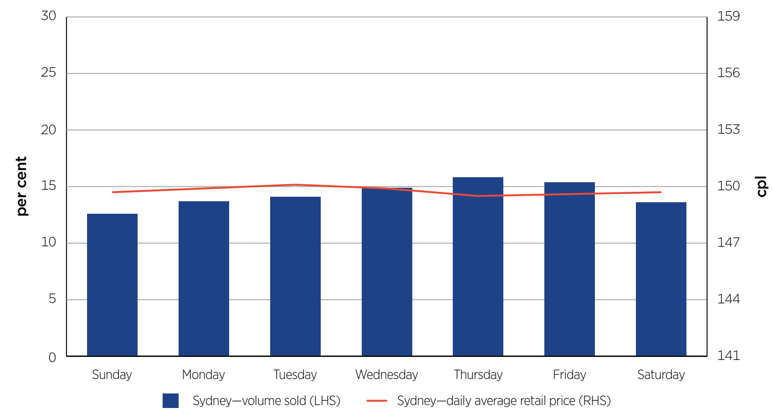
Source: ACCC analysis based on Informed Sources data, and information provided by the monitored companies.

(iii) Melbourne



Source: ACCC analysis based on Informed Sources data, and information provided by the monitored companies.

(iv) Sydney



Source: ACCC analysis based on Informed Sources data, and information provided by the monitored companies.

Source: Monitoring of the Australian Petroleum Industry, Report of the Australian Competition and Consumer Commission Inquiry into the Price of Unleaded Petrol. Chart 8.4, 8.5, 8.7, 8.8 from Chapter 8 reproduced.

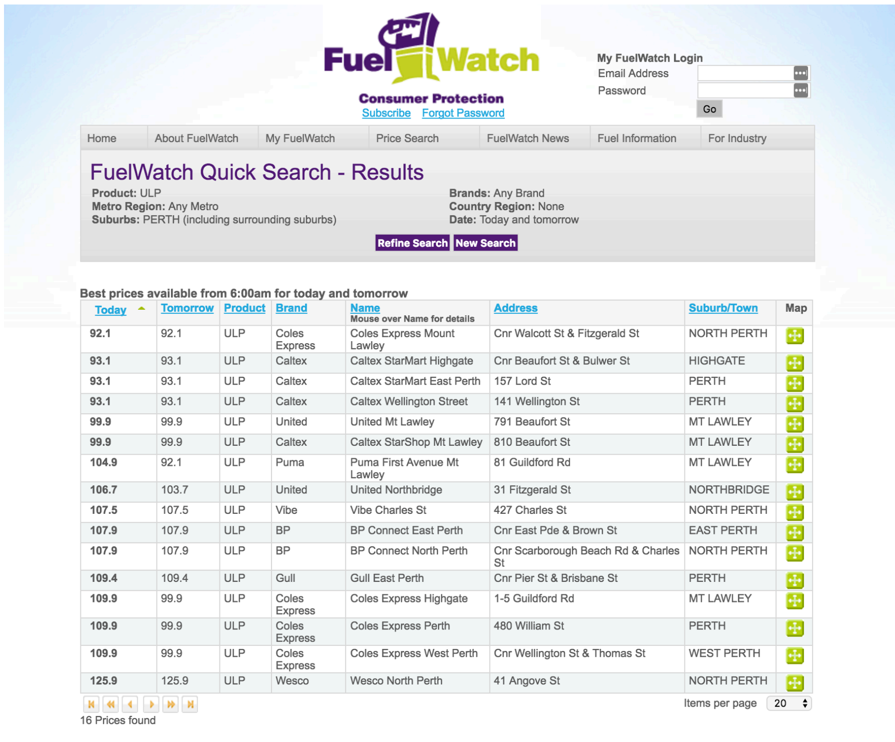
As ACCC (2007) discusses, and as we show in Appendix B.4 and Figure B.7 below, a critical piece of context in interpreting these patterns is that Adelaide, Melbourne and Sydney all have regular weekly price cycles with Thursday jumps in 2006-7. In contrast, Perth has irregular, 14 to 21 day cycles with unpredictable price jump timing. Regular weekly demand cycles appear to be associated with regular weekly price cycles. This provides preliminary evidence that consumers indeed engage in inter-temporal price search to avoid price jumps.

Figure A.3 provides an interesting contrast. In 2013-14, Perth has a regular demand cycle, while Adelaide, Melbourne and Sydney have relatively uniform shares of volumes sold across days of the week. In Perth, 24% of weekly gasoline volumes are sold on Wednesdays. Sales volumes bottom out at 11% on Sundays. In terms of price cycles, the situation is also reversed from 2006-07: in 2013-14, Perth has a regular weekly cycle with Thursday jumps, while Adelaide, Melbourne and Sydney have irregular 14 to 21-day cycles with unpredictable price jump timing.

We believe that the contrasting set of results for 2006-07 and 2013-14 highlight a link between having regular price cycles and daily demand cycles for gasoline. With regular price jump days, there is a sufficient degree of inter-temporal consumer search such that volumes sold jump to 20-24% of total weekly volumes just prior to price jumps occuring. Despite regular price jump days, however, there remains a non-negligible share of gasoline sold on price jump days (11-15%) and on days just after price jumps (15-16%).

We find this pattern to be particularly interesting for Perth in 2013-14 as virtually every market price jump between 2010 and 2014 occurs on a Thursday. Even though the timing of 10-20% price increases on Thursdays week-to-week are perfectly predictable over this period, a large share of consumers still “mistime” their fuel purchases week-to-week. We believe this is revealing of consumers’ time and inconvenience cost of making fuel purchases once per week prior to price jumps. For many consumers, such a strategy would likely involve filling up a partially empty fuel tank week-to-week. The evidence in Figure A.3 for Perth suggests that for a large share of consumers, making such an effort to help minimize the net present value of fuel costs over time is not worth it.

Figure A.4: Fuelwatch Price Comparison Website
(www.fuelwatch.gov.au)



Today	Tomorrow	Product	Brand	Name (Mouse over Name for details)	Address	Suburb/Town	Map
92.1	92.1	ULP	Coles Express	Coles Express Mount Lawley	Cnr Walcott St & Fitzgerald St	NORTH PERTH	
93.1	93.1	ULP	Caltex	Caltex StarMart Highgate	Cnr Beaufort St & Bulwer St	HIGHGATE	
93.1	93.1	ULP	Caltex	Caltex StarMart East Perth	157 Lord St	PERTH	
93.1	93.1	ULP	Caltex	Caltex Wellington Street	141 Wellington St	PERTH	
99.9	99.9	ULP	United	United Mt Lawley	791 Beaufort St	MT LAWLEY	
99.9	99.9	ULP	Caltex	Caltex StarShop Mt Lawley	810 Beaufort St	MT LAWLEY	
104.9	92.1	ULP	Puma	Puma First Avenue Mt Lawley	81 Guildford Rd	MT LAWLEY	
106.7	103.7	ULP	United	United Northbridge	31 Fitzgerald St	NORTHBRIDGE	
107.5	107.5	ULP	Vibe	Vibe Charles St	427 Charles St	NORTH PERTH	
107.9	107.9	ULP	BP	BP Connect East Perth	Cnr East Pde & Brown St	EAST PERTH	
107.9	107.9	ULP	BP	BP Connect North Perth	Cnr Scarborough Beach Rd & Charles St	NORTH PERTH	
109.4	109.4	ULP	Gull	Gull East Perth	Cnr Pier St & Brisbane St	PERTH	
109.9	99.9	ULP	Coles Express	Coles Express Highgate	1-5 Guildford Rd	MT LAWLEY	
109.9	99.9	ULP	Coles Express	Coles Express Perth	480 William St	PERTH	
109.9	99.9	ULP	Coles Express	Coles Express West Perth	Cnr Wellington St & Thomas St	WEST PERTH	
125.9	125.9	ULP	Wesco	Wesco North Perth	41 Angove St	NORTH PERTH	

A.3 Regulation

Finally, industry reports in ACCC (2009), (2010), (2011), (2012), (2013), (2014) do not reveal any other major policy or regulatory changes or anti-trust investigations of note.

The Fuelwatch policy with daily 2pm price reporting and the 24-hour fixed retail price rule are unchanged since 2001. From our discussions with the Fuelwatch team we understand that the Fuelwatch website has remained largely unchanged since 2001. Price information is made available over the entire sample period through the website. Fuelwatch has not yet released a mobile phone app. Figure A.4 depicts the Fuelwatch price comparison website.

B Retail pricing and margins in other markets

In this Appendix, we address the following question: does the equilibrium transition we find in Perth occur in other markets? As we state in the paper, the short answer is no. Moreover, retail margins grow by an additional **3.49** cpl in Perth starting in 2010 relative to other major cities in Australia. This represents a **64%** margin increase relative to average station-level profit margins in Perth prior to 2010. We now provide details on these headline margin calculations, and show that the equilibrium transition we document in the paper is local to Perth.

B.1 Data

We purchased supplemental data from Fueltrac (http://fueltrac.com.au/), a private company that collects daily average retail gasoline price data for Australian cities. The company provided us with average daily retail prices for Adelaide, Melbourne and Sydney from January 1, 2001 to January 1, 2016.

Why do we focus on these cities? Adelaide, a city of 1.3 million people and capital of neighboring South Australia, is the most comparable Australian market to Perth in terms of size, location and demographics. Melbourne and Sydney are the largest markets in Australia with 4.1 and 4.3 million people, respectively. They provide useful benchmarks for Perth and Adelaide in terms of retailers' pricing strategies and margins.

We link these retail price data to daily wholesale terminal gate prices available from the Australian Institute of Petrol (http://www.aip.com.au/pricing/tgp/). In linking the retail and wholesale price data, we match each city to its nearest terminal gate. The daily retail margin on a given date for each city is computed as the difference between its average retail price and its local terminal gate price (TGP). This is precisely how we compute average daily retail margins in the paper.

B.2 Prices

Figure B.1 plots average daily retail prices from 2001 to 2015 for each of the four cities. We also plot the daily average of the TGP across the cities. The figure highlights a few notable differences between Perth and the other markets:

1. Prior to 2010, Perth's cycle has smaller amplitude and greater length than the cycles in Adelaide, Melbourne and Sydney. The latter three markets exhibit very similar cycles in terms of amplitude, length and price jump timing week-to-week.

2. Perth's cycle collapses in 2004, 2005 and 2008 in response to aggregate shocks (Coles Entry, Hurricanes Katrina and Rita, Crude Oil Price Shock). In contrast, the cycles in the other markets do not collapse. This potentially highlights the impact of Fuelwatch's 24-hour rule on price coordination.

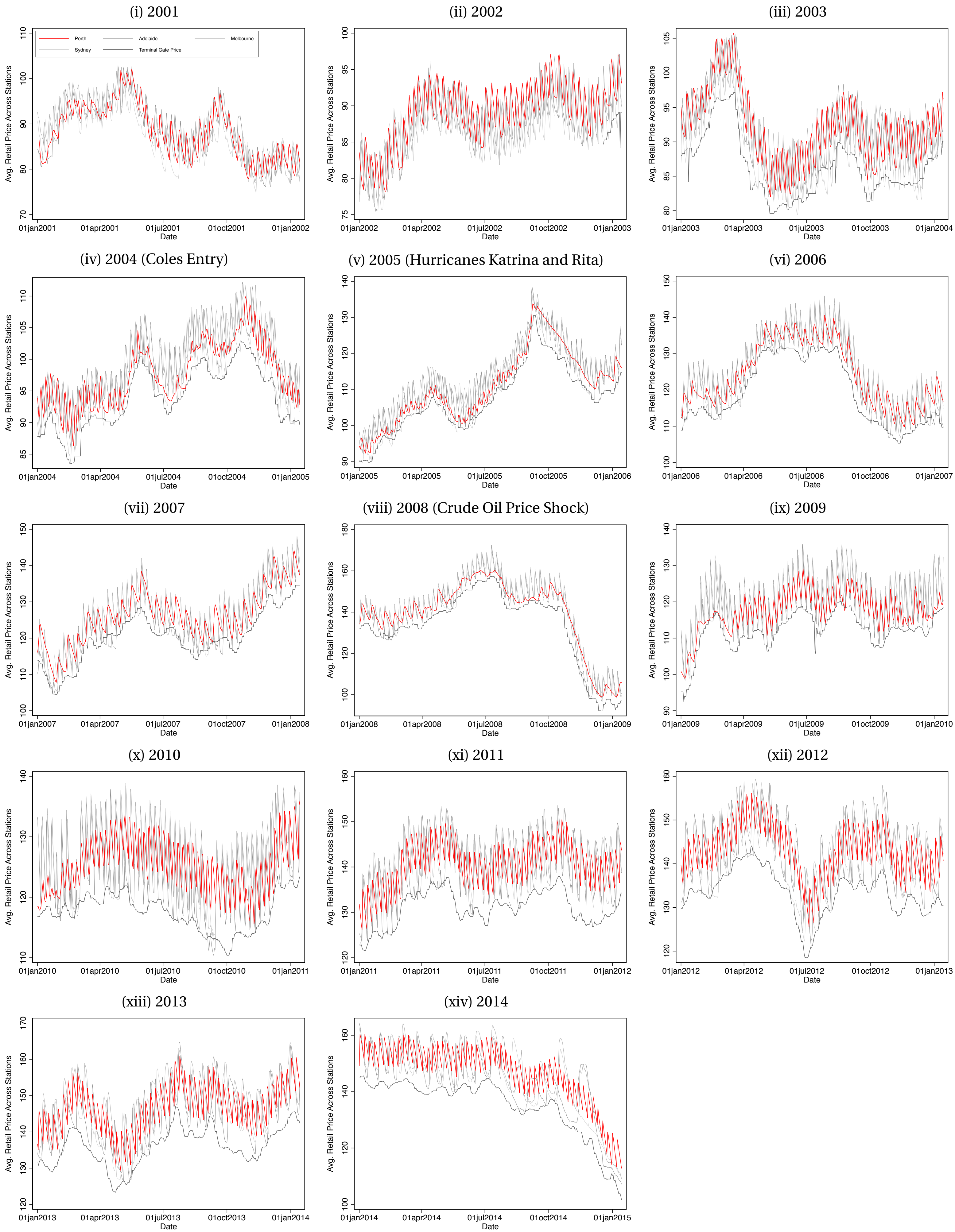
   – In Perth, firms simultaneously set prices day-to-day and cannot engage in within-day price changes to coordinate on a cycle in response to wholesale cost volatility arising from aggregate shocks.

   – In the other markets, where the ability to coordinate and communicate is easier given station-level price changes occur at hourly or higher frequencies, coordination on the cycle remains stable in the face of substantial wholesale cost volatility.

3. After 2010, the cycle in Perth is stable. The amplitude, length and the timing of price jumps are unchanged through 2015. Moreover, Perth continues to have smaller amplitude than cycles in other markets,

4. From 2010 onwards, however, the cycles in Adelaide, Melbourne and Sydney become noisier and transition from having a weekly to monthly length.

Figure B.1: Retail Pricing in Perth, Adelaide, Melbourne and Sydney



B.3 Price coordination

We further investigate how price cycles evolve over time across the four markets by replicating Figures 2 and 3 from the paper for each market. Recall that these figures describe inter-temporal dispersion in the timing of market price jumps by day of the week, the length of market cycles, and the magnitude of market price cuts by day of the undercutting phase of the cycle. Because we only have daily average prices for Adelaide, Melbourne, and Sydney, we use a variant on Definitions 1 (iii) and (iv) from the paper to define market price jumps, cycle length and undercutting days in these markets:

Definition. 1a

(iii) A *market price jump* occurs on date t if $\text{mean}_t(p_{it}) - \text{mean}_t(p_{it-1}) \geq 4$ cpl, where on date t $\text{mean}_t(p_{it})$ is the mean of p_{it} across all stations.

(iv) A *market cycle* commences on date t if $\text{mean}_t(p_{it}) - \text{mean}_t(p_{it-1}) \geq 4$ cpl. This is denoted as "day 1" of the market cycle. Days $2, 3, 4\ldots$ of the market cycle correspond to the undercutting phase until the next market-level price jump occurs and a new cycle begins. *Market cycle length* is the number of days between market price jumps.

To help make the figures comparable across markets, we compute $\text{mean}_t(p_{it})$ for dates across all stations (both cycling and non-cycling) in Perth using the Fuelwatch data, and use this alternative definition for market price jumps, cycle length and undercutting days.[7]

Figure B.2 presents our results. The three columns respectively present inter-temporal variation in the timing of price jumps by day of the week, cycle length, and price cut magnitudes by day of the cycle. For Perth, the results are similar to what we report in the paper. Thursday price jumps and -2 cpl price cuts emerge as focal pricing rules in 2010. This results in regular cycles that are one week in length.

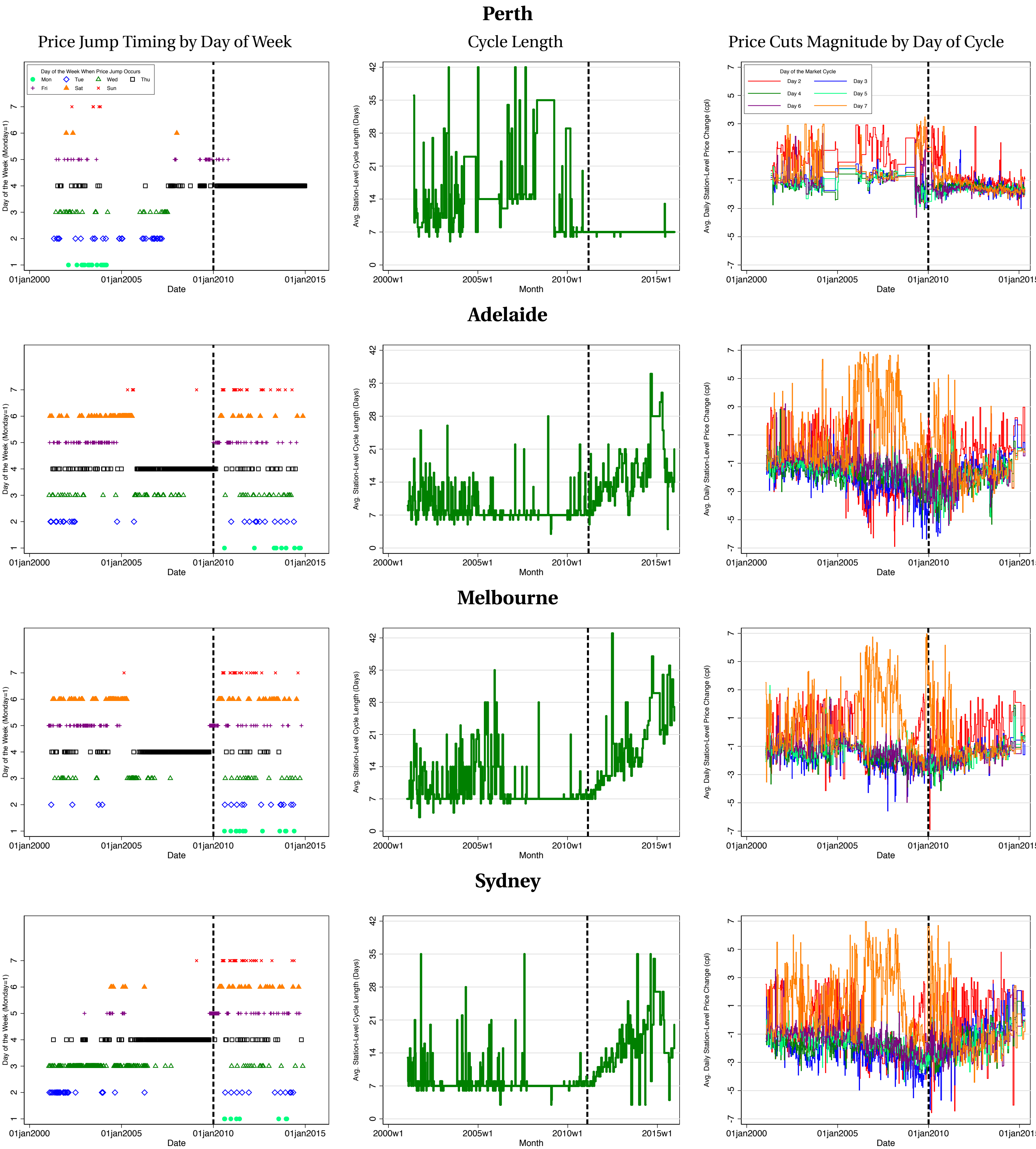
[7] Recall from the paper that we use a 6 cpl threshold and the median of station-level price changes among cycling stations in Perth to identify price jump events. We use a smaller threshold of 4 cpl in this alternative definition because the inclusion of non-cycling stations in computing mean prices dampens daily changes in mean prices around price jump events.

Quite different dynamics emerge in Adelaide, Melbourne and Sydney. In 2010, there is a transition *away* from Thursday jumps toward random mixing of price jump timing across days of the week. Moreover, the regularity of Thursday jumps in these markets prior to 2010 suggests that retailers in Perth had experience with Thursday jumps prior to implementing this pricing rule because of multi-market contact in Adelaide, Melbourne and Sydney.

As a result of the change in price jump timing in the other markets, we find a gradual increase in price cycle length over time starting in 2010. Cycle length is also relatively more volatile after 2010 in the other markets compared to Perth.

Finally, with price cutting, we again find large differences between Perth and the other markets. Whereas Perth converges on 2 cpl cuts, the other markets exhibit substantial volatility in daily price changes over the undercutting phase of the cycle. Indeed, we often find positive average price changes on days two and seven of the market cycle in Adelaide, Melbourne and Perth, which is potentially driven by stations being uncoordinated on the timing of their price jumps day-to-day. For instance, stations that increase their prices a day before (after) a market price jump occurs can result in average price increases on day seven (two) of the market cycle.

Figure B.2: Evolution of Price Jump Timing, Cycle Length, and Price Cuts



B.4 Margins

In this final section, we examine how margins evolve across the four markets over time. We begin with Figure B.3, which plots daily average retail margins. We further highlight longer-run trends in margins by plotting 90-day moving averages for margins. To facilitate comparison of trends in margins across markets, we plot the 90-day moving averages together in Figure B.4. Collectively, these figures reveal a change in the overall level and trend in Perth's margin at the start 2010 that is not found in Adelaide, Melbourne or Sydney.

B.4.1 Difference-in-difference analysis

To estimate the local change in Perth's retail margin relative to other markets in March 2010, we estimate a difference-in-difference regression model:

$$m_{it} = \beta_0 + \beta_1 1\{Post\ T\}_t + \beta_2 1\{Post\ T\}_t \times 1\{Perth\}_i + \nu_i + \tau_t + \epsilon_{it} \tag{1}$$

where $m_{it} = p_{it} - c_{it}$ is the average daily retail margin in city i in week t, $1\{Post\ T\}_t$ is a dummy variable that equals one for all weeks after T where T is week 9 of 2010 in our base specification, $1\{Perth\}_i$ is a dummy variable that equals one for observations from Perth, ν_i and τ_t correspond to market i and week t fixed effects, and ϵ_{it} is the error term. We choose March 2010 as the break date in our base specification because this is when both Thursday jumps and 2 cpl cuts are cemented as focal points; see Sections 4.2 and 4.3 of the paper, and Appendix G.2 for the corresponding structural break tests that identify when the structural breaks emerge. We check the robustness of our margins results to changing the break date in equation (1) below. The difference-in-difference estimate of the local change in Perth's margin relative to other markets after T is $\hat{\beta}_2$.

We work with weekly time frequencies for two reasons. First, they net out the daily price cycle across markets. This dramatically reduces the volatility in the dependent variable, and allows us to focus on lower frequency trends in margin levels. Second, as we will see, by working at weekly frequencies we can empirically identify the week(s) around the start of 2010 in which the break in Perth's margins emerges. This allows us to connect this margin analysis back to when the focal points emerge in Perth.

Figure B.3: Retail Margins in Perth, Adelaide, Melbourne and Sydney

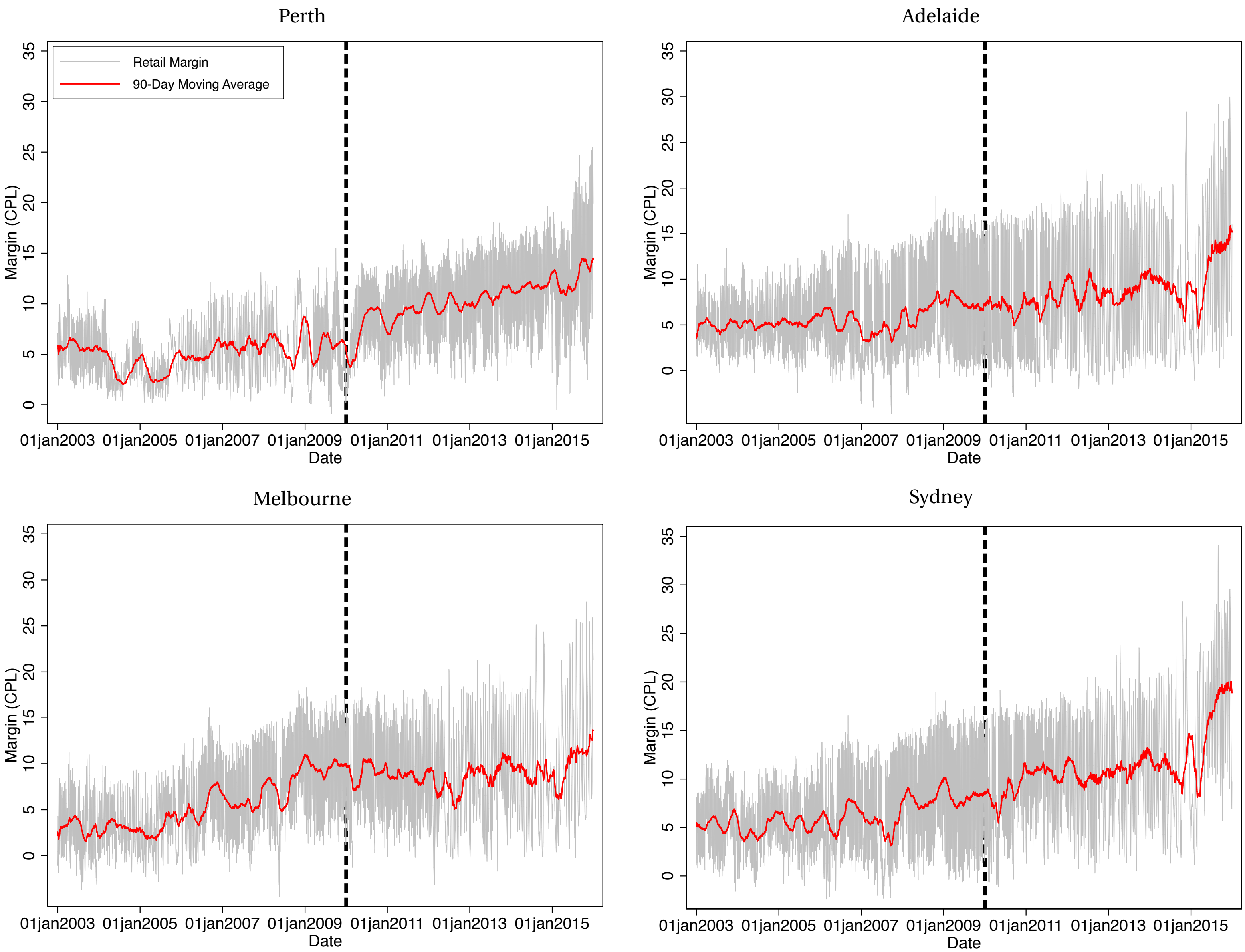


Figure B.4: Retail Margins in Perth, Adelaide, Melbourne and Sydney

(90 Day Moving Averages)

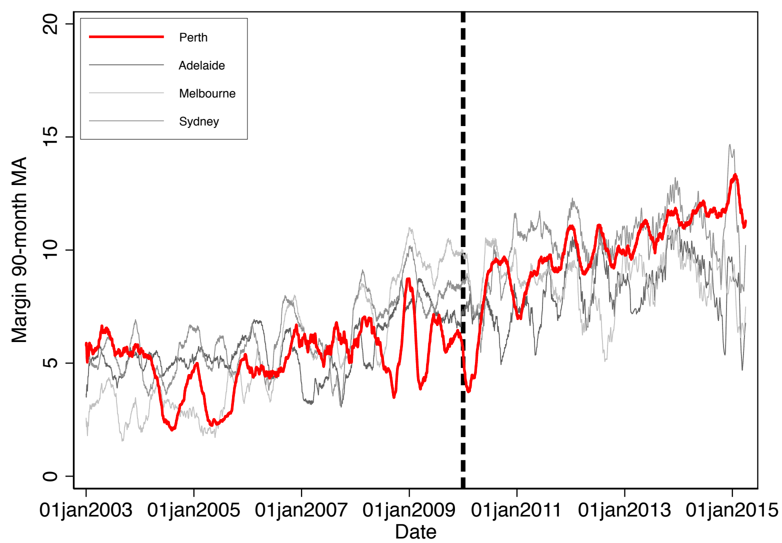


Table B.1 presents our estimation results. Each column of the table varies the starting year of the sample used in estimation. Column (1) therefore corresponds to a longer-horizon estimate, while column (7) reveals a shorter-horizon, more local change in Perth's retail margin in March 2010. The latter estimate is more effective in holding other factors fixed in comparing margins across markets, such as local market shares and demand conditions.

The difference-in-difference estimates in the Table B.1 range from 1.51 cpl to 3.50 cpl. These estimates respectively correspond to 30% and 64% increases in retail margins in Perth in March 2010 above and beyond the before-and-after changes in margins in Adelaide, Melbourne and Sydney. **In the paper, it is precisely the 3.49 cpl estimate and 64% increase that we cite.** We focus on this estimate because, as just discussed, it represents the most "local" change in margins in Perth in March 2010. Moreover, by focusing on the period from 2009 onwards, we largely omit the confounding issue of price cycle collapses in Perth between 2004 and 2008 that, as we showed in Figure B.1 above, do not occur in other markets.

Table B.1: Difference-in-Difference Estimates of the Change in Perth's Margin in 2010

	Starting Year for Sample Period						
	2003	2004	2005	2006	2007	2008	2009
$1\{Post\ T\}_t \times 1\{Perth\}_i$	1.51	1.85	1.92	1.90	2.04	2.92	3.49
	(0.23)	(0.24)	(0.25)	(0.26)	(0.29)	(0.32)	(0.39)
$1\{Post\ T\}_t$	10.37	10.81	10.06	8.18	8.91	6.16	4.96
	(3.83)	(3.93)	(3.90)	(3.75)	(3.98)	(3.74)	(3.82)
Perth	-0.26	-0.67	-0.82	-0.91	-1.03	-1.80	-2.26
	(0.16)	(0.16)	(0.18)	(0.21)	(0.25)	(0.29)	(0.37)
Adelaide	-0.00	-0.17	-0.36	-0.62	-0.65	-0.57	-0.44
	(0.16)	(0.17)	(0.18)	(0.20)	(0.21)	(0.24)	(0.26)
Sydney	1.52	1.44	1.41	1.33	1.44	1.66	1.88
	(0.15)	(0.16)	(0.17)	(0.18)	(0.20)	(0.22)	(0.24)
Week Fixed Effects	Y	Y	Y	Y	Y	Y	Y
Average Perth Margin Pre March 2010	5.08	4.97	5.21	5.65	5.82	5.78	5.43
Implied % Δ by DiD Estimate	30%	37%	37%	34%	35%	51%	64%
R-Squared	0.56	0.55	0.52	0.49	0.46	0.42	0.41
Observations	2704	2496	2288	2080	1872	1664	1456

Notes: Outcome variable is average weekly retail gasoline margin in cents per litre. The break date for the change in margins is set to T=Week9_2010. Robust standard errors reported in parentheses. The sample includes all weeks between the stated starting year at the top of the table through to 2015 (inclusive). The "Implied % Δ by DiD Estimate" is computed as the implied percentage change by the difference-in-difference estimate on the $1\{Post\ T\}_t \times 1\{Perth\}_i$ coefficient relative to the average retail margin in Perth of 5.07 cpl between 2001 and 2009 (see Section 3.1 of the paper for details).

Cycle Collapses. As a robustness check, we compute an analogous set of difference-in-difference estimates, except we drop all weeks in the sample where the cycle collapses. There are four episodes of cycle collapse in Perth: (1) Coles entry between June and October 2004; (2) Hurricanes Katrina and Rita between August and December 2005; (3) the global crude oil price shock between April 2008 and April 2009; and (4) the BP-Caltex price war between December 2009 and January 2010.[8] In contrast, there are no price cycle collapses in Adelaide, Melbourne, or Sydney over our entire sample period. This is shown in Figure B.1 above.

Table B.2 reports our estimation results, where the comparison between Perth's margin trend after March 2010 relative to the other cities now only compares weeks with stable price cycles in all of the markets. The change in margins in Perth relative to the other markets remains statistically significant and large for

[8]Appendix C describes the first three cycle collapse period in detail; Appendix D describes the BP-Caltex price war.

Table B.2: Difference-in-Difference Estimates of the Change in Perth's Margin in 2010, Dropping All Cycle Collapse and Price War Weeks

	Starting Year for Sample Period						
	2003	2004	2005	2006	2007	2008	2009
$1\{Post\ T\}_t \times 1\{Perth\}_i$	1.00	1.36	1.44	1.23	1.13	1.99	2.40
	(0.23)	(0.24)	(0.25)	(0.26)	(0.30)	(0.36)	(0.40)
$1\{Post\ T\}_t$	10.50	10.93	10.18	8.35	9.14	6.39	5.80
	(3.83)	(3.91)	(3.90)	(3.77)	(3.95)	(3.78)	(3.89)
Perth	0.29	-0.16	-0.29	-0.15	-0.01	-0.74	-1.10
	(0.17)	(0.18)	(0.19)	(0.21)	(0.27)	(0.34)	(0.39)
Adelaide	-0.06	-0.27	-0.37	-0.56	-0.58	-0.48	-0.41
	(0.18)	(0.19)	(0.20)	(0.21)	(0.23)	(0.26)	(0.27)
Sydney	1.67	1.60	1.59	1.55	1.69	1.98	2.05
	(0.16)	(0.18)	(0.18)	(0.20)	(0.22)	(0.24)	(0.25)
Week Fixed Effects	Y	Y	Y	Y	Y	Y	Y
Average Perth Margin Pre March 2010	5.30	5.19	5.26	5.81	6.14	6.37	6.26
Implied % Δ by DiD Estimate	19%	26%	28%	21%	20%	31%	38%
R-Squared	0.56	0.54	0.53	0.50	0.47	0.41	0.40
Observations	2324	2116	2012	1868	1660	1452	1380

Notes: Outcome variable is average weekly retail gasoline margin in cents per litre. The break date for the change in margins is set to T=Week9_2010. Robust standard errors reported in parentheses. The sample includes all weeks between the stated starting year at the top of the table through to 2015 (inclusive). The "Implied % Δ by DiD Estimate" is computed as the implied percentage change by the difference-in-difference estimate on the $1\{Post\ T\}_t \times 1\{Perth\}_i$ coefficient relative to the average retail margin in Perth of 5.07 cpl between 2001 and 2009 (see Section 3.1 of the paper for details).

all pre-sample periods, ranging from 1.00 cpl to 2.40 cpl, or from a 19% to a 38% margin increase after 2010 relative to pre-2010 levels. While the increase in Perth's margin remains large, we note that the estimated increase is smaller than what we found in Table B.1. This change in the estimates in part reflects the margin-reducing impact of cycle collapses in Perth pre-2010.

Varying the Break Date. As a further check, we re-estimate the difference-in-difference model for margins, including again all dates in the sample, where we consider many different values of T in equation (1). In particular, we allow T to vary across all weeks between 2009 week 26 and 2010 week 26. In other words, six months before and after our baseline specification T value of 2010 week 1. Doing so allows us to check the sensitivity of our results in Table B.1 to the break date. This is important because there is a potential confound in identifying β_2:

the price war between BP and Caltex at the end of 2009 and start of 2010 led to a drastic drop in retail margins in Perth relative to other markets. By including part of this drop in the pre T period, we potentially over-estimate the change in local margins around the time when focal pricing rules and coordination emerges in 2010 in Perth.

Figure B.5 contains our results from varying T. In each panel, we vary the starting year of the sample to be 2003, 2005, 2007 and 2009. For a given starting year, we plot the difference-in-difference estimates and their 95% confidence intervals (vertical axis) as a function of their break date T (horizontal axis). In each panel we find that the estimates are quite stable regardless of the break date. The figures also show how we obtain relatively large short-run difference-in-difference estimates of the change in Perth's margin for the sample starting in 2009.

B.4.2 Structural break tests for unknown break in margins

Next, we conduct a statistical test for the most likely date of the structural break in margins. Specifically, we implement the Sup Wald (SupF) test from Andrews (1993). This test identifies an unknown structural break as the break date within some specified window of time that yields the supremum of the F-statistic for the coefficient estimates for the structural break among all candidate break dates. For this, we compute the F-statistic for the test of $\beta_2 = 0$ from our difference-in-difference regression.

Figure B.6 plots the F-statistics for all the potential break dates. Each panel explicitly shows the location of the maximum F-statistic (SupF), which corresponds to the location of the unknown structural break Perth's margin. Depending on the sample start date, the structural break in Perth's margins occurs between the fourth and fourteenth week of 2010. That is, between February and March 2010. From Section 4 in the paper, this is precisely when BP starts engaging in price leadership to create Thursday jumps and 2 cpl cuts as focal pricing rules.

