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Coordination and price leadership in an unregulated environment*

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Abstract

This paper studies price leadership and coordination in the retail gasoline market. Its main contribution is to show how firms use price leadership to both agree on and sustain a new margin-increasing equilibrium in a market free of price regulations. A unique dataset spanning 13.5 years with exact timing of price changes for almost all Norwegian gasoline stations is employed to study a transition led by the largest chain from irregular price jumps to weekly Monday price jumps, and later a transition led by the second largest chain to weekly additional Thursday price jumps. The transition to regular Thursday price jumps occurred a few months after a merger that increased the second-largest chain's market share, indicating that the merger contributed to the transition. The transition to Monday price jumps shows no substantial effect on margins, while the additional Thursday price jump has an economically large positive effect.

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1 Introduction

Collective price increases can be difficult to implement because firms fail to initiate coordination or because the supra-competitive outcome is not a stable equilibrium.[1] Initiation of a supra-competitive outcome demands that firms have mutual beliefs regarding the new strategy profile — they must coordinate on a focal point for the timing and level of price increases. The unlawfulness of direct communication may incentivize firms to employ other instruments to agree on a strategy profile. *Price leadership* – a practise in which a leading firm's repeated price changes are quickly followed by competitors – provides a natural solution to the coordination problem.[2] I employ a unique dataset with exact timing of retail gasoline price changes for all Norwegian gasoline stations from 2004 to 2017 to show how price leadership by large retail chains is used to both agree on and sustain a new equilibrium in which the frequency of price jumps increases. Furthermore, data on volume sold in each price spell allow me to estimate that the transition to the new equilibrium increases volume weighted margins substantially and that the cost of leading the additional price jumps is low compared to the margin increase they generate.

The market is dominated by 4 national chains with a combined national market share of more than 90%. During the start of the sample period prices follow a sawtooth-like pattern in which all stations carry out a large price jump within the same day once a week, but on different weekdays in different weeks. Many small price cuts follow before another large price jump occurs the next week. Every week, one of the national chains leads a price jump by increasing prices at most of its stations almost simultaneously, and the other chains follow a few hours later. Similar patterns have been found in markets for retail gasoline in the the United States, Canada, multiple European countries and Australia.[3] The pricing pattern is often rationalized by Maskin & Tirole (1988)'s model of ''Edgeworth cycles', in which firms are restricted to Markov strategies and undercut each other down to marginal cost, before playing a war of attrition game at the bottom of the cycle to decide who makes the next price jump to restore prices.

A transition to a fixed high price may be unattainable for the firms due to problems related to initiating or implementing this kind of equilibrium; see e.g. de Roos & Smirnov (in press) who show that equilibria with cycling prices can sustain higher collusive profit than collusion with a fixed price because consumers become less responsive to price changes, reducing deviation payoffs. Alternatively, profits can also be boosted by tacit or explicit coordination to shorten the time between price jumps. For example, Wang (2008) shows how explicit communication among retail gasoline stations is used to resolve the war of

[1] See Harrington (2017).

[2] See e.g. Markham (1951).

[3] See Eckert (2013) for a review of the literature on price cycles in retail gasoline. Price cycles have recently also been observed in procurement auctions for pharmaceuticals (Hauschultz & Munk-Nielsen (2017)), bank deposit rates (Fung (2018)), equity markets (Hasbrouck (2018)), bidding for search-engine advertising (Zhang & Feng (2011)) and supermarkets (Seaton & Waterson (2013)).

attrition problem at the bottom of the cycle, and Lewis (2012) documents that price leadership is prevalent in U.S. cities with retail gasoline price cycles and suggests that price leadership can be a measure to avoid the war of attrition game. Similarly, Foros & Steen (2013) argue that ''calendar-synchronization' of price jumps (price jumps occur at the same time every week) in the Norwegian retail gasoline market stops the war of attrition phase and increases prices. However, Noel (2019) argues that calendar-synchronization is not necessarily anticompetitive because consumers can use the more predictable price pattern to shift purchases to low-price days. Furthermore, he argues that if the period between price jumps decreases, prices at the top of the cycle can competitively adjust downwards, leaving the price at the bottom of the cycle unchanged.

I show how price leadership is used to first *initiate* calendar-synchronized price jumps, and then to increase the frequency of price jumps from 1 to 2 per week. A large body of theoretical literature is dedicated to the *implementation* of collusive equilibria and a growing body of empirical literature provides evidence of the pervasiveness of both tacit collusion and price leadership, but research on the initiation of tacit collusion is sparse.[4] A notable exception is Byrne & de Roos (2019), who analyse the emergence of price coordination in the market for retail gasoline in Perth, Australia. A dominant chain initiates Wednesday price jumps, leading other retailers to follow on Thursdays and gradually increase margins on the top of the cycle by increasing the size of the Wednesday price jumps. Recent research also investigates the emergence of collusion related to explicit secret communication between the firms (Chilet (2018)), price matching guarantees (Cabral et al. (2018), explicit public announcements and mergers. Ones (2018) shows how a chain publicly announces a change to its retail price policy, and moves the Norwegian market for retail gasoline to a new equilibrium where the timing of price jumps is signalled through changes in recommended prices. Miller et al. (2019) estimate a repeated oligopoly model in which a leader publicly announces a supermarkup in the U.S. beer market and suggest that a merger would have relaxed the incentive compatibility constraints and increased the equilibrium supermarkup. Like Byrne & de Roos (2019), I focus on price leadership in actual prices rather than secret communication or public pre-announced prices. However, the events leading to price coordination in my study differ from those in Byrne & de Roos (2019), and unlike Perth, the Norwegian retail gasoline market is not subject to any price regulation, giving a more general unregulated environment.[5]

I show how price jumps synchronize as the largest chain, with a 30% market share, emerges as a price leader and initiates price jumps at the same time every Monday. From

[4]See Green et al. (2014) for a discussion of the initiation phase and the implementation phase for collusive agreements and Byrne & de Roos (2019) for a short review of the empirical literature on tacit collusion.

[5]Regulations in Perth ensure that the stations in the Byrne & de Roos (2019) study can have only one price per day and next-day prices are posted at a price comparison webpage.

the very first week, the Monday price jumps are followed within a few hours by the 4 other chains present in the market. Chain A goes on to lead Monday price jumps for the next 13 years. I find that the calendar-synchronization of the cycles likely does not cause an immediate increase in retail margins. The regular Monday jumps do, however prepare the ground for more frequent price jumps. Chain A tries to initiate Thursday price jumps as well at the time the Monday price jumps are initiated, but after several failed attempts (one or more chains do not follow the price jump and prices quickly revert to the pre-jump path), the Thursday jumps are abandoned.

8 months after the Monday price jumps are solidified, a period with more or less irregular Thursday or Friday price jumps (as these are in addition to the Monday price jumps, I call them *second price jumps*) starts. Over the next 4 years, second price jumps occur in 57% of the weeks and 65% of the attempts fail. All the 4 national chains lead second price jumps in this period. Both the frequency and success rate of the second price jumps are higher in periods when one of the chains acts as a regular price leader than in periods when price leadership changes from week to week. Furthermore, second price jumps are more likely in weeks when margins on Thursday/Friday are low. By estimating the different changes in margins and volumes from Tuesday to other weekdays in weeks with Thursday price jumps compared to a counterfactual consisting of weeks without price jumps, I find that the leader of second price jumps loses a small amount of market share (about 0.6%) for a possible large increase (41%) in margins for the rest of the week if the price jump is successful.

In August–December 2008, an acquisition transferring stations between two of the national chains increases one of the chains' market share from about 23% to almost 29% creating a clear number 2 in the market. A few months later, the period with irregular and often failed *second price jumps* comes to an end as the acquiring chain becomes a leader of regular Thursday price jumps. The chain starts to initiate price jumps every Thursday, and the rate of failure drops to zero as all other chains follow the second price jumps. Once the Thursday price jumps are cemented, both Monday and Thursday price jumps occur every week for more than 8 years.[6] Having two different chains leading price jumps on one weekday each solve the coordination problem related to the timing of price jumps and who should lead price jumps, and makes it possible to share the cost of price leadership. The downward adjustment in maximum prices predicted by Noel (2019) does not materialize after the transition, and volume-weighted retail margins increase 8-18% compared to the period with irregular second price jumps. Coordinating on an additional weekly price jump allows the chains to avoid the trough of the cycle while still reaping the benefits of high prices at the peak of the cycle.

The newly crowned market share runner-up takes over Thursday price leadership just a few months after it gains control over the acquired stations. The chain immediately

[6]The only exception is that price jumps never occur on public holidays; see Section 3.1.

increases the frequency of Thursday price jumps and the other chains start to always follow all Thursday price jumps. These events indicate that the acquisition contributed to the transition to regular Thursday price jumps. However, as the acquisition increased the asymmetry between the chains and did not increase multi-market contact or decrease the number of firms active in the industry, I find that changes in the incentive compatibility constraints after the acquisition are an unlikely explanation for the transition to regular Thursday price jumps after the acquisition. A more likely explanation is that the increase in the runner-up's size increased its incentives and ability to initiate price jumps. Evidence of both size differences across chains and within-chain changes in size suggest that large chains are more likely to be price leaders. Price leadership also seems to be more effective when large firms lead price increases, resulting in more frequent and more successful price jumps.

The paper is organized as follows. Institutional details and a description of data, supply and demand are presented in Section 2. An analysis of the transition to different equilibria appears in Section 3. Section 4 investigates the cost of price leadership. Section 5 discusses the relationship between size and price leadership. Section 6 concludes.

2 Institutional details and data

As in in most other countries, the Norwegian retail gasoline market is dominated by large retail chains. 4 national chains have a combined national market share of more than 90% during the whole sample period from 2004–2017. Chain A is the largest with 30-35% market share, and the other 3 national chains are fairly equal in size until a merger makes Chain C a clear number 2 during fall 2008. One major difference between the Norwegian retail gasoline market and other frequently studied gasoline markets is the lack of regulation. In Australia, Germany and Chile, gasoline stations are obliged to report prices to a price comparison web page, giving perfectly transparent prices. In Australia and Austria, the frequency of price changes is also regulated, and in some regions of Canada a price floor regulation is implemented. Norwegian gasoline stations can change prices as often as they want and are not obligated to report prices to any price comparison web site. Prices are, however, posted on large signs next to each station, and the retail chains closely monitor each other's prices at a local level.[7] Gasoline is a homogeneous good, suppliers share the same input costs, and in most retail gasoline markets, prices are controlled by a few chains. Together with the high price transparency, this has led multiple academic studies and competition authorities to conclude that the market for retail gasoline is conducive to tacit collusion.[8] The Norwegian Competition Authority has

[7]See Konkurransetilsynet (2015).
[8]See e.g Byrne & de Roos (2019), Borenstein & Shepard (1996) and Bundeskartellamt (June 2011)

also concluded that the Norwegian market is subject to tacit collusion.[9]

Below I describe the supply and demand side of the market during the sample period and the data used for the analysis. The sources used to characterize supply and demand are mainly the data described in Section 2.3, various reports from the Norwegian Competition Authority and publicly available information from an association representing the interests of Norwegian fuel and energy companies (Drivkraft Norge).

2.1 Data

Data on prices, volumes and station characteristics is obtained from the Norwegian Competition Authority which collected the data directly from the retail motor fuel chains in various cases. The data includes all unleaded 95 octane gasoline[10] price spells for all gas stations in Norway from January 2004–June 2017, and the accompanying volume sold during each price spell.[11] In total, the data consists of 20 million spells with an average length of 6.5 hours.[12] An important feature of the data is exact (to the minute) time of price changes, permitting analysis of intra-day pricing patterns. The data also includes station characteristics such as chain affiliation and location, and for the period January 2004–November 2008, convenience store revenue per station per day. As explained in the next section, detailed data on marginal costs, consisting of transportation costs to each station, wholesale costs of gasoline, and taxes, is also available.

2.2 The supply side and costs

During the sample period, the number of gas stations in Norway is between 1660 and 1780, and 4 national chains with a combined market share of more than 90% are dominating the market. Before 2012, the only other notable competitor is a regional chain active in the south-eastern part of Norway. Figure 1 plots the national market shares over time for these 5 chains.[13]

[9]See Konkurransetilsynet (2015).

[10]No gas stations sold leaded gasoline during the sample period. The share of non-95 octane fuel (98 octane) was low during the period, starting at 8% of retail gasoline sales in 2004 and steadily falling to 2% in 2017 (source: data from Drivkraft Norge).

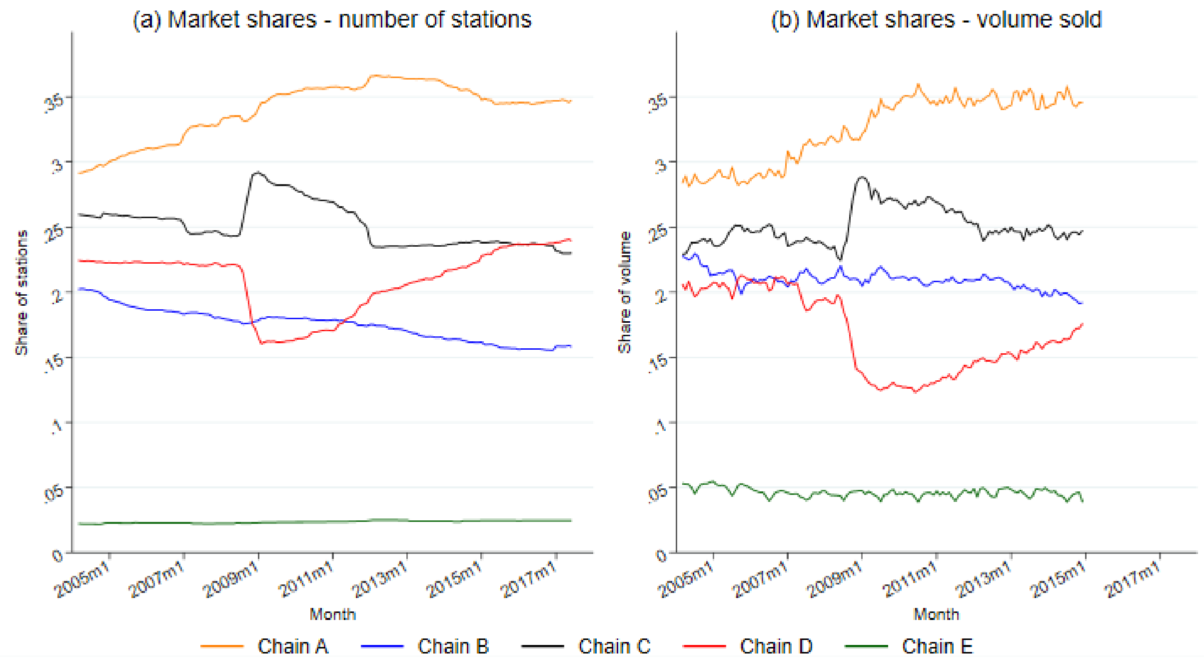
[11]There are a few periods with missing data. Spell data is missing for Chain A between January 2012 and September 2013, but daily quantities, volume-weighted daily prices, and all posted prices during each day (but not the exact time each price was posted) for each of Chain A's stations during this period are available. Spell data for Chain C before November 2004 is missing, but daily quantities and volume-weighted daily prices for Chain C's stations during this period is available. Spell data for Chain E is missing between November 2008 and June 2009. Spell volumes for Chain E are missing before 2012, but daily volumes for the chain are available from 2004–2009.

[12]Some spells have the same price as the previous spell, meaning that price did not change but volume is split in two different periods. Combining the spells where prices did not change gives 13 million price spells with an average length of 10 hours.

[13]Chain A's market share includes a small chain with stations located in rural areas. The small chain's stations are supplied by Chain A's depots, accept Chain A's loyalty cards, and seem to be bound by the same vertical restraints as the dealer-owned stations connected to Chain A (see Neset

Chain A is the largest chain with 30–35% market share during the sample period. Chain B, C and D have about 20-25% market share each until August 2008. Between August and December 2008, Chain C begins controlling and operating 90 gas stations it gained control over after an agreement with Chain D. By December 2008, Chain C' market share has increased to almost 30%, while Chain D's share is reduced to less than 15%.[14] Before 2012, independent stations and small local chains constitute only 1-4% of all stations in the market. After 2012, some of the smaller chains expand, leading to a gradual increase in the share of stations controlled by a non-major chain to almost 10% in 2017.

Figure 1: Market shares of major chains



All the 4 national chains have both manned stations with a convenience store co-located with the station and unmanned stations where consumers have to pay at the pump with a credit or debit card. The share of unmanned stations in the market slowly increases from about 20% in 2004 to about 27% in 2017.[15]

The chains have a combination of fully vertically integrated retail outlets and vertically separated retail outlets owned by the local dealers. Through the whole sample period, about 2/3 of the gas stations are fully vertically integrated. The dealer-owned stations have exclusive long-term contracts (usually for five years or more) with one of the major

(2010)). Independent stations and some local chains are not included when market shares in the figure are calculated because we do not have volumes for these stations.

[14] 4 other mergers are proposed in the sample period. 3 of these are vertical, and one horizontal merger is solved with structural remedies (see Appendix C).

[15] On average throughout the sample period, about 80% of Chain A's stations, 93% of Chain B's stations, 87% of Chain C's stations, 57% of Chain D's stations and none of Chain E's stations are manned.

chains.[16] Foros & Steen (2013) document that the 4 major chains use vertical restraints to transfer price control from the local dealers to the chain headquarters, meaning that the chains control prices of both vertically integrated and vertically separated stations.

Gasoline is obtained from refined crude oil. In the sample period, there are mainly two Norwegian and one Danish refinery supplying Norwegian gasoline stations. Chain A owns one of the Norwegian refineries until 2012, and Chain B the other one until 2017. Chain C owns the Danish refinery until 2015. Refinery prices are negotiated bilaterally, but are based on the European reference price for wholesale gasoline from Platts.[17] When calculating profit margins, I proxy the wholesale price of retail gasoline with the European reference price from Platts.[18] There are large variations in wholesale prices during the sample period, but no asymmetric price cycles (see e.g. Appendix Figure E.3).

Gasoline is transported by ship from refineries to depots along the Norwegian coast, and then by road to the gas stations. All the national chains own depots both separately and jointly. To minimize transportation costs from depots to gas stations, the chains also have bilateral agreements to buy gasoline from each others depots.[19] The chains use a system in which each station is assigned a transportation cost that is factored in when retail prices are set.[20] The average cost of transporting gasoline from a depot to a given gasoline station is stable at 0.14-0.15 NOK/litre during the sample period, and the within-station variation from year to year is very small.[21]

There are large VAT and environmental taxes on motor fuels. The VAT increases from 24% to 25% in 2005 and stays at 25% afterwards, while the environmental taxes on gasoline increases January 1 every year, leading to a steady increase from 4.72 NOK in 2004 to 6.23 NOK in 2017.

Throughout the paper, volume-weighted margins for station i in period t are defined as $y_{it} = p_{it} - Platts_t - tax_t - c_{it}$, where y_{it} is the average volume-weighted margin of station i in period t, p_{it} is the average volume-weighted price of gasoline at station i in period t (the average price the consumer paid), $Platts_t$ is the wholesale price of gasoline, tax_t is VAT and other taxes, and c_{it} is the station specific cost of transporting gasoline from depots to the gasoline stations.

[16] Foros & Steen (2013) offer a description of the relationship between chains and dealer-owned stations.

[17] Platts is a global provider of energy information that collects and publishes details on bids and offers for specialized oil products. See point 33 in Konkurransetilsynet (2015) and page 53 in Jakobsen (2012) explaining how refinery prices are determined, and which wholesale price indexes Norwegian gasoline retailers use when determining retail prices.

[18] By using the reference price from Platts as a proxy for wholesale costs, I abstract from components such as quantity discounts. This approach is standard when calculating profit margins in retail gasoline; see e. g. Byrne & de Roos (2019).

[19] See chapter 4.3 in Konkurransetilsynet (2015).

[20] See Foros & Steen (2013) and Konkurransetilsynet (2015).

[21] About 40%, 80%, 98% and 99.5% of stations have a transportation costs below 0.1 NOK/litre, 0.2 NOK/litre, 0.4 NOK/litre and 0.6 NOK/litre respectively.

2.3 Demand

Norway has a population of about 5 million people sharing 385 203 km^2. About 80% of the population live in urban areas. The total volume of gasoline is declining steadily in the sample period. This is mainly due to higher taxes on vehicles with gasoline engines relative to vehicles with diesel engines, leading to a large decrease in the number of vehicles with gasoline engine and a corresponding increase in vehicles with diesel engines in the sample period.[22] The decline in gasoline sales has been offset by a corresponding increase in diesel sales, and the combined volume of gasoline and diesel is stable during the sample period (between 3.9 and 4.3 billion litres in all years). Norway experiences stable economic growth during most of the sample period, and the financial crisis has a much smaller impact compared to other European countries.[23] Together with the stable development in total fuel sale, this suggests that there are no major demand shocks during the sample period.

From January to the end of April 2004, market-wide price jumps occur once every week on either Tuesday, Wednesday, or Thursday (see Section 3.1). Figure 2 depicts average retail gasoline prices and share of weekly volume for each weekday for this period for both stations with almost no intra-week price variation and those with large intra-week price variation.[24] We see relatively small variations in volumes on different weekdays for stations both with and without intra-week price variation, with slightly higher volumes on Fridays than other days.[25] Higher volumes on days with low average prices (Monday and Tuesday) and lower volumes on days with high average prices (Thursday and Friday) for the stations with strong intra-week price variation indicate some consumer response to the irregular price cycles.

Both stations with strong price cycles and stations without price cycles have higher sales and higher prices during the summer months, cp. Figure 3. The volumes in the figure are average volumes sold per station per day in different months of the year over the whole sample period. The monthly margins in the figure in each month relative to January results from the month of year fixed effects, τ_m in Eq. 1, estimated separately for *strong cycle* stations and *no cycle* stations:[26]

$$y_{it} = \alpha + \beta Platts_t + \rho Holiday_t + year_j + week_t + \tau_m + \varepsilon_{it} \tag{1}$$

[22]See Pilskog (2018). I focus on retail gasoline. However, retail diesel prices follow the same pattern as retail gasoline prices, with price jumps the same days and generally the same chains leading price jumps.

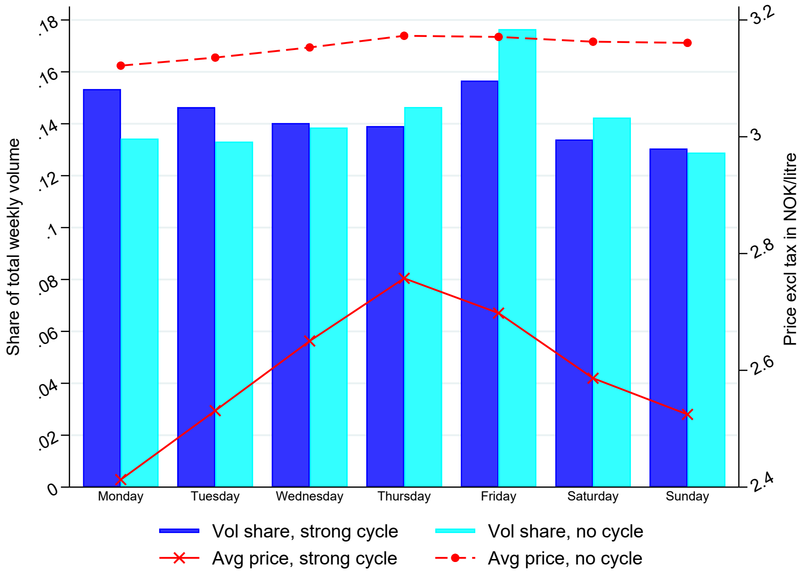
[23]See Finanskriseutvalget (2011). Furthermore, there is no fall in fuel sales during the crisis.

[24]*No cycle* and *strong cycle* stations are defined in Section 3.

[25]The volume pattern for stations without intra-week price variation is very similar to the volume pattern in areas without intra-week price variation in Australia; see Byrne & de Roos (2018).

[26]y_{it} is the average volume-weighted margin of station i in week t. $Platts_t$ is the wholesale price of gasoline, $Holiday_t$ is a dummy for weeks with one or more public holidays, $year_j$ represents year fixed effects and $week_t$ is a linear time trend.

Figure 2: Share of volume on different weekdays Jan2004–Apr2004

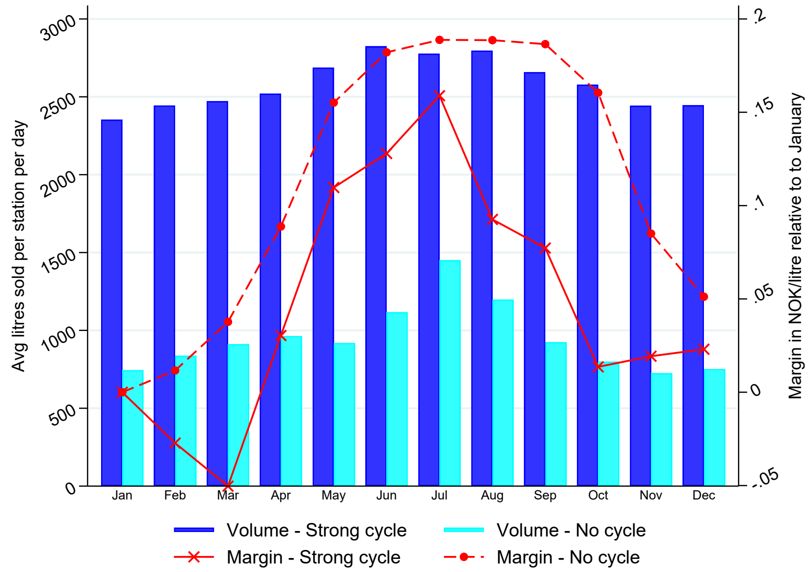


Note: The figure depicts average prices excl. taxes, and average share of weekly volume of gasoline sold on different weekdays for both *strong cycle* stations (prices represented by the solid red line and volume shares by the dark blue bars), and *no cycle* stations (prices represented by the dashed red line and volume shares by the light blue bars). Take note of the following:

1. Both *strong cycle* and *no cycle* stations experience relatively small variations in volumes on different weekdays, but sell slightly higher volume on Fri than on other days.
2. *Strong cycle* stations sell higher volumes than *no cycle* stations on days with low average prices (Mon and Tue) and lower volumes on days with high average prices (Thu and Fri).

We see that margins for both groups of stations follow a similar seasonal pattern with higher prices during the high-volume summer months.

Figure 3: Month of year volume and margins



Note: The figure depicts average margins per litre of gasoline for different months of the year relative to January (τ_m in Eq. 1), and average volume sold per station per day in different months. Results are plotted for both *strong cycle* stations (margins represented by the solid red line and volume shares by the dark blue bars) and *no cycle* stations (margins represented by the dashed red line and volume shares by the light blue bars). Take note of the following:

1. Both *strong cycle* and *no cycle* stations sell more gasoline during the summer months.
2. Both *strong cycle* and *no cycle* stations have higher prices during the summer months.

3 Price leadership and the emergence of focal points

The market is characterized by asymmetric price cycles during the whole sample period, as shown in Figure 4. Prices slowly decrease over multiple days before all chains in quick succession initiate sudden large price jumps for most of their stations. Each chain increases prices for most of its stations within a very short period of time, cp. Table 1.[27]

In the following section I study the transition from cycles with irregular price jump days, to regular Monday jumps and finally to regular price jumps on both Monday and Thursday. To aid the analysis, I provide the following definitions:

(a) A *station price jump* occurs at station i on day d at time of day t if $\Delta p_{idt} \geq 0.25NOK$ where p_{idt} is the retail price, $\Delta p_{idt} = p_{idt} - min[p_{idz}]$, and p_{idz} is a vector of all prices at station i on day d before time t.[28]

(b) Station i is a *strong cycle* station in year y if the average difference between maxi-

[27] The within-chain difference in timing of Thursday price jumps is similar, but slightly higher.

[28] Byrne & de Roos (2019) use a threshold of 6 cpl, equalling 0.33 NOK on average during the sample period. The 0.25 NOK threshold strikes a balance between including most price jumps occurring when a chain carries out a collective price jump for most of its stations, and excluding more random station-specific price increases. The results are robust to increasing or decreasing the threshold.

Table 1: Within-chain timing of Monday price jumps 2005-2009

	Perc30	Perc50	Perc75
Chain A	0.64	0.87	2.62
Chain B	0.16	0.25	0.50
Chain C	0.21	0.33	0.56
Chain D	0.22	0.60	1.91
Chain E	0.77	1.34	2.12
Mean of A-E	0.39	0.67	1.54

Note: The table shows the average time in hours from when the first 10% of each chain's stations initiated a Monday *station price jump* until when the first 30%, 50% and 75% of stations initiated a Monday *station price jump*. Take note of the following:

1. On average, the chains initiate price jumps at the first 30%, 50%, and 75% of stations within respectively 0.39 hours, 0.67 hours and 1.54 hours after the first 10% of stations initiate price jumps.
2. All four national chains initiate price jumps for the first 30% 50%, and 75% of stations within respectively 0.64, 0.87, and 2.62 hours after the first 10% of stations initiate price jumps.

*The averages are based on observations from January 2005-December 2009. The within-chain time between *station price jumps* is generally lower after 2009.

***No cycle* stations are excluded from the analysis.

mum and minimum price within each non-holiday week is greater than 0.25 NOK.[29] Station i is a *no cycle* station in year y if the difference between maximum and minimum price within each week on average is less than 0.05 NOK in year y. Stations that are neither *no cycle* nor *strong cycle* in year y are *weak cycle* stations.[30]

(c) A *chain price jump* for chain c occurs on day d at time t when *station price jumps* have occurred on at least 30% of chain c's *strong cycle* and *weak cycle* stations.[31]

(d) A *price jump attempt* occurs on day d at time t, where t is the time of day of the first *chain price jump* on day d.

(e) A *successful price jump* occurs on day d at time t when *chain price jumps* have been carried out by each of the 5 major chains.

(f) Stations with 4 competing major chains within a 15 minute drive time during the whole sample period are categorized as *competitive stations*.[32]

[29] Station i active in weeks t in year y is a *strong cycle* station in year y if $1/t \sum_{t=1}^{t}[max[p_t^i] - min[p_t^i]] > 0.25NOK$.

[30] Byrne & de Roos (2019) define station i as a cycling station in year y if station-level price jumps occur at least 15 times during year y. The amplitude-based definitions I employ are useful in the Norwegian market, where cycle amplitude varies greatly between stations (see below). Most *strong cycle* and *weak cycle* stations would also be considered cycling stations according to Byrne & de Roos (2019)'s definition.

[31] Results are robust to changing this definition to e.g. 20 or 50%. The timing of price jumps would change slightly, but the identity of leaders, and the order of followers would be very similar.

[32] Drive times between all stations are calculated in ArcGIS using the Elveg road network dataset from the Norwegian Public Roads Administration (Statens Vegvesen).