Figure B.5: Difference-in-Difference Estimates of Change in Perth Retail Margin

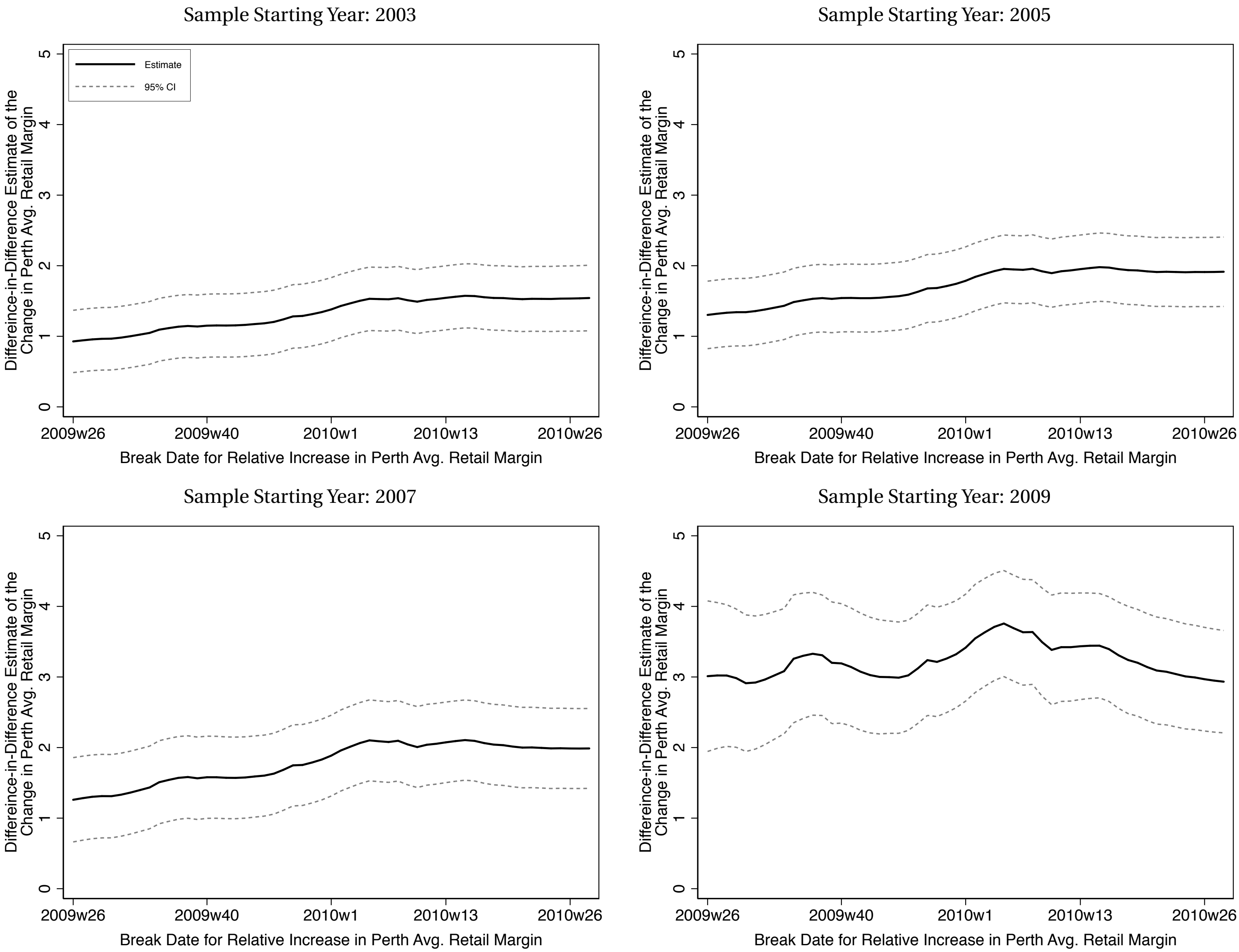
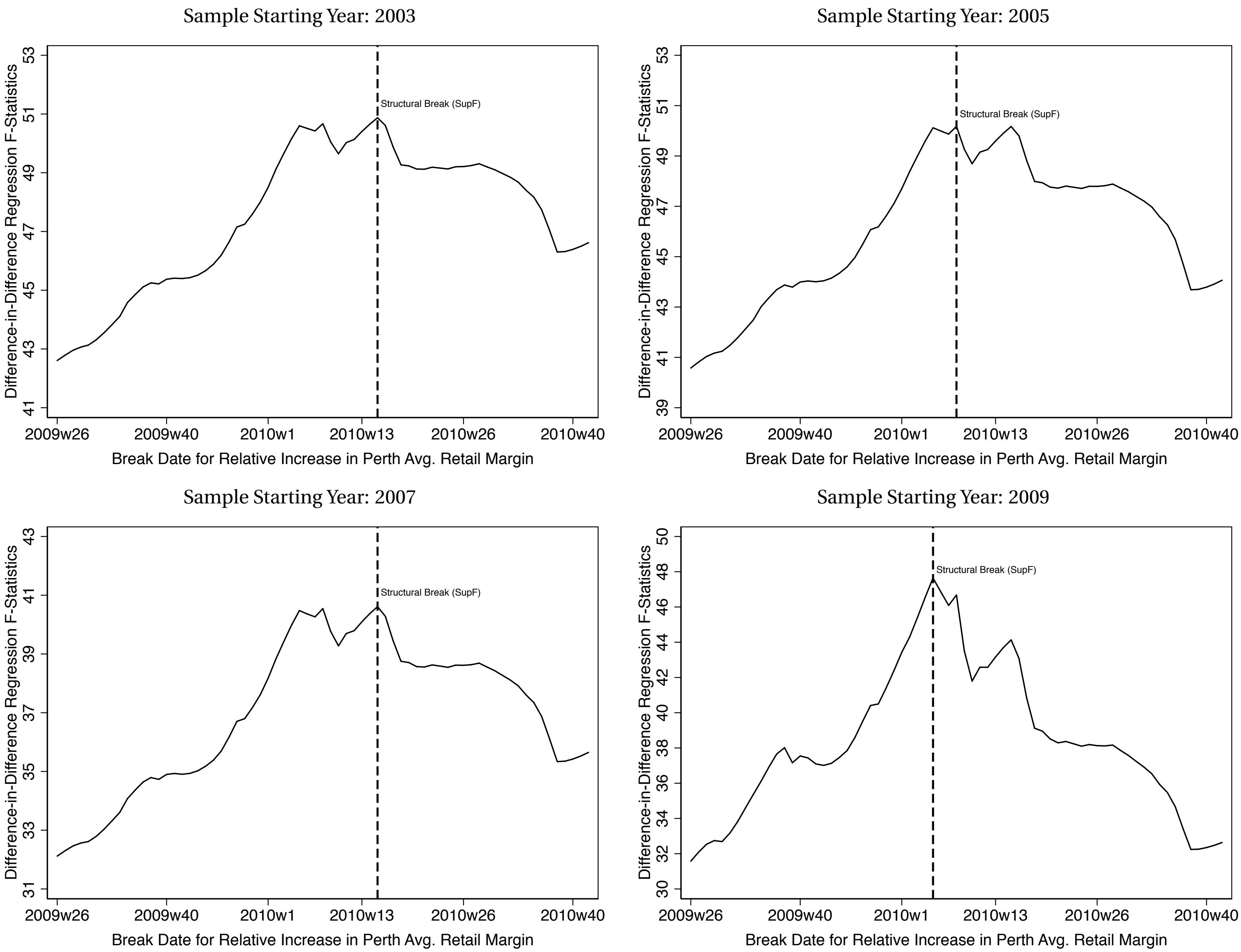


Figure B.6: SupF Tests for Unknown Structural Break (Andrews 1993)



B.4.3 Volume-weighted margins

Our analysis in Section B.4.1 implicitly gives equal weight to margins on each date in identifying and estimating a structural break in Perth's margin. A natural concern in markets with price cycles is that uniform weighting ignores the fact that consumers may engage in inter-temporal price search and limit gasoline purchases on price jump days. Indeed, we find evidence of this in Figures A.2 and A.3 in Appendix A.2 above. Ideally, we would use volume-weighted margins in estimating the break in Perth's margin. Unfortunately, daily, market-level data on gasoline volume sold are not available in Australia.

In light of this data limitation, we compute volume-weighted margins in Perth using the information on daily volumes contained in Figures A.2 and A.3. Recall that these figures are originally sourced from industry reports ACCC (2007) and (2014). Using these graphs, and exact numbers for maximum and minimum shares of gasoline sold by day of the week for each market and year cited in ACCC (2007) and (2014), we construct estimates for the shares of volumes sold by day of the week in 2006-07 and 2013-14. We report these shares for each period in Table B.3.

Using these shares, we weight each day's margin by the share of gasoline sold from Table B.3, and compute a weekly volume-weighted margin for each week and market. Using these margins, we re-estimate our difference-in-difference model from equation (1) above. This allows us to examine the extent to which the use of volume weighted margins affects our estimate of the break in Perth's margin in 2010. For our analysis, we continue to focus on the main sample period of interest, 2009-2014.

For Adelaide, Melbourne and Sydney we use 2006-07 shares for computing volume-weighted margins in 2009. This is supported by Figure B.2 above, which shows that regular weekly cycles with Thursday jumps exist in these markets in 2009. This suggests that weighting margins using 2006-07 shares, an earlier period with regular weekly cycles and Thursday jumps, is appropriate.

Similarly, we use shares for 2013-14 for weighting margins in 2010-2014 in Adelaide, Melbourne and Sydney. In both 2013-14, and the broader 2010-2014 period, Figure B.2 shows cycles are irregular in these markets, and the timing

Table B.3: Average Shares of Gasoline Volumes Sold by Day of the Week

	Period	Price Cycle	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Perth	2006-07	Irregular	13.1	14.1	14.3	15.8	**16.0**	14.8	12.0
	2013-14	Regular	13.0	15.3	**24.0**	14.8	12.0	11.0	10.0
Adelaide	2006-07	Regular	14.6	**24.0**	16.2	11.0	11.8	11.3	11.1
	2013-14	Irregular	14.0	14.8	15.0	**16.0**	15.5	12.3	12.5
Melbourne	2006-07	Regular	14.3	**22.0**	17.1	11.0	12.1	11.9	11.7
	2013-14	Irregular	13.0	14.0	15.0	**16.0**	15.0	14.5	12.5
Sydney	2006-07	Regular	14.7	**21.0**	15.5	11.0	12.6	12.6	12.6
	2013-14	Irregular	13.0	13.5	15.0	**16.0**	15.5	14.5	12.5

Notes: 2006-07 average shares are constructed using data reported in Appendix P of ACCC (2007) and Figures P.1, P.2, P.4 and P.5 in that Appendix. 2013-14 average shares are constructed using data reported in Chapter 8 of ACCC (2014) and Charts 8.4, 8.5, 8.7 and 8.8 from that Chapter. Maximum shares of volume sold for a given period and city are highlighted in bold.

of price jumps is unpredictable. Hence, the shares from 2013-14 are the best available for weighting daily margins in these markets for the 2010-2014 period.

For Perth, we use the shares from 2013-14 in weighting daily margins for both 2009 and 2010-2014. This is also motivated by Figure B.2. The figure shows weekly cycles with regular Thursday jumps start to emerge in Perth in 2009, and eventually become stable in 2010. Hence, for Perth, using shares from 2013-14 with regular weekly cycles and Thursday jumps is likely to be our best available option for both 2009 and 2010-2014.

Panels (i) and (ii) of Figure B.7 presents 3-month moving averages of unweighted and volume-weighted weekly margins for all markets. The figures do not reveal a substantial change in the level or trend in margins in Perth relative to other markets when we instead use volume-weighted margins. The similarity in the figures reflects the fact price jump margins receive similar weights in both figures. In particular, when markets have stable cycles and predictable price jumps, 11 to 15% of volumes sold on average occur on price jump days (see Table B.3). This volume-based weighting of price jump margins when cycles are stable and predictable is not substantially different than applying a simple uniform weighting of 14.3% to price jump margins.

Figure B.7: Average Weekly Margins in Perth, Adelaide, Melbourne and Sydney
(12-Week Moving Averages)

(i) Unweighted Average Weekly Margins (ii) Volume-Weighted Average Weekly Margins

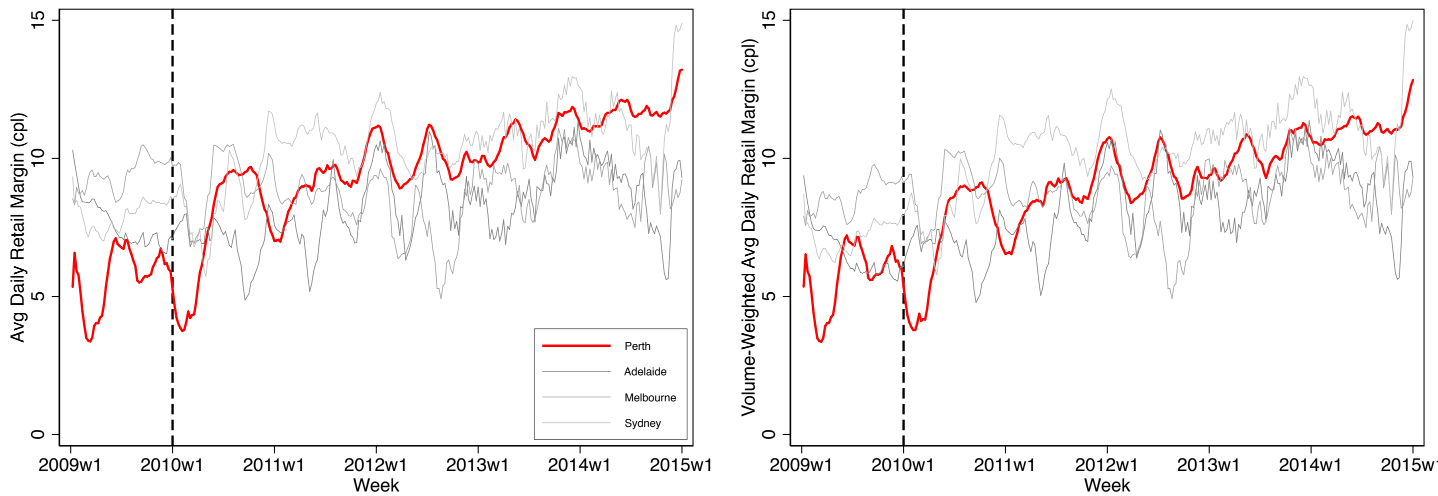


Table B.4 reports our difference-in-difference estimates of the break in Perth's margin in 2010. All of these results assume a break date T of 2010 week 9.[9] Column (1) reproduces our unweighted margins estimate of 3.49 cpl for the break in Perth's margin. Column (2) shows that using volume-weighted margins indeed reduces this estimate to 2.66 cpl. However, the break remains statistically significant, and economically large. Indeed, the 2.66 cpl relative increase in Perth's weighted average margin after 2010 is 45% of its 2009 volume-weighted average margin of 5.85 cpl.

As a final check, we instead weight Perth's daily margins in 2009 according to its daily shares of volumes sold from 2006-07. Given shares of volumes sold are more uniformly distributed across days of the week in 2006-07, this puts more weight on price jump margins in 2009 compared to using volume-weighted margins based on 2013-14 data. Therefore, by weighting 2009 margins by 2006-07 shares, and weighting 2010-2014 margins by 2013-14 shares, we obtain the lowest possible growth rate of weighted margins before and after 2010 for Perth. In

[9] All of our findings based on volume-weighted margins are robust to varying the break date, as they were above with unweighted margins.

Table B.4: Difference-in-Difference Estimates of the Change in Perth's Margin in 2010

		Volume Weighted Margins	
	Unweighted Margins	Best Estimate	Most Conservative
	(1)	(2)	(3)
$1\{Post\ T\}_t \times 1\{Perth\}_i$	3.49	2.66	2.34
	(0.39)	(0.38)	(0.39)
$1\{Post\ T\}_t$	4.96	8.29	8.37
	(3.82)	(4.41)	(4.42)
Perth	-2.26	-1.83	-1.51
	(0.37)	(0.36)	(0.38)
Adelaide	-0.44	-0.47	-0.47
	(0.26)	(0.26)	(0.26)
Sydney	1.88	1.89	1.89
	(0.24)	(0.24)	(0.24)
R-Squared	0.41	0.43	0.43
Observations	1456	1456	1456

Notes: Outcome variable is average weekly retail gasoline margin in cents per litre. Margins in the first column correspond to unweighted average daily margins week-to-week. Margins in the second column correspond to average daily margins weighted by volumes sold by day of the week. See the text for discussion of volumes data and weighting. The break date for the change in margins is set to T=Week9_2010. Robust standard errors reported in parentheses. The sample includes all weeks between the stated starting year at the top of the table through to 2015 (inclusive).

words, this weighting scheme assumes: (1) naive Perth shoppers for all of 2009 who do not time purchases to avoid price jumps; and (2) immediately sophisticated Perth shoppers in 2010 who more frequently time their purchases to avoid price jumps according to the long-run daily volume shares that emerge by 2013-14 in Figure A.3. Weighting Perth's margins in this way thus yields the most conservative difference-in-difference estimate of the break in Perth's margin, given the available information on daily volumes of gasoline sold. Panel (3) of Table B.4 shows this most conservative estimate of the break remains statistically significant and economically large at 2.34 cpl.

C Aggregate shocks and BP price leadership: Mar 2004-Apr 2009

At the start of Section 4, we state that BP is an established price leader by 2010. This is because BP reinitiates the cycle after it collapses following Coles's entry into gasoline retailing (2004), Hurricanes Katrina and Rita (2005), and a global crude oil price shock (2008-09). In this Appendix, we describe these cycle collapses, and show how BP reinitiates the cycle through price leadership.

C.1 Coles entry

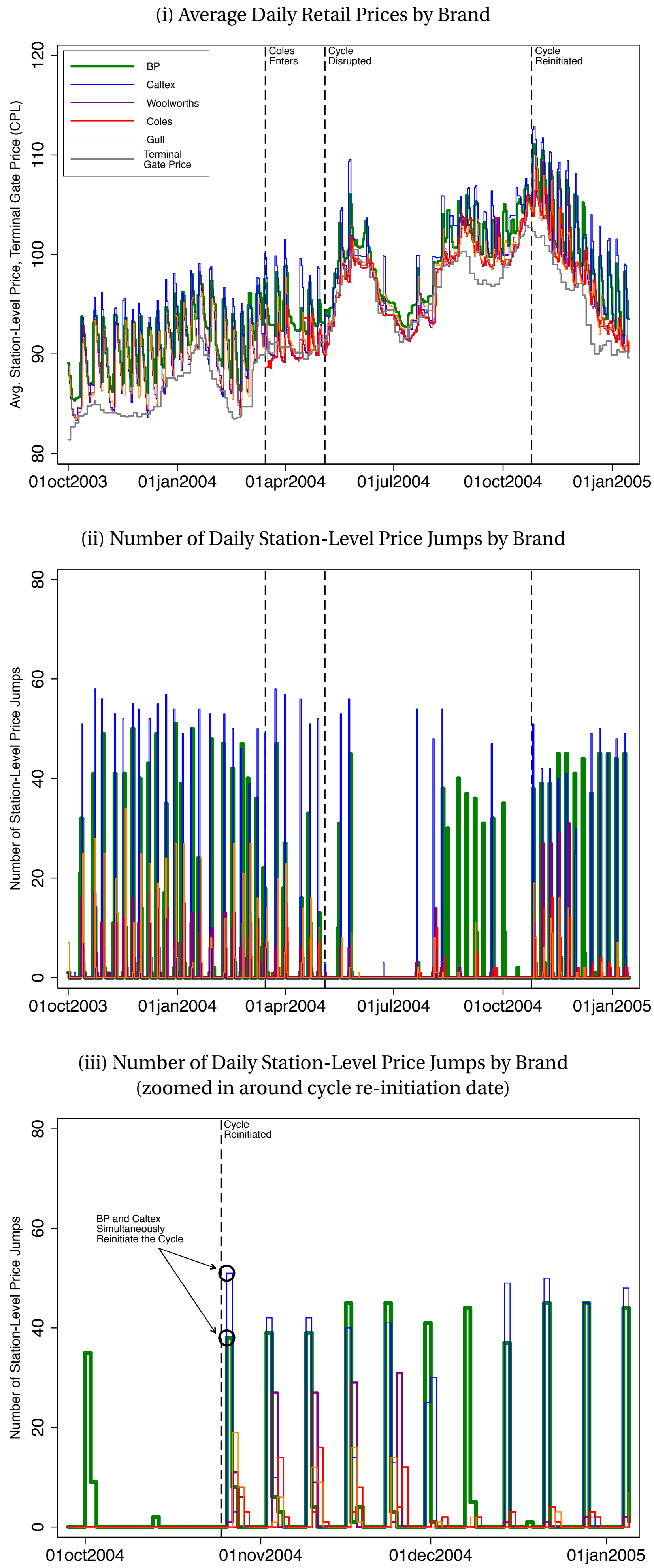
Figure C.1 depicts cycle collapses and BP's and Caltex's roles in reinitiating the cycle. Panel (i) plots the average daily retail price for each retailer. The figure also highlights Coles's entry into gasoline retailing on March 15, 2004. As the figure shows, six weeks after Coles's entry, the cycle begins to destabilize. It eventually collapses in June 2004. Between June and September 2004, the cycle remains disrupted. However, starting in September 2004, an unstable cycle exhibits signs of restarting. By November 2004 a stable cycle is re-initiated.

Underlying the period of cycle instability is the fact that Coles fails to coordinate on price jumps. Indeed, the daily average retail prices for Coles (the red line in panel (i)) track closely with the wholesale terminal gate price. In contrast, BP and Caltex repeatedly engage in price jumps between June and September 2004. This is illustrated by the spikes in the green and blue lines in panel (i).

Panel (ii) of Figure C.1 plots, by retailer, the number of daily station-level price jumps over the same period.[10] The green and blue spikes in the figure show BP and Caltex consistently engaging in price jumps to coordinate the cycle prior to Coles entry. During the period when the cycle destablizes and collapses, both Caltex and BP attempt to restart the cycle, often in mutually exclusive weeks. Panel (ii) shows, however, that the two retailers fail to coordinate on a stable cycle with Woolworths, Coles, Gull until November 2004.

[10] Recall the definition of a daily station-level price jump from Definition 1(i) in the paper: a *station-level price jump* occurs at station i on date t if $\Delta p_{it} \geq 6$ cpl, where p_{it} is the retail price and $\Delta p_{it} = p_{it} - p_{it-1}$.

Figure C.1: Coles Entry: Cycle Collapse and Reinitiation



Panel (iii) is analogous to panel (ii), except that it zooms in around November 2004, when the cycle is reinitiated. It shows that BP and Caltex eventually *simultaneously* coordinate on a cycle at the start of November after multiple failed attempts by BP to reinitiate the cycle in September 2004. From this point onward, BP and Caltex simultaneously lead price cycles each week. The other retailers, including Coles, exhibit a willingness to follow BP's and Caltex's lead, and a stable cycle is established.

C.2 Hurricanes Katrina and Rita

Figure C.2 describes cycle breakdown and reinitiation following Hurricanes Katrina and Rita. Panels (i) and (ii) highlight the date that Hurricane Katrina landed in the Gulf of Mexico (August 25, 2005). Hurricane Rita landed three weeks later on September 15, 2015. For the sake of brevity, we do not mark this latter event in Figure C.2.

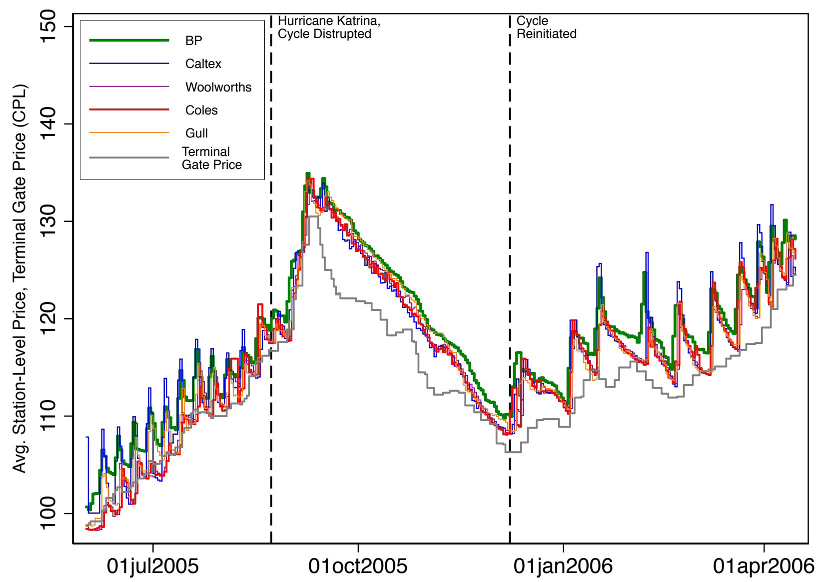
As a result of the Hurricanes-induced supply shock to world oil prices, there is a large jump in the terminal gate price from 120 cpl to 135 cpl between August and September 2005. As panel (i) shows, from this peak, terminal gate prices fall substantially between September and December 2005, reaching a low of 108 cpl. During this entire period the price cycle collapses. The price cycle restarts after world oil prices stabilize in December 2005.

Panel (ii) plots the number of daily price jumps by retailer over this period. The figure shows that during the period when the cycle collapses between September and December 2005, none of the retailers attempt to reinitiate the cycle through price jumps. The exception is two failed attempts by BP to reinitiate the cycle immediately after Hurricane Katrina. This is illustrated in panel (ii) by the green spikes that peak at 18 and 19 stations in September 2005.

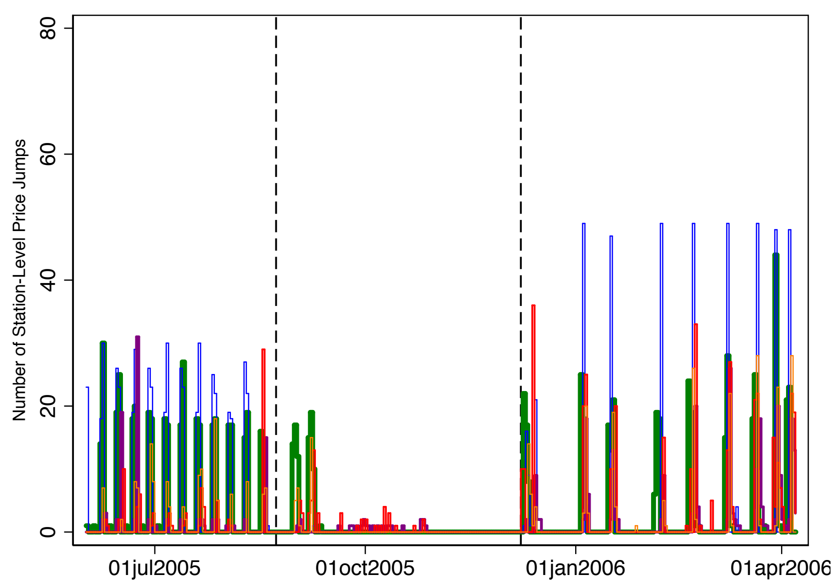
Zooming in around December 2005 in panel (iii), we see that BP is the price leader who reinitiates the cycle. The figure also shows how, from the initial BP-led cycle in December 2005, BP leads four additional cycles between January and March 2006. At this point BP is coordinating the market on a two-week cycle.

Figure C.2: Hurricanes Katrina and Rita: Cycle Collapse and Reinitiation

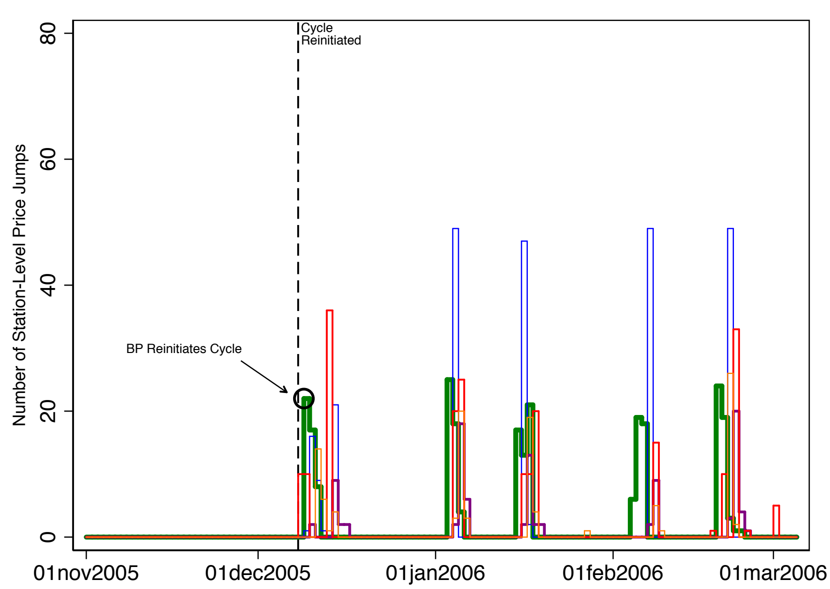
(i) Average Daily Retail Prices by Brand



(ii) Number of Daily Station-Level Price Jumps by Brand



(iii) Number of Daily Station-Level Price Jumps by Brand
(zoomed in around cycle re-initiation date)



C.3 Global crude oil price shock

The final cycle-collapsing shock is the 2008-09 global crude oil price shock.[11] Figure C.3 describes cycle collapse, reinitiation and price leadership following this shock.

Panel (i) shows that the shock leads to a cycle collapse in April 2008. From this point until April 2009, the cycle is highly unstable or completely collapsed. Wholesale price volatility is substantial during this period: the terminal gate price falls from a high of 155 cpl in August 2008 to a low of 95 cpl in December 2008. After this volatility settles, a stable cycle emerges in April 2009.

Panel (ii) shows that during the period of cycle and wholesale cost instability, there are multiple failed attempts by both BP and Caltex to reinitiate the price cycle. This is illustrated in panel (ii) by the green and blue spikes between April 2008 and April 2009.

Zooming in around April 2009 in panel (iii), we see that BP reinitiates a weekly price cycle. Panel (iii) further shows from April 2009 onwards, BP is the market leader in coordinating price jumps week-to-week. As discussed in Section 4.1 of the paper, April 2009 is precisely the point where BP starts engaging in Wednesday price jump leadership. Its rivals follow with price jumps on both Thursdays and Fridays during this period of BP-led cycle re-initiation.

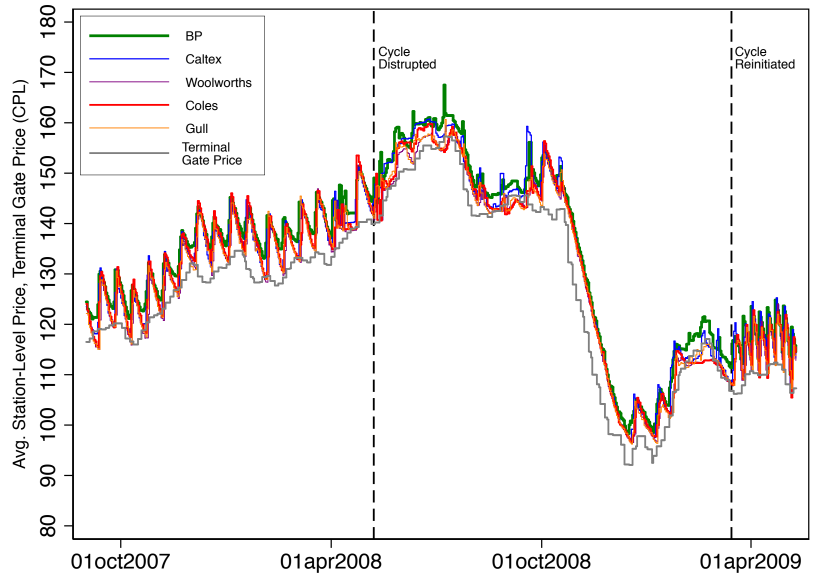
C.3.1 Summary

This Appendix has provided a detailed analysis of the first contextual factor of note in 2010: BP is an established price leader in coordinating rivals' pricing on a cycle. Following Coles's entry, Hurricanes Katrina and Rita and the global crude oil price shock, BP always emerges as a price leader in reinitiating the cycle.

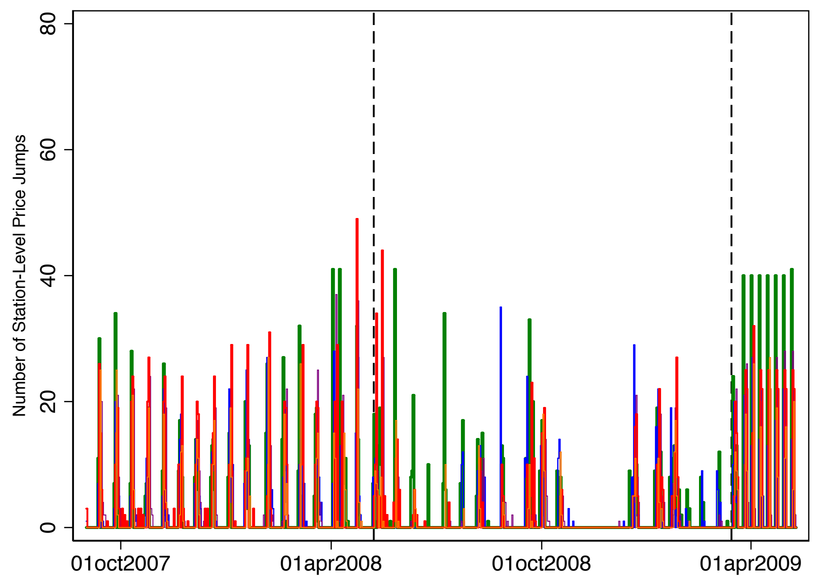
[11]While there is not a definitive date for when this shock occurs, Hamilton (?) identifies the shock period as running from 2007Q3 to 2008Q3. He identifies an unexpected fall in Chinese oil demand, combined with the growth in speculative trading on world oil prices, as the main drivers of this shock. As Hamilton discusses, these factors contributed to generating one of the largest oil price shocks in history.

Figure C.3: Crude Oil Price Shock: Cycle Collapse and Re-initiation

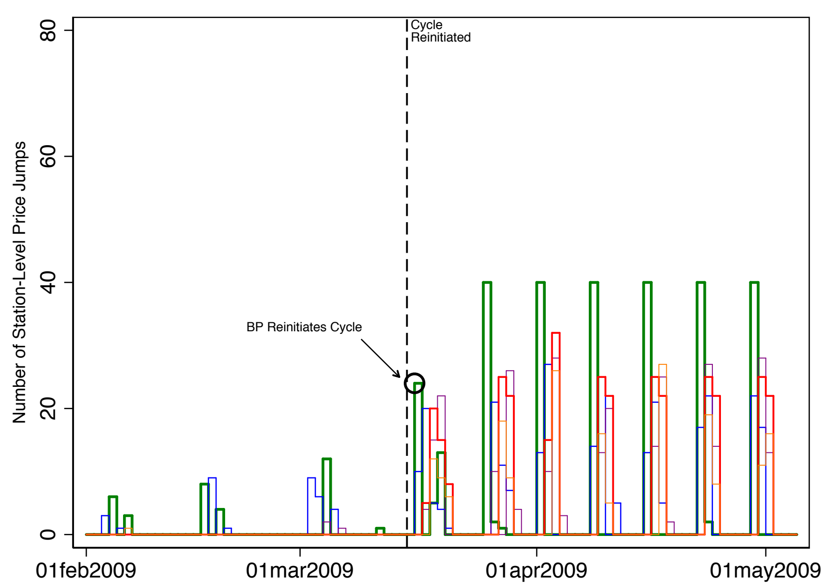
(i) Average Daily Retail Prices by Brand



(ii) Number of Daily Station-Level Price Jumps by Brand



(iii) Number of Daily Station-Level Price Jumps by Brand
(zoomed in around cycle re-initiation date)



D BP-Caltex price war: Apr 2009 - Jan 2010

Having re-initiated the price cycle in April 2009 (see Appendix C.3), BP would soon find itself in a price war with Caltex. In this Appendix, we describe the war with Figures D.1 and D.2. Figure D.1 plots daily average prices across BP, Caltex, Woolworths, Coles and Gull stations between April 2009 and June 2010. Figure D.2 plots, for each week and retailer, the day of the week where the most station-level price jumps occur. This figure therefore highlights how the timing of retailers' price jumps evolves between April 2009 and July 2010.[12]

Panels (i) of Figures D.1 and D.2 reveal a stable price cycle between April and August 2009. During these months, BP leads price jumps on Wednesdays and its rivals follow on Thursdays. That is, there is a one day gap between BP's and its rivals' main price jump day.

This gap widens to two days starting in August 2009. Panel (ii) of Figure D.1 shows Caltex starts delaying its weekly price jump to Fridays in August 2009. The figure further shows that the other retailers, except BP, quickly follow Caltex and engage in Friday jumps. Panels (ii) and (iii) of Figure D.2 shows this two day gap in price jump timing between BP and Caltex stations persists for four months until December 2009. Despite BP being exposed for *two days* as a price leader during the August to December 2009 period, the cycle remains stable.[13]

Panel (iii) of Figure D.2 shows BP's eventual reaction to Caltex's persistent Friday jumps: in December 2009, it starts matching Caltex on Friday jumps in December 2009. In fact, panels (iii) and (iv) of the figure show that BP matches Caltex's main price jump day week-to-week for two months between December 2009 and January (2010).

We interpret this as a form of "negotiation through prices" that eventually leads to conflict resolution between BP and Caltex. More specifically, by match-

[12]For brevity, we only present plots for BP and Caltex in Figure D.2 since all other retailers follow the timing of Caltex's price jumps week-to-week.

[13]Being exposed as a two day price leader is likely extremely costly for BP. This is because, under the Fuelwatch 24-hour rule, BP is exposed for 48 hours as a price jump leader with prices that are 10-15% above average prices in the market. Given local demand elasticities between gasoline stations are on the order of 15 (Clark and Houde, 2013), this defection by Caltex and the other rival stations is likely very costly to BP in terms of lost revenue

ing Caltex on the timing of price jumps, BP signals a desire to engage in cyclical pricing, but an unwillingness to be exposed as a two day price leader. Panels (iii) and (iv) of Figure D.1 shows that during this negotiation process, absent BP price jump leadership, the cycle is unstable or collapsed.