(g) A *double jump week* is a week when one or more *chain price jumps* are carried out on two different weekdays. *Second price jump* refers to the *chain price jumps* carried out on the second day with *chain price jumps* in a given *double jump week*.

Not all stations have price cycles during the whole sample period; cp. Appendix Figure B.1. Furthermore, the figure reveals that price cycles are more likely to occur in areas where multiple chains are present, and more stations become *strong cycle* over time. Three factors are important to understanding these correlations. First, the 4 national chains operate with national list prices.[33] Second, as Foros & Steen (2013) and Konkurransetilsynet (2014) show, the national chains increase prices to list price+transportation costs for all stations when *chain price jumps* are initiated. Third, prices fall faster in the undercutting phase at stations facing strong local competition, and stations facing very weak competition stay at or close to the list price during the whole week.[34] As prices increase to the same level (adjusted for transportation costs) for all stations in a chain regardless of how low prices are at the end of the undercutting phase, price jumps are larger for stations facing strong local competition. This means that the cycle amplitude (the difference between maximum and minimum prices for each station during each cycle) is larger for stations facing strong competition, leading to a higher probability of being *strong cycle*. After 2012, the cycle amplitude gradually increases due to higher margins at the peak of the cycle, leading to more *strong cycle* stations.

3.1 Weekly price jumps on irregular weekdays

The sample period starts January 1 2004. In the first 16 weeks, price jumps occur once a week but on different weekdays — 7 Tuesdays, 4 Wednesdays and 5 Thursdays.[35] The first 5 panels of Figure 4 depict price cycles for the last 5 of these weeks, and Figure 5 plots the time of day each chain completes *chain price jumps*. As is evident from the figures, price jump attempts are followed by all other chains, and there is no regular price leader — all national chains are leading price jumps in one or more weeks.[36]

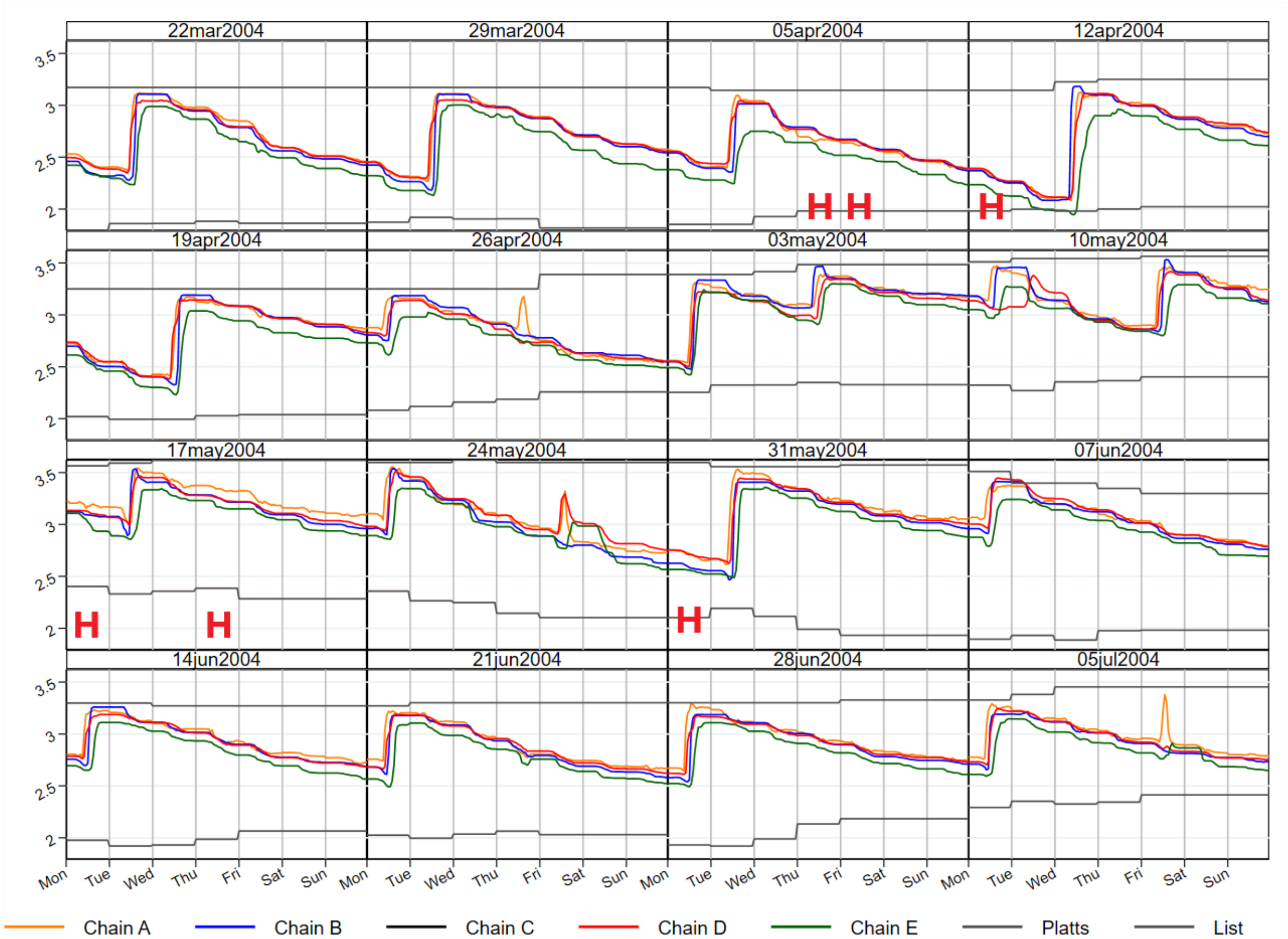
[33] Chains A, C and D have also been publishing list prices on their websites during the whole sample period. See Foros & Steen (2013), page 652 and Konkurransetilsynet (2015), page 9.

[34] See Konkurransetilsynet (2014) page 22.

[35] Note that Foros & Steen (2013), based on pooling observations from an unbalanced panel of user-reported price observations from different weekdays, find that prices on average are highest on Thursdays between March 2003 and April 26 2004. This is not surprising, as the gradual price decreases after price jumps lead to fairly high prices on Thursday even when price jumps occur on Tuesday or Wednesday; see Figure 2.

[36] Intra-day prices for Chain C are missing before October 26 2004. Theoretically, Chain C could be leading all price jumps before May 2004. This does however seem highly unlikely as Chain C rarely leads in the first years after October 26 2004. Moreover, most *price jump attempts* in the first 16 weeks are initiated earlier (between 9:00 and 10:00) or at the same time of day as *price jump attempts* after October 26 2004 (between 10:00 and 11:00). Chain C is most likely participating in all the price jumps before April 26 2004 (and all the Monday price jumps after April 26 2004), because prices do not quickly revert to the pre-jump path after the price jumps (see Figure 4 and the note on Figure 10).

Figure 4: Price cycles, March 2004 – July 2004



Note: The figure plots average prices excluding taxes for each chain during each hour of the week starting from March 1 2004 to July 12 2004. The bottom grey line is the wholesale price (Platts) and the upper grey line is the average list price. The red 'H's mark public holidays. Take note of the following:

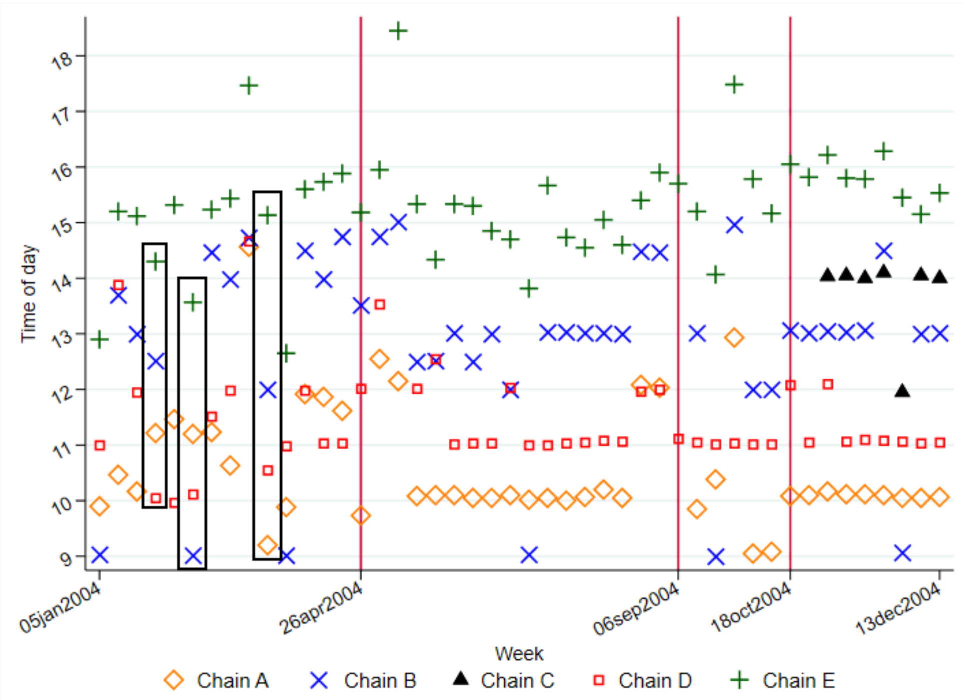
1. Price jumps occur on different weekdays and only once each week before the week of April 26.
2. Successful price jumps occur every Mon starting the week of April 26.
3. Attempts at Thu/Fri price jumps start the week of April 26. The first week only Chain A implements a Thu price jump; the second and third week successful price jumps occur on Thu and then Fri, respectively; before a failed Thu price jump occurs in the week of May 24 when only Chain A and Chain D implement price jumps. 5 weeks without any attempt at *second price jumps* follow, before Chain A alone implements a Thu price jump the week of July 5.
4. There are no price jumps Sat, Sun, or on other public holidays. Mon is a public holiday in the weeks of May 17 and May 31, and price jumps occur on Tue rather than Mon in these two weeks.

*Only *competitive stations* are included when average prices are calculated.

In this period, the price pattern resembles the Edgeworth cycles predicted in Maskin & Tirole (1988) and Noel (2008) that are observed in retail gasoline markets in multiple other countries. Prices gradually decrease over multiple days until one firm (not the same one every time) makes a sudden large price increase, then the other firms quickly follow and prices start to decrease again.

During the whole sample period, not a single price jump occurs on Saturday or Sunday. Furthermore, price jumps never happen on public holidays.[37] In periods with regular Monday price jumps (see the next section), *successful price jump* take place on Tuesday instead of Monday if Monday is a public holiday; see Figure 4 for two examples. Later, when *double jump weeks* occur regularly, the *second price jump* is often not carried out, or attempts fail, in weeks with public holidays. A likely explanation for the lack of weekend/holiday price jumps is that the chains' head offices are closed and management at each station may not be present, making it more difficult to initiate price jump attempts and decreasing the probability that competitors will quickly detect and respond to attempts. As price patterns in weeks with public holidays deviate from the regular patterns, holiday weeks are excluded from the following figures and regressions.

Figure 5: Time of day of chain price jumps, 2004



Note: The figure shows the time of *chain price jumps* for each chain for all weeks in 2004. Each dot represents the time of day a given chain initiates a *chain price jump*. Take note of the following:

1. Chain A (third black rectangle), Chain B (second black rectangle) and Chain D (first black rectangle) are all first to initiate price jumps in multiple weeks before the week of April 26 2004.
2. There is no clear pattern to the time the different chains initiate price jumps before April 26 2004.
3. On April 26 2004 (first vertical red line), Chain A starts to initiate price jumps every Mon. In the periods with regular Mon price jumps (between the first and second red line and after the third red line), Chain A leads price jumps around 10:00 almost all weeks. The other chains follow in a fairly orderly fashion 1–4 hours later.

*In the 5 *double jump weeks* starting the week of April 26 2004 only the Mon price jumps are depicted.
**Data is missing for Chain C before the week of October 26 2004.

[37]There are 4–6 weeks in March–June with one or two public holidays related to Easter, Whitsun, the Ascension, Labour Day (May 1), and Independence Day (May 17). There are also 1-2 weeks with public holidays during Christmas.

3.2 Regular Monday price jumps

The week of April 26 2004, is the first *double jump week* in the sample period with attempts at coordinated price jumps on both Monday and Thursday; see Figure 4. Both attempts are initiated by Chain A; see Figure 4 and Figure 5.[38] The Thursday price jump is not followed by any other chains, and after a few more attempts, only the Monday price jumps are left (see Section 3.3). However, the first Monday price jump is successful, and Chain A continues to initiate successful Monday price jumps around 10:00 with the other chains following 1–4 hours later until September 2004; see Figure 5.

After 4 months of successful Monday price jumps, Chain A does not initiate a price jump the first Monday in September 2004; see Appendix E. Only Chain D completes a price jump this Monday. When Chain A refrains from initiating a price jump the following Monday as well, no other chains jump prices. Foros & Steen (2013) argue that the four national chains have established an arrangement whereby they de facto simultaneously decide to increase prices on Mondays (without knowledge of their rivals' prices). However, the absence of Monday price jumps when Chain A does not lead indicates that price leadership is important to keep the new equilibrium stable and that firms – at least in the first period of a new equilibrium – make sequential rather than simultaneous decisions when market-wide price jumps are initiated.[39]

In mid-October, Chain A starts to initiate regular price jumps again. The next 13 years, Chain A leads Monday price jumps that are followed by all other chains every Monday. As we see in Figure 6, Chain A initiates price jumps at 10:00 until January 2005 and at 11:00 the rest of the sample period. The timing of price jumps is very stable with only a few minor changes during the 13 years. Chain D follows 1–2 hours after Chain A. The other two major chains with mainly manned stations carry out price jumps between 13:00 and 14:00, 2-3 hours after Chain A. The last chain out is the smaller regional player with only unmanned stations, Chain E, which implements price jumps between 14:30 and 16:00 during the whole sample period.

Noel (2019) argues that calendar synchronisation of price jumps need not be anticompetitive: On the one hand, firms can time the price jumps so that the high-price days coincide with the days of the week when gasoline demand is high, but on the other hand, the troughs and peaks of the cycle become easier to predict, making it easier for consumers to plan ahead and fill up on low-price days. Furthermore, he shows that in Perth, the second effect dominates and volume-weighted margins fall with calendar-synchronization.

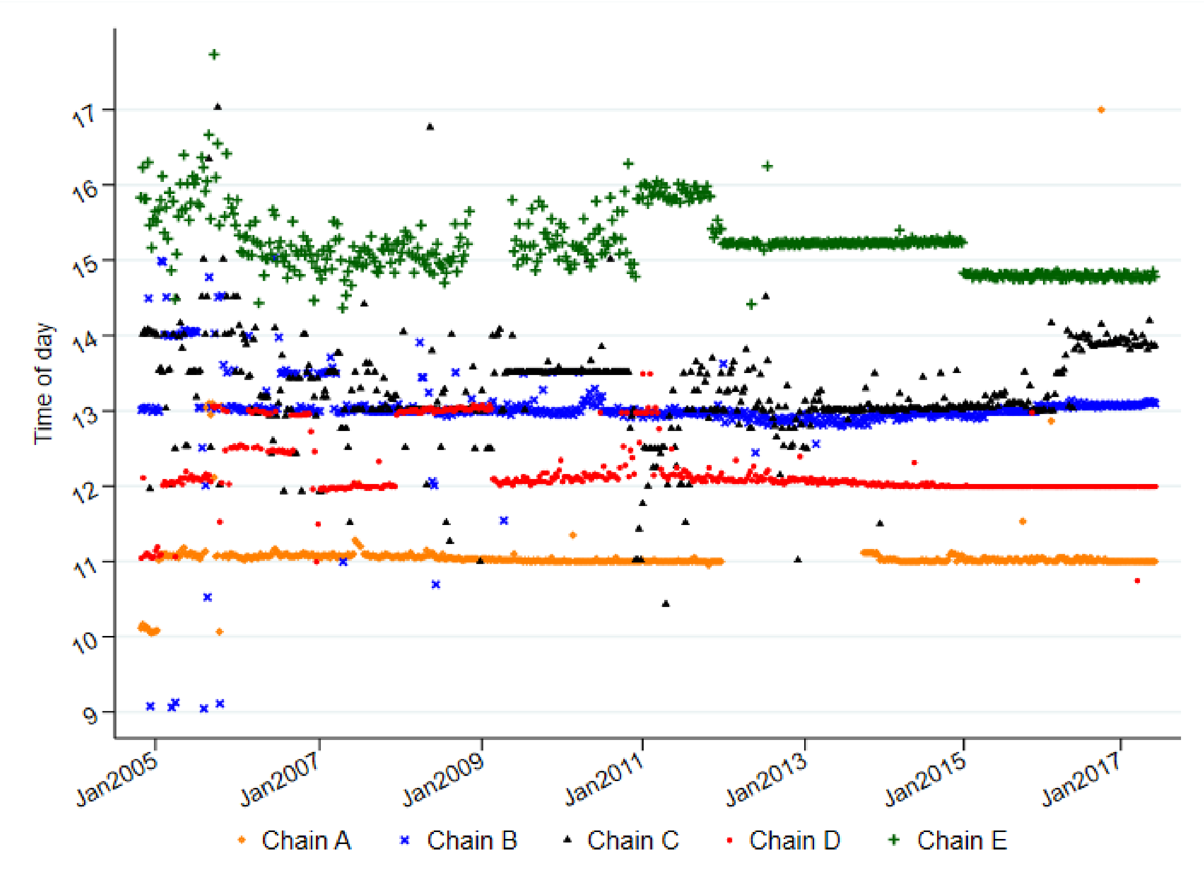
I investigate the effect the transition to regular Monday price jumps has on volume-weighted retail margins in Appendix B. A short pre-period limits the robustness of the

[38] Foros & Steen (2013) were first to identify the change to regular Monday price jumps, but do not analyse price leadership or how the change was initiated.

[39] The importance of price leadership, and evidence of sequential decision making is also evident when irregular Thursday and Friday price jumps occur; see Section 3.3.

results, but overall the evidence suggests that the transition does not have a substantial effect on volume-weighted retail margins. An increase in margins would be surprising as the new high-margin days (Monday, Tuesday and Wednesday) are not days with particularly high demand (see Figure 2). Furthermore, customers do not (at least in the short term) appear to be shifting enough demand to periods with low prices to generate a decline in volume-weighted margins. The results are contrary to Foros & Steen (2013), who find a large positive effect of the transition to regular Monday price jumps in the Norwegian market for retail gasoline. The differing results could be due to the fact that Foros & Steen (2013) employ an unbalanced sample of user-reported and unweighted prices in their analysis, and due to the short pre-period in my study.

Figure 6: Time of day of Monday chain price jumps, 2004–2017



Note: The figure depicts the time of Monday *chain price jumps* for each chain for all weeks from October 2004 to June 2017. Each dot represents the time of day a given chain initiates a *chain price jump*. Take note of the following:

1. Chain A implements price jumps every Mon at 10:00 until January 2005, and 11:00 the rest of the sample period.
2. Chain D follows 1–2 hours after Chain A.
3. Chain B and Chain C carry out price jumps 2–3 hours after Chain A.
4. Chain E implements price jumps 4–5 hours after Chain A.

*Two Chain E observations with price jumps around 01:00 are removed.
**Data is missing for Chain E November 2008–June 2009 and for Chain A January 2012–October 2013.

3.3 The emergence and collapse of double jump weeks

The week the regular Monday price jumps are introduced (April 26 2004) is also the first *double jump week* in the sample period. As shown in Figure 4 and Figure 7 (marked by the first red vertical line), Chain A also leads a price jump on Thursday this week, but no competitors follow the Thursday price jump. Multiple attempts at coordinating *second price jumps* on Thursday or Friday follow the next weeks. However, the *second price jumps* are mostly unsuccessful (3/5 fail; see Figure 7) and quickly vanish.

The simultaneous introduction of regular Monday price jumps led by Chain A and the first Thursday price jumps led by Chain A suggests that the market leader tried to increase the frequency of price jumps. By leading price jumps at the same time every Monday, Chain A can potentially reduce the cost of leading Monday price jump attempts by making price jump attempts more visible and predictable for competitors — reducing the length of the restoration phase and increasing the chance that price jumps are successful (Noel (2019)).

Furthermore, regular Monday price jumps pave the way for *second price jumps* by allowing for a 3 to 4 day undercutting phase before the *second price jumps*.[40] As prices keep falling every day during the undercutting phase, margins will be lower and the probability of a *second price jump* will be higher when the number of days between price jumps increases.[41]

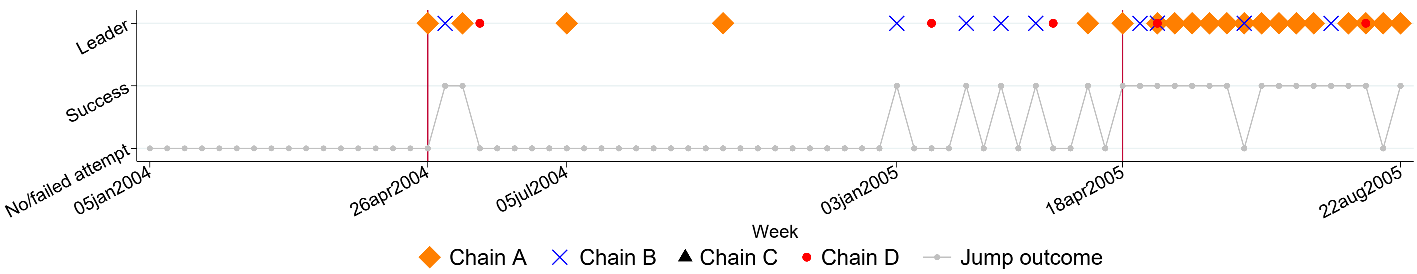
Beyond the first few attempts at *second price jumps* just after the Monday jump is initiated in April 2004, there are no *double jump* weeks before January 2005. From January to mid-April 2005, there are some Thursday price jumps, mainly initiated by Chain B. Starting April 18 2005 (highlighted by the first red vertical line in Figure 7 and Appendix Figure A.1), Chain A starts to initiate Thursday price jumps at 11:00 every week. This time, the Thursday price jumps are immediately followed by the other chains and remain mostly successful for several months. Chain A seem to have finally managed to increase the frequency of price jumps by initiating price jumps both Monday and Thursday.

However, the regular double jump weeks end at the end of August 2005, as hurricanes Katrina and Rita land and cause large supply shocks to the world oil market and extreme volatility in the wholesale price of gasoline (See Appendix E). Chain A stops initiating Thursday price jumps but continues to lead Monday price jumps through the period with extreme wholesale price volatility. The other major chains follow most of Chain A's Monday price jumps even in this period. On October 31 2005, all Monday price jumps are successful again, while the regular Thursday price jumps are gone. The hurricane-related supply shocks hit gasoline retailers in the rest of the world as well, and price

[40] Price jumps never occur on weekends (see Section 3.2), meaning only the combination Mon+Thu, Mon+Fri and Tue+Fri allow for 3–4 days between price jumps.

[41] The probability of both second price jump attempts and the success of the second price jump attempts are inversely related to margins (see Appendix F).

Figure 7: Second price jumps, Jan 2004–Aug 2005



Note: The figure shows the prevalence and success of *second price jumps* from January 2004–August 2005. The coloured symbols in the upper row indicate which chains (if any) lead the second *price jump attempt* in a given week. If 2 chains initiate price jump attempts within the same hour (and before other chains), both are considered price leaders this week. The connected grey dots indicate whether the price jumps were successful or not. Take note of the following:

1. There are no *double jump weeks* before April 26 2004 (first vertical red line).
2. The second price jump the week of April 26 2004 is initiated by Chain A. Chain A initiates 3 of the 5 *second price jumps* just after April 26 2004. Of the first 5 price jumps, 3 fail.
3. With one exception, there are no *double jump weeks* between the week of July 5 2004, and January 2005.
4. From January to mid-April 2005, there are 6 weeks with *chain price jumps*. Chain B initiates *chain price jumps* first on 4 of these Thursdays.
5. Starting April 18 (second red vertical line), Chain A initiate second price jumps every week until the end of August. The second price jumps are followed by all other chains in all but 2 weeks.

cycles in both Australia and the United States vanish for some time even after wholesale prices stabilize. The disappearing Thursday price jumps in Norway and the cycle collapse in other countries demonstrate that cost volatility can destabilize both calendar-synchronized price cycles and price cycles with irregular restoration days. This is in line with Noel (2008), who shows that false starts become more frequent when there is greater market uncertainty. Contrasted with the events in Perth and the vanished Thursday price jumps in Norway, Chain A's persistent price leadership on Mondays during the periods with wholesale price volatility appears to have been instrumental to keep the cycle from collapsing.

3.4 Transition towards more frequent double jump weeks

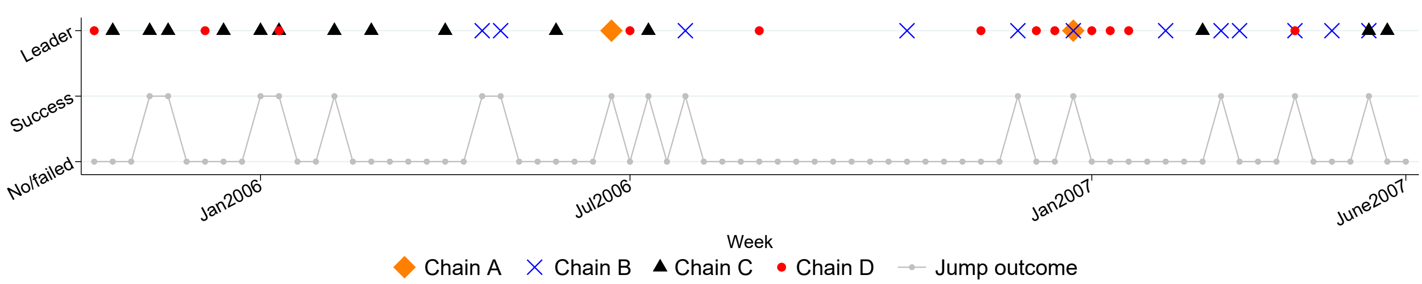
From the end of October 2005 to mid-June 2007 irregular price jump attempts occur on Thursday or Friday in 50% of weeks; cp. Figure 8.[42] Chain A almost never initiates *second price jumps* in this period, and the other 3 national chains initiates about 1/3 of

[42] *Second price jumps* occur only on Thursday or Friday during this period. With one exception, price jumps never occur on both Thursday and Friday the same week.

these price jumps each. Until mid-June 2007, there is no clear pattern in the time of day the different chains increase prices (see Appendix Figure A.2), and 58% of the price jumps fail, with all chains being frequent non-followers.

In June 2007, Chain B starts to lead most *second price jumps*, and from June 2007 to March 2009, the chain leads 79% of the *second price jumps*. In this period, *second price jumps* are almost exclusively initiated on Thursdays[43] and the timing of the price jumps becomes more orderly, with Chain B typically initiating price jump attempts around 10:00–11:00, the other national chains following a few hours later at fairly regular times of day, and Chain E being last to increase prices (see Appendix Figure A.2.) The *second price jump* attempts happen more frequently in this period than before July 2007 (71% vs 50%), but still fail quite often (38% vs 58%).

Figure 8: Second price jumps, October 2005–June 2007



Note: The figure shows the prevalence and success of *second price jumps* from the week of October 24 2005 to the week of June 11 2007. The coloured symbols in the upper row indicate which chains (if any) lead the second price jump attempt in a given week. If 2 chains initiate price jump attempts within the same hour (and before other chains), both are considered to be price leaders this week. The connected grey dots indicate whether the price jumps were successful or not. Take note of the following:

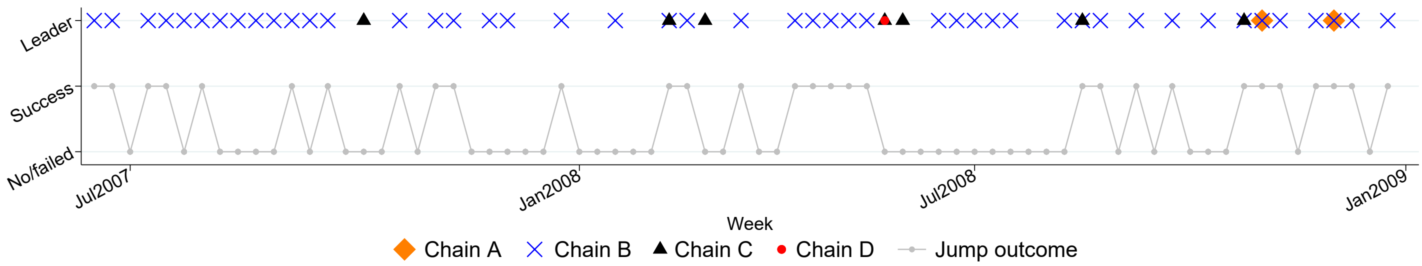
1. Chain A leads in 2 weeks only. The other 3 national chains lead about the same number of price jumps (Chain B, 12; Chain C, 14; and Chain D, 12).
2. Second price jump attempts occur in 50% of the weeks, and 58% of the attempts fail.

Summing up, after the largest chain stops initiating Thursday price jumps, the market goes through a chaotic 1 and 3/4 year period with no established leader of *second price jumps* and relatively few and often unsuccessful *second price jumps*. When Chain B emerges as price leader, *second price jumps* become more frequent and their success rate higher.

There is also a lot of within-quarter/month variation in which weeks *second price jumps* occur during the whole period from fall 2005 until March 2009. I employ various survival models to describe how different factors influence the probability of *second price jump*

[43] Only two Friday price jumps (November 2 2007, and January 23 2009) are initiated after June 2007.

Figure 9: Second price jumps, July 2007–June 2009



Note: The figure shows the prevalence and success of *second price jumps* from the week of June 18 2007 to March 16 2009. The coloured symbols in the upper row indicate which chains (if any) lead the second *price jump attempt* in a given week. If 2 chains initiate price jump attempts within the same hour (and before other chains), both are considered to be price leaders this week. The connected grey dots indicate whether the price jumps were successful or not. Take note of the following:

1. Chain B leads 79% of the price jumps from the week of June 18 2007 to March 2 2009.
2. Second price jump attempts occur in 71% of the weeks and 38% of the attempts fail.

attempts and success in this period (see Appendix F). Taken together, the results (see Appendix Table F.1) suggest that lower margins strongly increase both the probability of *second price jumps* attempts and the probability that the *second price jump* attempts are successful. These results are in line with Atkinson (2009), who finds that price restorations in several Canadian cities with non-synchronized price cycles depend on proximity to marginal costs.