In the last week of January 2010, BP again attempts to lead price jumps on Wednesdays. This immediate and persistent return to Wednesday jumps by BP is clear in panel (iv) of Figure D.2. Panel (iv) further shows that despite BP's return to Wednesday jumps, Caltex continues to persist with Friday jumps. Panel (iv) of D.1 shows, however, that the cycle begins to stabilize over this period. Despite this, BP continues to be exposed as a two day price jump leader.

Finally, panels (v) of Figures D.1 and D.2 show how the war is eventually resolved. In these panels, we overlay Gap 1. Recall from Section 4.1 of the paper that this is a week where BP breaks from Wednesday jumps for a single week, and instead engages in Thursday jumps with its entire station network. As we discuss in the paper, Gap 1 is a key week for the coordinated transition toward an equilibrium with Thursday jumps and 2 cpl cuts. Through Gap 1, BP communicates to the market, through its prices, that jumps are to take place on Thursdays. Such communication is effective as BP's rivals immediately shift to Thursday jumps the following week. Panels (v) of Figures D.1 and D.2 illustrate this dynamic, and persistent transition to an equilibrium with BP Wednesday price jump leadership and Thursday jumps by its rivals.

Figure D.1: BP-Caltex Price War of 2009-10
(Average Daily Station-Level Prices by Brand)

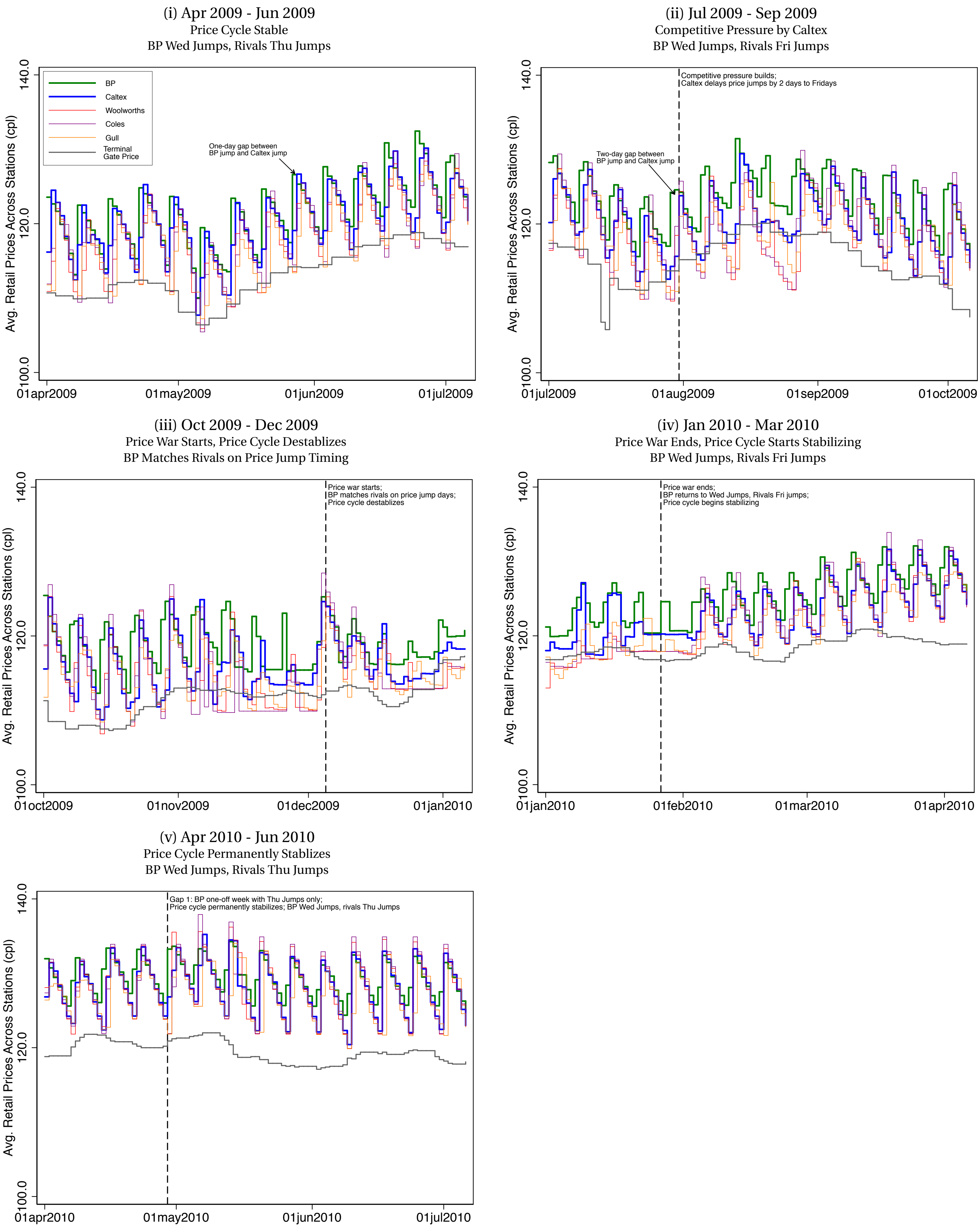
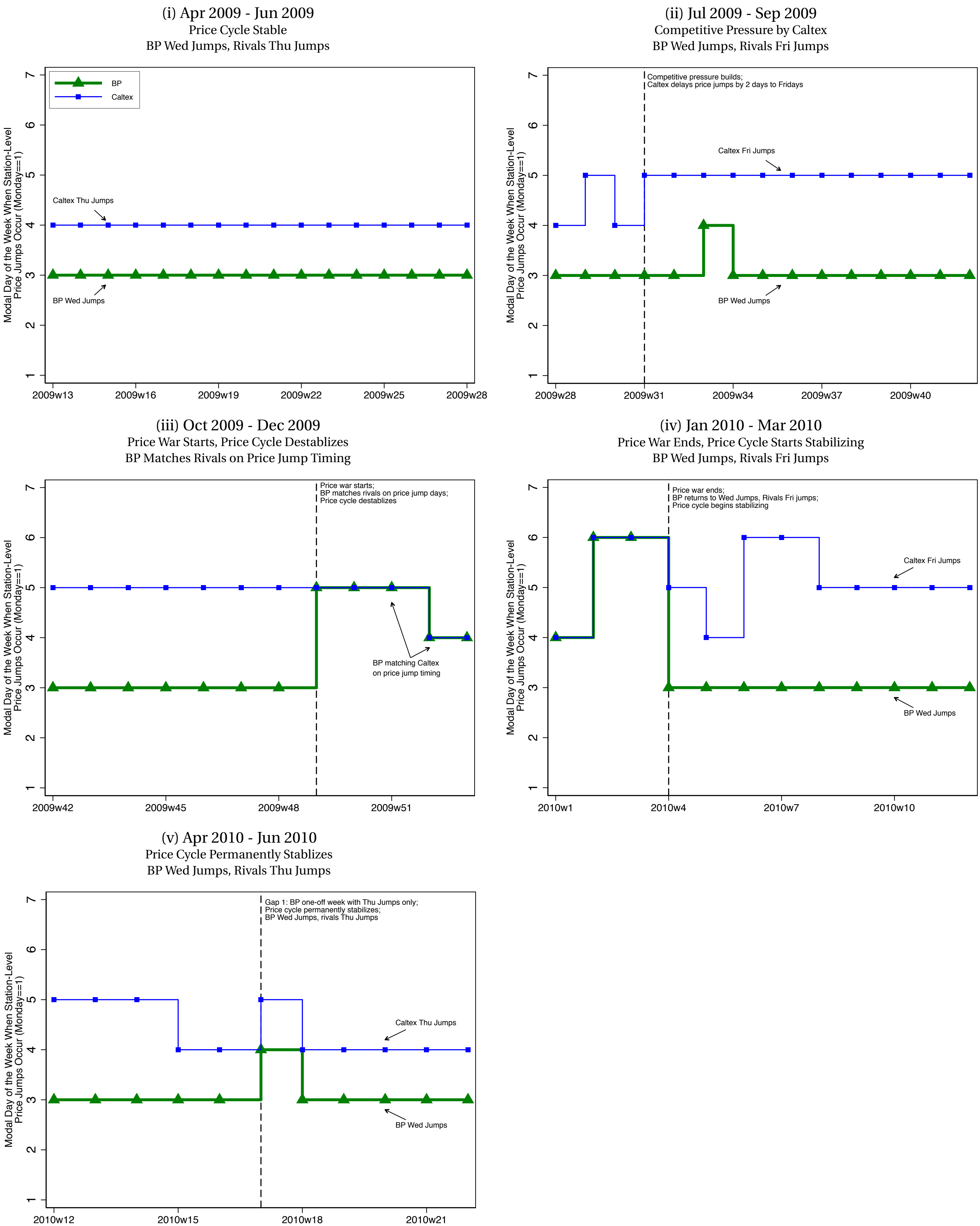


Figure D.2: BP-Caltex Price War of 2009-10
(Modal Station-Level Price Jump Day of the Week by Week and Brand)



E Characterizing cycling stations and price jump leading BP stations

E.1 Cycling and non-cycling stations

In the paper, we classify stations as either being cycling or non-cycling . Definition 1(v), which we re-state here, classifies cycling stations:

Definition 1

(v) Station i is a *cycling station* in year y if $\Delta p_{it} \geq 6$ cpl at least 15 times in year y.

In words, station i is *cycling* in year y if it engages in 15 or more daily station-level price increases of $\Delta p_{it} \geq 6$ cpl in year y. In this Appendix, we examine the characteristics of cycling and non-cycling stations.

E.1.1 Engagement in price cycles

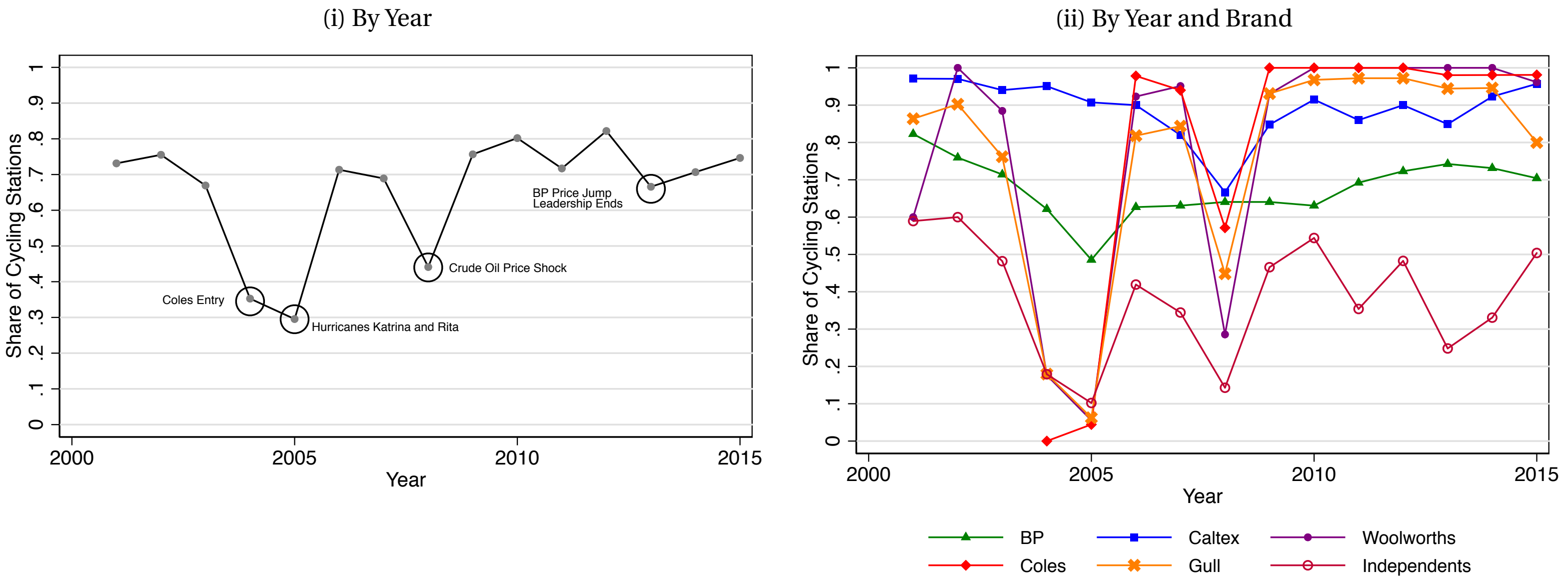
We start by examining stations' propensity to engage in cyclical pricing. Panel (i) of Figure E.1 plots the share of cycling stations year-to-year. This share ranges from 30% in 2005 to 82% in 2012. On average, 65% of stations engage in price cycles year-to-year. Omitting years with aggregate shocks that cause cycle collapses,[14] we find 74% of stations are cycling on average.

Panel (ii) of Figure E.1 breaks down the share of cycling stations by retailer type. We find that the largest two firms, BP and Caltex, have stable shares of cycling stations in years with aggregate shocks. In contrast, other retailers exhibit large drops in station-level cycling propensities following aggregate shocks.

Panel (ii) further shows that from 2010 onward, when Thursday jumps and 2 cpl cuts are established as focal pricing rules, more than 95% of Coles, Woolworths and Gull stations are cycling year-to-year on average. 70% and 90% of BP and Caltex stations are engaged in price cycles on average after 2010.

[14] We omit 2004 (Coles's Entry), 2005 (Hurricanes Katrina and Rita) and 2008 (global crude oil price shock). See Appendix C for a detailed analysis of aggregate shocks and cycle collapses.

Figure E.1: Share of Stations Engaged in Cyclical Pricing



The cycling shares of other independent stations in panel (ii) provide an interesting contrast. After 2010, 41% of these stations are cycling year-to-year on average. Moreover, there is no discernible trend in the share of cycling stations among independents after 2010 despite the emergence of Thursday jumps and 2 cpl cuts focal pricing rules. That is, independents tend to maintain their non-cyclical pricing conduct despite the emergence of a standardized price cycle.

E.1.2 Characteristics of cycling and non-cycling stations

Beyond retailer type, do any other station-level characteristics predict cycling status? We first consider a station's geographic location. Panels (i)-(iv) of Figure E.2 present maps that highlight the locations of cycling and non-cycling stations across Perth. Each panel corresponds to a year without aggregate shocks when price cycles are stable: 2002, 2006, 2010, and 2014. Visual inspection does not suggest that cycling stations are located in particular parts of the city.

Figure E.2: Locations of Cycling and Non-Cycling Stations: 2002, 2006, 2010, 2014

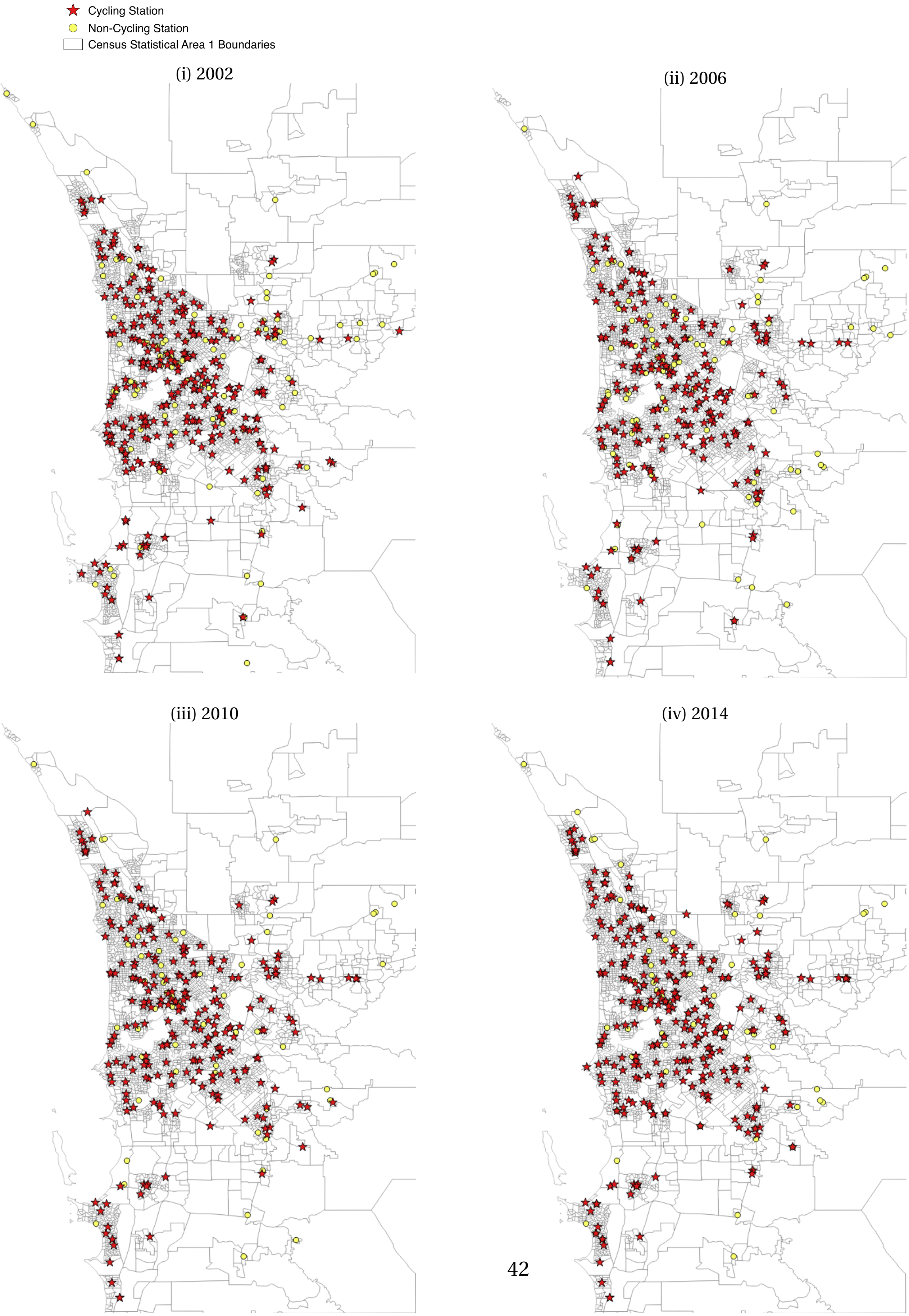


Figure E.3: Share of Stations Engaging in Cycles by Distance From the City Center: 2002, 2006, 2010, 2014

(i) Distance Deciles

(ii) Distances Quintiles

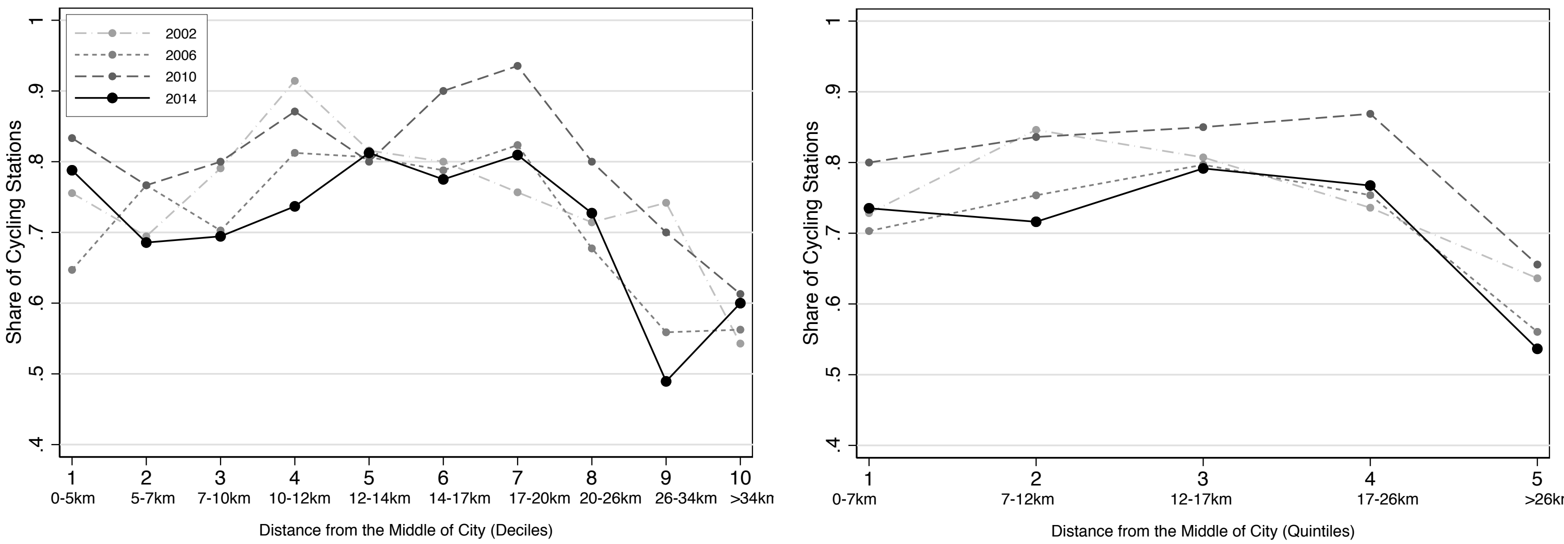


Figure E.3 plots, by distance from city center and year, the fraction of stations engaged in cyclical pricing. Panel (i) is based on distance deciles, while panel (ii) is based on distance quintiles.[15] Both panels indicate that stations above the 20^{th} percentile of the distribution of the distance from the city center, which are located more than 26 kilometers from the city center, exhibit between an 11% to 24% percentage point drop in propensity to engage in price cycles across the four sample years considered.

Regression analysis. We use Linear-in-Probability Models (LPM) to examine whether retailer type, geographic location, local market structure and demographics predict cycling status.[16] Table E.1 provides summary statistics for the local market structure and demographic variables that we use. The local market

[15] We construct the deciles and quintiles based on the distribution of station locations in 2010. We hold fixed the distance bands from city center in each year to facilitate cross-year comparisons of cycling propensities by proximity to the city's core. Allowing the distance deciles or quantiles to vary year-to-year do not change our main results.

[16] Probit and logit models yield similar results.

structure variables include station i's nearest neighbor and the number of stations within 2km and 5km distance bands. We also construct variants on these local market structure measures based on oil major stations, independent stations, and stations that are the same retailer type as station i.

The demographics variables are collected from the Australian Bureau of Statistics (ABS). These correspond to data collected from the 2011 Census and are at the "Statistical Area 1" (SA1) census block level.[17] We match each station to its corresponding SA1 and use the SA1-level variables to characterize local demographics around each station. We collect demographic data on income, age, education, employment, and place of birth. In addition, we collect data on households' primary modes of transportation, vehicle stock and housing type.[18]

With these covariates, we estimate the following LPM model:

$$1\{\text{Cycling}\}_{iy} = \mathbf{d}_i\delta^y + \mathbf{r}_{iy}\eta^y + \mathbf{m}_{iy}\gamma^y + \mathbf{x}_i\beta^y + \epsilon_{iy} \tag{2}$$

where $1\{\text{Cycling}\}_{iy}$ equals 1 if station i is cycling in year y and is 0 otherwise. The covariates include a vector of distance-from-center-of-city quintile dummy variables $\mathbf{d}_i$, retailer dummies for BP, Caltex, Woolworths, Coles, Gull and Independents $\mathbf{r}_{iy}$, local market structure variables $\mathbf{m}_{iy}$, and demographic variables $\mathbf{x}_i$. The regression coefficients have y superscripts as we estimate LPMs for years $y = 2002, 2006, 2010, 2014$.

[17] From the ABS, SA1s are narrowly-defined geographies that on average have 400 individuals living in them. Figure E.2 depicts the SA1 boundaries around Perth. The large SA1s in the rightmost part of the maps correspond to sparse populations toward the center of Australia. For more information on SA1s see `http://www.abs.gov.au/`.

[18] Unfortunately, station characteristic data such as the number of pumps, convenience store, car garage, car warsh and so forth are not available for all retailers. In our retailer-specific analyses of cycling stations in Section E.1.3 below, we use information on whether a BP or Caltex station has a convenience store. We have such information for BP and Caltex stations only.

Table E.1: Characteristics of Cycling and Non-Cycling Stations

	2002			2006			2010			2014		
	Cyc	Non-Cyc	Diff.	Cyc	Non-Cyc	Diff.	Cyc	Non-Cyc	Diff.	Cyc	Non-Cyc	Diff.
(A) Local Market Structure												
Distance from City Center (km)	15.37	16.42	-1.05	15.50	18.66	-3.16	15.71	18.08	-2.37	16.03	16.79	-0.76
			1.54			1.54			2.03			1.36
Distance to Nearest Station	1.01	2.10	-1.08	1.04	1.76	-0.72	1.10	1.34	-0.24	1.26	0.87	0.38
			0.47			0.46			0.48			0.40
Number of Stations Within 2 km	2.15	0.91	1.24	2.07	0.90	1.17	2.09	0.86	1.23	2.51	1.04	1.47
			0.27			0.27			0.27			0.17
Number of Stations Within 5 km	12.18	5.46	6.72	11.64	5.30	6.34	11.53	5.46	6.06	14.07	5.49	8.58
			1.39			1.29			1.47			0.90
Distance to Nearest Oil Major Station	1.73	2.95	-1.23	1.74	3.66	-1.92	1.84	2.45	-0.61	2.25	1.87	0.38
			1.07			0.76			0.65			0.59
Number of Oil Major Stations Within 2 km	0.82	0.31	0.50	0.79	0.30	0.49	0.84	0.31	0.53	0.89	0.44	0.45
			0.10			0.12			0.11			0.07
Number of Oil Major Stations Within 5 km	4.86	2.19	2.68	4.68	2.08	2.60	4.83	2.28	2.55	5.60	2.28	3.32
			0.56			0.52			0.57			0.36
Distance to Nearest Independent Station	1.39	2.27	-0.89	1.44	2.17	-0.73	1.44	1.93	-0.48	1.57	1.43	0.14
			0.49			0.52			0.72			0.42
Number of Independent Stations Within 2 km	1.24	0.57	0.67	1.17	0.53	0.65	1.12	0.50	0.62	1.39	0.49	0.90
			0.17			0.12			0.11			0.07
Number of Independent Stations Within 5 km	6.87	3.11	3.76	6.38	2.98	3.40	6.02	2.89	3.13	7.21	2.55	4.66
			0.80			0.47			0.45			0.26
Distance to Nearest Same Brand Station	2.01	1.79	0.22	2.13	1.52	0.61	2.22	1.32	0.90	3.17	1.27	1.90
			0.55			0.61			1.06			0.49
Number of Same Brand Stations Within 2 km	0.24	0.06	0.17	0.21	0.11	0.11	0.23	0.10	0.12	0.30	0.10	0.20
			0.05			0.06			0.05			0.03
Number of Same Brand Stations Within 5 km	1.82	0.62	1.20	1.65	0.98	0.67	1.69	0.89	0.80	2.17	0.74	1.43
			0.27			0.24			0.28			0.15
(B) Demographics												
People Per Square Kilometer	1604.47	1302.31	302.16	1565.81	1339.57	226.24	1562.60	1281.79	280.81	1556.17	1469.60	86.57
			146.66			156.87			155.14			127.53
Median Household Income ($)	1303.31	1311.17	-7.86	1312.60	1383.83	-71.23	1343.44	1309.06	34.38	1347.09	1379.94	-32.85
			76.02			81.00			125.80			100.16
Median Age	37.14	37.74	-0.60	37.01	37.69	-0.68	36.45	38.86	-2.41	36.68	37.34	-0.66
			1.12			1.18			1.44			1.24
Median Number of People in Home	2.19	2.24	-0.06	2.20	2.33	-0.13	2.21	2.31	-0.10	2.24	2.24	-0.00
			0.09			0.09			0.12			0.09
Median Weekly Rent ($)	275.53	295.06	-19.52	277.72	306.24	-28.51	285.41	276.15	9.26	284.50	286.57	-2.07
			14.41			16.09			20.72			15.66
Median Monthly Mortgage Payment ($)	1694.74	1887.64	-192.90	1715.46	1878.38	-162.92	1730.40	1792.42	-62.02	1750.97	1753.08	-2.11
			89.48			97.77			123.37			96.25
Total Population	400.35	400.97	-0.62	403.79	399.65	4.14	405.68	396.00	9.68	398.69	411.23	-12.54
			22.20			21.94			25.95			22.65
18-65 Years Old	63.71	64.24	-0.53	63.72	65.83	-2.10	64.04	64.02	0.02	63.29	64.31	-1.02
			0.02			0.02			0.02			0.02
65+ Years Old	14.81	15.13	-0.32	14.56	14.10	0.47	13.68	16.11	-2.43	14.09	14.46	-0.37
			0.01			0.01			0.01			0.01
FT Unemployment Rate	8.66	8.23	0.43	8.51	8.36	0.15	8.26	9.14	-0.89	8.62	8.40	0.22
			0.01			0.01			0.02			0.01
FT and PT Unemployment Rate	8.53	8.12	0.41	8.44	8.08	0.36	8.29	8.40	-0.11	8.55	8.19	0.36
			0.01			0.01			0.01			0.01

Notes: Robust standard error of the difference in means between cycling and non-cycling markets below the differences in means.

Characteristics of Cycling and Non-Cycling Stations (Continued)

	2002			2006			2010			2014		
	Cyc	Non-Cyc	Diff.	Cyc	Non-Cyc	Diff.	Cyc	Non-Cyc	Diff.	Cyc	Non-Cyc	Diff.
(C) Modes of Transportation												
% of People Whose Main Mode of Transportation to Work is …												
Train	3.31	3.57	-0.26	3.15	3.75	-0.60	3.10	3.13	-0.02	2.71	3.48	-0.77
			0.01			0.00			0.01			0.00
Bus	4.94	4.26	0.68	4.80	4.34	0.46	4.60	4.70	-0.10	4.15	4.91	-0.76
			0.01			0.01			0.01			0.01
Ferry	0.04	0.04	-0.00	0.04	0.04	0.00	0.05	0.04	0.01	0.07	0.02	0.05
			0.00			0.00			0.00			0.00
Tram	0.02	0.00	0.02	0.01	0.01	-0.00	0.01	0.01	0.00	0.00	0.03	-0.03
			0.00			0.00			0.00			0.00
Taxi	0.29	0.17	0.11	0.30	0.15	0.15	0.30	0.20	0.10	0.26	0.25	0.01
			0.00			0.00			0.00			0.00
Car	77.14	76.62	0.52	77.49	78.67	-1.17	77.08	80.11	-3.03	78.34	76.57	1.77
			0.03			0.03			0.04			0.03
Bike	1.40	1.82	-0.42	1.39	1.67	-0.28	1.34	1.43	-0.09	1.25	1.46	-0.21
			0.00			0.00			0.00			0.00
			(0.01)			(0.02)			(0.03)			(0.02)
(D) Vehicle Stock												
% of Households Who Own …												
0 Vehicles	7.58	8.18	-0.61	7.49	6.76	0.72	7.18	7.05	0.13	6.31	7.68	-1.37
			0.01			0.01			0.01			0.01
1 Vehicle	33.66	33.66	-0.00	33.37	34.11	-0.74	32.97	34.00	-1.03	31.29	34.41	-3.12
			0.02			0.02			0.03			0.02
2 Vehicles	33.09	33.77	-0.68	33.36	35.15	-1.79	33.84	33.85	-0.01	34.74	33.85	0.89
			0.02			0.02			0.02			0.02
3 Vehicles	9.97	10.76	-0.79	10.16	11.63	-1.47	10.23	11.35	-1.12	10.40	10.71	-0.31
			0.01			0.01			0.01			0.01
4+ Vehicles	6.18	7.14	-0.96	6.22	8.06	-1.84	6.30	8.15	-1.85	6.99	6.63	0.36
			0.01			0.01			0.01			0.01
(E) Housing Stock												
% of Households Who Live In A/An …												
Free-standing House	54.60	62.55	-7.95	54.90	64.96	-10.06	54.85	63.60	-8.75	57.69	57.13	0.57
			0.04			0.04			0.05			0.04
Townhouse	12.63	10.39	2.24	12.42	8.62	3.80	11.99	9.19	2.80	8.93	11.65	-2.73
			0.02			0.02			0.02			0.02
Apartment/Flat	11.35	8.71	2.64	11.04	9.77	1.27	11.25	9.26	1.99	10.50	11.16	-0.66
			0.02			0.02			0.03			0.02
Number of Observations		380			330			303			303	

Notes: Robust standard error of the difference in means between cycling and non-cycling markets below the differences in means.

Table E.2: Linear Probability Models that Predict Cycling Station Status

	2002			2006			2010			2014		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Distance from city center (quintiles)												
7-12km	0.12	0.12	0.12	0.05	0.07	0.07	0.04	0.05	0.05	-0.02	0.01	0.01
	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.08)	(0.06)	(0.06)
12-17km	0.08	0.08	0.08	0.09	0.06	0.06	0.05	0.03	0.03	0.06	0.03	0.03
	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
17-26km	0.01	-0.01	-0.01	0.05	0.11	0.11	0.07	0.10	0.10	0.03	0.08	0.08
	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
>26km	-0.09	-0.07	-0.07	-0.14	-0.02	-0.02	-0.14	-0.07	-0.07	-0.20	-0.07	-0.07
	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
Retailer												
BP		0.15	0.15		0.19	0.19		0.06	0.06		0.38	0.38
		(0.06)	(0.06)		(0.08)	(0.08)		(0.09)	(0.09)		(0.07)	(0.07)
Caltex		0.36	0.36		0.47	0.47		0.35	0.35		0.58	0.58
		(0.04)	(0.04)		(0.07)	(0.07)		(0.07)	(0.07)		(0.06)	(0.06)
Woolworths		0.39	0.39		0.48	0.48		0.43	0.43		0.65	0.65
		(0.04)	(0.04)		(0.07)	(0.07)		(0.06)	(0.06)		(0.04)	(0.04)
Coles		0.00	0.00		0.55	0.55		0.43	0.43		0.63	0.63
		(.)	(.)		(0.06)	(0.06)		(0.06)	(0.06)		(0.05)	(0.05)
Gull		0.30	0.30		0.41	0.41		0.42	0.42		0.61	0.61
		(0.06)	(0.06)		(0.08)	(0.08)		(0.07)	(0.07)		(0.06)	(0.06)
Local Market Structure and Demographic Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y
F-Test for Joint Equality of Dist. Coefs.	3.16	3.25	3.25	3.24	1.08	1.08	2.98	2.26	2.26	4.73	2.09	2.09
R-Squared	0.03	0.16	0.16	0.03	0.24	0.24	0.04	0.26	0.26	0.04	0.40	0.40
Observations	380	380	380	328	328	328	303	303	303	382	382	382

Notes: F-Test for distance quintile coefficients corresponds to the joint test that the regression coefficients on 7-12km, 12-17km, 17-26km and >26km are equal. Excluded groups are the first quintile of the distribution from city center and all other independent stations. Control variables include all variables in Table E.1 except distance from city center. Robust standard errors in parentheses.

Table E.2 presents our LPM estimates. The table also presents F-Tests of the null that $\eta_2^y = \eta_3^y = \eta_4^y = \eta_5^y$, that is, the null of joint equality of the coefficient estimates on the distance from city center quintile dummies. In line with Figure E.3, columns (4), (7) and (10) yield reductions in cycling probabilities 14, 46 and 20 percentage points among the furthest 20% of stations from city center (> 26 km) in 2006, 2010 and 2014. All of these coefficients are statistically significant at the 5% level. Moreover, the F-statistics in columns (4) and (7) reject the null of joint equality of the distance quintile coefficient estimates.

However, once we control for retailer identity in columns (5), (8) and (11) of Table E.2, all of the distance quintile coefficient estimates shrink and become statistically insignificant. Moreover, in each of these columns, the joint test of equality of the distance coefficients fail to reject the null. In contrast, all of the retailer identity coefficients are statistically and economically significant in columns (2), (5), (8) and (11). Collectively, these results imply that retailer type, not geographic location, primarily drive whether a station is cycling.

These conclusions are unchanged once we control for local market structure and demographics in columns (3), (6), (9) and (12) of Table E.2. For the sake of brevity, we do not present the coefficient estimates for these variables. Few are statistically significant once retailer type is controlled for. Moreover, none of the coefficients on the local market structure and demographic variables are statistically significant across multiple years in Table E.2. This reinforces our main overarching result that retailer type is the key determinant of whether a station is cycling.

E.1.3 Cycling and non-cycling BP, Caltex and independent stations

Finally, we examine whether certain station-level characteristics predict cycling status among BP, Caltex and independent stations. Recall from panel (ii) of Figure E.1 above that each of these retailer types have non-negligible shares of cycling and non-cycling stations. This makes retailer-specific analyses possible for BP, Caltex and independents.

For these analyses, we estimate analogous LPMs for each retailer type. Because our sample sizes are smaller in these regressions, we limit the number of control variables. Local market structure variables include distance to nearest rival station and the number of rival stations within 5 km. Demographic regressors include urban density, median household income, median age, share of individuals with bachelors degrees and high school education, and all the mode of transportation variables from Table E.1 except bus, ferry and tram.

For the BP and Caltex LPMs, we add one additional regressor: a convenience store dummy variable. While station-level characteristic data are unavailable, the naming of BP and Caltex stations in the raw Fuelwatch data reveal which stations have convenience stores. In particular, BP "2go" and "Connect" stations and Caltex "Starmart" and "Starshop" stations have convenience stores. Regular "BP" and "Caltex" named stations do not. A simple tabulation of the cycling and convenience store data reveals some interesting results. Between 2010 and 2015, 100% of BP 2go and Connect station are cycling, while only 45% of regular BP stations are cycling. For Caltex, 85% of Starmart and Starshop stores are cycling, while 66% of regular Caltex stations are cycling.

Table E.3 presents our retailer-specific LPM results. Among BP stations, convenience stores have a large, statistically significant coefficient in all years. The coefficients imply between a 47 and 81 percentage point increase in cycling propensity among BP stations with convenience stores.

Geography is less predictive of cycling status for BP stations. Indeed, after 2006, none of the distance quantile dummies have statistically significant coefficients. We also fail to reject the null of joint equality of the coefficients on these variables. Prior to 2014, however, we find some evidence that the number of rival stations within 5km of BP stations predicts cycling status. In particular, adding an additional competitor within 5km reduces a BP station's cycling propensity by 1 to 2 percentage points. All else equal, prior to 2014 BP is less likely to have a station cyclical pricing if there is more local competition.