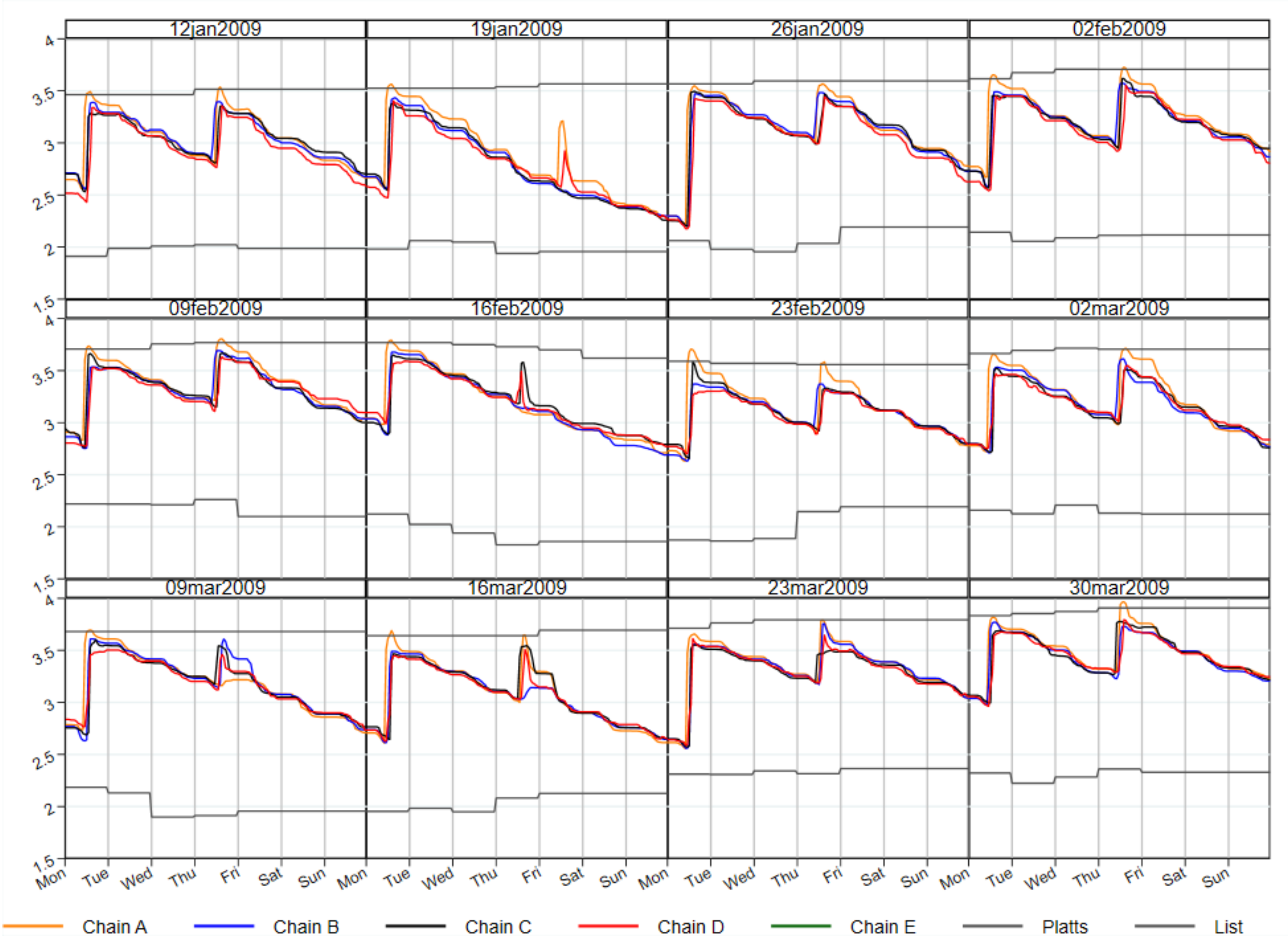
So far, we have seen that the frequency and success rate of *second price jumps* increase after Chain B becomes a regular price leader, and that within a given month/quarter, price jumps are more likely if margins are low. A natural question is, then, can the higher price jump frequency and success rate when Chain B become a regular price leader be explained by a decrease in the margin just before the *second price jumps*? Appendix Figure A.3 plots average margins Thursday mornings 8:00 (just before second price jumps are initiated) from October 2005 to December 2011. The figure reveals both short-term and long-term variation in the Thursday morning margin, but there is no indication that the increase in *second price jump* frequency from June 2007 is correlated with lower Thursday morning margins.

3.5 Regular Thursday price jumps

After 3.5 years of irregular and often unsuccessful Thursday/Friday price jumps, Thursday price jumps become regular in March 2009. The transition to regular Thursday price jumps occurs when Chain C takes over Thursday price leadership. Figure 11 depicts how

Chain C leads two late (12:30–13:00) price jumps in the weeks starting March 9 2009 and March 16 2009, after Chain B fails to initiate price jumps. The two late price jumps are not successful. The following week (March 23 2009), Chain C initiates a Thursday price jump at 11:00 that turns out successful, and continues to do so in the following months.

Figure 10: Price cycles, January–March 2009

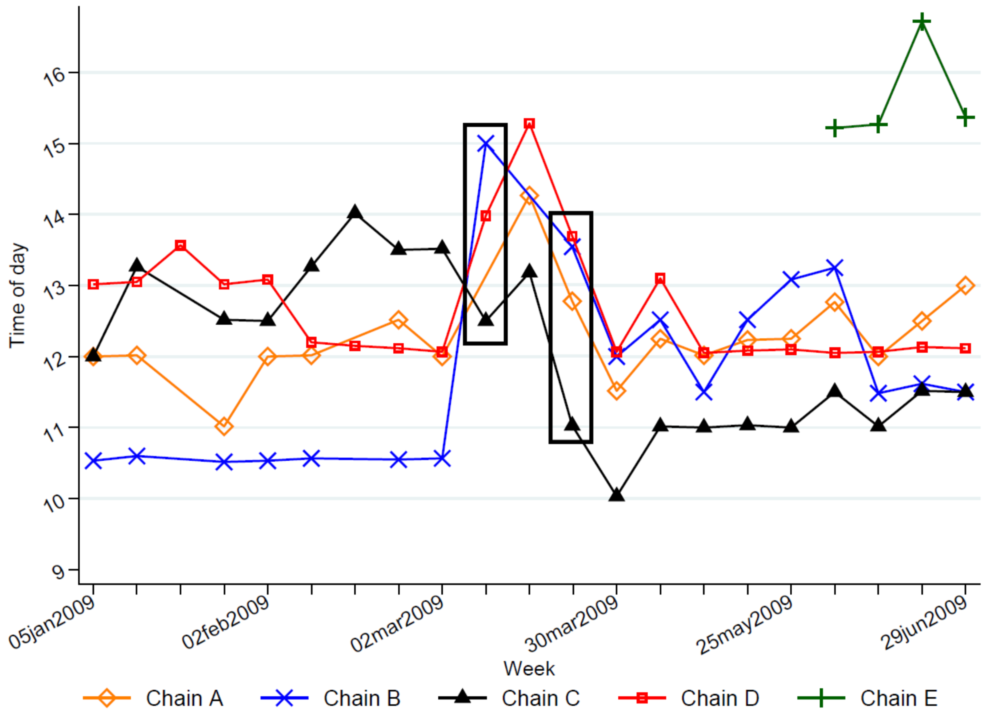


Note: The figure plots average prices excluding taxes for each chain during each hour of the week of August 22 2005 to the week of November 7 2005. The bottom grey line is the wholesale price (Platts) and the upper grey line is the average list price. Take note of the following:

1. *Second price jump attempts* are carried out every week in this period. With the exception of the week of January 19, all second price jumps are implemented on Thu.
2. Price jump attempts fail in 4 of the 12 weeks before the week of March 23 (the weeks of January 19, February 16, March 9 and March 16).
3. Data is missing for Chain E November 2008–June 2009. As we can see, prices quickly revert to the pre-jump path during the 4 weeks when one or more of Chains A, B, C and D do not carry out price jumps. In weeks when all 4 of Chains A,B, C and D carry out price jumps in the period with missing Chain E data, prices do not revert to the pre-jump path. As prices normally quickly revert to the pre-jump path if one or more chains fail to initiate price jumps, this observation suggests that Chain E also implements price jumps during all weeks when the other 4 chains implements price jumps.

After March 2009, both Monday and Thursday price jumps are initiated every non-

Figure 11: Time of day of second chain price jumps, first half of 2009



Note: The figure depicts the time of day of second *chain price jumps* for each chain for all weeks in the first half of 2009. Each dot represents the time of day a given chain initiates a *chain price jump*. Take note of the following:

1. Chain B leads price jumps at 10:30 in most weeks until the second week of March 2009.
2. When Chain B abstains from initiating a Thu price jump the week of March 9, Chain C initiates a price jump at 12:30 (first black vertical rectangle). Chain B and D, follow while Chain A does not. The following week is similar, but with Chain B being a lone non-follower.
3. The week of March 23, Chain C initiates a price jump at 11:00 and all other chains follow (second black rectangle). The following weeks Chain C continues to initiate price jumps around 11:00, and all other chains follow.

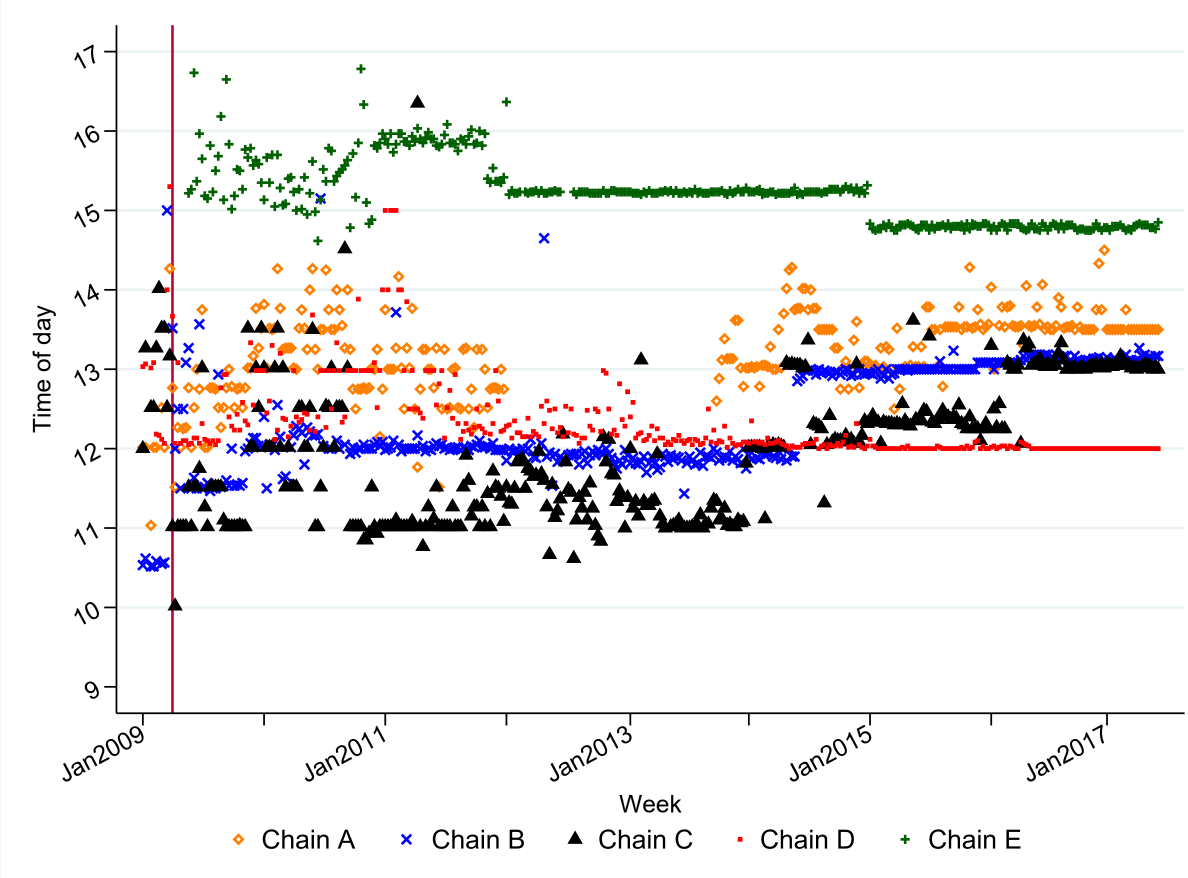
holiday week for more than 8 years.[44] Starting the week of March 23 2009, Thursday price jumps are always successful.[45] Figure 12 depicts the timing of the Thursday price jumps from 2009-2017, with a red vertical line marking the week the Thursday price jumps were solidified. The timing of price jumps is fairly stable once the new equilibrium is solidified, with the most important change being that Chain D starts to lead in 2014 (see discussion in Section 5).

In a model with an infinitely repeated game, history dependent strategies and price leadership, Mouraviev & Rey (2011) demonstrate that firms can rotate price leadership or

[44]The pricing pattern changes in November 2017 when Chain A publicly announces a change to a new pricing policy; see Ones (2018).

[45]There are only 4 weeks without Thursday price jumps: After a period when Chain C mostly postpone Thursday price jumps to a few hours after 11:00, Chain B do not initiate price jumps on 4 Thursday late summer 2010; see Appendix Figure E.4. The events when Chain B fails to follow do not impact the other chains willingness to initiate price jumps, but seem to persuade Chain C to once again initiate price jumps at 11:00.

Figure 12: Time of day of Thursday chain price jumps, 2009–2017



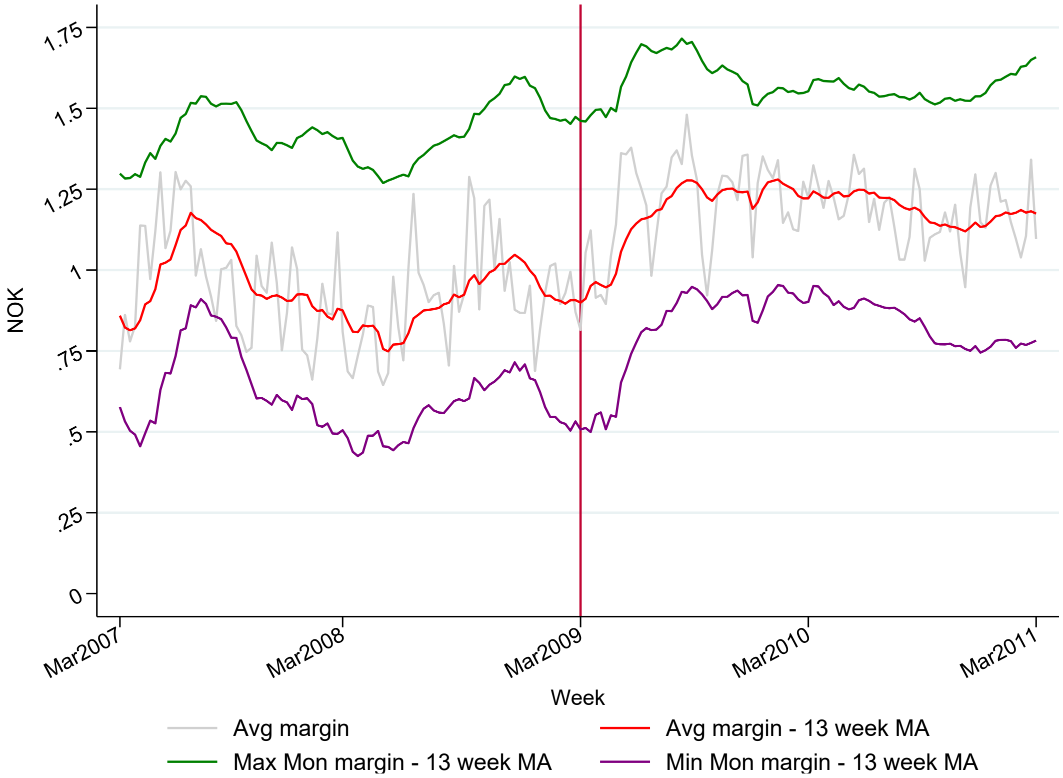
Note: The figure depicts the time of Thu *chain price jumps* for each chain for all weeks from January 2009–June 2017. Each represents the time of day a given chain initiates a *chain price jump*. The vertical red line highlights the week of March 23 2009, when successful Thu price jumps are solidified. Take note of the following:

1. Chain C is first to initiate Thu price jumps most weeks (between 11:00 and 11:30) from the week Thu price jumps are solidified until January 2014.
2. Chain B normally initiates price jumps 0.5–1 hour after Chain C, but in some weeks when Chain C initiates price jumps at 12:00 or even later, Chain B initiates price jumps about the same time or before Chain C.
3. Chain A initiates price jumps 1-3 hours after the price leader.
4. Chain E is the last chain to initiate price jumps 3–5 hours after the price leader.
5. When Chain B and Chain C delay price jumps to 12:30-13:00 starting in 2014, Chain D is first to initiate price jumps (at 12:00).

lead in different segments to share the gains of collusion. Similarly, in models with Markov strategies and Edgeworth cycles, firms can play mixed strategies to rotate price leadership to share the cost of leading price increases (see Wang (2009)). I have documented how two of the national chains (first A and B, and then A and C) share price leadership by leading price jumps on different weekdays. Having two different chains leading price jumps on one weekday each solve the coordination problem related to the timing of price jumps and who should lead price jumps, and makes it possible to share the cost of price leadership.

So, do the transition increase margins? According to Noel (2019), a decrease in the period between price jumps need not be anticompetitive. He argues that the theory of Edgeworth cycles predicts that prices at the top of the cycle will competitively adjust downwards if the period between jumps decreases, leaving the price at the bottom of the cycle unchanged. This gives two testable predictions: Following the regular Thursday price jumps, we should see 1) a decrease in the Monday maximum margin, and 2) no change in the minimum margin on Monday (the margin just before price jumps were carried out). Additionally, if the decrease in the period between jumps is not anticompetitive, retail margins should not increase after the Thursday price jumps solidify.

Figure 13: Average margins, March 2007–March 2011



Note: The figure depicts weekly average volume-weighted retail margins from 2 years before the transition to regular successful Thu price jumps (red vertical line) to 2 years after the transition, and the 13-week moving average of volume-weighted margins. Furthermore, the 13-week moving average of the average maximum Mon margin, and the 13-week moving average of the minimum Mon margin are plotted. Take note of the following:

1. The average max Mon margin is not decreasing after the transition to regular Thu price jumps.
2. The average volume-weighted margin and the min Mon margin increase greatly just after the transition to regular Thu price jumps.

*Only stations that are *strong cycle* stations all years from 2007–2011 are included when averages are calculated. The results are qualitatively the same if *some cycling* stations are also included.

Figure 13 reveals that maximum margins do not decrease after the transition — the mitigating effect related to decreasing maximum prices that Noel (2019) predicts does not materialize. The figure also reveals that pre-jump margins on Mondays were already far above marginal costs before the transition to regular Thursday price jumps, and that they increase greatly after the transition. The pre-jump margins on Thursdays after the transition are even higher than the Monday margins (average min margin across weak and strong cycle stations between Mar 23 2009 and March 23 2011 are 0.83 NOK on Monday and 1.04 NOK on Thursday).

The high pre-jump margins suggest that coordination on two weekly price jumps not only helps the chains to avoid the war of attrition game at the very bottom of the cycle; it enables them to avoid large parts of the trough of the cycle, while still reaping the benefits of high prices at the peak of the cycle.

I further investigate the effect of the transition to regular Thursday price jumps on volume-weighted retail margins with various fixed effect and difference-in-difference models in Appendix B. The estimates varies between the different models, but all estimates point to an economically large and statistically significant effect on volume-weighted margins. My preferred specifications give estimates from 8% to 18% increase in volume weighted margins. Note that this is not the effect of going from 1 to 2 price jumps per weeks; it is an estimate of the change from a setting with regular and successful Monday price jumps and irregular and often failed Thursday or Friday price jumps, to a setting with regular and always successful Monday and Thursday price jumps.

4 The costs and benefits of leading price jumps

Before Thursday price jumps are solidified in early 2009, the irregular *second price jumps* are typically initiated by one of the national chains between 10:00 and 11:00 on Thursday (83%) or Friday (17%). The other national chains follow after 1–3 hours, and the regional chain another 2 hours later (see Appendix Figure A.1 and Appendix Figure A.2). Loss of demand in the period when the leader is alone with a high price and the risk of developing a reputation as a high priced firm can increase the cost of leading price jumps. On the other hand, the pricing pattern seen in e.g. Figure 10 points to the prospect of large gain in terms of higher prices for the rest of the week if the *second price jump* is successful.

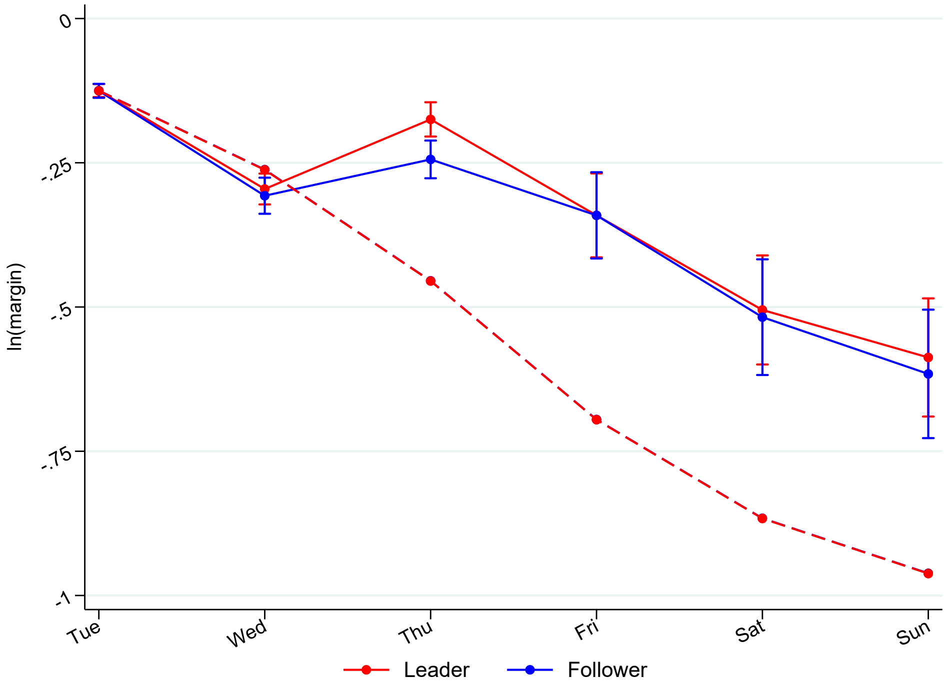
Harrington (2017) shows that this trade-off between losing current demand for the prospect of higher future prices, rather than incentives to deviate can be the constraining factor on price in a model with an infinitely repeated game, grim trigger strategies, and uncertainty about competitors' strategies. Similarly, Harrington & Zhao (2012) find that even if all firms want to collude, failure to coordinate regarding who should lead price increases may prevent collusion from emerging. In models with Edgeworth cycles, problems related to coordinating a price leader can delay price jumps. Furthermore, coordination problems between the non-leaders related to the order of followership can leave the leader stranded at the top of the cycle for several periods, and false starts where the leader abandons its attempt to raise prices can ensue; see Noel (2008) for a theoretical discussion. Wang (2009) argues that the cost of leading price jumps increased after a new regulation in Perth forced the price leader in the retail gasoline market to be alone with a high price for 24 hours, leading to a temporary collapse in the price cycle. To the best of my knowledge, the only paper studying the immediate loss of market share resulting from price leadership, is by Clark & Houde (2013) who study volume transfers between cartel members where stronger firms delay price increases. However, the authors do not have access to within-week volume data, and their estimates are based on assumptions about the share of weekly volume that is sold in the period with price differences, and estimates of the elasticities of demand.

In the following section, I explore the costs and benefits of leading price jumps by estimating how station i's margin, volume, and market share are impacted by leading, following, and not following *second price jumps*.[46] More details on the data and the estimation procedure, and the results in table form, are available in Appendix D. I employ a difference-in-difference strategy in which the first difference is the change in the outcome variable for station i from Tuesday to other weekdays. The second difference is between weeks with a *second price jump* (treatment) and weeks without a second price jump (control). Different treatment groups are defined based on whether the price jump is successful or fails, and whether the chain station i belongs to is leading, following or not following the price jump. Figure 14 depicts results for weeks with successful price jumps with ln(volume-weighted margins) as the outcome variable, and can be used to further explain the strategy. The solid red line plots the margins of the leader (treatment) and the dashed red line how the margins of the leader would have developed if a *second price jump* did not occur, given that the change from Tuesday margins would be the same as in weeks without *second price jumps* (control). The diff-in-diff estimate of the effect of a successful price jump on the margins of the price leader is the difference between the solid and dashed red lines. The same estimate for the follower, is the difference between the solid and dashed blue line. The effect on margins of being a leader compared to being a follower, is given by the difference between the solid red and solid blue lines.

The identifying assumption when studying the effect on margins is that absent a *second price jump*, margins for leaders/followers/non-followers would have a common trend with margins in weeks without *second price jumps*. We know from Appendix F that *second price jumps* are more likely when margins are low. Consistent with this, Figure 14 and Appendix Figure D.1 show that Tuesday margins for leaders, followers and non-followers are lower in weeks with Thursday price jumps. This is not a problem for identification as the identifying assumption rests on common trends from Tuesday to other weekdays, not a common level. The decreases in margins from Tuesday to Wednesday (before Thursday jumps) are similar in weeks with price jumps and weeks without price jumps. Furthermore,

[46] Weeks with Friday price jumps are removed from the sample (11% of all weeks, and 17% of the weeks with *second price jumps*) so that all *second price jump* attempts in the sample occur on Thursdays. The results are similar (but delayed one day) in weeks with Friday price jumps.

Figure 14: Margins of leaders and followers – success



Note: The solid red line plots the volume-weighted margins for stations belonging to the price leader in weeks with successful *second price jumps* on Thu relative to margins on Tue in weeks without second price jumps. The dashed red line plots how margins would have developed in weeks with successful second price jump if a *second price jump* did not occur, assuming the change from Tue margins would be the same as in weeks with no price jumps ('the counterfactual'). The dashed and solid blue lines plot the same values for followers. Take note of the following:

1. Margins for both leaders and followers are 0.12 log points (lp) lower on Tue and fall 0.03–0.04 lp faster from Tue to Wed relative to weeks with no price jumps.
2. On Thu, margins for leaders are 0.07 lp higher than for followers, and margins for leaders and followers are respectively 0.28 and 0.21 lp higher than the counterfactual.
3. Margins on Fri, Sat and Sun are almost identical for leaders and followers, and are 0.35–0.37 lp higher than the counterfactual.

*The solid lines plot the sum of β_1 through β_7 in Eq. D.1 for leaders and followers on different weekdays in weeks with successful price jumps. The dashed lines simply subtract β_1 from the Tue value of the sum of β_1 through β_7 for leaders and followers. Coefficients are reported in Table D.1 in Appendix D.
**95% confidence intervals are shown. Standard errors for the combined coefficients are calculated using the delta method.

in the days after the price jump is initiated, margins fall about equally fast (from Friday to Saturday/Sunday) in weeks with and without second price jumps.[47] Taken together, the evidence supports the common trends assumption as margins, except for days with *second price jumps*, fall with about the same factor regardless of whether a price jump will be carried out or has been carried out.

[47]The price jumps normally occur between 10:00 and 16:00 on Thursdays, meaning part of the Thursday volume is sold at pre-jump prices. This means that the volume-weighted Thursday margin in weeks with price jumps is lower than margins just after the price jumps are initiated, and the change from Thursday to Friday as expected is smaller in weeks with price jumps than in weeks without price jumps.

Figure 14 shows a large increase in margins for both leaders and followers on Thursdays in weeks with successful price jumps, and the margins stay on the higher path through the rest of the week. The leader's margin is slightly higher on Thursdays because the leader increases price before the followers. A successful price jump has a large positive effect on the leader's average volume-weighted margin, which increases by about 42% from Thursday until the next regular Monday price jump compared to the counterfactual, and by about 31% over the whole week compared to the counterfactual.[48]

In weeks with failed price jump attempts, the margins of both leaders and followers increase on Thursday, but not as much as in weeks with successful price jumps (see Appendix Figure D.1). As expected, non-followers' Thursday margins are about the same as in weeks without price jumps. On Friday, the leader's and followers' margins decrease almost to the level of the non-followers. The smaller increase in leader and follower margins on Thursdays and the large decrease from Thursday to Friday, reflect that price jumps are quickly reversed if one or more chains do not follow them.

Turning to market shares, Figure 15 suggests that the early price jump causes the leader a loss of about 3% market share on Thursdays in weeks with successful price jump attempts. The leader's lost market share is shared between the followers, who on average gain 1% market share in successful weeks. In weeks with failed price jump attempts, both the leader (3% loss) and the followers (1% loss) lose market share, while the non-followers' lower prices cause a 4% increase in their market share.[49] Thursdays constitute about 20% of volume until the next Monday price jump occurs, meaning the leader, in the short run, sacrifices only about 0.6% market share for the prospect of 42% higher margins if the price jump is successful.[50]

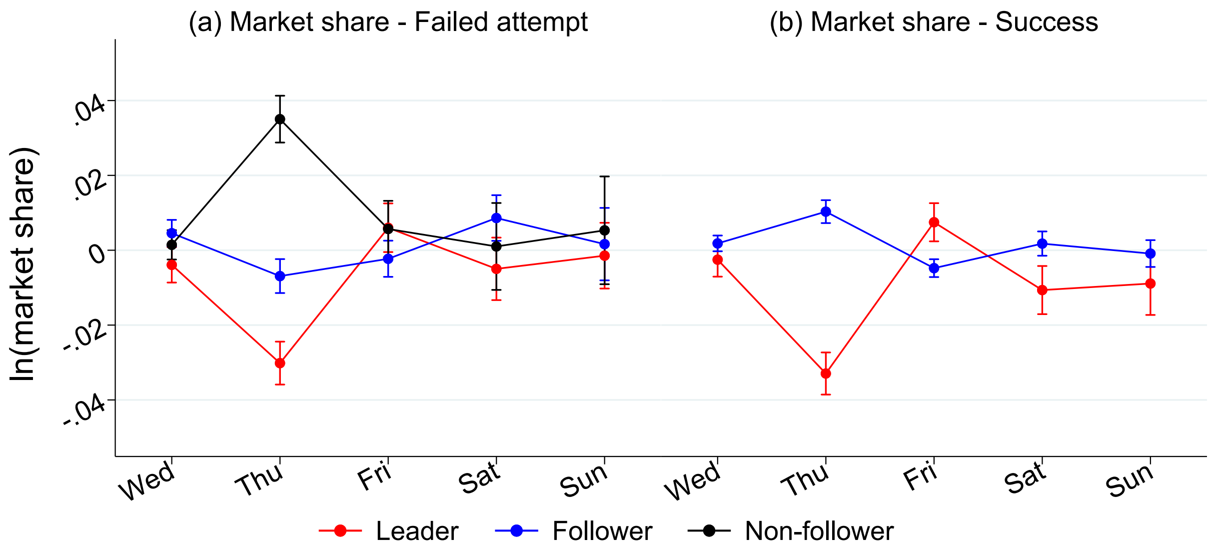
A possible concern in the models with market share as dependent variable, is that price jumps are endogenously decided as a result of supply side responses to unobserved demand shocks. Our main interest is the differential effect Thursday price jumps have on volume sold for leaders, followers, and non-followers respectively. Unobserved firm-specific demand shocks would threaten identification, while demand shocks common to all firms will not because they will only impact market demand and not the distribution of market shares. Apart from spatial differentiation, gasoline is a very homogeneous product, and all the 4 largest chains have stations in all parts of Norway, meaning firm-specific demand shocks are unlikely to be a determinant of price jumps. This is also supported by the fact that in both weeks with failed and successful price jumps, Thursday is the only day with

[48]Assuming 50% of the Monday volume is sold before the regular Monday price jump is initiated, that the Monday margin prior to the Monday price jump is equal to the Sunday margin, and that the Monday margin after the Monday price jump is equal to the Tuesday margin.