The main result for Caltex in panel (B) of Table E.3 is that stations 26km or further from the city center tend not to be cycling. Columns (4), (6) and (8) imply large, 86, 69 and 65 percentage point reductions in cycling probabilities among Caltex stations 26 km or further from the city center.[19] Whereas convenience stores matter for BP stations' cycling status, geographic location relative to the city center is the key determinant of cycling status for Caltex stations.

Finally, we find mixed and largely statistically insignificant results across years and covariates for the independent LPMs. Relative to BP and Caltex, the cycling status of independent stations are far less predictable.

[19]We do not report 2002 results for Caltex because 77 of 79 Caltex stations are cycling in that year, which leads to LPM parameter instability.

Table E.3: Linear Probability Models that Predict Cycling Station Status by Firm

	2002		2006		2010		2014	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(A): BP Stations								
7-12km	0.25	0.00	0.16	0.06	0.07	0.06	0.13	0.15
	(0.14)	(0.17)	(0.18)	(0.14)	(0.18)	(0.14)	(0.18)	(0.16)
12-17km	0.09	-0.04	-0.07	-0.01	-0.20	-0.01	0.03	0.29
	(0.16)	(0.21)	(0.20)	(0.18)	(0.20)	(0.18)	(0.19)	(0.19)
17-26km	0.05	-0.21	0.10	-0.14	-0.02	-0.16	0.16	0.36
	(0.16)	(0.22)	(0.19)	(0.19)	(0.19)	(0.18)	(0.17)	(0.21)
>26km	-0.09	-0.59	0.10	-0.28	0.00	-0.22	-0.07	0.03
	(0.20)	(0.26)	(0.21)	(0.23)	(0.22)	(0.23)	(0.21)	(0.25)
Convenience Store		0.47		0.80		0.81		0.55
		(0.08)		(0.07)		(0.07)		(0.09)
Number of Stations Within 5km		-0.01		-0.02		-0.02		0.01
		(0.01)		(0.01)		(0.01)		(0.01)
Demographic Controls	N	Y	N	Y	N	Y	N	Y
F-Test for Joint								
Equality of Dist. Coefs.	2.01	3.54	0.56	1.15	0.77	1.01	0.61	1.98
R-Squared	0.06	0.36	0.03	0.68	0.04	0.70	0.03	0.49
Observations	79	79	67	67	65	65	67	67
(B): Caltex Stations								
7-12km			-0.15	-0.26	-0.17	-0.27	-0.08	-0.12
			(0.11)	(0.15)	(0.11)	(0.15)	(0.08)	(0.08)
12-17km			-0.00	-0.18	0.00	-0.20	-0.00	-0.07
			(0.00)	(0.16)	(0.00)	(0.14)	(0.00)	(0.08)
17-26km			-0.10	-0.26	0.00	-0.22	-0.00	-0.06
			(0.10)	(0.27)	(0.00)	(0.18)	(0.00)	(0.10)
>26km			-0.29	-0.60	-0.29	-0.55	-0.33	-0.31
			(0.18)	(0.33)	(0.18)	(0.29)	(0.17)	(0.17)
Convenience Store				0.03		0.04		0.08
				(0.07)		(0.08)		(0.08)
Number of Stations Within 5km				-0.00		-0.01		-0.00
				(0.01)		(0.01)		(0.00)
Demographic Controls			N	Y	N	Y	N	Y
F-Test for Joint								
5 Equality of Dist. Coefs.			1.88	1.27	2.32	1.38	2.53	1.20
R-Squared			0.11	0.41	0.15	0.68	0.21	0.68
Observations			50	50	47	47	52	52
(C): Independent Stations								
7-12km	0.13	0.12	0.24	0.10	0.27	0.53	-0.05	0.01
	(0.12)	(0.13)	(0.17)	(0.21)	(0.21)	(0.26)	(0.14)	(0.15)
12-17km	0.22	0.14	0.37	0.26	0.47	0.48	0.04	-0.01
	(0.11)	(0.14)	(0.20)	(0.25)	(0.22)	(0.27)	(0.16)	(0.18)
17-26km	-0.04	-0.16	0.29	0.18	0.44	0.49	0.12	0.15
	(0.13)	(0.17)	(0.16)	(0.24)	(0.18)	(0.29)	(0.14)	(0.18)
>26km	-0.11	-0.23	0.11	-0.03	-0.00	0.06	-0.02	0.03
	(0.12)	(0.17)	(0.15)	(0.23)	(0.18)	(0.29)	(0.13)	(0.16)
Number of Stations Within 5km		0.00		0.01		-0.02		-0.02
		(0.00)		(0.01)		(0.01)		(0.01)
		(0.01)		(0.01)		(0.02)		(0.01)
Demographic Controls	N	Y	N	Y	N	Y	N	Y
F-Test for Joint								
Equality of Dist. Coefs.	3.69	4.31	0.95	0.96	3.81	3.39	0.70	0.42
R-Squared	0.06	0.17	0.05	0.09	0.17	0.37	0.02	0.10
Observations	170	170	93	93	68	68	130	130

Notes: F-Test for distance quintile coefficients corresponds to the joint test that the regression coefficients on 7-12km, 12-17km, 17-26km and >26km are equal. Excluded groups are the first quintile of the distribution from city center and all other independent stations. Control variables include all variables in Table E.1 except distance from city center. Robust standard errors in parentheses.

E.2 Price jump leading BP stations

E.2.1 Persistence of price jump leading stations

This appendix studies the characteristics of BP stations engaged in Wednesday price jump leadership between 2009 and 2012. These results supplement Section 4.1 of the paper, which documents BP's 3-year transition from Wednesday to Thursday price jumps between 2009 and 2012.[20]

We begin our analysis by examining station-level persistence in Wednesday price jump leadership week-to-week. This is useful because it allows us to see whether certain BP stations are always price jump leaders, or whether the identity of price jump leading stations changes over time.

Figure E.4 provides scatter plots for 2009-2012 that visualize station-level persistence in price jump leadership. The vertical axis consists of discrete BP station identifiers counting from $i = 0, \ldots, 45$. We order these identifiers from closest to furthest from the city center such that stations at the bottom of the figure are closer to the city center. The horizontal axis corresponds to the week of the year. A green circle in the figure indicates that station i in week t engages in a leading Wednesday price jump. White gaps correspond to stations not engaging in Wednesday jumps.

The decline in green dot density across panels (i)-(iv) of Figure E.4 correspond to BP's gradual, 3-year transition away from Wednesday price jump leadership that we show in Figure 6 of the paper. The station-level persistence in price jump leadership in panels (i) and (ii) of Figure E.4 shows that between 2009 and 2010, BP tends to have particular stations permanently engaged in price jump leadership.

In terms of geography, panels (i) and (ii) do not provide clear evidence that stations close to or far from the city center tend to engage in price jump leadership. In particular, panels (i) and (ii) depict similar rates of "thinning out" of green dots at the top and bottom of the graphs over time. Below we use regressions to further investigate the relationship between a station's location and

[20] We examine Wednesday price jump leadership among BP stations that are cycling, as per Definition 1(v) in the paper. Recall from Figure E.1 above in this appendix that between 64% and 72% of BP stations are engaged in price cycles between 2009 and 2012.

whether it engages in price jump leadership.

Panel (iii) reveals an interesting shift in BP's conduct in 2011. Comparing panels (ii) and (iii), we find a notable drop in station-level persistence in price jump leadership. In 2010 there are long, multiple month runs of price jump leadership by individual BP stations. Starting in 2011 we find BP stations begin alternating as price jump leaders for four consecutive weeks at a time. This shift in pricing can also be seen in Figure E.5. The figure plots the distribution of unique, station-level runs of consecutive weeks of Wednesday price jump leadership in each year. Four weeks emerges as the dominant run length in 2011: 48% of the runs in station-level Wednesday price jump leadership are 4 weeks long.

Figure E.4: Persistence in Which BP Stations Engage in Wednesday Price Jump Leadership

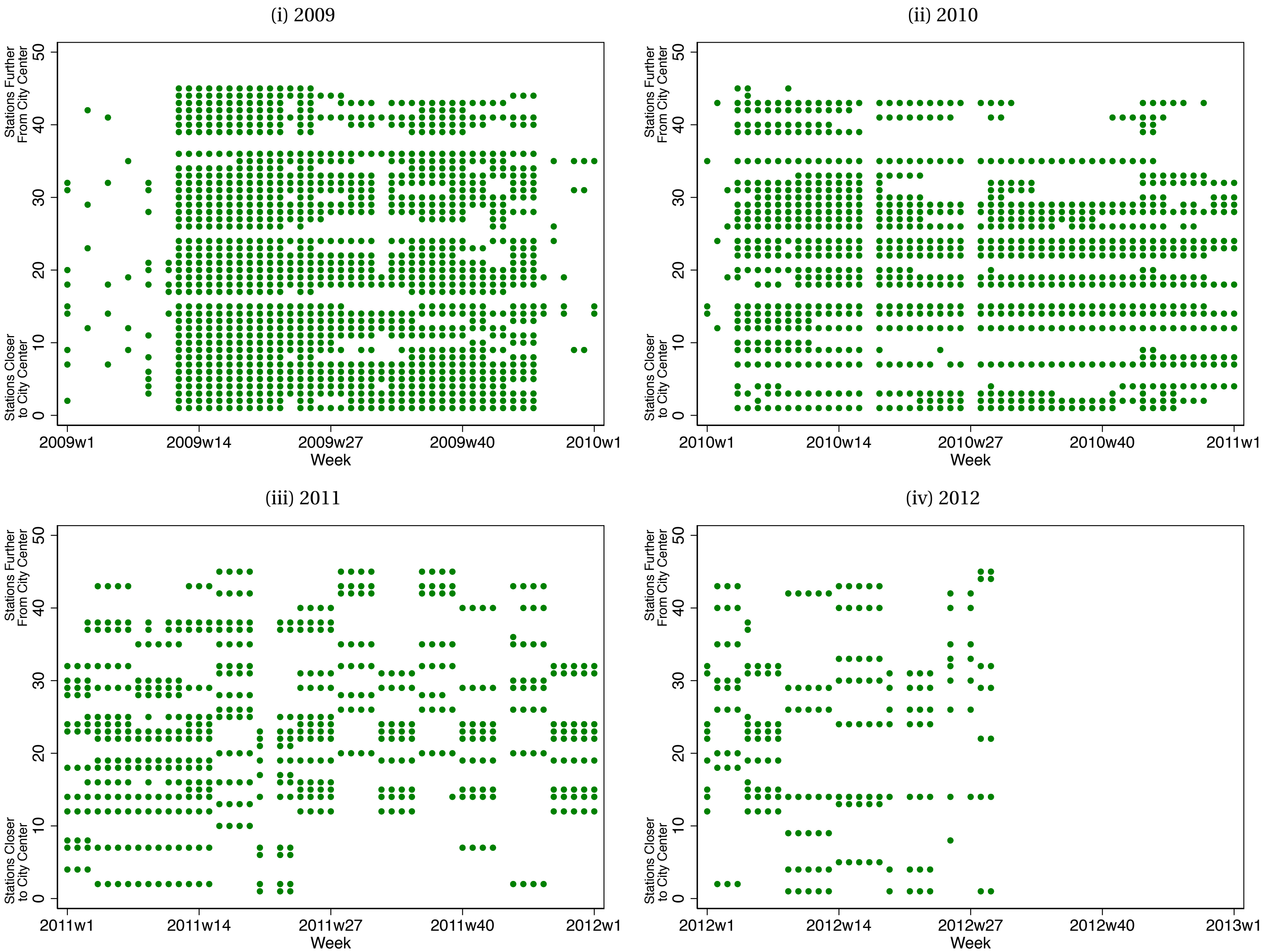
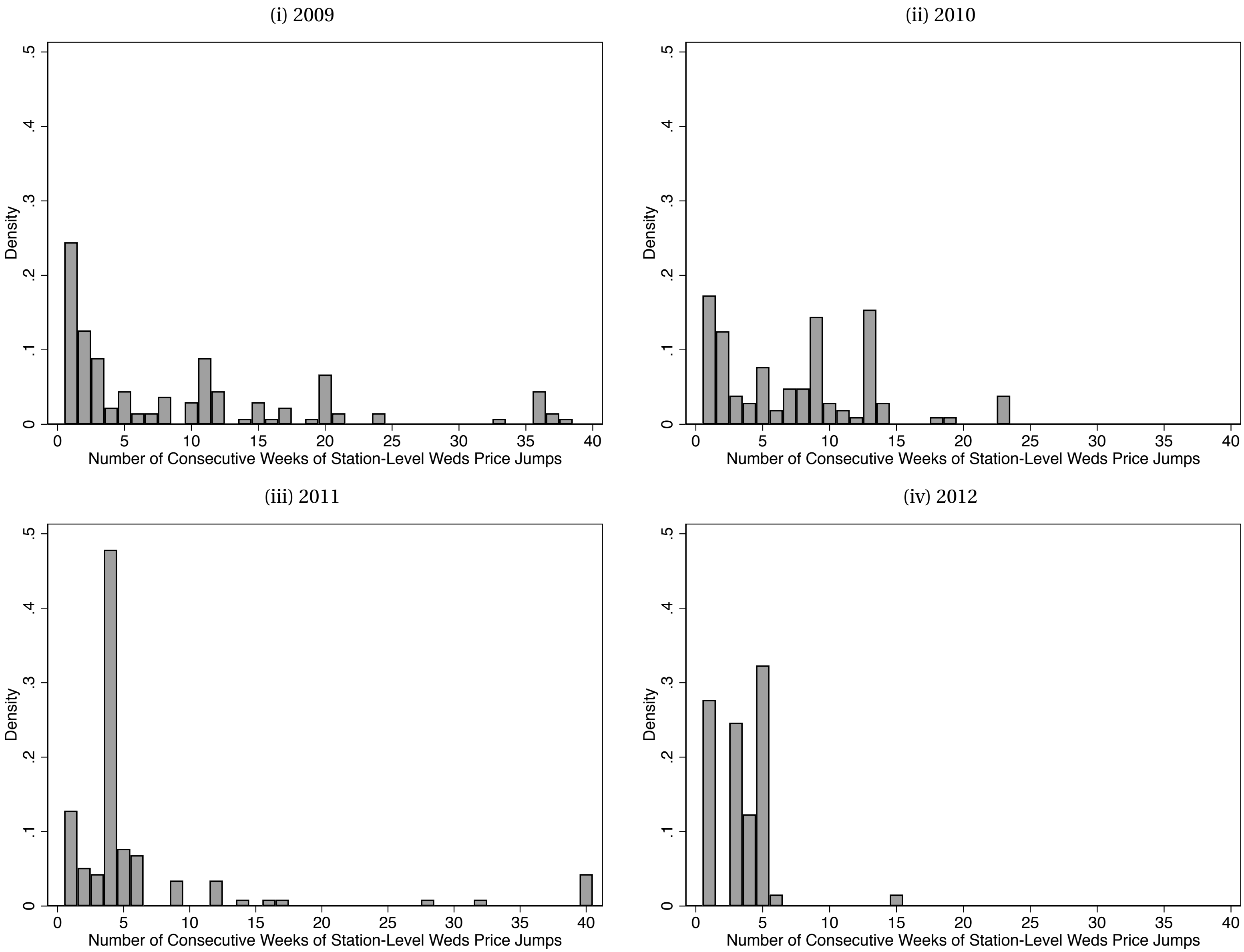


Figure E.5: Distribution of Station-Level Runs of Consecutive Weeks of Wednesday Price Jumps



E.2.2 Characteristics of price jump leading BP stations

What are the characteristics of price jump leading BP stations? Figure E.6 presents the geographic location of cycling BP stations year-to-year.[21] Each panel plots the location and propensity that a given BP station engages in price jump leadership in a given year. We measure this propensity as the percentage of weeks a BP station engages in Wednesday price jump leadership in a year. The four categories of intensity in Figure E.6 correspond to the quartiles of the distribution of intensity of Wednesday price jump leadership across all BP stations and years.[22]

We complement the maps in Figure E.6 with a corresponding set of scatter plots in Figure E.7. In these scatter plots, the vertical axis is the share of weeks in a given year that a BP station engages in Wednesday price jump leadership. The horizontal axis is the distance a station is from the city center

Panels (i) and (ii) of Figures E.6 and E.7 provide preliminary evidence that in 2009 and 2010, BP stations in the core of the city more intensely engage in Wednesday price jump leadership. The negative regression slope in both panels is indeed statistically significant.

However, panels (iii) and (iv) in Figure E.7 show this relationship permanently disappears in 2011. Interestingly, this shift in the relationship between the distance from the city center, and a station's intensity in engaging in Wednesday price jump leadership, occurs when BP starts mixing between price jump leading stations for four consecutive weeks at a time.

Taken together, Figures E.4 and E.7 imply that before 2011, the identity of price jump leading BP stations is persistent over time, and tends to be closer to the city center. From 2011 onwards, however, price jump leading BP stations more often change and are more evenly spread across the market. In sum, BP appears to start randomizing which stations engage in price jump leadership both across time and space in 2011.

[21]Throughout, we focus on cycling BP stations and compare the characteristics of BP stations engaged and not engaged in price jump leadership in a given week. We focus strictly on cycling stations as location does not predict whether a given BP station is cycling or not. We show this in Section E.1.3 of this appendix above.

[22]We assume 30 weeks is total number of potential weeks that a station could engage in price jump leadership in 2012. We assume this because BP stops price jump leadership in August 2012.

Figure E.6: Locations of Price Jump Leading BP Stations: 2009, 2010, 2011, 2012

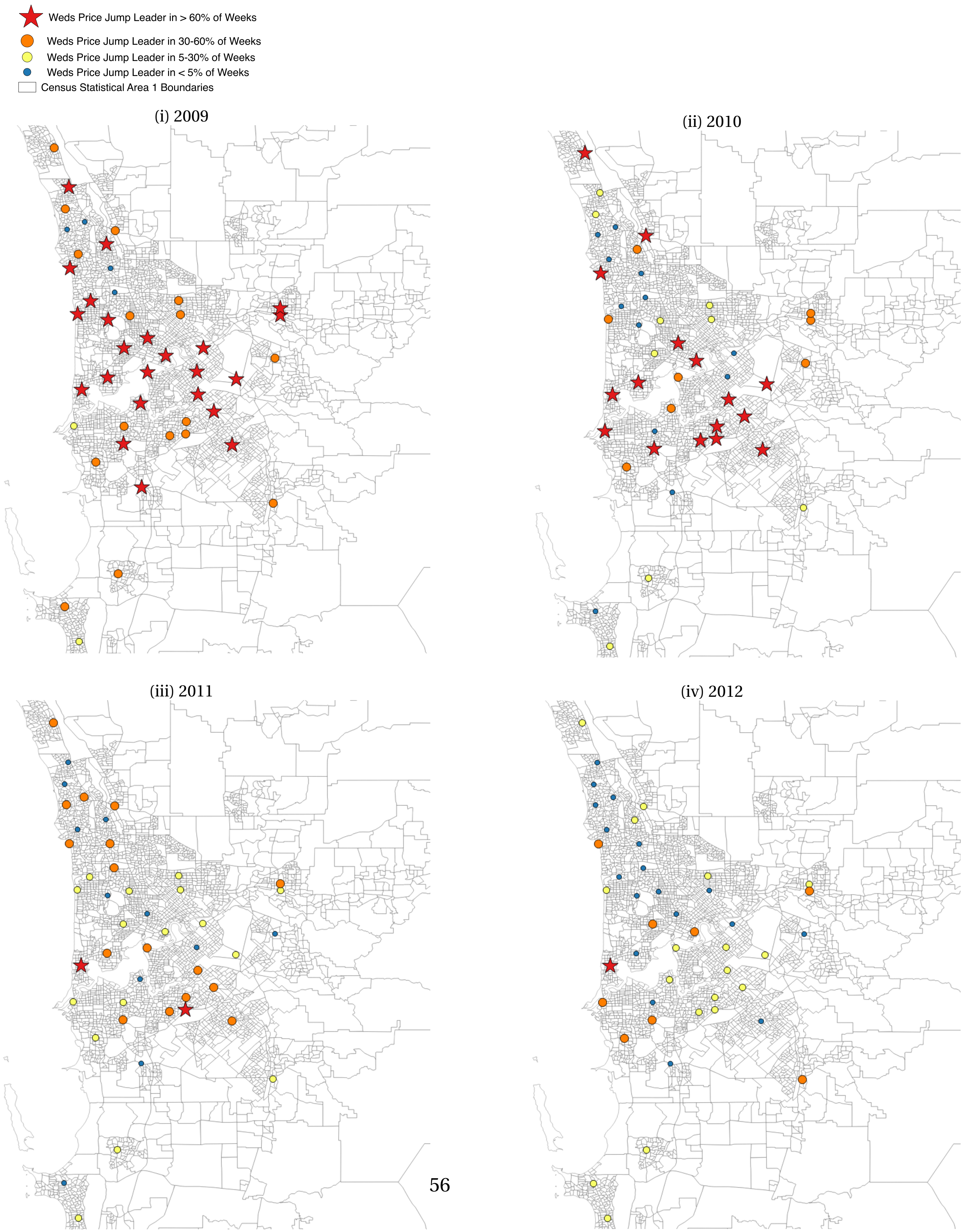
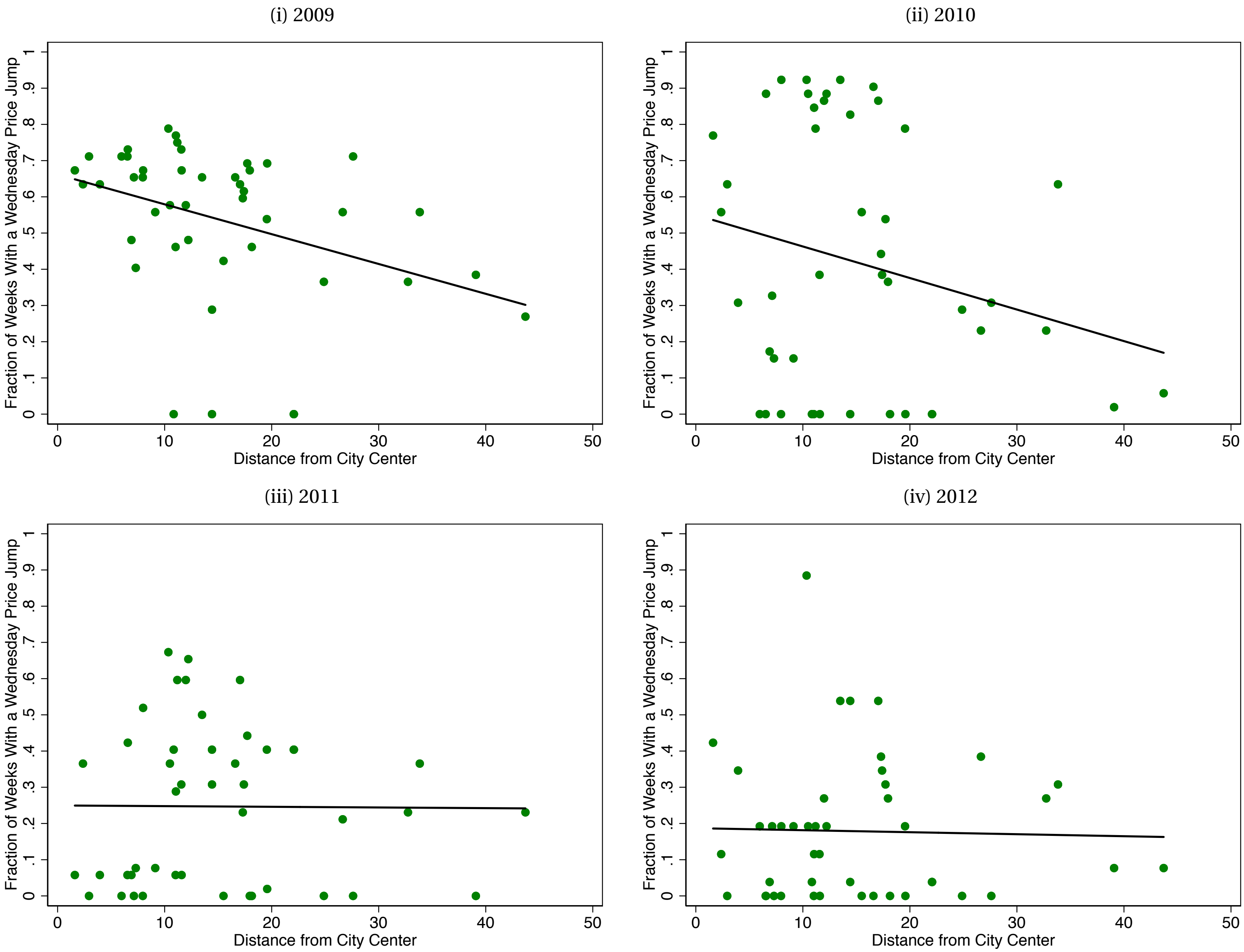


Figure E.7: Relationship Between Percentage of Weeks a Station Engages in Wednesday Price Jumps and Distance from City Center



Regression analysis. For the final part of our analysis, we estimate Linear-in-Probability Models (LPMs) of the following form:

$$1\{\text{PriceJumpLeader}\}_{it} = \delta^m d_i + \alpha^m s_i + \mathbf{m}_i \gamma^m + \mathbf{x}_i \beta^m + \nu_t + \epsilon_{it} \tag{3}$$

where $1\{\text{PriceJumpLeader}\}_{it}$ is an indicator equalling one if station i on date t is a price jump leading station. For reference, we restate Definition 2 from the paper for price jump leading stations here:

Definition.

> Station i is a *price leader* on date t if: (1) it engages in a station-level price jump on date t; (2) a market cycle begins on dates t or $t+1$; and (3) less than 2.5% of other stations engage in station-level price jumps on date $t-1$.

In practice, *all* BP price leaders between 2009 and 2012 are stations that engage in Wednesday price jumps. Therefore, in estimating the LPM in equation (3), we only include dates t that are Wednesdays.

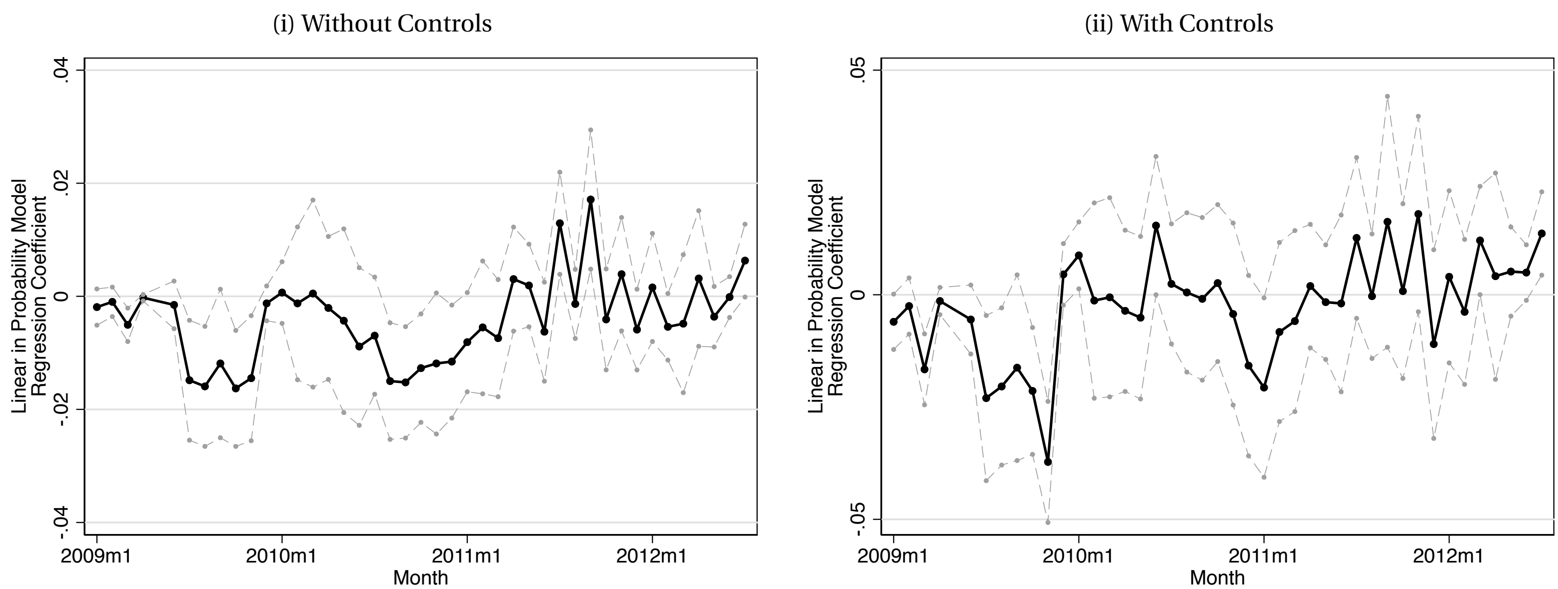
The covariates in (3) include the distance station i is from the city center d_i, a dummy variable s_i that equals one if BP station i has a convenience store, local market structure variables $\mathbf{m}_i$ and demographic variables $\mathbf{x}_i$. Because of our smaller sample size of BP stations only, we use a restricted set of variables in $\mathbf{m}_i$ and $\mathbf{x}_i$ as we did in Section E.1.3 of this appendix above. Specifically, $\mathbf{m}_i$ includes the distance to nearest rival station and number of rival stations within 5km, and $\mathbf{x}_i$ includes urban density, median household income, median age, share of individuals with bachelors degrees and high school education, and all the mode of transportation variables from Table E.1 except bus, ferry and tram.[23]

The m superscripts on the parameters in (3) imply that we estimate the LPM month-by-month. This allows us to investigate how the relationship between stations' price jump leadership intensity and its characteristics evolve over time.[24]

[23]We have experimented with richer specifications that include other covariates from Table E.1 in $\mathbf{m}_i$ and $\mathbf{x}_i$. We do not find the inclusion of any other variables affects our main findings.

[24]For instance, Figure E.7 points to a breakdown over time in the relationship between a station's distance from city center and its propensity to be a price jump leader.

Figure E.8: Linear Probability Model Estimates of the Relationship Between a Station's Propensity to Engage in Wednesday Price Jump Leadership and Distance from City Center



Therefore month m's regression coefficients are estimated with 4 (Wednesdays) $\times$ 45 (stations)=180 observations.

Finally, each monthly LPM includes a week fixed effect ν_t. By including these fixed effects, we control for the systematic decline in Wednesday price jump leadership among BP stations between 2009-2012.

We present our LPM estimation results graphically in Figures E.8 and E.9. These figures plot the parameter estimates and 95 percent confidence intervals from the month-specific LPM models. Figure E.8 presents LPM coefficient estimates of δ^m for a model without controls (panel (i)) and with controls (panel (ii)). The earlier patterns in Figure E.7 foreshadow the results in panel (i) of Figure E.8: in 2009 and 2010 there are multiple months where there is a negative relationship between a station's price leadership propensity and distance from city. In these months, BP stations that are closer to the city center are more likely to be price jump leaders. From 2011 onwards, however, the δ^m estimates in panel (i) of Figure E.8 converge to 0 and become statistically insignificant. The location of price jump leading stations eventually becomes less predictable.

Panel (ii) of Figure E.8 shows distance from city center becomes a noisier and more unstable predictor of whether a BP station engages in leading Wednesday price jumps once other station characteristics are controlled for.

Figure E.9 presents LPM parameter estimates for other variables of interest. For brevity, we focus on four variables: convenience store dummy, number of rival stations within 5km, median household income and share of the local population with post-secondary education.[25]

Panel (i) of the figure shows BP stations with convenience stores are less likely to engage in Wednesday price jump leadership, particularly in 2010 and the first half of 2011. Quantitatively, the coefficients are large: stations with convenience stores are more than 50 percentage points less likely to engage in Wednesday price jumps between March 2010 and February 2011. Panel (i) further shows that in 2011, as BP starts randomizing across time and space which stations engage in Wednesday jumps, that convenience store status becomes less able to predict Wednesday jumps.

Panel (ii) yields another set of interesting results. In the first half of 2010, price jump leading BP stations are more likely to be those which have more local competitors. For example, in May 2010, one additional local competitor increases the probability that a BP station engages in Wednesday price jump leadership by 3.7 percentage points.[26] This is consistent with BP choosing stations to engage in price jump leadership that have greater ability to geographically signal price jump timing and magnitude to rivals. We find it interesting that BP pursues this approach in the first half of 2010 which, recall from Section 4 of the paper, is when BP engages in price leadership and experimentation to create Thursday jumps and 2 cpl cuts as focal pricing rules.

As BP scales back its price jump leadership position between 2011 and 2012, and begins randomizing which stations engage in price jump leadership across

[25]All other variables in the LPMs yield unstable and statistically insignificant parameter estimates across most months.

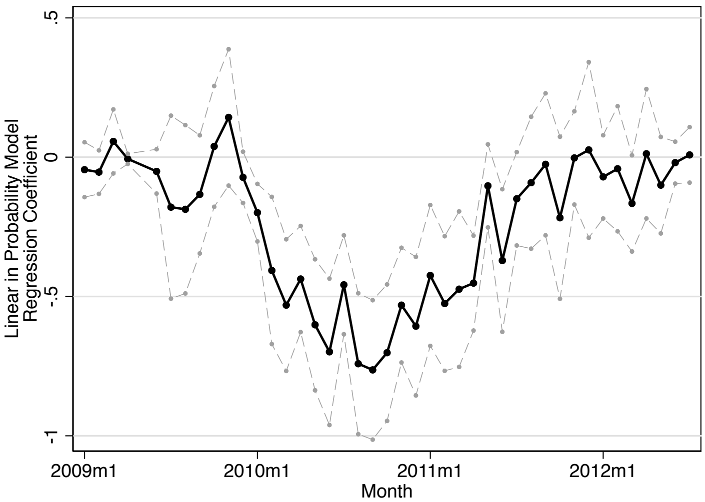
[26]There are two points of reference for the scale of these coefficient estimates. First, in May 2010, 57% of cycling BP stations engage in Wednesday price jumps week-to-week. Second, on average a BP station has 8 other rival stations within 8 kilometers.

time and space, we find the LPM regression coefficients on the number of local rivals converges to 0 and becomes statistically insignificant.

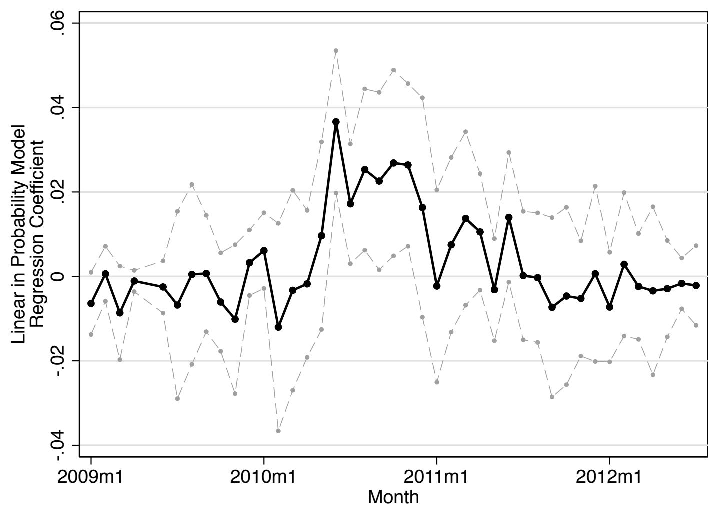
Finally, in panels (iii) and (iv) of Figure E.9 we investigate whether local income and education levels influences whether a BP station engages in price jump leadership. Panel (iii) shows local income does not predict Wednesday price jump leadership. In contrast, panel (iv) shows BP stations in areas with higher levels of educational attainment are less likely to engage in price jump leadership after 2010.

Figure E.9: Linear Probability Model Estimates of the Relationship Between a Station's Propensity to Engage in Wednesday Price Jump Leadership and Station-Level Characteristics

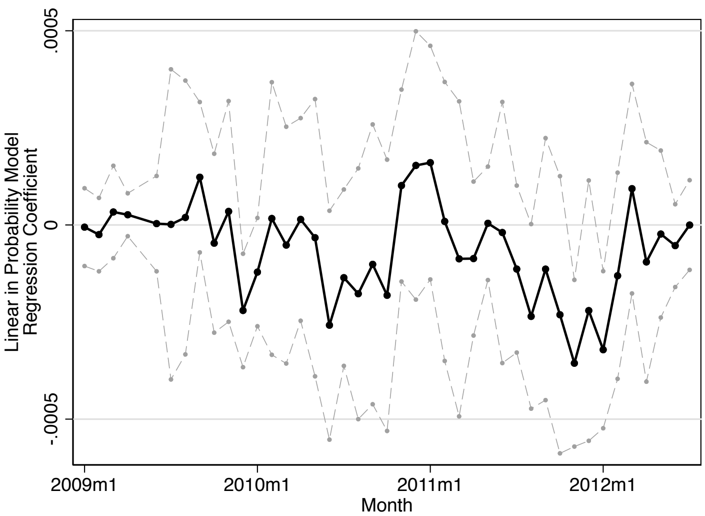
(i) Convenience Store



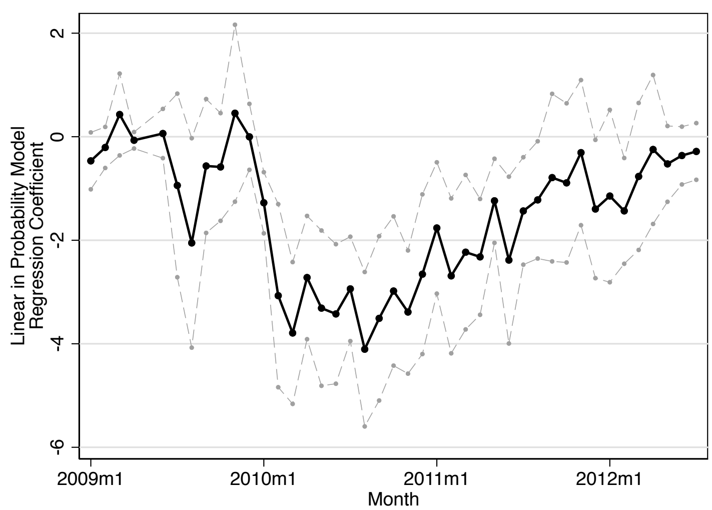
(ii) Number of Rival Stations Within 5km



(iii) Median Household Income (1000's)



(iv) Share of Population with Post Secondary Education



F Cycle synchronization and price dispersion

In this appendix, we further examine how the two focal pricing rules found in the paper – Thursday jumps and 2 cpl cuts – influence intertemporal and cross-sectional price dispersion. We develop this supplemental analysis over three sections. In Section F.1 we study price jump days. We then study the dispersion of price jump magnitudes in Section F.2. Finally, in Section F.3, we examine cross-sectional price dispersion on price jump and undercutting days.