[49]The same pattern emerges with volume rather than market share as the dependent variable: Figure D.2 panels (a) and (b) show that that both the leader and the follower lose volume to the non-follower on Thursdays in weeks with failed price jump attempts, and the leader loses volume to the follower on Thursdays in weeks with successful price jump attempts.

[50]Assuming 50% of Monday volume is sold before the Monday price jump occurs.

Figure 15: Market share gasoline



Note: The figure plots the difference between treatment and control with respectively ln(litres gasoline sold), ln(share of volume gasoline) and ln(share of convenience store revenue) as outcome variables. Take note of the following:

1. The difference in the change in market share between treatment and control from Tue to Wed is <0.5% in both failed and successful weeks.
2. Leaders lose 3.0–3.3% market share on Thu in successful and failed weeks, while followers lose 0.7% in failed weeks and gain 1.0% in successful weeks. Non-followers gain 3.5% on Thu.
3. Leaders gain 0.7% market share on Fri in successful weeks, and lose 0.9–1.1% on Sat/Sun.

*The lines plot the sum of coefficients from Eq. D.1. Only coefficients varying over weekdays are included when the plotted values are calculated. β_1 is common to both treatment and control and is negated. The values plotted are therefore $\beta_4 + \beta_5 + \beta_7$. Coefficients are reported in Table D.1 in Appendix D.

**95% confidence intervals are shown. Standard errors for the combined coefficients are calculated using the delta method.

substantial market share changes (see Figure 15).

The regressions with volume as dependent variable indicate that in successful weeks both leaders and followers lose 6–11% volume each day from Thursday to Sunday, suggesting that in the very short run (1–4 days), price elasticity is high and that successful price jumps lead to a substantial loss of volume (see Appendix Figure D.2). However, Levin et al. (2017) find a large response in the amount of gasoline purchased in the first days following a price change, but show that the response results almost entirely from a temporary change in the probability of making a purchase rather than a change in gasoline demand or usage. As in multiple other studies, Levin et al. (2017) find that in the longer run, market demand is low (-0.27 and -0.35). Consistent with this, I find that both leaders and followers experience a 3% increase in volume on Tuesdays and Wednesdays in weeks following a week featuring a successful *second price jump* (see Appendix D.2). The total effect of *second price jumps* on gasoline demand is likely negative, but much smaller than the decline in the very-short-run probability of making a purchase.

Noel (2019) postulates that longer-run effects can increase the cost of leading price jumps because leaders run the risk of developing a reputation as a high-priced firm. The risk could be exacerbated when relenting phases are longer and false starts are more common. Chilet (2018) provides some support for this in his study of volume transfers related to delayed price increases between members of a retail pharmacy cartel in Chile. Prices are increased once for a large number of different products. He finds that the first firm to increase prices loses market share in the month after all firms have increased prices. I find that leaders of successful Thursday price jumps experience a small gain in market share on Friday and a small loss on Saturday and Sunday in the same week (see Figure 15). In weeks with failed price jumps, the changes in market shares are insignificantly different from zero . I further investigate potential longer-run effects on market shares in Appendix B.2 and do not find evidence supporting leaders' loss of market share in the week after the week they initiate second price jumps. Taken together, the evidence does not point to a loss of market share for the leader in the period after the prices of the leader and the other chains have converged. However, my analysis concerns a period when price jumps are irregular and there are long periods with no regular price leader. The cost of leading price jumps could increase if the same firm leads price jumps at a specific time every week, because consumers learn to better predict the timing of price jumps and the identity of the price leader.[51]

A final possible cost of leading price jumps is spill-over effects from gasoline prices to convenience store sales. Most Norwegian gas stations also have an on-site c-store. I do not, however, not find evidence of an effect of being a price leader on Thursday on the convenience store market share on Thursday (see Appendix Figure D.2).[52]

Summing up, the evidence suggests that — in the period before *second price jumps* are solidified — the cost of leading the *second price jumps* is low compared to the potential gain. On average, the leader sacrifices about 0.6% market share for a chance of about 42% higher margins and only a modest reduction in total volume sold. The high rate of failure before second price jumps solidify in March 2009 reduces the benefits of leading price jumps. The low cost compared to the benefits of leading *second price jumps* could be contributing to the gradual emergence of *second price jumps* in 2005–2009 and the transition to regular second price jumps in March 2009.

[51] Confidentiality restrictions preclude me from studying the effect of being a regular price leader.

[52] Customers responding to the price difference between leaders and followers by changing gas station are likely more price-sensitive than the average customer and could be less inclined to buy items at the convenience store. Only data on total daily c-store revenue for each station (not volume and prices separately) is available.

5 Firm size and price leadership

We have seen that the market went through a transition from regular Monday price jumps to regular price jumps on both Monday and Thursday, with different chains leading in different periods and on different days and with varying rates of success. In this section I highlight the relationship between size, regular price leadership and the success of price jump attempts.

The largest chain, Chain A, leads Monday price jumps for more than 13 years, and is the first chain to initiate *second price jumps*. The chain's Monday price jumps are always successful, and when Chain A for a brief period also leads second price jumps in 2005, most of these are also successful. Chain A stops leading second price jumps during a period with wholesale price turbulence. After Chain A stops leading, second price jumps are first irregularly initiated by the other 3 national chains (different chains leading from week to week), and often fail. Both the frequency and success rate increase when Chain B becomes a regular leader, but the second price jumps only become regular and achieve a 100% success rate when Chain C starts to lead every Thursday in 2009. A final observation is that Chain D takes over Thursday price leadership in 2014.

An important event pre-dates the solidification of the Thursday price jumps. Between August and December 2008, Chain C began operating 90 gas stations it acquired from Chain D (see Appendix C), increasing Chain C's national volume based market share from 23% to almost 30% (see Figure 1) and creating a clear market share runner-up. The 90 stations were spread out in different parts of Norway, but were almost exclusively located in populous areas with both other Chain C stations and stations from other chains present.[53] The stations were also on average located only 2.9 minutes drive time from the closest non-Chain C station, much closer than the national average of 6.8 minutes. The local overlap with existing Chain C stations led to an increase in the chain's stations' average local volume based market share of the same magnitude as the increase in the national market share.[54]

The increase in Chain C's market share and decrease in Chain D's market share led to increased size asymmetries between the chains. Size asymmetries are generally considered to make tacit collusion harder rather than easier (see e.g. Motta & Fabra (2013).[55] An

[53]Of the stations, 93% were located in urban areas; 93% were located within 15 minutes' of another Chain C station; 47% were located within 15 minutes' of a station from each of the 4 other major chains; 80% were located within 15 minutes from 3 or more of the other major chains; and 93% were located within 15 minutes from 2 or more of the other major chains.

[54]Chain C's average volume based local market share increased from 33% in January 2008 to 39% in January 2009. A local market is defined around each station and includes all stations within a 15 minute drive time. The marked share of the centre station is calculated by adding the volume of the center station and all other stations from the same chain in the local market and dividing by the total volume of all stations in the local market.

[55]Miller et al. (2019) find that a merger in the U.S. beer market that increased symmetry between the two largest firms but decreased symmetry between the largest firms and other firms facilitated collusion between the two large firms. In the Norwegian gasoline market in the studied period, there are no

increase in the number of markets in which the same set of firms interact (multimarket contact) can also facilitate collusion. However, the overlap with existing Chain C stations ensured that the increase in multimarket contact was very limited as Chain C was already active in the areas where the acquired stations were located.[56] The lack of an increase in symmetry between the chains, lack of a reduction in the number of competing chains, and lack of an increase in multi-market contact make it unlikely that the merger facilitated tacit collusion by relaxing the firms' incentive compatibility constraint.

Changes in incentives and ability to lead price increases following the transaction can also impact the identity of the price leader and the frequency and success rate of price jumps. Eibelshäuser & Wilhelm (2018) show that in a framework with Markov strategies and Edgeworth cycles, a firm with a large share of retail outlet in a given area earn greater profits at high prices and therefore has stronger incentives to set high prices and lead price jumps.[57] Noel (2007), Atkinson (2009), and Lewis (2012) find evidence partially supporting this prediction by finding that price jumps are generally led by retail gasoline chains controlling a large number of stations. The authors also point out that an increase in the number of stations that initiate price jumps and spatial closeness to competing stations make it easier for competitors to observe that a market-wide price jump has been initiated and thereby enhance a chain's ability to signal the onset of a price jump. Byrne & de Roos (2019) find that the largest chain is leading price jumps in an effort to move the market to a more profitable equilibrium.

The transaction increases Chain C's average local market share, and could increase the chain's incentives to initiate price jumps. Chain C begins leading Thursday price jumps just a few months after the transaction, and also increases the frequency of price jumps right away. Furthermore, the price jumps the chain initiates are successful from the very start, indicating that competitors are more inclined to follow the chain's price jumps. The changes are consistent with an increase in Chain C's incentives to initiate price jumps, and an increase in the chain's ability to signal the onset of market-wide price jumps. The evidence of substantial changes in the pricing pattern following the transaction is consistent with theoretical prediction, and indicates that the transaction contributes to the transition to regular Thursday price jumps.

A final observation is that Chain C continues to lead most Thursday price jumps until Chain D takes over as a Thursday price leader in 2014 (see Figure 12). In the period between 2009 and 2014, Chain D's volume-based market share steadily increases (both due to organic growth and due to poaching dealer-owned stations from the other chains) from 12% to 16%, while Chain C's market share decreases from 29% to 24% (see Figure 1). Price leadership changes from a chain that has experienced a declining market share

indications of tacit collusion only between the two largest firms.

[56] Multimarket contact is normally measured as the number of markets that two distinct firms concomitantly serve. That is, it depends on exposure rather than intensity; see Evans & Kessides (1994).

[57] See also Eckert (2003).

to a chain that has experienced an increasing market share.

Taken together, evidence of both size differences across chains and within-chain changes in size suggest that large chains are more likely to be price leaders. Price leadership also seems to be more effective when large firms lead price increases, resulting in more frequent and more successful price jumps. The results correspond with Lemus & Luco (2019), who find that markets in Chile with a persistent price leader have higher margins and more price matching.

6 Concluding remarks

In this paper, I employ a unique dataset of extremely detailed price and volume information to show how retail gasoline chains use price leadership to both initiate and sustain coordination of new supra-competitive equilibria in a market without price regulations. The largest chain leads Monday price jumps to initiate a transition from irregular price jumps to regular Monday price jumps, preparing the ground for additional price jumps later in the week. After a period with irregular and often failed *second price jumps*, the second-largest chain leads a transition to regular second price jumps every Thursday. After the transition, Thursday price jumps occur more frequently and are always successful, leading to a substantial increase in retail margins. The equilibrium with two successful price jumps per week, in which the chains share the burden of price leadership by consistently leading price jumps on different weekdays, lasts for more than 8 years. The study agrees with previous research by Byrne & de Roos (2019) showing that price leadership is an effective tool to initiate and sustain coordination. Contrary to what Noel (2019) postulates, the increase in volume-weighted margins following the transition to more frequent price jumps suggests that regulators should be concerned with increases in the frequency of price jumps.

I also show that the cost of leading Thursday price jumps in the period before the transition to regular Thursday price jumps is low compared to the gains. The low cost may have contributed to the transition to more frequent price jumps. Increasing consumer price sensitivity in the period when the leader is stuck alone with a high price would increase the cost of leading price jumps and make it harder to initiate and sustain equilibria with frequent price jumps. Gasoline price comparison webpages and regular data collection mean that the authorities in some countries already have detailed, up-to-date data on gasoline prices. For example, the ACCC already updates Australian consumers online regarding *when* they should purchase gasoline.[58] The lowest prices during a cycle are typically available at non-leading retailers in the period just after the leader jumps prices.

[58]See ACCC (2019). The Norwegian Competition Authority collects also price data from the retail gasoline chains every six months and has issued reports and press releases focusing on what days prices increase; see e.g. Konkurransetilsynet (2014).

Informing customers about exactly when price jumps normally occur and also identifying price leaders and early/late followers, could steer customers towards the non-leaders and thus increase the leader's loss. This could possibly prevent more frequent price jumps from being initiated, or cause the frequency of price jumps to decline.

Finally, I present evidence suggesting that larger chains are more likely to act as price leaders and more frequently initiate successful price jumps. The results support Byrne & de Roos (2019)'s conclusion that firm asymmetries can facilitate collusion because the dominant firm can act as a price leader and initiate price coordination. Furthermore, the solidification of Thursday price jumps after the acquisition, creating a clear number two in the market, indicates that mergers increasing the size of the runner-up can give rise to equilibria with higher prices. Similarly, Miller et al. (2019) find that a merger increasing symmetry between the two largest firms in the beer industry would relax incentive compatibility constraints and increase prices. However, I argue that changes in the incentives and ability to initiate price jumps are more likely mechanisms behind the changes in the pricing pattern after the acquisition than are relaxed incentive compatibility constrains. Future research could further explore constraints caused by the cost of price leadership in the presence of firm asymmetries in settings with Markov strategies or repeated games with history-dependent strategies.