Definition 1 from the paper, which defines price jumps and cuts at both the station and market level, plays a central role throughout this appendix. For reference, we restate it here:

Definition 1.

(i) A *station-level price jump* occurs at station i on date t if $\Delta p_{it} \geq 6$ cpl, where p_{it} is the retail price and $\Delta p_{it} = p_{it} - p_{it-1}$.

(ii) A *station-level price cycle* commences at station i on date t if $\Delta p_{it} \geq 6$ cpl. This is denoted as "day 1" of the station-level cycle. Days $2, 3, 4 \ldots$ of the station-level cycle correspond to the undercutting phase until the next station-level price jump occurs and a new cycle begins. *Station-Level cycle length* is the number of days between station-level price jumps.

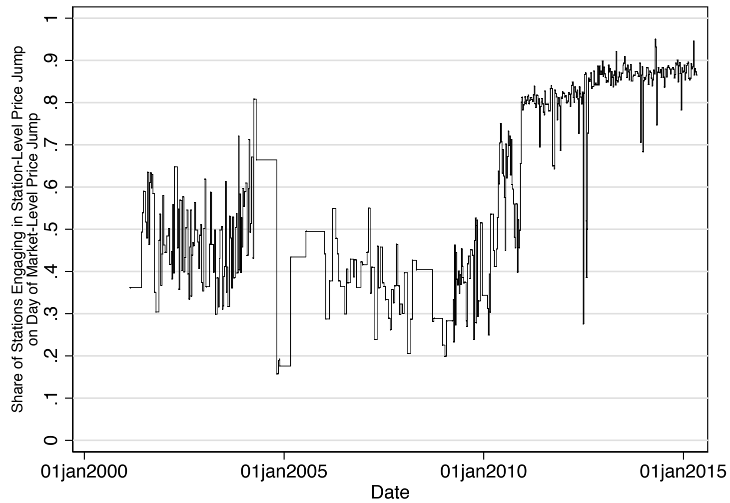
(iii) A *market price jump* occurs on date t if $\text{median}_t(\Delta p_{it}) \geq 6$ cpl, where on date t $\text{median}_t(\Delta p_{it}) \geq 6$ cpl is the median of $p_{it} - p_{it-1}$ across all stations.

(iv) A *market cycle* commences on date t if $\text{median}_t(\Delta p_{it}) \geq 6$ cpl. This is denoted as "day 1" of the market cycle. Days $2, 3, 4 \ldots$ of the market cycle correspond to the undercutting phase until the next market price jump occurs and a new cycle begins. *Market cycle length* is the number of days between market price jumps.

(v) Station i is a *cycling station* in year y if $\Delta p_{it} \geq 6$ cpl at least 15 times in year y.

Throughout this appendix, we focus on price coordination and dispersion among cycling stations.

Figure F.1: Share of Stations Engaged in Station-Level Price Jumps on Days When Market Price Jumps Occur



F.1 Price jump timing

To measure the degree of coordination on price jump timing, we construct the following measure of stations' "success rate" in coordinating on a market price jump on date t:

$$success\_rate_t = \frac{\sum_i^{N_t} 1\{\Delta p_{it} \geq 6 \text{ cpl}\}}{N_t}$$

where $1\{\cdot\}$ is an indicator function, $\Delta p_{it} = p_{it} - p_{it-1}$ is the daily change in stations i's price on date t, and N_t is the number of cycling stations in the market on date t. In words, $success\_rate_t$ measures the share of stations engaging in a station-level price jump when a market price jump occurs on date t.

Figure F.1 plots $success\_rate_t$ for dates where market price jumps occur. Prior to 2010, 43% of stations on average simultaneously coordinate on station-level price jumps during market price jumps. This average rises to 58% in 2010 and grows steadily to 87% by 2015. As the figure shows, there is a rapid jump in coordination immediately after 2010, which is when BP engages in price leadership to establish Thursday jumps as a focal pricing rule. Indeed, in 2010, 58%

of stations coordinate on the timing of market price jumps on average. Between 2010 and 2015, $success\_rate_t$ gradually rises, reaching an average of 88% of stations by 2015.

Figure F.2 provides analogous plots of $success\_rate_t$ broken down by retailer type. After 2010, on average 80%, 92%, 88% and 90% of BP, Caltex, Woolworths and Coles stations coordinate on station-level price jumps when market jumps occur. BP's average rises to 94% after August 2012, which is when it stops engaging in Wednesday price jump leadership.[27]

Among Gull and other independent stations, the average of $success\_rate_t$ after 2010 in panels (v) and (vi) of the figure is 79% and 38%, respectively.[28] Relative to the major firms and Gull, other independent stations exhibit far less coordination on price jump timing. Figure F.3 shows why: while the major firms and Gull stations primarily engage in Thursday price jumps after 2010, independent stations engage in Thursday jumps *and* Friday jumps. On average, 46% and 47% of independent stations' price jumps occur on Thursdays and Fridays week-to-week.[29]

As will become clear throughout this appendix, delayed price jumps, particularly by independent stations, have important implications for cross-sectional price dispersion. For example, after 2010, stations who delay price jumps to Fridays undercut the median price in the market on Thursdays by 13.3 cpl on average. This price cut is 9.4% of the average retail price of 140.7 cpl between 2010 and 2015.

[27] The large common drops in $success\_rate_t$ across the major firms in Figure F.2 between 2010 and 2011 correspond to Gap 2. Recall from Section 4.1 and Figure 7 of the paper in Gap 2 BP runs its first experiment in not engaging in Wednesday price jump leadership. Similarly, the common drops in $success\_rate_t$ half way through 2012 correspond to Gaps 3 and 4, which from Figure 8(i) in the paper are weeks where BP begins stopping to engage in Wednesday price jumps, just before it permanently stops doing so in August 2012.

[28] For reference, after 2010 BP, Caltex, Woolworths and Coles collectively run 76% of the stations in the market. Gull and all other independents respectively run 11% and 13% of stations.

[29] Overall, on average 12% (or 28 of 233 cycling stations) attempt to steal market share on Thursdays by delaying price jumps to Fridays. Despite having only a 13% market share in terms of total station counts, independent stations account for 5% of the 12% (42%) of delaying stations.

Figure F.2: Price Jump Timing Coordination Across Stations by Retailer

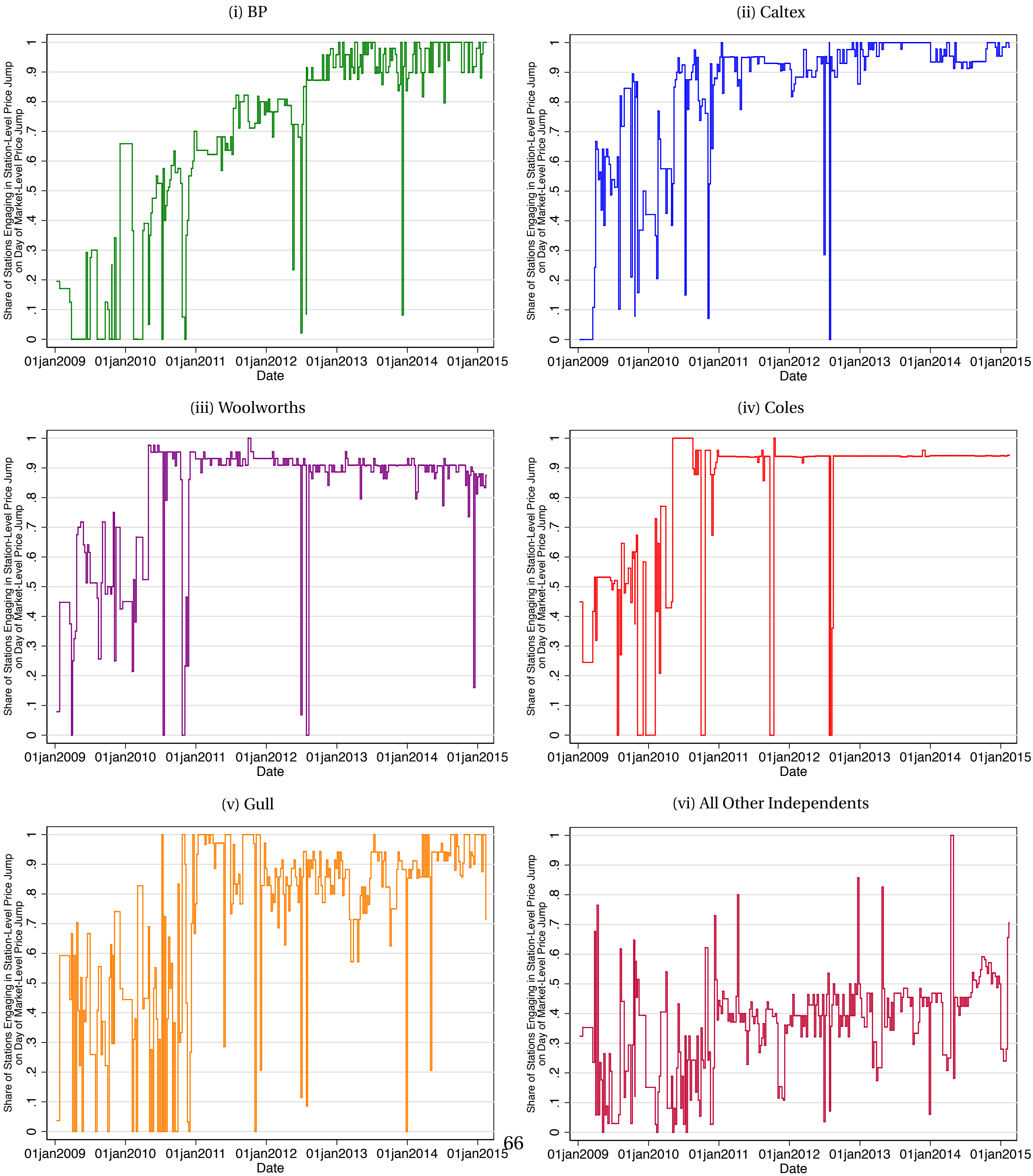
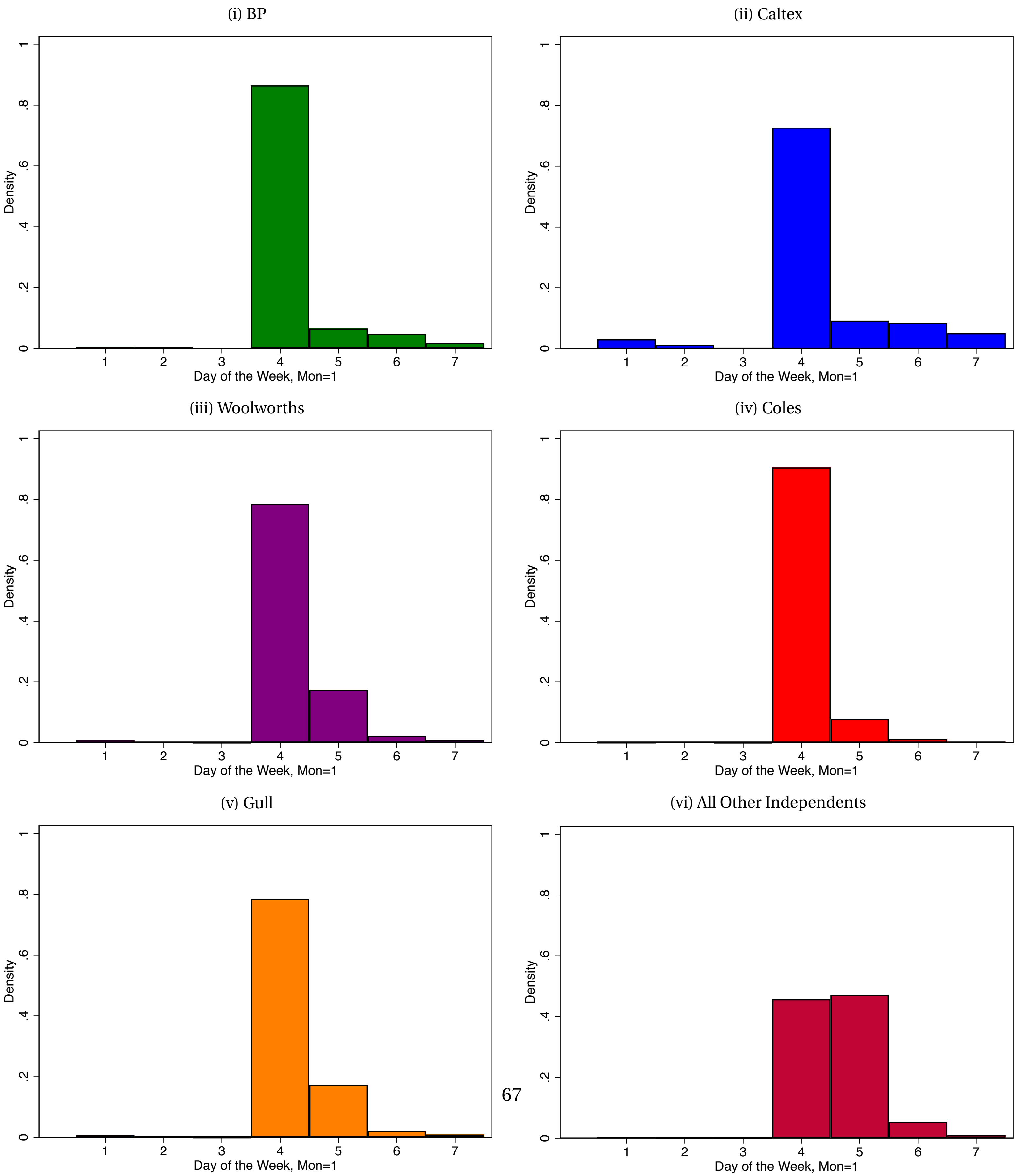


Figure F.3: Distribution of Station-Level Price Jump Timing Across Days of the Week by Retailer, 2010-2015

(Monday==1)



F.2 Price jump dispersion

We now examine dispersion in price jump magnitudes between 2009 and 2014. For our analysis, we use box plots of daily price changes across stations on Thursdays week-to-week, with one exception. For BP stations engaged in leading Wednesday jumps in a given week, we use their Wednesday price change and not their Thursday price change in constructing the box plots. Recall from Section 5.2 of the paper that Thursday jumps are calibrated to match the prices set by leading BP stations on Wednesdays. Therefore, Wednesday jumps by leading BP stations are the relevant price change for measuring cross-sectional price jump dispersion in a given week.

Panels (i)-(vi) of Figure F.4 present box plots of price jumps among the four major firms' stations. After the cycle is reinitiated by BP in April 2009,[30] we find non-negligible price jump dispersion throughout 2009.[31] This dispersion in price jump magnitudes persists until Gap 1 in week 18 of 2010, which recall from the paper is when BP initiates the Thursday jumps focal point through price leadership.[32] This can be seen in panel (ii) by the collapse of the inter-quartile range of prices. For 10 weeks following Gap 1, panel (ii) highlights minimal price jump dispersion among the four major firms' stations.

Following BP's experiment in Gap 2,[33] which occurs 10 weeks after Gap 1, we find a temporary, two-week rise in price jump dispersion in panel (ii). This is followed by 10 weeks of minimal dispersion, and then 14 weeks of higher price jump dispersion at the end of 2010. While Thursday jumps remains a stable focal pricing rule throughout 2010, we show in Figure 11 (ii) in the paper that BP tem-

[30] See Appendix C.3 for an analysis of cycle reinitiation by BP in April 2009 after the crude oil price shock.

[31] The collapse in price dispersion at the end of 2009 and start of 2010 corresponds to a BP-Caltex price war that causes the cycle to collapse. See Appendix D for an analysis of the price war.

[32] More specifically, recall from the paper that in this week, BP signals Thursday jumps to the market by breaking from past behavior and engaging in a Thursday jump with the majority of its station network. See Figure 7 and related discussion in Section 4.2 of the paper.

[33] Recall from Figure 7 and related discussion in Section 4.2 of the paper, that in Gap 2 BP experiments with not engaging in Wednesday price jump leadership for the first time in over a year. The experiment reveals that at the time Coles and Woolworths are not willing to engage in Thursday price jumps without BP Wednesday price jump leadership.

porarily engages in large leading Wednesday price jumps at the end of 2010.[34] Panel (ii) indicates that this temporary rise in Wednesday price jump magnitudes by BP temporarily generates price jump dispersion across retailers at the end of 2010.

Panels (iii) and (iv) of Figure F.4 show price jump dispersion is remarkably low and stable through 2011 and the first half of 2012. During this time, the major firms tightly coordinate on the timing and magnitude of price jumps. Undoubtedly, this coordination is facilitated by BP Wednesday price jump leadership. Indeed, panel (iv) of the figure reveals a permanent rise in price jump dispersion starting in August 2012. This is precisely when BP stops engaging in price jump leadership. These results highlight the effectiveness of BP's costly price signaling in coordinating both the timing and magnitude of price jumps prior to August 2012.

Independent stations. Figure F.5 provides an analogous set of box plots for weekly price jump dispersion that includes Gull and all other independent stations. Relative to Figure F.4, we find an increase in dispersion overall. Comparing panels (ii)-(iv) across Figures F.4 and F.5, we find growth in the mass of the distribution *below* the median price jump, particularly after 2010. This dispersion arises because independent stations engage in delayed Friday price jumps (see panel (vi) of Figure F.3 above), and because independent stations tend to have smaller price jumps.[35]

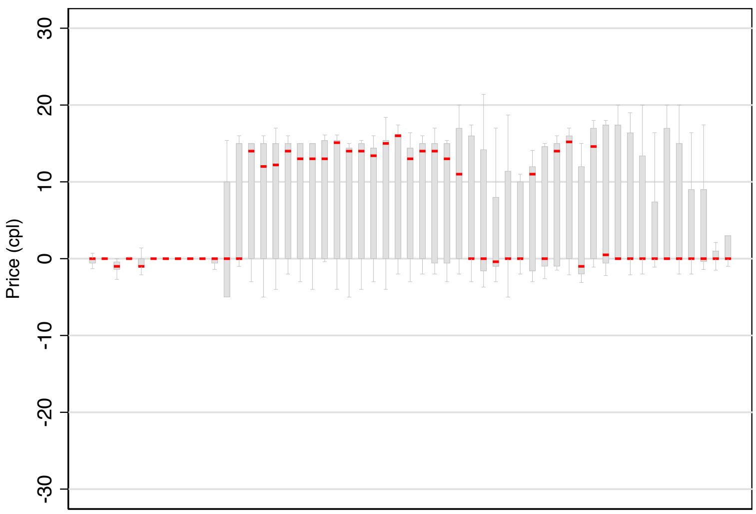
The final notable result from Figures F.4 and F.5 is that price jump dispersion is similar in the two figures after August 2012. That is, in the absence of BP Wednesday price jump leadership, we find price jumps by the major firms' and independents' stations exhibit similar dispersion. In contrast, under BP price jump leadership, independent stations more consistently priced below the median price jump on Thursdays.

[34] More specifically, Figure 11 (ii) in the paper shows that at the end of 2010 BP temporarily engages in 12-16 cpl Wednesday price jumps, before returning to typical 9-12 cpl levels.

[35] For instance, after 2010, the average price jumps of major firms' and independent stations are 13.8 cpl and 12.6 cpl, respectively.

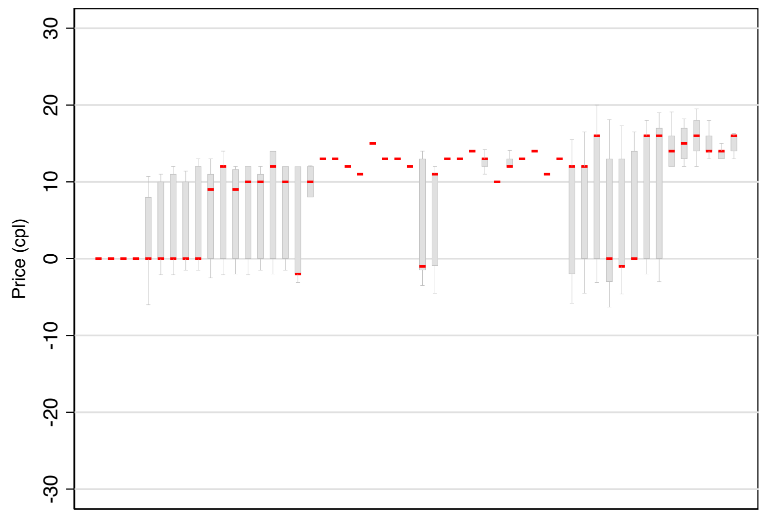
Figure F.4: Box Plots for the Distribution of Daily Station-Level Price Changes During Market Price Jump Days (Thursdays), Four Major Firms Only, 2009-2014

(i) 2009



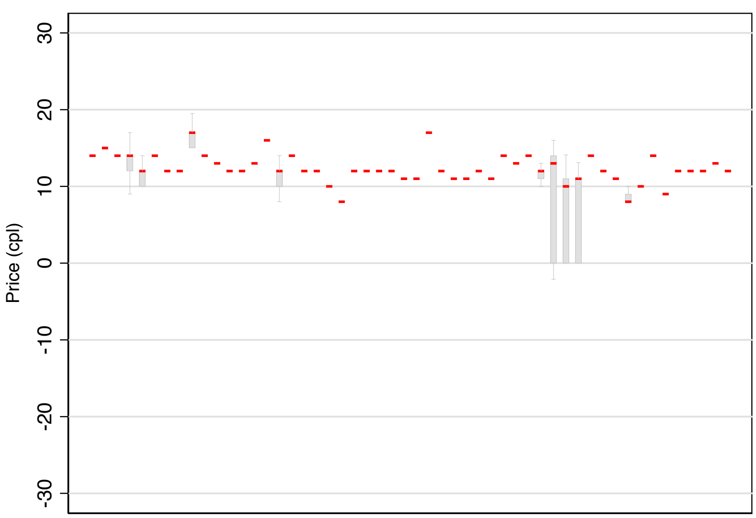
Horizontal axis is the week of the year
Box plots for distribution of station-level price jumps plotted for each week in year 2009

(ii) 2010



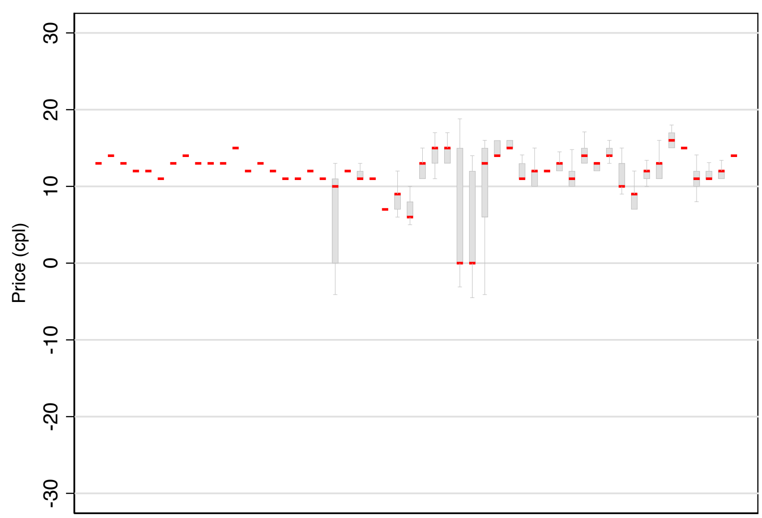
Horizontal axis is the week of the year
Box plots for distribution of station-level price jumps plotted for each week in year 2010

(iii) 2011



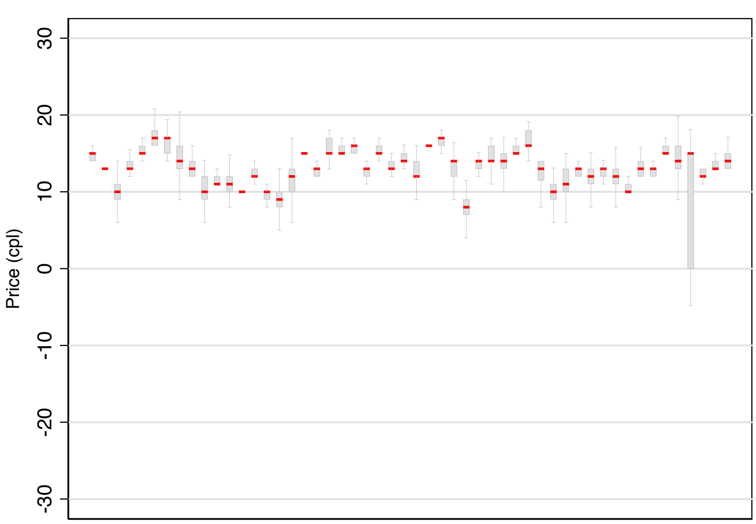
Horizontal axis is the week of the year
Box plots for distribution of station-level price jumps plotted for each week in year 2011

(iv) 2012



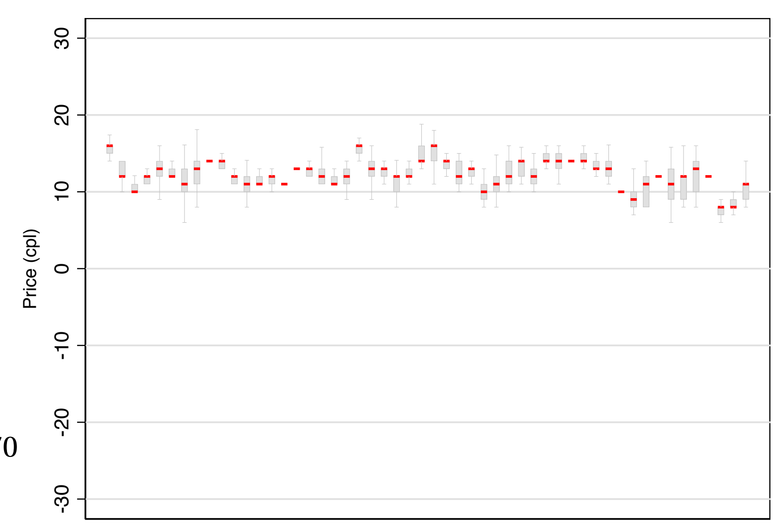
Horizontal axis is the week of the year
Box plots for distribution of station-level price jumps plotted for each week in year 2012

(v) 2013



Horizontal axis is the week of the year
Box plots for distribution of station-level price jumps plotted for each week in year 2013

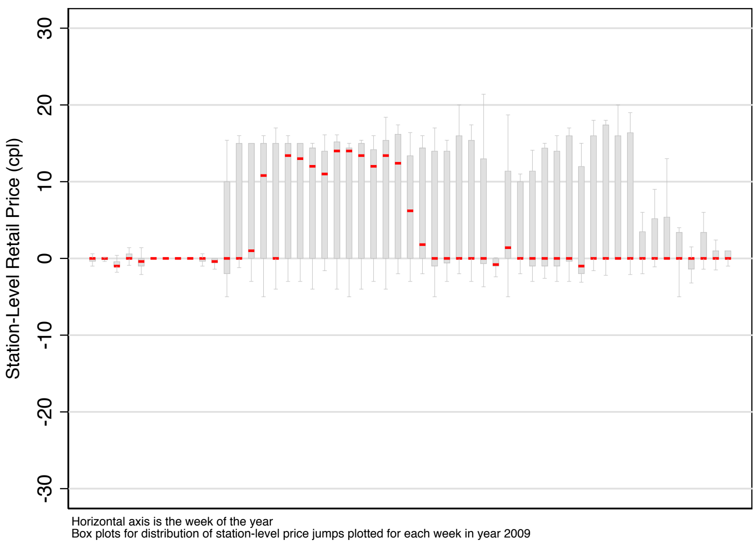
(vi) 2014



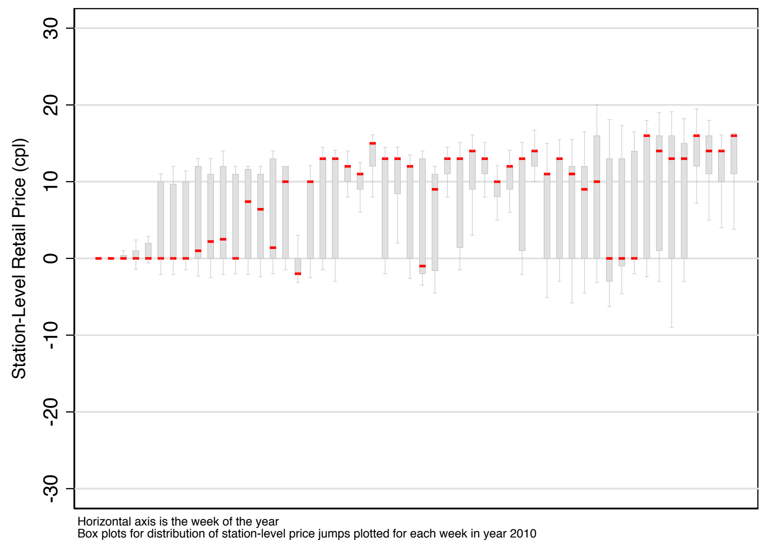
Horizontal axis is the week of the year
Box plots for distribution of station-level price jumps plotted for each week in year 2014

Figure F.5: Box Plots for the Distribution of Daily Station-Level Price Changes During Market Price Jump Days (Thursdays), All Retailers, 2009-2014

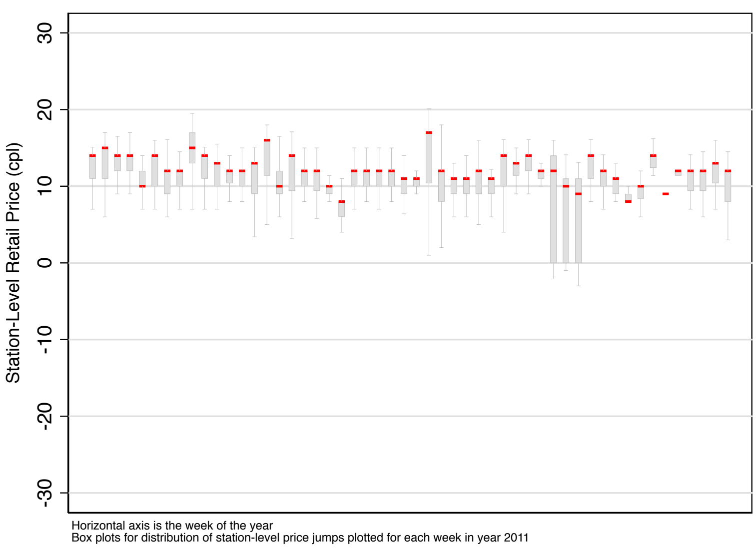
(i) 2009



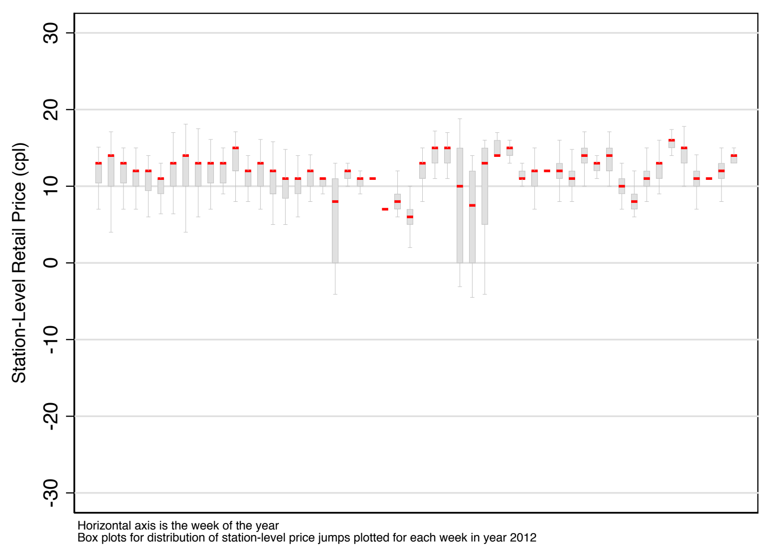
(ii) 2010



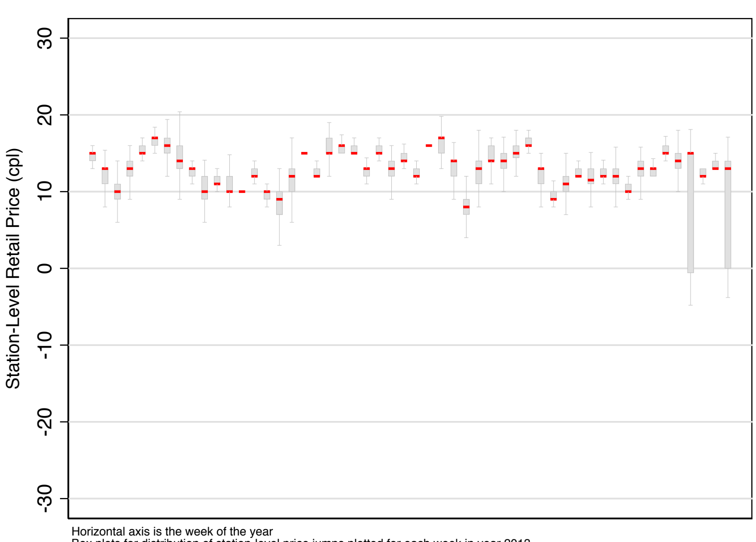
(iii) 2011



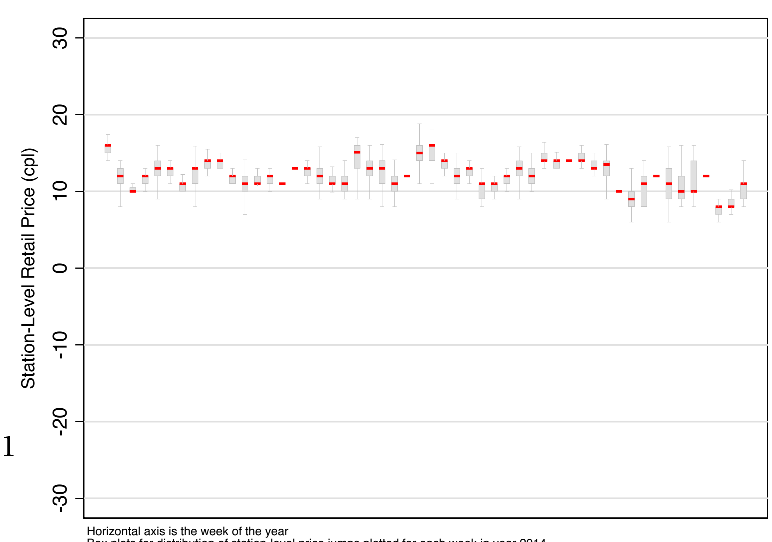
(iv) 2012



(v) 2013



(vi) 2014



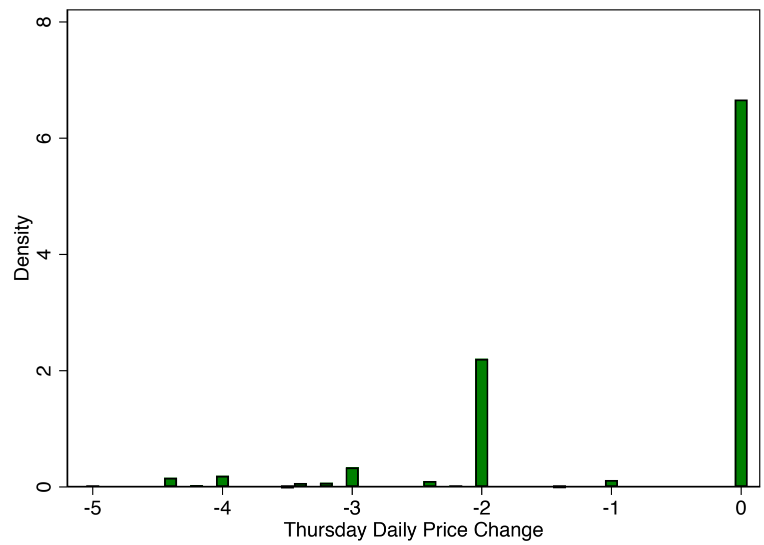
Wednesday jumps by leading BP stations. Before moving onto cross-sectional price dispersion, it is helpful to discuss how BP stations that engaged in Wednesday price jumps in a given week adjust their prices on Wednesdays and Thursdays. Regarding dispersion in Wednesday jumps, on 75% of Wednesdays between 2009 and 2014, the distribution of price jumps across leading BP stations has a range of 0. On 95% of Wednesdays, the range of BP price jumps is 2 cpl or less. In short, leading BP stations exhibit very little price jump dispersion on Wednesdays.

Thursday cuts by leading BP stations. Regarding Thursday price adjustments by price jump leading BP stations, Figure F.6 plots the distribution of daily price changes among BP stations on Thursdays, conditional on having engaged in a Wednesday jump the day before. The figure shows that leading BP stations set a price cut of exactly 0 cpl on Thursday 68% of the time. After jumping on Wednesday, leading BP stations tend to "pause" their cycle on Thursday.

As mentioned in Section 5.2 of the paper, this pausing has important implications for coordination on price levels over the cycle. On Thursdays, non-price jump leading stations target the prices set by leading BP stations on Wednesdays. This is precisely what we show in panel (i) of Figure 11 in the paper. Therefore, because price jump leading BP stations pause price cutting on Thursdays, the price level of leading BP stations on Wednesdays serves as a signal to BP's rivals for price levels on Thursdays. Ultimately, Wednesday price leadership and price signaling by BP allows BP and its rivals to start the undercutting phase of the cycle from the same price level at the top of the cycle week-to-week.

Figure F.6 does, however, reveal some evidence of price cut leadership by leading BP stations. Specifically, on 31% of Thursdays, price jump leading BP stations engage in price cuts of 2 cpl or greater. Conditional on a Thursday cut occurring by a leading BP station, we find in 38% of subsequent station-level cycles, that leading BP stations stay ahead of rivals' price cutting, and continue cutting their prices by 2 cpl or more per day until the next market price jump occurs. That is, BP stations engaged in price jump leadership on Wednesdays subsequently engage in price cut leadership during the subsequent price cycle

Figure F.6: Distribution of BP Stations' Thursday Price Change Conditional on Engaging in a Wednesday Price Jump the Day Before



in 31% × 38%=11.8% of cycles.

F.3 Cross-sectional price dispersion

F.3.1 Price jump days

Finally, we examine the evolution of cross-sectional price dispersion on market price jump days among the major firms only, and across all retailers. We measure dispersion in retail prices across stations on a given day using the *standard deviation*, *inter-quartile range*, and *range*.

Motivated by Baye et al. (2006), we also measure dispersion using the *value of information*, which is the difference between the average price and the minimum price on a given date. In the context of retail search models (e.g,. Varian 1980) this difference corresponds to the expected difference in prices paid by uninformed non-shoppers who randomly sample retail prices, and informed shoppers who pay a search cost to become informed about the lowest prices in the market. That is, the difference provides a measure of the gains from search. This is a useful measure in the specific context of a retail gasoline market, which is a canonical example of a retail market with Bertrand pricing and where consumers face search costs (Eckert **?**).

Panels (i)-(iv) of Figure F.7 present our four price dispersion measures on market price jump days (Thursdays) among stations run by the four major firms: BP, Caltex, Coles, and Woolworths. In each panel, we plot the raw daily dispersion measures (in grey scale) and its 3-month moving average (in red) to highlight lower frequency trends. Panels (i) and (ii) show the standard deviation and IQR falls between January 2009 and January 2011, which highlights the impact of BP Wednesday price jump leadership and the Thursday jumps focal point on price jump coordination.

Panel (ii) further reveals an immediate and permanent rise in the IQR on price jump days starting in August 2012. This corresponds precisely to when BP stops engaging in Wednesday price jump leadership. This mirrors our findings in Figure 11 (ii) in the paper, and in Figure F.4 above. Panel (iii) of Figure F.7 also highlights a break in the trend in the price range starting in August 2012. This further reveals the dispersion-creating impact of BP ceasing to engage in Wednesday price jump leadership. The value of information in panel (iv) grows betwen 2009 and 2012, and is generally stable thereafter.

Figure F.8 presents an analogous set of price dispersion results based on all retailers in the sample. The fall in price dispersion between 2009 and 2012 is again highlighted in panels (i) and (ii). However, we do not see an immediate and permanent jump in the IQR starting in August 2012 as we found in Figure F.7. This implies that the absence of BP Wednesday price jump leadership primarily affects dispersion in in the middle of the price distribution among the four major firms who were tightly coordinating on price jumps prior to August 2012. Finally, panels (iii) and (iv) in Figure F.8 reveal similar trends in the price range and value of information to those in Figure F.7.

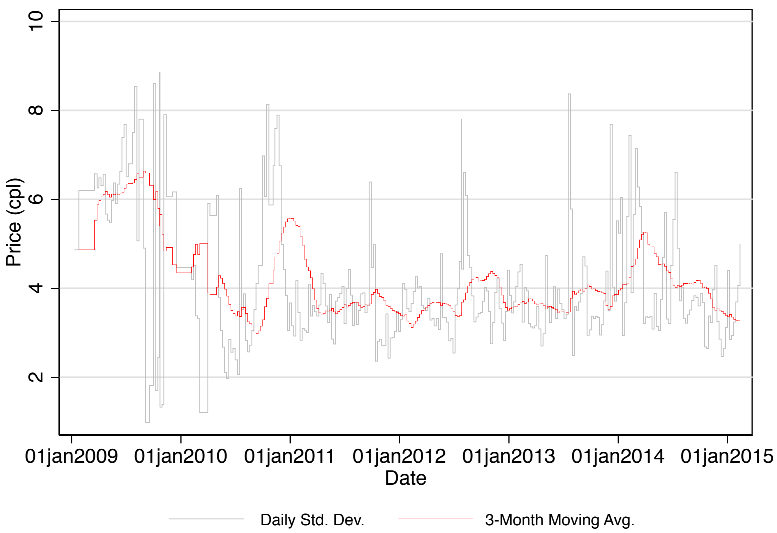
Where are the Gains from Search? To further investigate *where* in the price distribution the gains from search arise, we construct analogous plots to panel (iv) from Figure F.8, except that we consider differences between the mean price and the 5^{th}, 10^{th}, 15^{th}, and 20^{th} percentiles of the price distribution. To facilitate comparison in these variations on the value of information, we plot the 3-month moving averages of these time series in Figure F.9. For reference, we again plot the 3-month moving average of the daily difference between the mean and minimum price, which is our baseline value of information measure.

The figure shows the gains from searching among the bottom 10 percent of stations in the price distribution grow over time. However, once the 15$^{\text{th}}$ percentile is reached, the gains from search collapse. Notice that the percentiles for where the gains from search exist generally align with our findings from Section F.1 above that on average 12% of stations delay price jumps by one day to Friday week-to-week. In-line with Figure F.9, these delaying stations have prices 10-15 cpl below average prices on Thursdays, and hence drive the gains from cross-sectional search on price jump days.

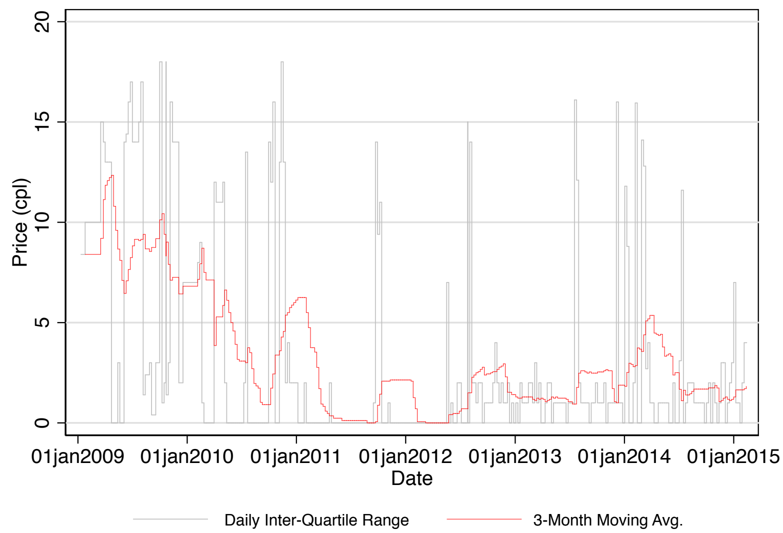
Figure F.7: Cross-Sectional Price Dispersion on Market Price Jump Days, Four Major Firms Only, 2009-2014

(Daily Values and 3-Month Moving Average of Daily Values Presented)

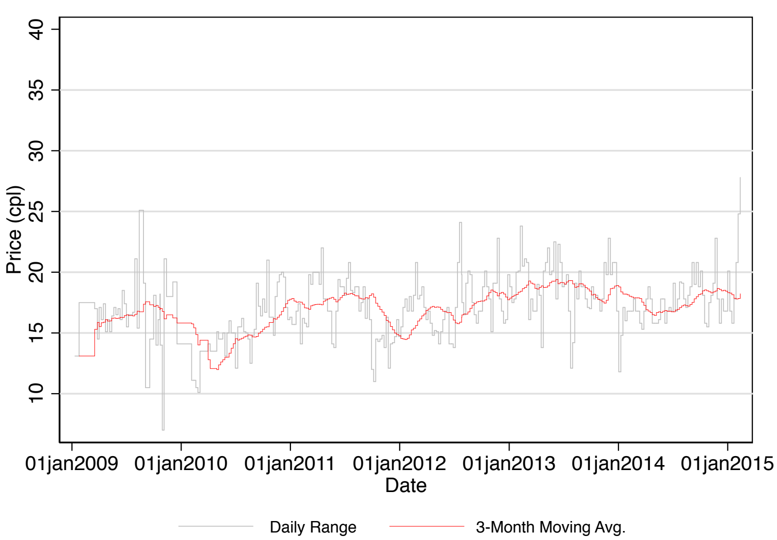
(i) Standard Deviation



(ii) Inter-Quartile Range



(iii) Range



(iv) Value of Information (Mean$_i(p_{it})$- Min$_i(p_{it})$)

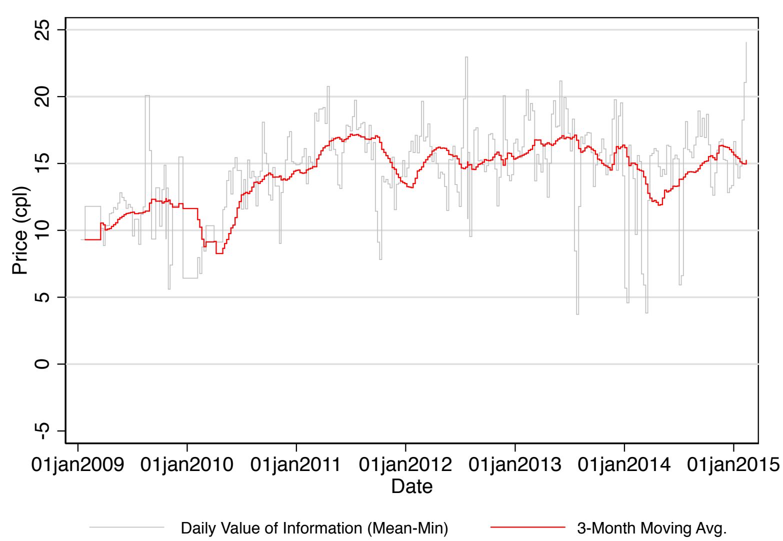


Figure F.8: Cross-Sectional Price Dispersion on Market Price Jump Days, All Retailers, 2009-2014

(Daily Values and 3-Month Moving Average of Daily Values Presented)

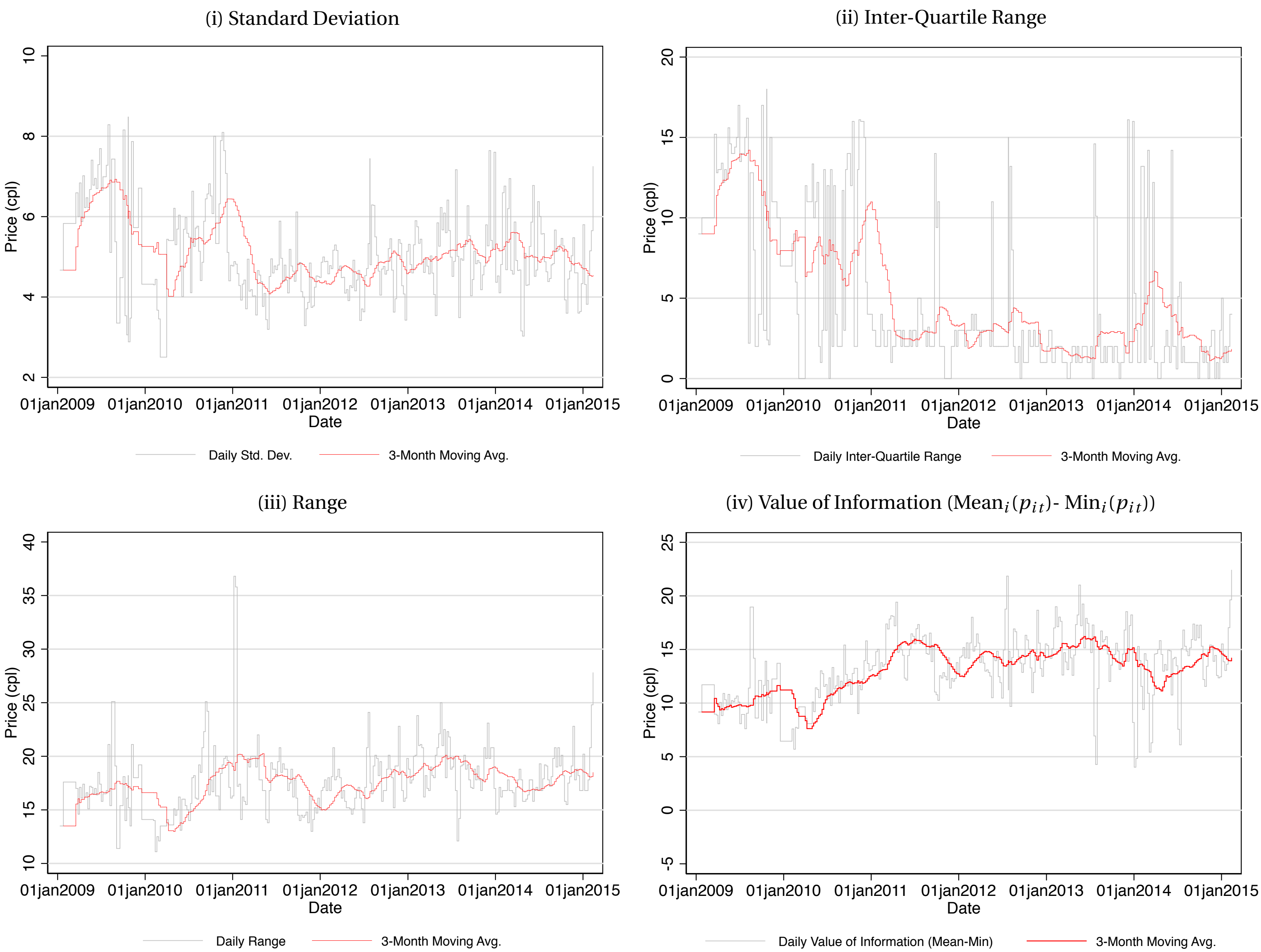
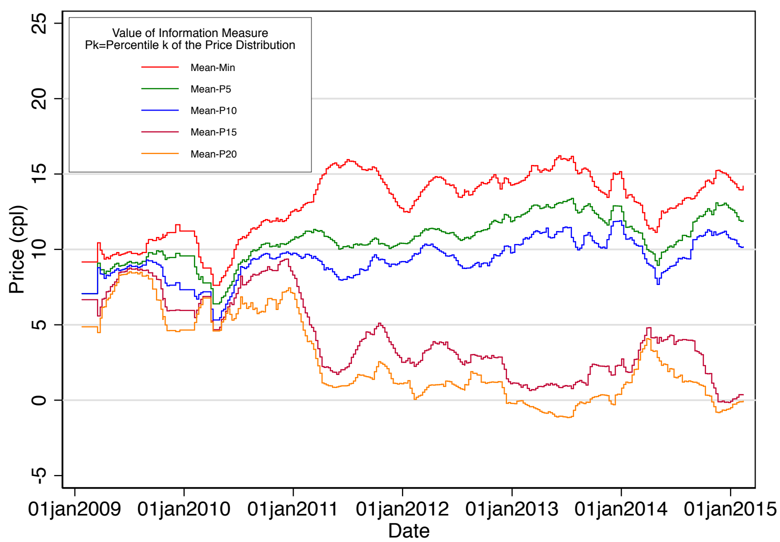


Figure F.9: Value of Information on Market Price Jump Days
(3-Month Moving Averages Presented)



F.3.2 Undercutting days

In this final section, we study cross-sectional price dispersion over the undercutting phase of the cycle. Figure F.10 plots our four measures of price dispersion – *standard deviation*, *inter-quartile range*, *range*, *value of information* – for days 2 to 6 of the market cycle. Rather than plotting raw daily values for each dispersion measure, we again plot 3-month moving averages for each market cycle day. This facilitates comparisons of lower frequency trends in price dispersion across each day of the undercutting phase.

Panel (i) of Figure F.10 yields two findings of note. First, on days 6 and 7 of the undercutting phase, price dispersion gradually falls over time. The large and smooth drop in price dispersion on day 7 is again driven by BP's transition away from Wednesday price jump leadership, which generates significant cross-sectional price dispersion on day 7 of the market cycle.

Second, panel (i) shows that cross-sectional price dispersion *rises* between 2010 and 2011 on days 2 to 5 of the market cycle and is stable thereafter. In addition, we find that earlier days in the undercutting phase (e.g., cycle day 2) exhibit greater cross-sectional price dispersion than later days (e.g., cycle day 6).

Panels (ii)-(iv) provide insight into what drives these different trends in the standard deviation of prices. Starting in panel (ii), we find that the inter-quartile range of prices collapses on all cycle days midway through 2010. As with price jumps, there is little dispersion in the middle of the price distribution throughout the undercutting phase. This lack of dispersion arises from coordination on price jump timing and magnitudes by the four major firms' and Gull's stations (see Sections F.1 and F.2 above), and tight coordination on 2 cpl daily price cuts during the undercutting phase (see Figure 9 in Section 4.2 of the paper). In other words, as Thursday jumps and 2 cpl cuts solidify as focal pricing rules, the four major firms' and Gull's stations start cutting prices from the same level at the top of the cycle, and cut prices by the same 2 cpl amount day-to-day throughout the undercutting phase. Ultimately this yields little dispersion in the middle of the price distribution during the undercutting phase, thereby limiting search opportunities.

Panels (iii)-(iv) yield an interesting contrast to panel (ii). The gaps between the maximum and minimum price, and between the mean and minimum price, grow over time on days 2 to 5 of the cycle. Moreover, the growth in these gaps is largest on earlier days of the undercutting phase. In other words, during the undercutting phase of the market cycle, the gains from search are largest immediately after price jumps occur, and become relatively muted as the undercutting phase progresses.

In Figure F.11, we investigate at which quantiles of the price distribution the gains from search emerge throughout the undercutting phase. As in our analysis of cross-sectional price dispersion on price jump days, for each date we compute the difference between the mean price and the minimum price, as well as the 5$^{\text{th}}$, 10$^{\text{th}}$, 15$^{\text{th}}$ and 20$^{\text{th}}$ percentiles of the price distribution. We construct separate plots for days 2 to 7 of the market cycle, and plot the 3-month moving averages of these daily differences. Focusing on moving averages again facilitates comparison between these variations on the value of information.

Panels (i)-(vi) of Figure F.11 show that the gains from search during the undercutting phase mainly exist among stations below the 5$^{\text{th}}$ percentile of the price distribution.[36] For example, panel (i) of Figure F.11 suggests a 5 to 10 cpl price savings from purchasing at the 5$^{\text{th}}$ percentile price relative to purchasing at the average price the day after a price jump. In contrast, there is very little dispersion between the mean price and the 10$^{\text{th}}$ percentile on other cycle days. This highlights a lack of gains from search for the vast majority (87%) of stations run by the four major firms or Gull who coordinate their prices.

Panels (i)-(vi) further show that the gains from search fall dramatically over the undercutting phase of the market cycle. Indeed, by cycle day 7, just before the next price jump occurs, the difference between the mean and minimum price is less than 4 cpl on average. So while there are large gains from inter-temporal price search in timing purchases at the bottom of the cycle before price jumps, there are limited gains from cross-sectional search on these days.

[36] This contrasts with price jump days, where recall from above that the gains from search exist below the 10$^{\text{th}}$ percentile of the price distribution.

Figure F.10: Cross-Sectional Price Dispersion by Day of the Market Undercutting Phase

(3-Month Moving Averages Presented)

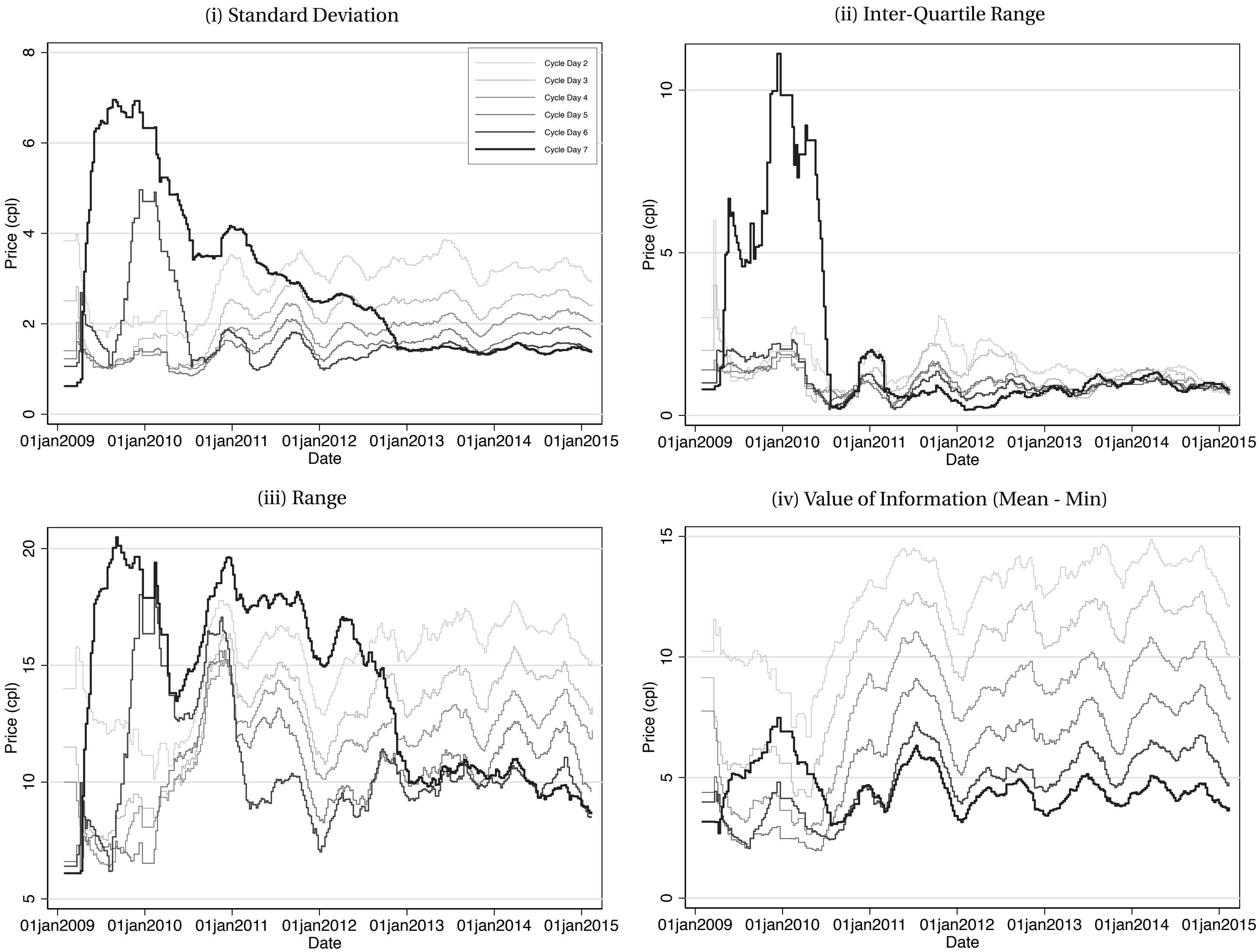
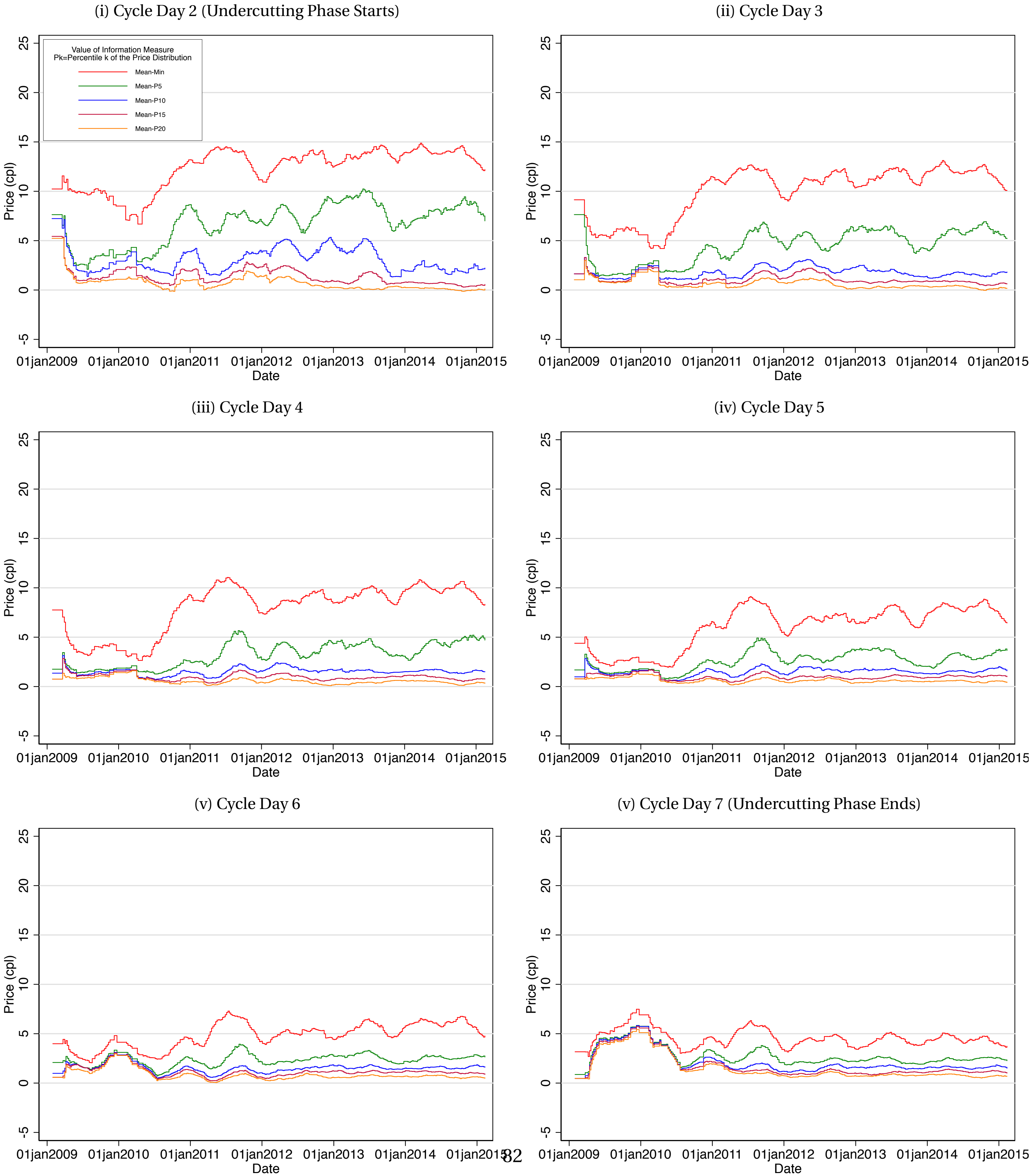


Figure F.11: Value of Information by Day of the Market Undercutting Phase
(3-Month Moving Averages Presented)



G Additional results and robustness checks

In this Appendix we present auxiliary results that support our main findings in the paper. Section G.1 presents supplemental figures related to price jump timing and price jump and cut magnitudes. Section G.2 presents our exhaustive set of structural break tests that confirm whether there are breaks in pricing behavior and margins after early 2010 (when the focal points first emerge), and after August 2012 (when BP stops engaging in Wednesday price jump leadership). In Section G.3, we estimate a range of probit models designed to test the predictability of the price experiments discussed in Section 4.2 of the paper. Finally, Section G.4 provides supplemental results for Section 5.3 of the paper. Specifically, we test for a focal firm for price coordination; we document price mis-coordination over the cycle and over time after BP exits its role as price jump leader; and we perform structural break tests for margins around the time of BP's exit from price jump leadership.

G.1 Supplemental figures

We present four sets of supplemental figures. Figure G.1 graphs the propensity for BP, Caltex, Woolworths, Coles, and Gull to engage in Wednesday and Thursday jumps, as well as price jumps on other days of the week, month to month between 2008 and 2015. These figures supplement Figure 6 in the paper by showing all firms follow BP's lead and quickly adhere to the Thursday jumps focal point starting in 2010.

Figure G.2 supplements the discussion in Section 4.3 of the paper by presenting the share of stations engaging in 2 cpl price cuts at a weekly frequency in the first half of 2009. At the weekly frequency, it is evident that BP is the first to experiment with 2 cpl price cuts, and there is some evidence that other firms follow BP's lead in engaging in 2 cpl price cuts.

Figure G.3 presents the propensities for BP, Caltex, Woolworths, Coles, and Gull to engage in exactly 2 cpl cuts month to month between 2009 and 2015. These figures supplement Figure 9 in the paper by showing that price leadership and experimentation only happens with 2 cpl cuts.

Figure G.4 presents the median of Wednesday price jumps by price jump leading BP stations each week between January 2010 and August 2012. This figure supplements Figure 11 in the paper by showing that for a temporary period at the end of 2011, BP engages in substantially larger Wednesday price jumps of 14 to 16 cpl.

Figure G.1: Price Leadership with Thursday Price Jumps

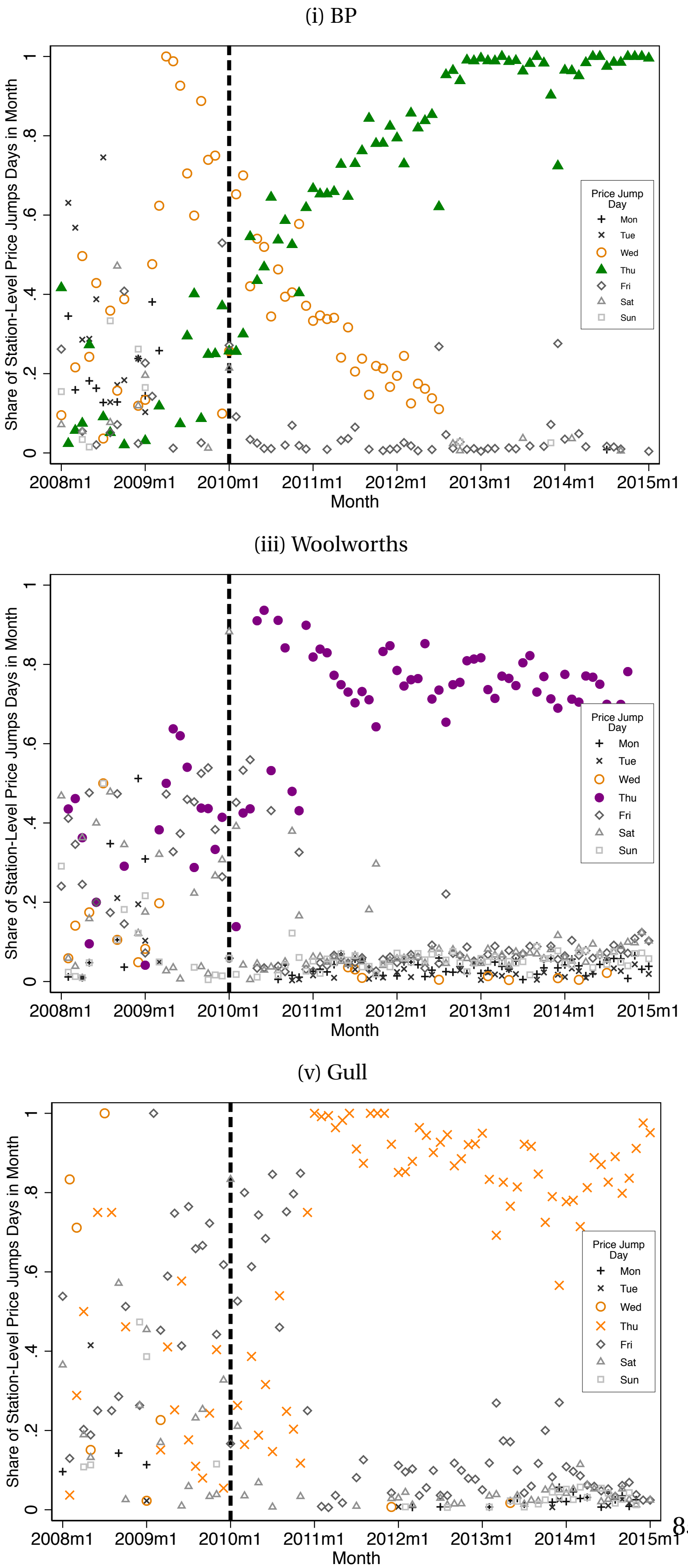


Figure G.2: BP Price Leadership with 2-cpl Price Cuts (Weekly Frequencies)

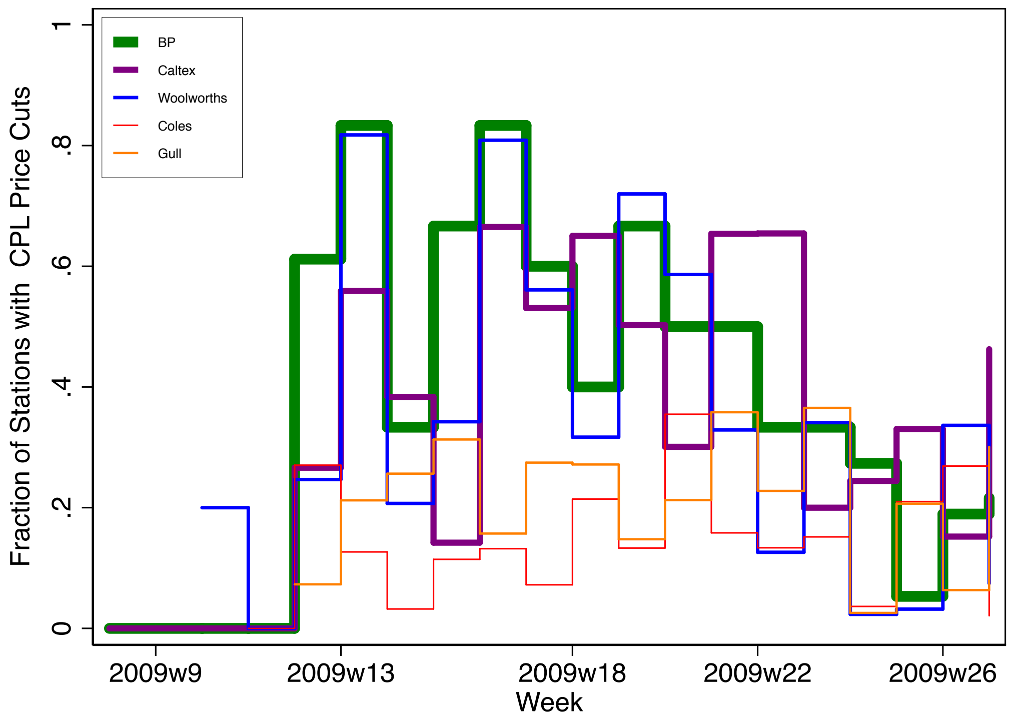


Figure G.3: BP Price Leadership with 1, 2, 3, 4 CPL Cuts

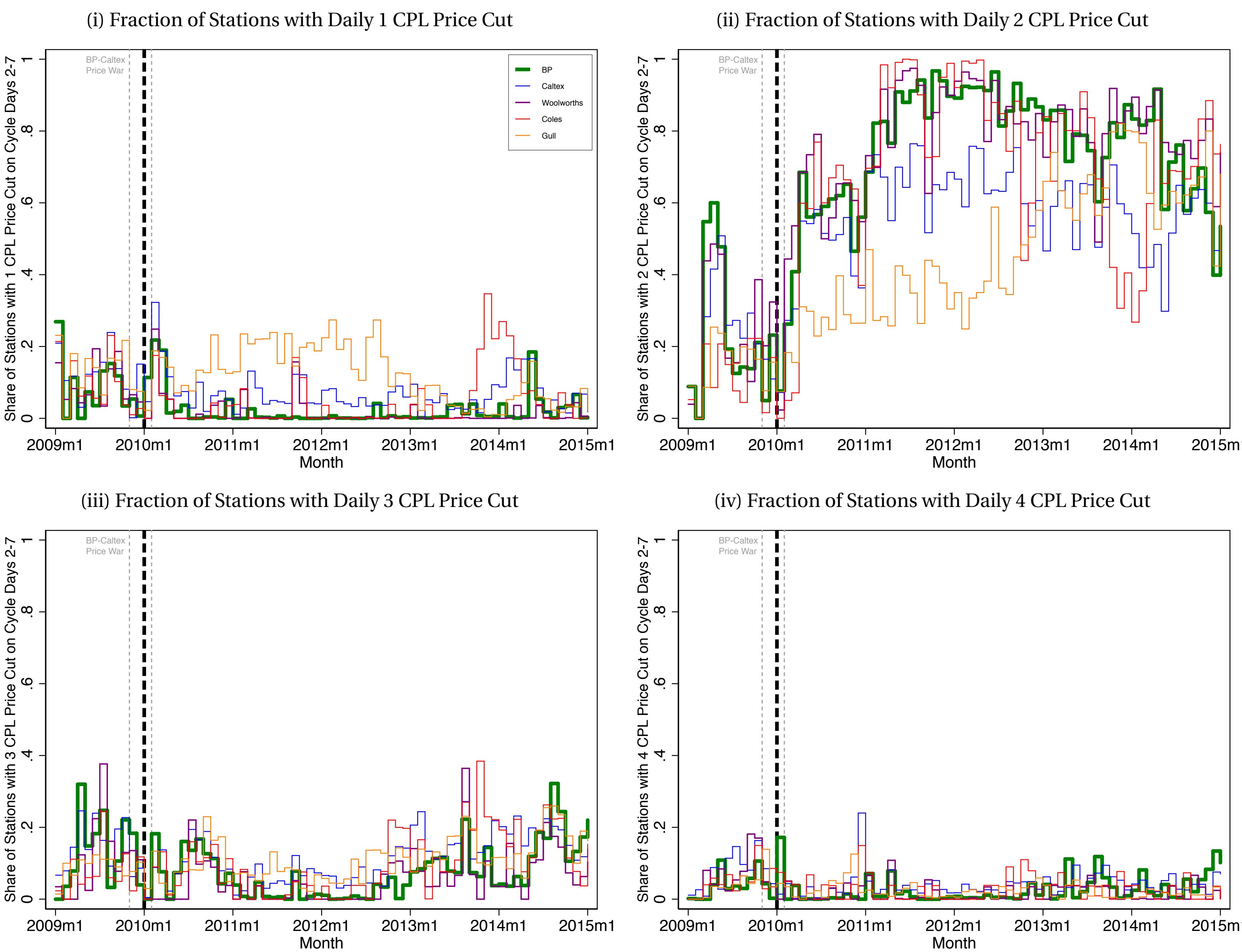
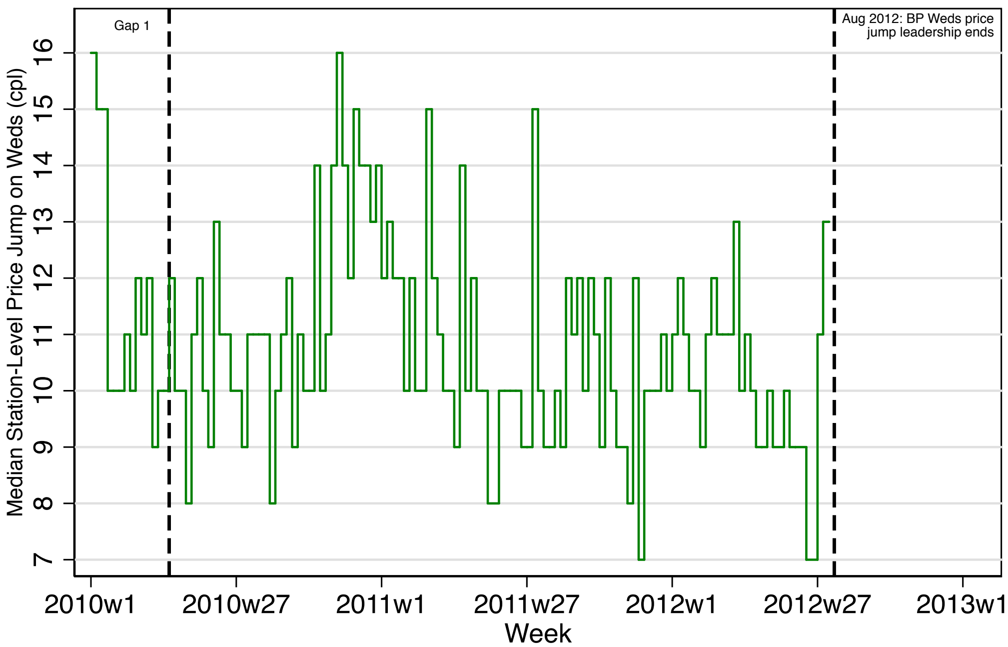


Figure G.4: BP Wednesday Price Jump by Week



G.2 Structural break tests

In this Appendix, we conduct a series of structural break tests that correspond to various figures in the paper. Throughout, we follow the same four-step approach in implementing each structural break test:

1. Summarize the figure and structural break of interest.
    - The break either corresponds to the start of 2010 (when the Thursday jumps and 2 cpl cuts focal points emerge) or August 2012 (when BP price jump leadership ends).
2. Specify the econometric model for an outcome variable of interest used to implement the structural break test
3. Graphically plot the F-statistics for various structural break tests based on various potential break dates
4. Identify the SupF statistic (Andrews 1993), which finds the location of the unknown structural break. In this way, we allow the data to tell us when a break occurs, if one exists.

The exact sample period used through for detecting structural breaks is April 1, 2009 to December 31, 2014. To help the reader move between the figures in the paper and their respective break tests in this appendix, we use subsection headers that correspond to the figure titles in the paper.

Figure 2 (i): Timing of Market Price Jumps by Day of Week

In Figure 2 (i), we examine a structural break in the timing of market price jumps at the start of 2010.[37] In particular, the figure shows this is when Thursday jumps emerges as a focal point for coordinating the timing of price jumps week to week. Prior to 2010, price jumps occur across different days of the week.

[37] See Definition 1 (iii) in Section 3 of the paper for the definition of a market price jump. Also see this definition for station and market cycle lengths, and station-level price jumps. We examine breaks in all of these variables throughout this section.

To estimate when the structural break occurs, we use regressions of the following form:

$$\begin{aligned}
1\{Jump_t\} =& \alpha_0 + \alpha_1 1\{Mon_t\} + \alpha_2 1\{Tue_t\} + \alpha_3 1\{Wed_t\} + \alpha_4 1\{Thu_t\} + \alpha_5 1\{Fri_t\} + \alpha_6 1\{Sat_t\} \\
&+ \beta_0 1\{t > T\} + \beta_1 \left(1\{Mon_t\} \times 1\{t > T\}\right) + \beta_2 \left(1\{Tue_t\} \times 1\{t > T\}\right) + \beta_3 \left(1\{Wed_t\} \times 1\{t > T\}\right) \\
&+ \beta_4 \left(1\{Thu_t\} \times 1\{t > T\}\right) + \beta_5 \left(1\{Fri_t\} \times 1\{t > T\}\right) + \beta_6 \left(1\{Sat_t\} \times 1\{t > T\}\right) + \epsilon_{it}
\end{aligned}$$

where $1\{Jump_t\}$ is a dummy variable that equals one if a market price jump occurs on date t, $1\{Mon_t\}$ is a dummy variable equaling one if date t is a Monday (and similarly for the other days of the week), and $1\{t > T\}$ is a dummy variable that equals one if date t falls after a break date T.

We run this regression, varying T from January 1, 2009 to January 1, 2011. For each value of T, we compute the F-statistic for testing the null that $\beta_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6$. Figure G.5 plots these F-statistics, and highlights their largest value, which is the SupF statistic from Andrews (1993).

In the figure, we find that the F-Statistics start rising at the end of 2009, implying an increasingly better fit with a model that includes the variables that include interactions with the structural break dummy variable, relative to a model without any structural breaks. A structural break test that assumes a break date of January 1, 2010 would yield a statistically significant break at the 1% level. The SupF for the break to Thursday jumps occurs on May 1, 2010.

Notice, however, that we also find an initial peak on April 1, 2009, which corresponds to BP's break to Wednesday jumps, with rivals following with Thursday jumps, following the 2008-09 crude oil price shocks. Throughout the paper, we focus on this initial local break to Thursday jumps in April 2009 as the start of the equilibrium transition to Thursday jumps. The BP-Caltex price war that would commence in August 2009 temporarily undermined the focal point, as evidenced by the decline in the F-statistics in Figure G.5 over this period. Following BP's signalling and testing Thursday jumps in Gap 1 and Gap 2 2010, we find a permanent, stable break to Thursday jumps in May 2010.

Figure G.5: Structural Break Test: Figure 2 (i)

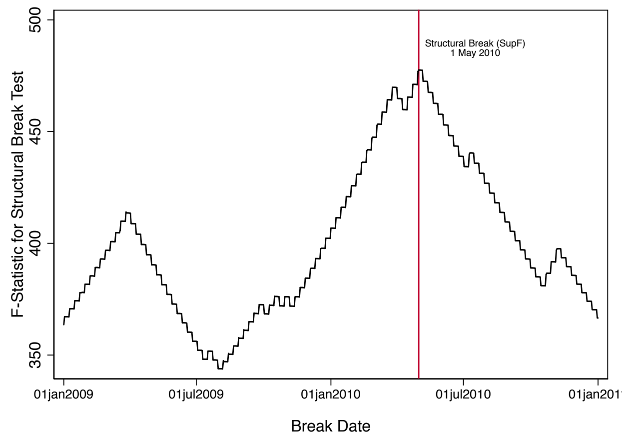


Figure 2 (ii): Average Station-Level Cycle Length by Firm and Month

In Figure 2 (ii), we find evidence of a shift to regular weekly cycles for each firm at the start of 2010. This is a result of the Thursday jumps focal pricing rule. We use the following regression to test for a structural break in station-level cycle length:

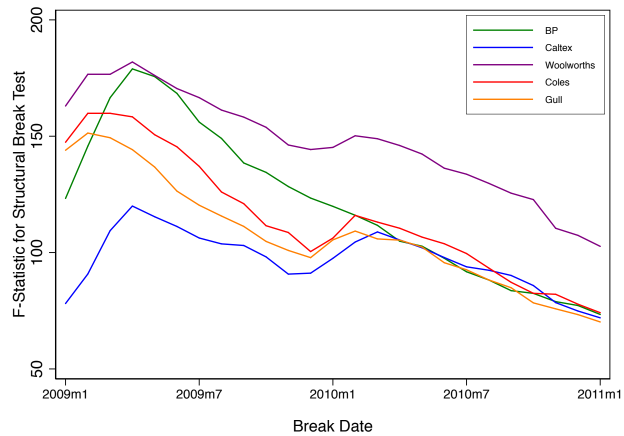
$$Length_{it} = \alpha_0^i + \alpha_1^i c_t + \sum_{j=1}^{12} \alpha_{2j}^i 1\{month_t == j\} + \beta_0^i 1\{t > T\}$$

where $Length_{it}$ is the average station-cycle length for firm i in month t, c_t is the average daily wholesale terminal gate price in month t,[38] $1\{month_t == j\}$ is a dummy variable equaling one if month t is month of year j for $j = 1, \ldots, 12$, and $1\{t > T\}$ is the structural break dummy that equals one if month t is after break month T. Motivated by Figure 2 (ii) in the paper, we test for a break in the level of station-level cycle lengths around the start of 2010. As before, we allow T to run from January 2009 to January 2011, and look for the SupF for the test of the null that $\beta_0^i = 0$. The superscripts on the coefficients in the regression indicate that we run separate structural break tests for each firm i.

Figure G.6 plots the F-Statistics over the range of break months T consid-

[38] We have experimented with including lags of c_t and found doing so has little impact on our structural break tests in this subsection, and in all the subsections that follow.

Figure G.6: Structural Break Test: Figure 2 (ii)



ered. With the exception of BP, we find local maxima in the F-Statistics for each firm within the first 6 months of 2010, which implies that a model with structural breaks has an increasingly better fit relative to a model without breaks at the start of 2010. For instance, if we had restricted our range of T values to be after 2010, we would have obtained SupF dates of March 2010, February 2010, February 2010, and February 2010 for Caltex, Woolworths, Coles and Gull, respectively. This corresponds to a local break to weekly cycles relative to previous weeks by these firms over this period.

In contrast, we do not find a local break in early 2010 for BP because it more persistently engages in weekly cycles throughout 2009 and 2010 relative to its rivals. See, for example, Appendix D for evidence of BP's relative persistence in engaging in weekly cycles relative to its rivals over this period.

Over a broader time scale between January 2009 to January 2011, we find the SupF emerges in the first half of 2009 for each firm. BP's SupF, which occurs in April 2009, corresponds precisely to when BP starts engaging in Wednesday jumps with the majority of its stations to reinitiate the cycle after its collapse between 2008-09.[39] In other words, the SupF for the break in cycle length across the firms over this period is driven by the re-emergence of price cycles in the first half of 2009.

[39] See Appendix C.3 for cycle reinitiation by BP in April 2009. See also Figure 6 in the paper.

Figure 3: Average Daily Station-Level Price Changes by Day of the Market Cycle

Figure 3 in the paper highlights the emergence of the 2 cpl cuts focal point in 2010. The figure plots average daily price changes across stations by day of the market cycle. To estimate a structural break in these average daily price cuts, we estimate the following regression model:

$$\Delta p_{it} = \alpha_0^i + \alpha_1^i c_t + \sum_{j=1}^{12} \alpha_{2j}^i 1\{month_t == j\} + \beta_0^i 1\{t > T\}$$

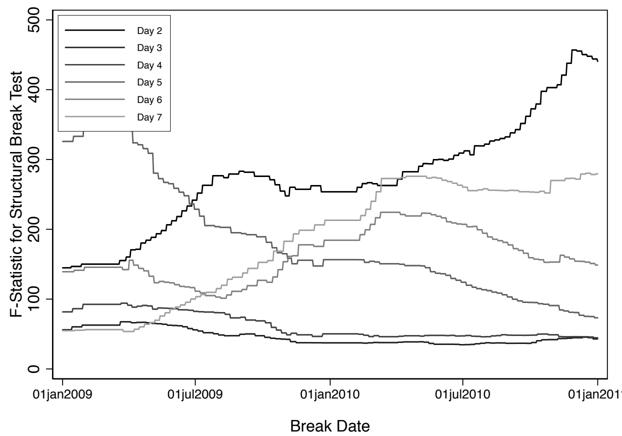
where i indexes the day of the market cycle, and Δp_{it} is the average daily price change on date t, which is on day i of the market cycle. All other variables in the regression have been defined in this section above. We vary the break date T between January 1, 2009 and January 1, 2011, and estimate breaks for days $i = 2, \ldots, 7$ of the market cycle.

Figure G.7 presents our structural break test results. Here we plot the F-test statistics for the test of the null that $\beta_0^i = 0$ for all cycle days i. Statistically, the break in the level of cuts to 2 cpl is significant if T is set to dates in January 2010, as indicated by the large scale of the F-Statistics in the figure. While Figure 3 in the paper is useful for providing preliminary evidence on the emergence of 2 cpl cuts, structural break tests based on it presented here do not provide a clear depiction of breaks to 2 cpl price cuts at the start of 2010. However, as we will see below in the subsection based on Figure 9 from the paper, where we analyze breaks to 2 cpl cuts at the firm level using station-level (and not market level) cycles, the breaks to 2 cpl cuts at the start of 2010 becomes clear.

Figure 4 (ii): Average Station-Level Margins by Firm and Month

In Figure 4(ii) of the paper, we highlight breaks in the trend of margin growth for each retailer around the start of 2010. Specifically, the graph shows an increase in the margin trends for each firm in 2010. To estimate a structural break in the

Figure G.7: Structural Break Test: Figure 3



trend, we estimate the following regression model:

$$margin_{it} = \alpha_0^i + \alpha_1^i t + \sum_{j=1}^{12} \alpha_{2j}^i 1\{month_t == j\} + \beta_0^i (t \times 1\{t > T\})$$

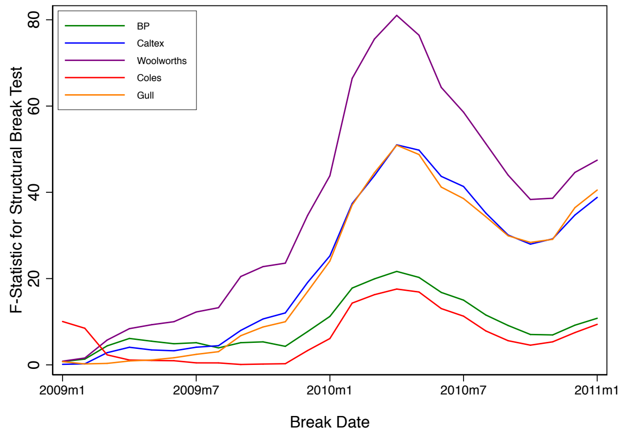
where $margin_{it}$ is the average daily margin for firm i in month t. All other variables in the regression have been defined in this section above. The superscripts on the regression coefficients indicate that we run the structural break test for each firm i. As above, we vary the break date T from January 2009 to January 2011, and plot the F-statistics for the test of the null that β_0^i, which is the coefficient that governs the break in the margin trend for firm i.

The results in Figure G.8 clearly highlight a break in margin growth at the start of 2010. Specifically, we find the SupF for the break in margin trends for each firm occurs in March 2010. All of the F-Statistics in this month imply a statistically significant break in margin trends.

Figure 6: Share of BP/Caltex Station-Level Price Jumps by Day of the Week and Month

Figure 6 in the paper highlights the transition toward Thursday jumps for BP and Caltex stations. The figures reveal that the transition begins around the start of 2010 for Caltex, and perhaps earlier for BP. To estimate when the structural break

Figure G.8: Structural Break Test: Figure 4



toward Thursday jumps occurs, we use regressions of the following form:

$$share\_thu\_jump_{it} = \alpha_0^i + \sum_{j=1}^{12} \alpha_{1j}^i 1\{month_t == j\} + \beta_0^i 1\{t > T\}$$

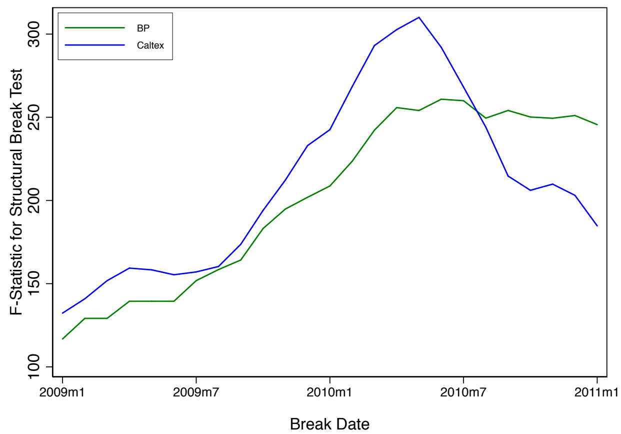
where $share\_thu\_jump_{it}$ is the share of price jumps that occur on Thursday for firm i in month t. The superscripts on the regression coefficients indicate that we estimate the model separately for BP and Caltex. We vary the break date T from January 2009 to January 2011, and plot the F-statistics for the test of the null that $\beta_0^i = 0$

Our structural break test results are reported in Figure G.9. We find the SupF for BP and Caltex occurs in June 2010 and May 2010, respectively. This is consistent with our interpretation of Figure 7 in the paper, and a break to Thursday jumps in early 2010.

Figure 9 (i): Share of Stations with 2 CPL Daily Price Cut on Undercutting Days by Firm and Month, 2009-2015

Figure 9 (i) in the paper describes the formation of the 2 cpl price cuts focal point at the start of 2009. Keeping with the figure, we estimate a structural break in

Figure G.9: Structural Break Test: Figure 6



firms' propensity to set 2 cpl cuts month to month using the following regression:

$$share\_2cpl\_cut_{it} = \alpha_0^i + \alpha_1^i c_{it} + \sum_{j=1}^{12} \alpha_{2j}^i 1\{month_t == j\} + \beta_0^i 1\{t > T\}$$

where $share\_2cpl\_cut_{it}$ is the share of days of the undercutting phase of station-level cycles where firm i sets exactly a 2 cpl price cut in month t. The superscripts indicate that we run the structural break tests separately for each firm i. For the tests, we vary T from January 2009 to January 2012 and plot the F-Statistics for the test of the null that $\beta_0^i = 0$.

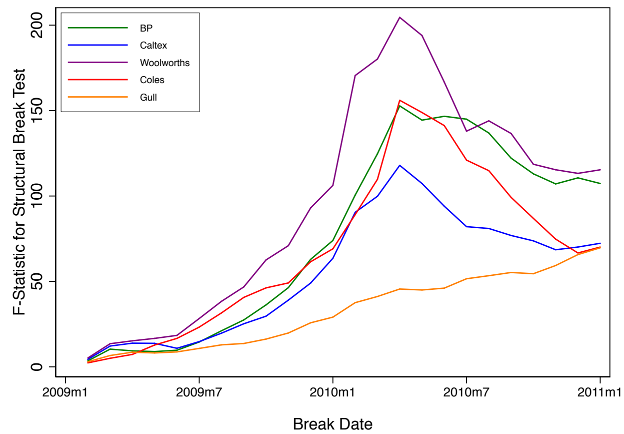
Figure G.10 presents a clear set of findings: the SupF for each of the oil majors and supermarkets occurs in May 2010. All of these tests imply statistically significant breaks to 2 cpl cuts for these firms in early 2010.

By contrast, we see the SupF for Gull occurs in January 2012, and is continuing to rise. This is driven by our finding in Figure 9 (i) in the paper that it takes longer for Gull to converge on the 2 cpl cuts focal point relative to the oil majors and super markets.

Figure 10: Average Margins by Station-Level Cycle Day and Month

Figure 10 in the paper illustrates the anchoring effect that the Thursday jumps and 2 cpl cuts focal points have on margins. It also reveals a break in margin

Figure G.10: Structural Break Test: Figure 9 (i)



trends by day of the cycle starting in 2010. To estimate the break date, we use regressions of the following form:

$$margin_{it} = \alpha_0^i + \alpha_1^i t + \sum_{j=1}^{12} \alpha_{2j}^i 1\{month_t == j\} + \beta_0^i (t \times 1\{t > T\})$$

where $margin_{it}$ is the average margin on market cycle day i in month t. As usual, we vary the break date T from January 2009 to January 2011, and compute F-Statistics for the test of the null that $\beta_0^i = 0$ to detect the timing of the structural break in the margin trend. The i superscripts in the regression imply that we conduct this test for each day of the market cycle i.

Our results are presented in Figure G.11. We find the SupF for days 1 to 4 of the cycle occurs either in April 2010 or May 2010. The break in the trend in margins on these days occurs in early 2010.

For days 5 to 7 of the cycle, we find their SupF occurs at the start of the sample window in January 2009, in the far left of the figure. That is, the break in the margin trends on these days is dominated by the end of the crude oil price shock period. We do find, however, local growth in the F-Statistics for a break in the margin trend in May 2010 for days 5 and 6 of the cycle as well.

Figure G.11: Structural Break Test: Figure 10

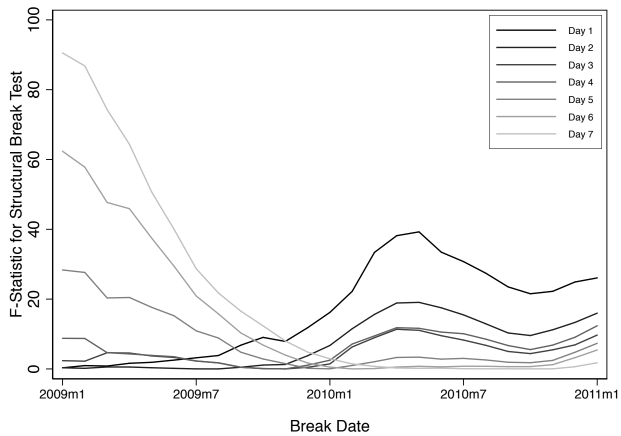


Figure G.12: Structural Break Test: Figure 11 (ii)

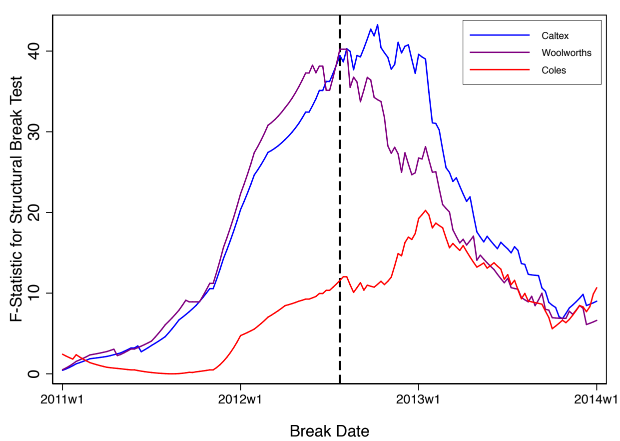
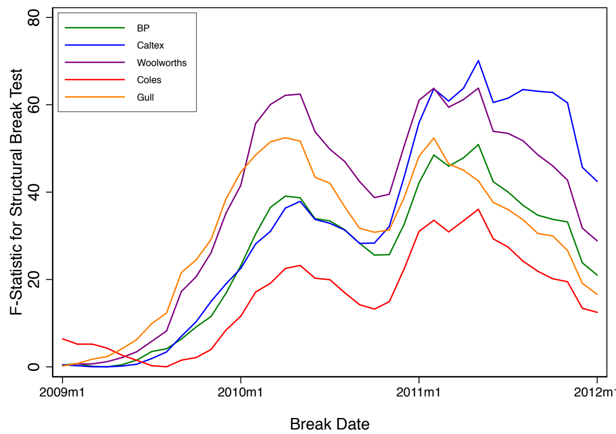


Figure 11(ii): Difference Between Median Thu Price Among All BP Stations and Median Thu Price Among Rival Stations

Figure 11 (ii) in the paper plots the difference between the median margin across BP stations on Thursdays and BP's rivals' median margin on Thursdays between 2010 and 2015. The figure highlights a break in August 2012 where the gap between BP's median margin and its rivals' median margin grows. Prior to August 2012, while BP is engaged in Wednesday price jump leadership, the gap is consistently 0.

To estimate when the structural break in the difference between median mar-

Figure G.13: Structural Break Test: Figure 14



gins of BP and its rivals occurs, we estimate the following regression:

$$diff\_thu\_p_{it} = \alpha_0^i + \sum_{j=1}^{12} \alpha_{1j}^i 1\{month_t == j\} + \beta_0^i 1\{t > T\}$$

where $diff\_thu\_p_{it}$ is the absolute value of the difference between BP's median margin on Thursday and rival firm i's median margin on Thursday in week t. We run the regression separately for each rival firm i using all weeks between 2010 and 2015. We vary the break date T between January 2011 and January 2014, and report the F-statistics for the test of the null that $\beta_0^i = 0$.

Figure G.12 presents our results. In addition to the F-Statistics, we include a dash line in the figure that indicates when BP Wednesday price jump leadership ends. As the figure shows, the SupF for the structural break in coordination on margin levels between BP and its three main rivals – Calex, Woolworths, and Coles – occurs within six months following the end of BP price jump leadership.

Figure 14: Average Station-Level Margins by Firm and Month

Our final set of structural break tests are based on Figure 14 in the paper. In this figure, we highlight a break in the trend in margins at the bottom of the cycle for each firm around the start of 2010. To find when the break in the trend occurs, we use the following regression model:

$$margin_{it} = \alpha_0^i + \alpha_1^i t + \sum_{j=1}^{12} \alpha_{2j}^i 1\{month_t == `j'\} + \beta_0^i (t \times 1\{t > T\})$$

where $margin_{it}$ is the average margin at the bottom of station-level cycles for firm i in month t.[40] As before, for our structural break tests, we vary the break date T from January 2009 to January 2011, and report the corresponding F-statistics for the test of the null that $\beta_0^i = 0$.

Our structural break test results are reported in Figure G.13. The figure reveals two humps for each firm in the F-statistics for structural breaks. This is driven by two breaks in margin trends at the bottom of the cycle just after the start of 2010 and 2011. These trend breaks can be seen visually in Figure 14 in the paper, and is confirmed by the structural break tests here in Figure G.13. In sum, margins at the bottom of the cycle exhibit a break in trend at the start of the 2010 with the emergence of the two focal points, and a second break in the trend in 2011 as the focal points are cemented.

[40] See Section 5.3 in the paper on how we identify dates at the bottom of station-level cycles in constructing these averages.

G.3 Predictability of Thursday jumps experiments

Section 4.2 of the paper discusses the use of price experiments to aid coordination on the Thursday price jump focal point. In this appendix, we estimate a range of probit models to test for alternative explanations for the timing of the price experiments. In each probit model, we attempt to predict a BP price experiment in week t as a function of aggregate state variables. The experiments we predict are Gaps $2, 3, \ldots, 7$. Recall that these are weeks in which BP witholds Wednesday price jump leadership. For our analysis, we use a sample of weeks between May 2010 and August 2012. Recall that this is the period where the price cycle with Thursday jumps is stable, and where BP engages in Wednesday price jump leadership, except in Gaps $2, 3, \ldots, 7$.

We consider three groups of state variables:

- Wholesale costs
  - c_t: mean TGP in week t
  - $c_{t-k}, k = 1, \ldots, 4$: 4 lags of weekly mean TGP
  - $c_{t+k}, k = 1, \ldots, 4$: 4 leads of weekly mean TGP
- Characteristics of price jump in the previous cycle in week $t-1$ (**Thursdays**)
  - $jump_{t-1}\_success$: fraction of stations successfully coordinating on the median price on the price jump day in week $t-1$
  - $jump_{t-1}\_\Delta p$: mean station-level price change on price jump day in week $t-1$
  - $jump_{t-1}\_margin$: mean station-level margin on price jump day in week $t-1$
  - $jump_{t-1}\_\sigma_p$: standard deviation of price across stations on price jump day in week $t-1$
  - $jump_{t-1}\_\sigma_{\Delta p}$: standard deviation of price change across stations on price jump day in week $t-1$

- Characteristics of bottom of the price cycle (e.g., the day before a market price jump occurs) in the previous cycle in week $t-1$ (**Wednesdays**)
  - $bottom_{t-1}\_success$: fraction of stations of successfully coordinating on the median price at the bottom of the cycle in week $t-1$
  - $bottom_{t-1}\_\Delta p$: mean station-level price change at the bottom of the cycle in week $t-1$
  - $bottom_{t-1}\_margin$: mean station-level margin at the bottom of the cycle in week $t-1$
  - $bottom_{t-1}\_\sigma_p$: standard deviation of price across stations at the bottom of the cycle in week $t-1$
  - $bottom_{t-1}\_\sigma_{\Delta p}$: standard deviation of price change across stations at the bottom of the cycle in week $t-1$
- Macroeconomic variables
  - Household Consumption Expenditure: monthly final consumption expenditure in Western Australia, chain volume measures
    (Australian Bureau of Statistics Table A299570F)
  - Total Employee Compensation: monthly employee compensation in Western Australia
    (Australian Bureau of Statistics Table A2299551X)
  - Business Investment: monthly gross fixed capital formation - business investment in Western Australia
    (Australian Bureau of Statistics Table A2299777R)
  - Unemployment: monthly unemployment rate in Greater Perth
    (Australian Bureau of Statistics Table A84595576J)
  - <u>Notes</u>: macroeconomic variables are not available at weekly frequencies; more than 80% of Western Australia's population lives in Perth, so macroeconomic variables for the state are a useful measure for economic activity in the city of Perth.

We also note an important caveat of our analysis is that we are unable to incorporate shocks in daily gasoline demand as such data is unavailable. See Appendix A.2 on demand for more details.

Results

Table G.1 presents our results. With one exception, none of the variables have a statistically significant relationship with the incidence of a BP price experiment. The exception is in column (2) of the table, in particular the coefficient on $jump_{t-1}\_margin$: a 1 cpl higher price jump margin in week $t-1$ is associated with a 3.5 percentage point increase in the probability of a BP price experiment in week t. An interpretation of this finding is that, through its Wednesday price jump leadership, BP raises margin levels the week before it engages in a Thursday price jump experiment.

We are unable to check the robustness of this finding to controlling for lags and leads of wholesale cost shocks, nor macroeconomic variables, because we run into collinearity problems when we jointly include the three different groups of regressors in Table G.1 in our probit models. This collinearity arises because we have so few BP experiments (6 out of 117 weeks).

Table G.1: Predictors of Thursday Jumps Experiments
(Marginal Effects Reported)

	(1)	(2)	(3)	(4)
Wholesale TGP Lags and Leads				
c_t	-0.005			
	(0.004)			
c_{t-1}	0.003			
	(0.003)			
c_{t-2}	0.002			
	(0.004)			
c_{t-3}	0.001			
	(0.002)			
c_{t-4}	-0.002			
	(0.002)			
c_{t+1}	0.001			
	(0.002)			
c_{t+2}	-0.001			
	(0.002)			
c_{t+3}	0.001			
	(0.003)			
c_{t+4}	-0.001			
	(0.001)			
Previous Price Cycle Characteristics				
$jump_{t-1}\_success$		-0.034		
		(0.065)		
$jump_{t-1}\_\Delta p$		-0.015		
		(0.016)		
$jump_{t-1}\_margin$		0.035		
		(0.017)		
$jump_{t-1}\_\sigma_p$		-0.040		
		(0.043)		
$jump_{t-1}\_\sigma_{\Delta p}$		0.063		
		(0.055)		
$bottom_{t-1}\_success$			-0.014	
			(0.064)	
$bottom_{t-1}\_\Delta p$			0.033	
			(0.041)	
$bottom_{t-1}\_margin$			0.009	
			(0.007)	
$bottom_{t-1}\_\sigma_p$			0.032	
			(0.046)	
$bottom_{t-1}\_\sigma_{\Delta p}$			-0.079	
			(0.065)	
Macroeconomic Variables				
Household Consumption Expenditure				-0.127
				(0.305)
Total Employee Compensation				0.155
				(0.359)
Business Investment				-0.056
				(0.186)
Unemployment Rate				-0.053
				(0.067)
Log-Likelihood	-13.18	-20.93	-16.87	-25.71
Observations	113	117	117	117

Notes: Robust standard errors presented in parantheses. See the text in Appendix G.3 for variable definitions.

G.4 Price coordination without signaling

This Appendix contains miscellaneous supplemental results for our analysis of margin growth and price coordination in Section 5.3 of the paper. These results are broken down into three parts:

- Why we focus on median prices across the four major firms in constructing station-level pricing errors on Thursdays after August 2012
- Pricing errors and error corrections over the cycle and over time between August 2012 and January 2015
- Structural break tests for a break in margin trends around August 2012

Why we focus on median prices across the four major firms in constructing pricing errors on Thursdays

Throughout Section 5.3, we computed station-level pricing errors on Thursdays relative to the median station-level price across the four major firms on a given date. In other words, we assumed that this particular median price was the *anchor price* for a given 7-day price cycle. In this section, we explain why we focus on this particular anchor price.

Given BP's history as a price leader in the market, one may think that BP would emerge as a focal firm with which rivals would correct Thursday mispricing relative to after August 2012. That is, BP's median price across stations on Thursdays would serve as the anchor price. However, as we now show, the data do not point to BP nor any other firm as emerging as a focal firm for setting anchor prices on Thursday week-to-week.

The analysis of the post-August 2012 pricing mechanism (absent BP price signaling on Wednesdays) in the paper focused on the distribution of station-level price changes on Fridays, conditional on a station's level of mispricing relative to an anchor price on Thursdays. We defined a station's *pricing error* on Thursdays as the difference between its price and the anchor price, which, as just mentioned, was assumed to be the median price across the four major firms' stations. In Figure 14 of the paper, we characterized the distribution of Friday price changes conditional on Thursday pricing errors of 2 cpl (panel i) and 1 cpl (panel ii) relative to the anchor price. Conditional on these respective Thursday pricing errors, we found that stations tend to set 4 cpl and 3 cpl price cuts on Fridays. That is, stations correct Thursday pricing errors on Fridays such that ther Friday price is the price they would have arrived at had they matched the anchor price on Thursday and cut their price by 2 cpl on Friday (as per the 2 cpl cuts focal pricing rule). Figure G.16 below shows similar error corrections of 2 cpl and 1 cpl cuts respectively occur on Friday conditional on mispricing relative to the anchor price by 0 cpl and -1 cpl on Thursday.

Such error correction is revealing of firms' sensitivity to mispricing relative to a given anchor price. We now study how this sensitivity in error correction varies assuming 5 different Thursday anchor prices: BP median price, Caltex median price, Woolworths median price, Coles median price, and the median price across BP, Caltex, Woolworths, and Coles stations (i.e., the anchor price we assume in the paper).[41] Such an analysis is revealing of whether or not there exits a particular firm's station-level median price on Thursdays that rivals based their Friday pricing error corrections upon.

Empirically, we are interested in understanding how the probability a station sets a 4, 3, 2, 1, and 0 cpl price cut on Friday varies depending on whether it had a 2, 1, 0, -1, -2 cpl pricing error relative to a particular anchor price on Thursday. These (Friday price cut, Thursday mispricing) pairs (such as e.g., Friday 4 cpl cut, Thursday 2 cpl mispricing) correspond to stations engaging in pricing error corrections on Fridays whereby they set a Friday price equal to an anchor price less 2 cpl.

For our analysis of Friday pricing error correction, we use linear probability models[42] of the following form:

$$\begin{aligned} 1\{\Delta p_{it} == j\} =& \beta_0^j + \beta_1^j 1\{err_{it-1} == 2\} + \beta_2^j 1\{err_{it-1} == 1\} + \beta_3^j 1\{err_{it-1} == 0\} \\ &+ \beta_4^j 1\{err_{it-1} == -1\} + \beta_5^j 1\{err_{it-1} == -2\} + \gamma c_{it} + \eta_m^j + \epsilon_{it} \end{aligned} \tag{4}$$

[41] Because there is minimal within-station price dispersion, focusing on the median price as a target price is virtually the same as focusing on the mean or modal price on a given date.

[42] Multinomial logit models yield very similar results. We use linear probability models for their ease of interpretation.

where $1\{\Delta p_{it} == j\}$ is an indicator variable equalling 1 if the change in station i's retail price cut on date t is j cpl and 0 otherwise. As just mentioned, we consider 5 different price cuts of $j = 4, 3, \ldots, 0$ cpl. We estimate a separate linear probability model for each of these 5 price cuts, as indicated by the j superscripts on the regression coefficients in equation (4). Throughout, we estimate our regression models using dates t that correspond to Fridays, which is the primary day of the week for Thursday mispricing error correction.

The explanatory variables of interest are based on a variable err_{it-1}, which is the difference between station i's price and the Thursday anchor price on date $t-1$. That is, err_{it-1} is station i's pricing error on date $t-1$. The indicator variable $1\{err_{it-1} == 2\}$ equals 1 if err_{it-1} is equal to 2 cpl (overpricing relative to the Thursday anchor price by 2 cpl) and 0 otherwise. The other indicator variables involving err_{it-1} in equation (4) are similarly defined, where we consider mispricing levels of 2, 1, 0, -1, and -2 cpl.

So, for example, in our regressions with dependent variable $1\{\Delta p_{it} == 4\}$ (a 4 cpl price cut on Friday), we expect the coefficient on β_1^2 to be largest, indicating stations tend to set a 4 cpl price cut on Friday when they overprice relative to the anchor price by 2 cpl on Thursday. More generally, for regression models for the different Friday price cuts $j = 4, 3, \ldots, 0$ cpl, we expect that β_1^2, β_2^1, β_3^0, β_4^{-1}, β_5^{-2} to be the largest magnitude coefficient in each respective regression. This corresponds to stations having Friday price changes that target a Thursday anchor price less 2 cpl, which is the pattern revealed in the raw data in Figure G.16 below.

Our regressions also control for wholesale cost (TGP) c_{it} and month-of-sample fixed effects η_m^j. Standard errors are clustered two ways, by station i and date t, to account for within and across station dependence in ϵ_{it}.

We estimate a linear probability model for 5 different Friday price cuts (4, 3, 2, 1, 0), separately for four different firms (BP, Caltex, Woolworths, Coles), and where we define err_{it-1} for 5 different anchor prices (BP median price, Caltex median price, Woolworths median price, Coles median price, median price across BP, Caltex, Woolworths, and Coles stations). Therefore, we estimate $5 \times 4 \times 4 = 80$ linear probability models to characterize how each firms' stations' correct mispricing on Fridays relative to the 5 different Thursday anchor prices that we consider.[43]

Intuitvely, the larger the β_1^2, β_2^1, β_3^0, β_4^{-1}, β_5^{-2} coefficients are in regressions based on Friday price cuts $j = 4, 3, \ldots, 0$ cpl, the more sensitive firms are to mispricing relative to a particular anchor price. In this way, the regressions can be used, for example, to see if firms are more likely to correct based on BP's median Thursday price versus Caltex's median Thursday price.

Results. Tables G.2, G.3, G.4, and G.5 present our estimation results for BP, Catlex, Woolworths, and Coles, respectively. That is, each table characterizes Friday price corrections for each respective firm assuming different Thursday anchor prices. Accordingly, each table has four different panels, where a given panel corresponds to a different assumed Thursday anchor price. Each row of a table corresponds to estimates from a different linear probability model. More specifically, each row presents OLS estimates of $\beta_1^j, \beta_2^j, \beta_3^j, \beta_4^j, \beta_5^j$ for a given (Thursday anchor price, firm, Friday price cut) combination.

The main diagonals of each of the panels, which highlight (Friday price cut, Thursday mispricing) pairs, are the main objects of interest. We highlight these in **bold**. The larger these coefficients are, the larger the increase in the probability of observing a Friday price change that corresponds to a station correcting Thursday mispricing. By comparing the magnitudes of the bolded coefficients across the four panels within each table, we can assess the sensitivity of a given firm's Friday price cuts to mispricing relative to a given anchor price on Thursday.[44]

Table G.2: BP

- Panels A and B: coefficients are of similar magnitude or are much larger in

[43] For each firm, there are four potential anchor prices: median prices of their three rivals individually, and the median price across the four major firms.

[44] For brevity, we do not present standard errors for the regression coefficients in Tables G.2, G.3, G.4, and G.5. In general, the coefficients in the tables are precisely estimated. 323 of the 400 coefficients presented across the four tables are statistically significant at the 5% level. In only 6 of 80 instances are the coefficients along the main diagonal in each panel statistically insignifcant. Given the precision of the estimates, particularly along the main diagonals, we focus our discussion on the magnitudes of the regression coefficient estimates.

panel A, in particular 0.717 vs 0.450 for the (-2 cpl Friday cut, 0 cpl Thursday mispricing) pair.

- Panels A and C: coefficients are of similar magnitude or are much larger in panel A, in particular 0.717 vs 0.559 for the (-2 cpl Friday cut, 0 cpl Thursday mispricing) pair.

- Panels A and D: coefficients are of similar magnitude or are much larger in panel A, in particular 0.256 vs 0.075 for the (-4 cpl Friday cut, 2 cpl Thursday mispricing) pair.

In summary, BP is not systematically more responsive to correcting mispricing relative to a particular rival's median price on Thursday that it is to correcting mispricing relative to the median price across the four major firms' stations. Indeed, BP is either as responsive or more responsive to mispricing based on the latter median price based on all firms' stations.

Table G.3: Caltex

- Panels A and B: coefficients along the main diagonal are all larger in panel A relative to B, with some large differences such as 0.444 vs. 0.192 for the (-2 cpl Fri. cut, 0 cpl Thu. mispricing) pair.

- Panels A and C: Similarly, panel A has similar magnitude or larger coefficients along the main diagonal relative to panel B, with notable differences for the (-4 cpl Fri. cut, 2 cpl Thu. mispricing) and (-2 cpl Fri. cut, 0 cpl Thu. mispricing) pairs.

- Panels A and D: We find comparable magnitude coefficients along the main diagonal for both panels A and B, with the (-4 cpl Fri. cut, 2 cpl Thu. mispricing) coefficient being larger for panel D, while the (-1 cpl Fri. cut, -1 cpl Thu. mispricing) is noticeable larger for panel A.

In summary, the panel A-B and A-C comparisons indicate that Caltex stations are as responsive or much more responsive to Thursday mispricing relative to an anchor price based on the median price across the four major firms than they are relative to anchor prices based on the median prices across BP or Woolworths stations. The panel A-D comparison reveals that Caltex exhibits similar responsiveness to mispricing relative to anchor prices based on Coles stations and based on the median price across the four major firms' stations.

Table G.4: Woolworths

- Panels A and B: The coefficients along the main diagnonal are of similar magnitude or larger in panel A relative to panel B. The 0.680 vs 0.473 coefficent difference for the (-2 cpl Fri. cut, 0 cpl Thu. mispricing) pair is notable.

- Panels A and C: The coefficients along the main diagnonal are of similar magnitude or larger in panel A relative to panel B. Note that the '0.000' coefficients in the 2 cpl column in panel C is due to very few observations in instances where there is a 2 cpl pricing error among Woolworths stations relative to the median price across Caltex stations.

- Panels A and D: The coefficients along the main diagnonal are of similar magnitude or larger in panel A relative to panel D. The larger differences are for the (-1 cpl Fri. cut, -1 cpl Thu. mispricing) and (-2 cpl Fri. cut, 0 cpl Thu. mispricing) pairs.

Summarizing, Woolworths' stations are either as responsive or more responsive to Thursday mispricing relative to an anchor price based on the median price across the four major firms's stations than it is relative to anchor based on the respective median prices across Caltex, Woolworths, and Coles stations. Like BP, Woolworths is not systematically more responsive to a particular rival's median price, and it is relatively more responsive to mispricing relative to the median price across the four major firms' stations.

Table G.5: Coles

- Panels A and B: The coefficients along the main diagnonal are larger in panel A relative to panel B. Notable differences are found for all five diagonal elements between panels A and B.

- Panels A and C: The coefficients along the main diagnonal are of similar magnitude or larger in panel A relative to panel C. Notable differences are found for the (-4 cpl Fri. cut, 2 cpl Thu. mispricing) and (-1 cpl Fri. cut, -1 cpl Thu. mispricing) pairs.

- Panels A and D: The coefficients along the main diagonal are of similar magnitude in panels A and D, with a notable difference for the (-4 cpl Fri. cut, 2 cpl Thu. mispricing) pair.

Like BP and Woolworths, Coles is not systematically more responsive to a particular rival's median price than it is relative to the median price across the four major firms' stations.

Summary of Findings. In summary, the results from Tables G.2, G.3, G.4, and G.5 establish that each firm is weakly most responsive with its Friday price cutting to mispricing relative to the median price across the four major firms' stations. That is, we do not find evidence for any firm that points to that particular firm systematically correcting mispricing relative to the median price of a particular rival's stations. It is in this sense we do not find evidence of a "focal firm" for setting anchor prices on Thursdays. Empirically, all four major firms play a role in setting the anchor price week-to-week. It is for these reasons in Section 5.3 of the paper that we work with a Thursday anchor price based on the median price across the four major firms' stations.

Table G.2: Predicting the Probability of a Particular Friday **BP** Station-level Price Change as a Function of Thursday Pricing Errors Relative to Different Target Median Prices

Daily Price Change on **Friday** (cpl)	Station-Level Pricing Error on **Thursday** Relative to Target Price				
	2 cpl	1 cpl	0 cpl	-1 cpl	-2 cpl
Panel A, Target Price:					
Median Price Across BP, Caltex, Woolworths, Coles Stations					
-4	**0.256**	-0.132	-0.127	-0.123	-0.136
-3	0.261	**0.363**	0.029	-0.049	-0.024
-2	0.032	0.435	**0.717**	0.673	0.458
-1	-0.080	-0.051	-0.013	**0.058**	0.094
0	-0.204	-0.207	-0.174	-0.111	**0.037**
Panel B, Target Price:					
Median Price Across Caltex Stations					
-4	**0.329**	-0.013	-0.070	-0.084	-0.062
-3	0.180	**0.357**	0.210	-0.041	-0.007
-2	0.029	0.282	**0.450**	0.628	0.483
-1	-0.105	-0.078	-0.026	**0.041**	0.054
0	-0.214	-0.215	-0.189	-0.168	**-0.072**
Panel C, Target Price:					
Median Price Across Woolworths Stations					
-4	**0.075**	-0.155	-0.186	-0.200	-0.189
-3	0.215	**0.451**	0.043	0.000	-0.090
-2	0.216	0.223	**0.690**	0.723	0.372
-1	-0.075	-0.008	-0.018	**-0.039**	0.235
0	-0.126	-0.112	-0.100	-0.044	**0.081**
Panel D, Target Price:					
Median Price Across Coles Stations					
-4	**0.193**	0.035	-0.099	-0.088	-0.086
-3	0.408	**0.373**	0.017	0.043	0.088
-2	-0.171	0.211	**0.559**	0.466	0.395
-1	-0.097	-0.139	-0.049	**-0.007**	-0.034
0	-0.174	-0.188	-0.135	-0.124	**-0.063**

Notes: Each row of the table reports coefficient estimates from a linear probability model that predicts the probability of observing the BP station-level price change stated in the first column of a given row. See equation (4) in the text for the definition of the linear probability model estimated for each row in the table. The sample period for all models is August 1, 2012 to January 1, 2015. All models control for daily terminal gate price and include fixed effects for each month in the sample period. Standard errors are clustered two ways, at the station and date levels. For brevity, standard errors are not reported in the table. Diagonal elements **in bold** in each panel highlight the Friday station level price change and Thursday pricing error pair that is consistent with a station engaging in a Friday price cut that targets the price that would have been realized had the station set the stated target median price on Thursday and cut its price by 2 cpl on Friday (as per the 2 cpl focal pricing rule).

Table G.3: Predicting the Probability of a Particular Friday **Caltex** Station-level Price Change as a Function of Thursday Pricing Errors Relative to Different Target Median Prices

Daily Price Change on **Friday** (cpl)	Station-Level Pricing Error on **Thursday** Relative to Target Price				
	2 cpl	1 cpl	0 cpl	-1 cpl	-2 cpl
Panel A, Target Price:					
Median Price Across BP, Caltex, Woolworths, Coles Stations					
-4	**0.227**	-0.054	-0.086	-0.118	-0.103
-3	0.217	**0.577**	0.200	-0.030	0.059
-2	0.172	0.074	**0.444**	0.233	0.399
-1	-0.023	-0.024	0.054	**0.540**	0.031
0	-0.204	-0.222	-0.221	-0.209	**0.166**
Panel B, Target Price:					
Median Price Across BP Stations					
-4	**0.162**	-0.067	-0.049	-0.024	-0.073
-3	0.462	**0.541**	0.257	0.156	0.000
-2	-0.212	-0.065	**0.192**	0.055	0.402
-1	-0.084	-0.133	-0.094	**0.103**	0.034
0	-0.185	-0.175	-0.180	-0.166	**-0.167**
Panel C, Target Price:					
Median Price Across Woolworths Stations					
-4	**0.560**	0.008	-0.013	-0.047	-0.076
-3	0.076	**0.562**	0.216	0.044	0.032
-2	0.006	0.030	**0.427**	0.375	0.225
-1	-0.003	0.008	0.024	**0.331**	0.011
0	-0.231	-0.247	-0.245	-0.248	**0.084**
Panel D, Target Price:					
Median Price Across Coles Stations					
-4	**0.009**	0.055	-0.009	-0.057	-0.077
-3	0.414	**0.450**	0.301	0.200	0.064
-2	0.198	0.053	**0.240**	0.283	0.381
-1	-0.194	-0.157	**-0.121**	-0.021	0.058
0	-0.170	-0.170	-0.172	-0.161	**-0.157**

Notes: Each row of the table reports coefficient estimates from a linear probability model that predicts the probability of observing the Caltex station-level price change stated in the first column of a given row. See equation (4) in the text for the definition of the linear probability model estimated for each row in the table. The sample period for all models is August 1, 2012 to January 1, 2015. All models control for daily terminal gate price and include fixed effects for each month in the sample period. Standard errors are clustered two ways, at the station and date levels. For brevity, standard errors are not reported in the table. Diagonal elements **in bold** in each panel highlight the Friday station level price change and Thursday pricing error pair that is consistent with a station engaging in a Friday price cut that targets the price that would have been realized had the station set the stated target median price on Thursday and cut its price by 2 cpl on Friday (as per the 2 cpl focal pricing rule).

Table G.4: Predicting the Probability of a Particular Friday **Woolworths** Station-level Price Change as a Function of Thursday Pricing Errors Relative to Different Target Median Prices

Daily Price Change on **Friday** (cpl)	Station-Level Pricing Error on **Thursday** Relative to Target Price 2 cpl	1 cpl	0 cpl	-1 cpl	-2 cpl
Panel A, Target Price:					
Median Price Across BP, Caltex, Woolworths, Coles Stations					
-4	**0.970**	0.302	-0.006	0.015	0.179
-3	0.080	**0.576**	0.247	0.029	-0.128
-2	-0.016	0.044	**0.680**	0.706	-0.036
-1	-0.085	0.002	-0.010	**0.150**	-0.001
0	-0.060	-0.065	-0.066	-0.061	**0.879**
Panel B, Target Price:					
Median Price Across BP Stations					
-4	**0.903**	0.117	0.072	0.016	0.033
-3	0.071	**0.615**	0.219	0.306	0.028
-2	-0.156	0.042	**0.473**	0.409	0.512
-1	-0.018	-0.004	-0.004	**0.005**	0.063
0	-0.046	-0.064	-0.060	-0.062	**0.016**
Panel C, Target Price:					
Median Price Across Caltex Stations					
-4	**0.000**	0.317	0.093	-0.037	0.063
-3	0.000	**0.557**	0.266	0.126	0.232
-2	0.000	0.021	**0.540**	0.736	0.374
-1	0.000	0.007	-0.012	**0.038**	0.007
0	0.000	-0.065	-0.069	-0.053	**0.132**
Panel D, Target Price:					
Median Price Across Coles Stations					
-4	**0.835**	0.147	-0.025	0.022	-0.026
-3	-0.012	**0.633**	0.172	0.184	0.194
-2	0.071	0.055	**0.689**	0.610	0.394
-1	-0.020	-0.002	-0.011	**-0.012**	0.137
0	-0.055	-0.071	-0.068	-0.055	**0.018**

Notes: Each row of the table reports coefficient estimates from a linear probability model that predicts the probability of observing the Woolworths station-level price change stated in the first column of a given row. See equation (4) in the text for the definition of the linear probability model estimated for each row in the table. The sample period for all models is August 1, 2012 to January 1, 2015. All models control for daily terminal gate price and include fixed effects for each month in the sample period. Standard errors are clustered two ways, at the station and date levels. For brevity, standard errors are not reported in the table. Diagonal elements **in bold** in each panel highlight the Friday station level price change and Thursday pricing error pair that is consistent with a station engaging in a Friday price cut that targets the price that would have been realized had the station set the stated target median price on Thursday and cut its price by 2 cpl on Friday (as per the 2 cpl focal pricing rule).

Table G.5: Predicting the Probability of a Particular Friday **Coles** Station-level Price Change as a Function of Thursday Pricing Errors Relative to Different Target Median Prices

Daily Price Change on **Friday** (cpl)	Station-Level Pricing Error on **Thursday** Relative to Target Price 2 cpl	1 cpl	0 cpl	-1 cpl	-2 cpl
Panel A, Target Price:					
Median Price Across BP, Caltex, Woolworths, Coles Stations					
-4	**0.596**	0.058	0.011	-0.005	0.026
-3	0.283	**0.633**	0.036	-0.030	-0.168
-2	0.206	0.253	**0.713**	0.109	0.066
-1	-0.348	-0.087	-0.018	**0.304**	0.039
0	-0.558	-0.569	-0.432	-0.102	**0.312**
Panel B, Target Price:					
Median Price Across BP Stations					
-4	**-0.004**	0.009	-0.056	-0.085	-0.064
-3	0.528	**0.394**	0.123	0.214	-0.046
-2	0.288	0.298	**0.528**	0.250	0.410
-1	-0.224	0.008	-0.025	**0.076**	0.038
0	-0.485	-0.489	-0.380	-0.311	**-0.141**
Panel C, Target Price:					
Median Price Across Caltex Stations					
-4	**0.432**	0.122	0.010	0.029	-0.023
-3	0.588	**0.576**	0.190	0.014	0.079
-2	0.010	0.195	**0.663**	0.557	0.083
-1	-0.154	-0.084	-0.006	**0.073**	-0.008
0	-0.541	-0.534	-0.558	-0.358	**0.154**
Panel D, Target Price:					
Median Price Across Woolworths Stations					
-4	**0.355**	0.010	0.006	-0.024	0.007
-3	0.268	**0.639**	0.046	-0.010	0.037
-2	0.202	0.244	**0.848**	0.504	-0.071
-1	-0.171	-0.078	-0.076	**0.181**	0.142
0	-0.667	-0.639	-0.635	-0.446	**0.064**

Notes: Each row of the table reports coefficient estimates from a linear probability model that predicts the probability of observing the Coles station-level price change stated in the first column of a given row. See equation (4) in the text for the definition of the linear probability model estimated for each row in the table. The sample period for all models is August 1, 2012 to January 1, 2015. All models control for daily terminal gate price and include fixed effects for each month in the sample period. Standard errors are clustered two ways, at the station and date levels. For brevity, standard errors are not reported in the table. Diagonal elements **in bold** in each panel highlight the Friday station level price change and Thursday pricing error pair that is consistent with a station engaging in a Friday price cut that targets the price that would have been realized had the station set the stated target median price on Thursday and cut its price by 2 cpl on Friday (as per the 2 cpl focal pricing rule).

Pricing errors and error corrections over the cycle and over time

In Section 5.3 of the paper, we stated that firms' pricing errors relative to the median price across the four major firms' stations fall over the undercutting phase of the cycle. Figure G.14 provides evidence of this. The figure plots the distribution of pricing errors by major firm and day of the cycle. Panels (i) (Thursdays, Cycle Day 1) and (vii) (Wednesdays, Cycle Day 7) are what we present in Section 5.3 of the paper. Visually, it can be seen across the panels of Figure G.14 that the distribution of pricing errors becomes more concentrated around 0 cpl as the cycle moves from day 1 to day 7. Table G.6, which presents the proportion of stations with 0 cpl pricing errors by cycle day and firm, further reinforces the finding that coordination on price levels improves over the undercutting phase of the cycle following a price jump

A separate question is does the level of coordination on Thursday price levels evolve over time? Figure G.15 addresses this question by plotting, for each Thursday between August 2012 and January 2015, the proportion of stations that are within 2, 1, and 0 cpl of the median price across major firms' stations on Thursdays. The figure reveals that these proportions are, on average, around 91%, 83% and 50%, respectively. The figure also shows that firms rapidly achieve this level of coordination by September 2012 (e.g., immediately after BP stops engaging in Wednesday price signaling), and it is stable thereafter.

Finally, we noted in the paper and above that stations with 2, 1, 0, -1, and -2 cpl pricing errors on Thursdays tend to have 4 cpl, 3 cpl, 2 cpl, 1 cpl, and 0 cpl price cuts the following Friday. Such price cutting targets a Friday price level that would have been realized if a station had set the median price on Thursday *and* had adhered to the 2 cpl cuts focal pricing rule on Friday. Figure G.16 provides evidence of this error correction mechanism. In particular, panels (i)-(v) of the figure plot conditional distributions of station-level error corrections on Fridays as a function of the pricing error on Thursday (either 2, 1, 0, -1, or -2 cpl). The figure is revealing of stations correcting Thursday mispricing through their price cuts on Friday, with the exception of the case of -2 cpl pricing errors. Recall from Figure 13 in the paper that this latter type of pricing error is rare, which implies a small sample to construct the noisy distribution in panel (v) of Figure G.16.

Figure G.14: Distribtion of Station-Level Thursday Pricing Errors Relative to the Median Station-Level Price by Firm Between August 2012 and January 2015

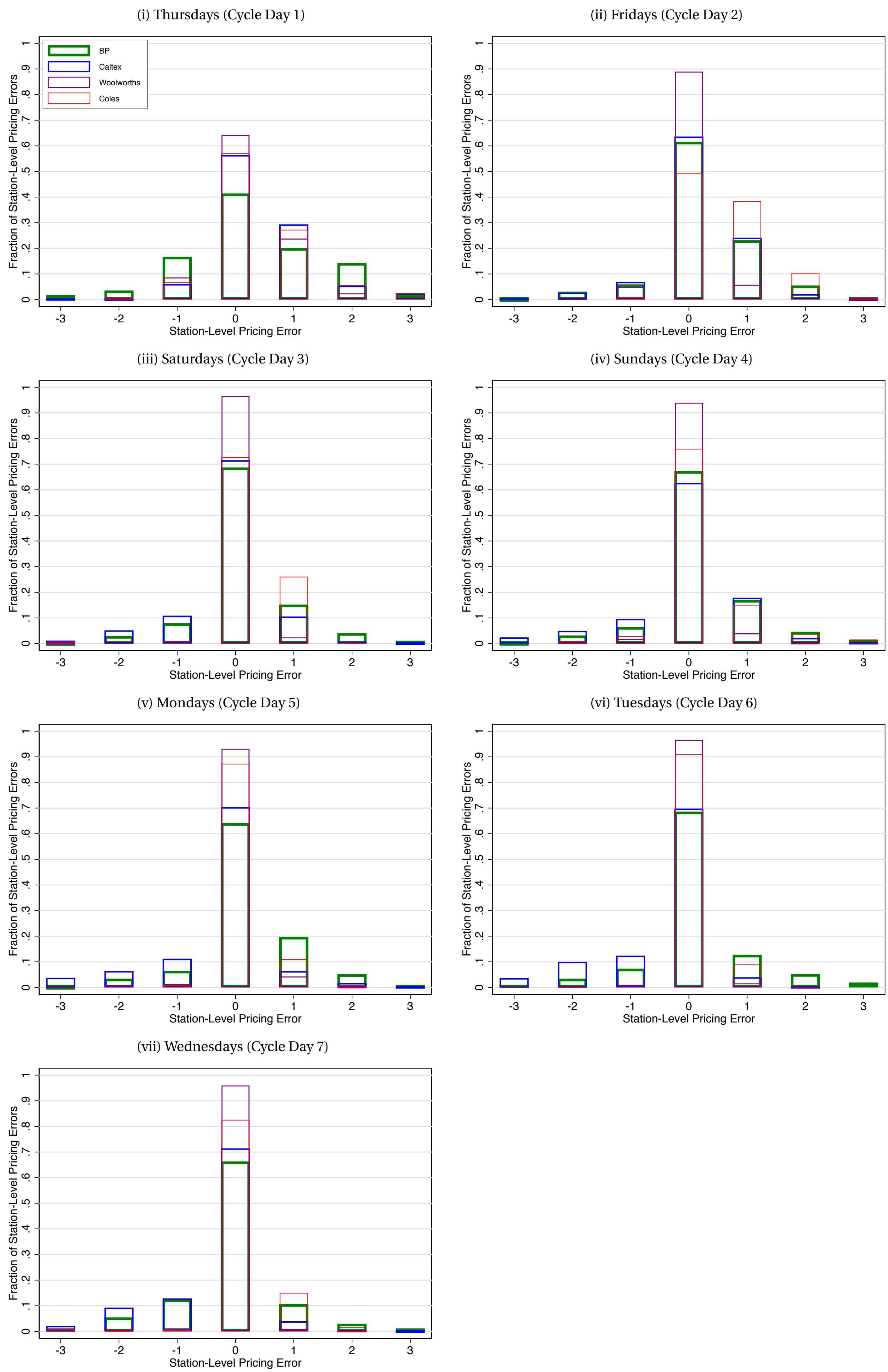


Table G.6: Share of Stations with 0 cpl Pricing Errors by Day of the Cycle

Cycle Day	BP	Caltex	Woolworths	Coles
1	0.40	0.54	0.56	0.54
2	0.60	0.52	0.80	0.47
3	0.67	0.62	0.87	0.69
4	0.66	0.56	0.85	0.71
5	0.61	0.65	0.84	0.82
6	0.63	0.67	0.88	0.86
7	0.58	0.69	0.89	0.78

Figure G.15: Fraction of Stations Coordinating on Prices Within 0 cpl, 1 cpl, and 2 cpl on Price Jump Days: August 2012 - January 2015

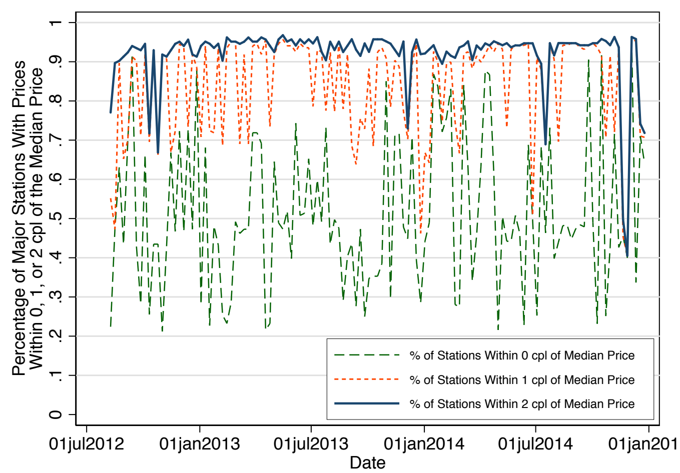
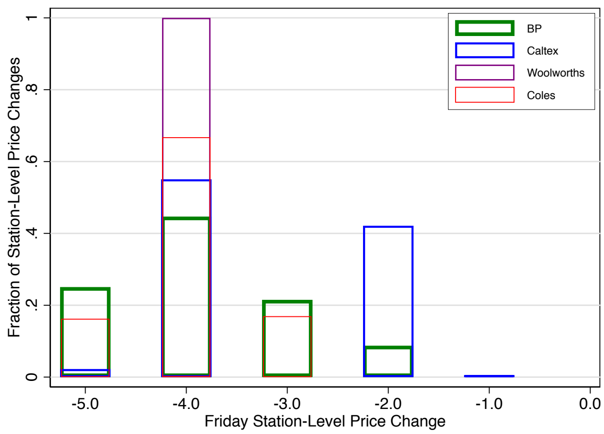
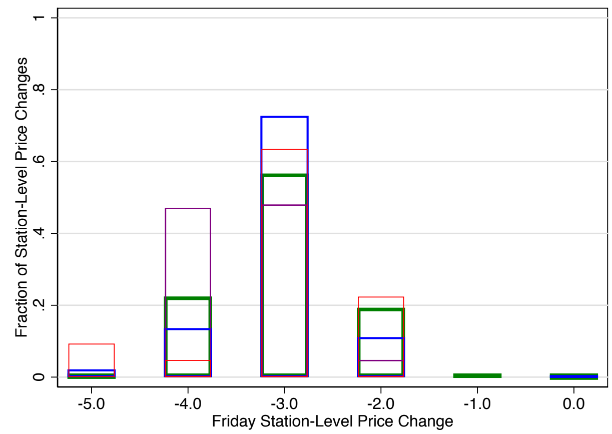


Figure G.16: Distribution of Station-Level Friday Price Adjustments Conditional on Mispricing Relative to the Median Station-Level Price on Thursday

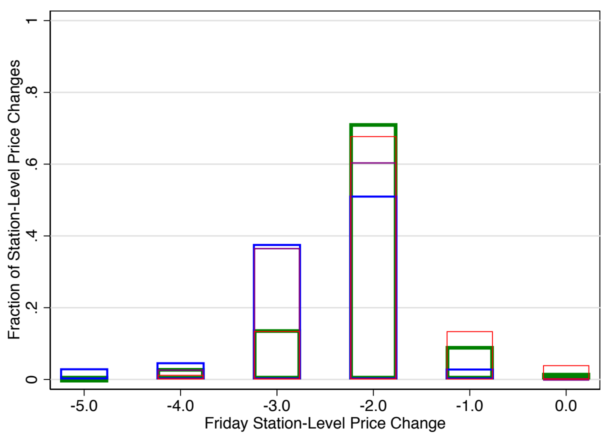
(i) Station-Level Fri. Price Adjustments if **2 CPL Above** the Thu. Median Price



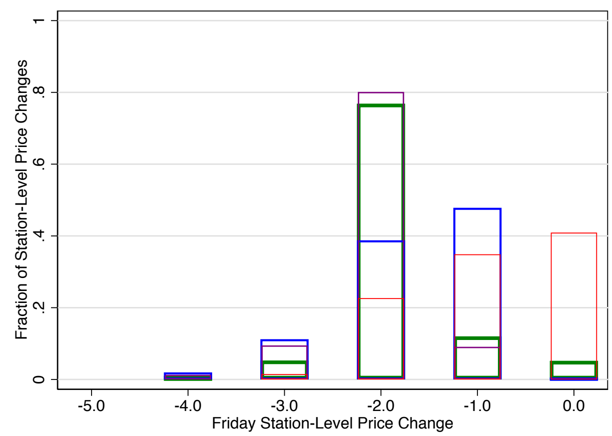
(ii) Station-Level Fri. Price Adjustments if **1 CPL Above** the Thu. Median Price



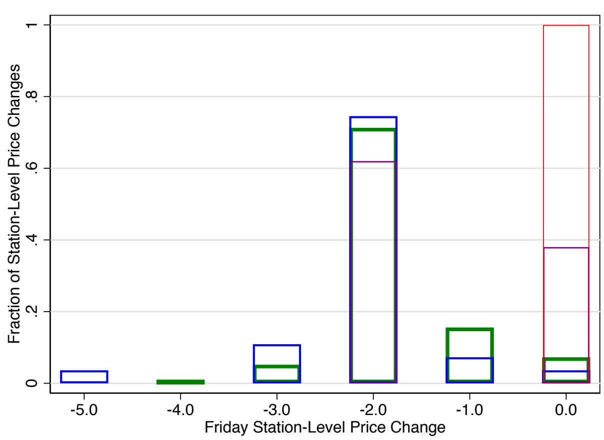
(iii) Station-Level Fri. Price Adjustments if **Equal to** the Thu. Median Price



(iv) Station-Level Fri. Price Adjustments if **1 CPL Below** the Thu. Median Price



(v) Station-Level Fri. Price Adjustments if **2 CPL Below** the Thu. Median Price



Structural break tests for a break in margin trends around August 2012

In the paper, we stated there were minimal changes in margin trends around August 2012, when the pricing mechanism changes from one involving BP Wednesday price signaling, to one without signaling but where stations correct for Thursday mispricing on Fridays (as just discussed). Here, we formally test for structural breaks in margins around August 2012 to see if the change in the pricing mechanism has a corresponding change in margin trends. As in Section G.2 above, we use structural break tests based on the SupF statistic (Andrews 1993), which identifies the timing of an unknown structural breaks in the data, if one exists.

Using the January 2011 to January 2015 sample period, we implement our test by estimating regression models of the following form:

$$margin_{it} = \alpha_0^i + \alpha_1^i t + \sum_{j=1}^{12} \alpha_{2j} 1\{month_t == j\} + \beta^i (t \times 1\{t > T\})$$

where $margin_{it}$ is the average daily margin for firm i in month t. All other variables in the regression are exactly as defined in Section G.2 above. The superscripts on the regression coefficients indicate that we run the structural break test for each firm i. The coefficient β^i is what governs the break margin trends on date T for firm i. For each firm, we vary the break date T from February 2012 to February 2013, and plot the F-statistics for the test of the null that β^i equals 0 against the alternative that it is not equal to 0. The SupF statistic is the maximum value of these F-statistics, and the break date is the date where the SupF is realized and where the test results imply a statistically significant β^i estimate.

The results in Figure G.17 show that the SupF statistic for the break in margin trends for each firm occurs in July 2012. All of the F-statistics in this month imply a statistically significant break in the margin trend. We show this in Table G.7, which presents the OLS regression coefficients estimates for α_1^i and β^i in July 2012. The table reveals our main finding: while a statistically significant break in the margin is detected, the break in the trend is negative and very small. Column (7) of the table implies a 1.6% to 2.2% reduction in the margin trend across the firms in the Table.

Figure G.17: Structural Break Test in Margins Around August 2012

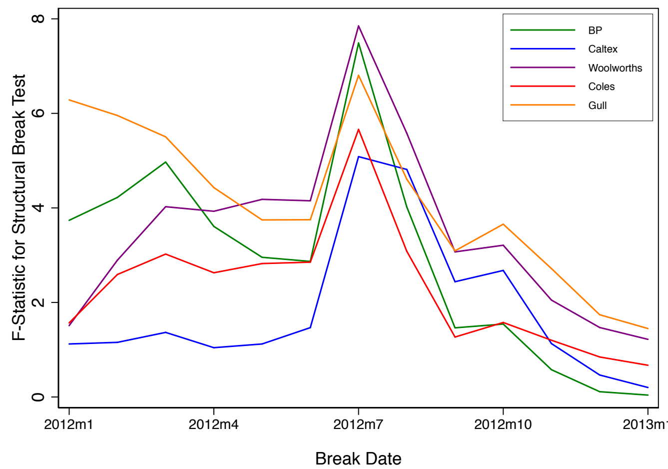


Table G.7: Structural Break Test Results for a Break in Margin Trends Around August 2012 by Firm

Firm	SupF Date	Trend Coef. (α_1^i)	Break in Trend Coef. (β^i)	F-Stat for Test $\beta^i = 0$	P-value for Test	Ratio of β^i / α_1^i
BP	July 2012	0.113	-0.002	7.489	0.009	-0.022
Caltex	July 2012	0.128	-0.002	4.938	0.031	-0.016
Woolworths	July 2012	0.141	-0.003	8.833	0.005	-0.024
Coles	July 2012	0.133	-0.003	6.805	0.012	-0.021
Gull	July 2012	0.140	-0.003	5.661	0.021	-0.020

References

Donald Andrews. Testing for parameter instability and structural change with unknown change point. *Econometrica*, 61:821–856, 1993.

Australian Competition and Consumer Commission. Assessing shopper docket petrol discounts and acquisitions in the petrol and grocery sectors, 2004.

Australian Competition and Consumer Commission. Petrol prices and Australian consumers. Report of the ACCC Inquiry into the Price of Unleaded Petrol, 2007.

Australian Competition and Consumer Commission. Petrol prices and Australian consumers. Report of the ACCC Inquiry into the Price of Unleaded Petrol, 2009.

Australian Competition and Consumer Commission. Petrol prices and Australian consumers. Report of the ACCC Inquiry into the Price of Unleaded Petrol, 2010.

Australian Competition and Consumer Commission. Monitoring of the Australian petroleum industry. Report of the ACCC into the prices, costs and profits of unleaded petrol in Australia, 2011.

Australian Competition and Consumer Commission. Monitoring of the Australian petroleum industry. Report of the ACCC into the prices, costs and profits of unleaded petrol in Australia, 2012.

Australian Competition and Consumer Commission. Petrol prices and Australian consumers. Report of the ACCC Inquiry into the Price of Unleaded Petrol, 2013.

Australian Competition and Consumer Commission. Petrol prices and Australian consumers. Report of the ACCC Inquiry into the Price of Unleaded Petrol, 2014.

Michael Baye, John Morgan, and Patrick Scholten. Information, search, and price dispersion. In Terry Hendershott, editor, *Handbook of Economics and Information Systems*. Elsevier, 2006.

Robert Breunig and Carol Gisz. An exploration of australian petrol demand: Lagged adjustment, unobservable habits, irreversibility and some updated estimates. *Economic Record*, 85:73–91, 2009.

Robert Clark and Jean-François Houde. Collusion with asymmetric retailers: Evidence from a gasoline price-fixing case. *American Economic Journal: Microeconomics*, 5:97–123, 2013.

Lucas W. Davis and Lutz Kilian. Estimating the effects of a gasoline tax on carbon emissions. *Journal of Applied Econometrics*, 26:1187–1212, 2011.

Jean-François Houde. Spatial differentiation and vertical mergers in retail markets for gasoline. *American Economic Review*, 102:2147–2182, 2012.

Jonathan E. Hughes, Christopher R. Knittel, and Daniel Sperling. Evidence of a shift in the short-run price elasticity of gasoline demand. *The Energy Journal*, 29:113–134, 2008.

Laurence Levin, Matthew S. Lewis, and Frank A. Wolak. High frequency evidence on the demand for gasoline. *American Economic Journal: Economic Policy*, 9: 314–347, 2017.

Sung Y. Park and Guochang Zhao. An estimation of u.s. gasoline demand: A smooth time-varying cointegration approach. *Energy Economics*, 32:110–120, 2010.

Reserve Bank of Australia. Reflections on the financial crisis. RBA Speech by Malcolm Edey, Assistant Government (Financial System). Address to the CFO Summit, Gold Coast. March 16, 2014, 2014. http://www.rba.gov.au/speeches/2014/sp-ag-160314.html (accessed November 15, 2016).

Margaret Slade. Conjectures, firm characteristics, and market structure: an empirical assessment. *International Journal of Industrial Organization*, 4:347–369, 1986.

Kenneth A. Small and Kurt Van Dender. Fuel efficiency and motor vehicle travel: The declining rebound effect. *The Energy Journal*, 28:25–51, 2007.

Hal Varian. A model of sales. *American Economic Review*, 70:651–659, 1980.

Zhongmin Wang. Station level gasoline demand in an Australian market with regular price cycles. *Australian Journal of Agricultural and Resource Economics*, 53:467–483, 2009.