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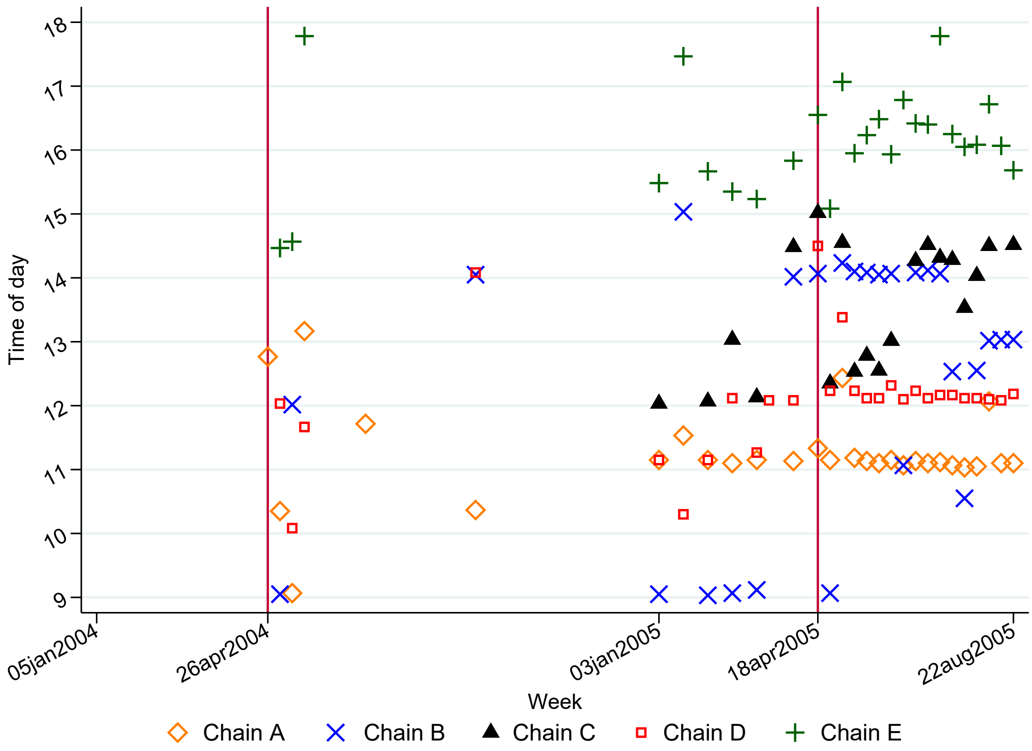
Online Appendices

A Additional figures

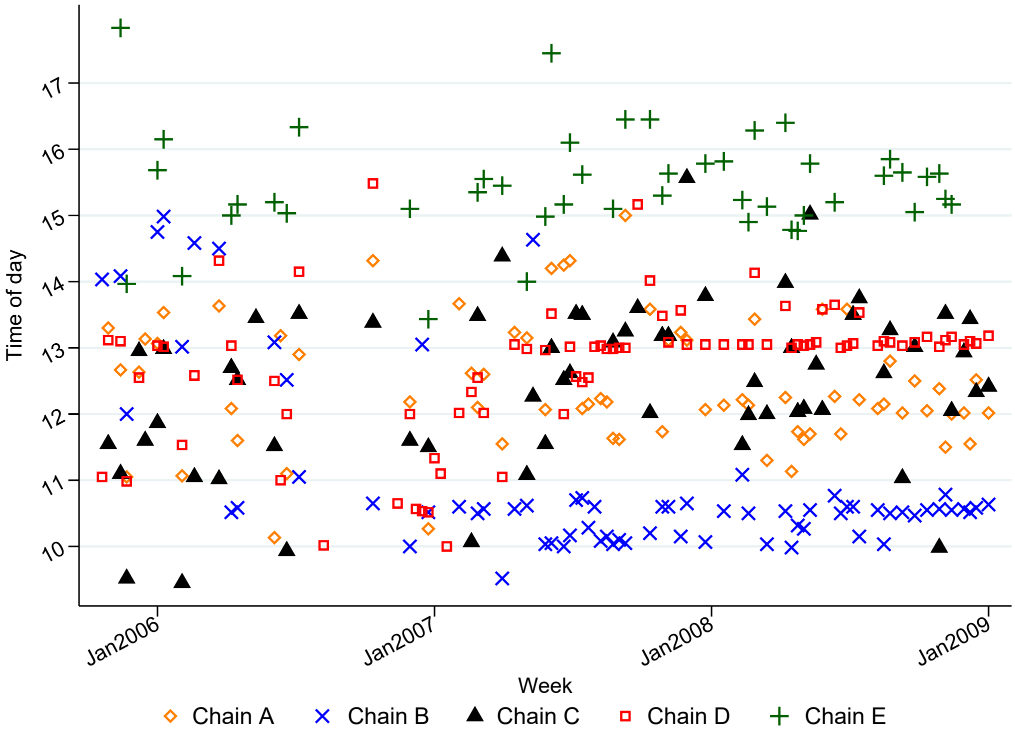
Figure A.1: Time of day of second price jumps, 2005



Note: The figure depicts the time of second *chain price jumps* from January 2004–August 2005. Each dot represents the time of day a given chain initiates a *chain price jump*. Take note of the following:

1. Starting the week of April 18 2005 (the second red vertical line), Chain A starts to initiate second price jumps at 11:00 every week until the end of August. These are all initiated on Thu.
2. The timing of the Thu price jumps is very similar to Mondays, with Chain B following 1 hour after Chain A, Chains B and C following 2–3 hours after Chain A, and Chain E following 4–5 hours after Chain A.

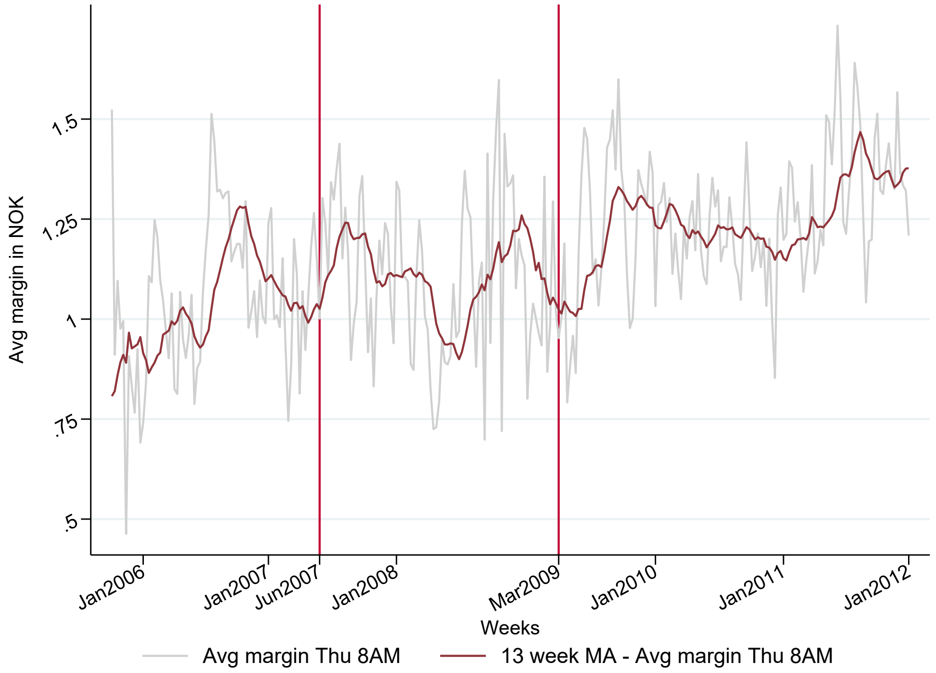
Figure A.2: Time of day – second price jumps, October 2005–December 2008



Note: The figure depicts the time of second *chain price jumps* for each chain for all weeks from the week of October 24 2005, to the last week of December 2008. Each dot represents the time of day a given chain initiates a *chain price jump.* Take note of the following:

1. Before mid-2007, second price jumps are infrequent and there are large variations from week to week in what time of day each chain implements price jumps.
2. Around June 2007, Chain B starts to initiate second price jumps between 10:00 and 11:00. The frequency of price jumps increases. The other national chains (A, C and D) typically initiate price jumps 1-3 hours after Chain B, and Chain E 5-6 hours after Chain B.

Figure A.3: Average margin Thursday at 8:00



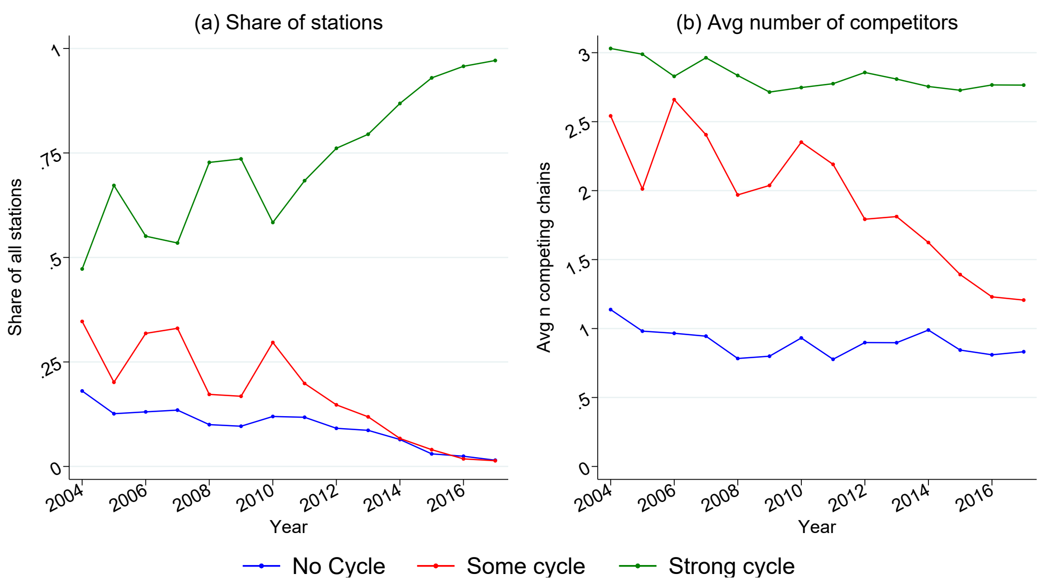
Note: The figure plots average margins at 8:00 Thu margins across all stations. A 13-week moving average is also included to highlight longer-term trends. Take note of the following:

1. There is large short-term and long term variation in average Thu 8:00 margins.
2. There is no clear break in the level or trend in average Thu 8:00 margins around the time Chain B becomes a regular price leader and the frequency of price jumps increases (first vertical red line).
3. Average Thu 8:00 margins are not particularly low when regular Thu price jumps are initiated (second red line), and average Thu 8:00 margins are generally higher after the regular Thu price jumps are introduced.

B Retail margin development

Difference-in-difference models with cycling stations as treatment group and non-cycling stations as control group are a natural approach to estimating the effect of the changes in the price cycles. However, average margins for *no cycle* stations are very similar to the *strong cycle* stations' maximum margin on price jump days. This is due to the pricing policy, in which all stations within each chain increase prices to about the same level when chain-wide price jumps occur, (see Section 3). *No cycle* stations stay at the maximum price of *strong cycle* stations through the whole week. National prices are normally determined as a weighted average of optimal prices in the different local markets.[59] As there are relatively few *no cycle* stations compared to *strong cycle* and *weak cycle* stations (see Figure B.1), national maximum prices (and thereby the average prices for *no cycle* stations) are likely mainly being determined by the optimal maximum price for the cycling stations rather than the optimal margin of the *no cycle* stations.

Figure B.1: Cycle groups - Shares and number of competitors



Note: Panel (a) plots the share of stations that are *strong cycle*, *weak cycle* and *no cycle* each year during the sample period. Panel (b) plots the average number of competing chains present within 15 minutes' drive time of each station time for the same groups. Please note the following:

1. Each year 47%–97% of stations are *strong cycle*, 1%–34% are *some cycle*, and 3%–18% are *no cycle*. The *strong cycle* share is increasing over time.
2. *Strong cycle* stations have on average 3 competing chains present within 15 minutes' drive time. *No cycle* stations have on average stations from 1 competing chain within 15 minutes drive time.

This means a control group consisting of *no cycle* stations could be contaminated if the maximum prices change due to changes in the weekly cycles. For this reason, I estimate both fixed effect models including only cycling stations in the sample, diff-in-diff

[59] See e.g. Dobson & Waterson (2005).

models with *no cycle* stations as control group. The dependent variable y_{it} is the average volume-weighted margin of station i in week t. $y_{it} = p_{it} - Platts_t - tax_t - c_{it}$, where p_{it} is the average volume-weighted price of gasoline at station i in week t, $Platts_t$ is the wholesale price of gasoline, tax_t is VAT and other taxes, and c_{it} is the station-specific cost of transporting gasoline from depots to the gasoline stations.[60]

B.1 Transition to regular Monday price jumps

Figure B.2 plots weekly volume-weighted average margins across all *no cycle* and *strong cycle* stations respectively, and the difference between the two groups.[61] Both in Figure B.2 and in all the following figures and regressions in Section B.1 and B.2, only stations that do not change cycling status during the period of interest (2004 and 2005 when studying the transition to Monday price jumps) are included.[62] To highlight long-run trends, 13-week moving averages are also plotted. No clear breaks in the level or trend in margins are visible around the time Monday price jumps are initiated, but *strong cycle* margins seem to be higher in the period with regular Monday price jumps.

Foros & Steen (2013) find that the transition to regular Monday price jumps leads to a substantial increase in margin (about 0.2 NOK/23%). I estimate a model similar to theirs by including strong and weak cycle stations in the sample and comparing margins before and after April 26 2004:

$$y_{it} = \alpha + \beta_1 Post_t + \beta_3 Rev_t + \beta_4 Platts_t + \delta_{it} + \gamma_i + \varepsilon_{it} \tag{B.1}$$

where $Post_t$ identifies all weeks after (and including) the week starting April 26 2004, except for the 6 weeks when prices revert to the old pattern. Rev_t identifies the 6 reversion weeks and, $Platts_t$ is the wholesale price of gasoline. δ_{it} is a fixed effect for the number of competing chains in the vicinity of station i in week t,[63] γ_i represents station fixed effects, and ε_{it} is the error term. I estimate the model both with and without a linear time trend.

The fact that the pre-period consists of 4 months when margins are normally lower than those during the summer months (see Figure 3 in the main text) raises concerns about Model B.1's ability to identify the true effect of the transition to regular Monday price jumps. I incorporate seasonal variation by including all weeks from January 2004–

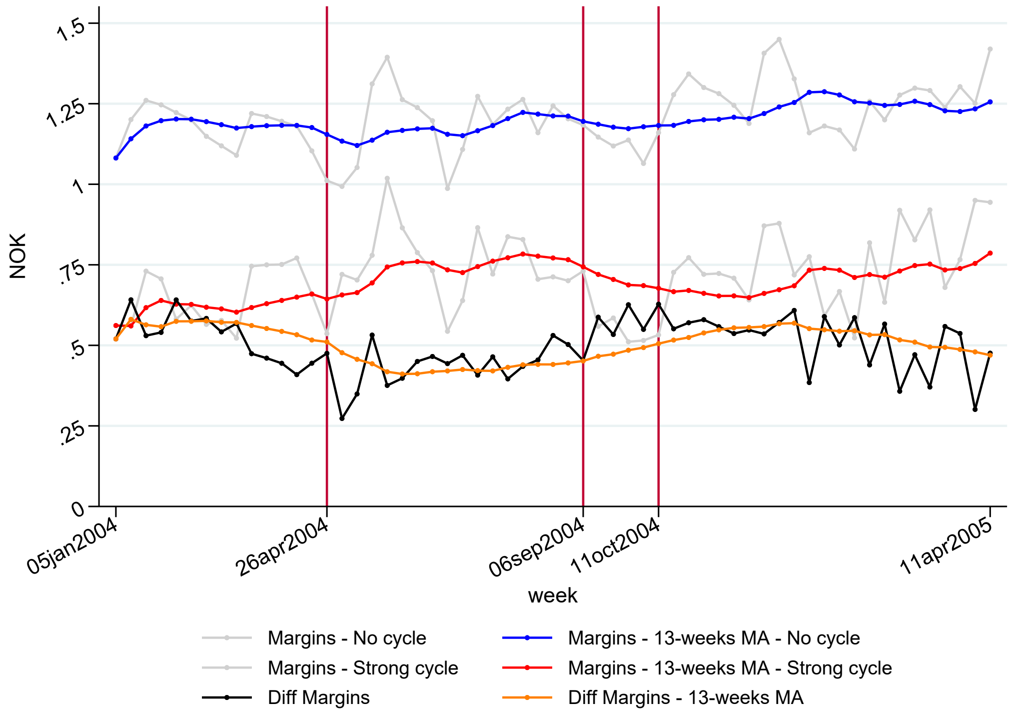
[60] I follow Byrne & de Roos (2019) in aggregating to weekly time frequency to net out the within-week price variation.

[61] The pre-period can not be extended as the sample period starts January 2004. To isolate the effect of the regular Monday jump from the effect of additional Thursday/Friday price jumps (see Section 3.3), I end the post-period just before the period with regular Thursday price jumps starting April 18 2005.

[62] Results in all models are very similar (changes <0.02 NOK) if stations changing cycling status are also included.

[63] Station entry, exit and temporary closure give some variation in how many competing chains are present in the vicinity of each station. δ_{it} is a vector of dummies indicating the number of chains present within 15 minutes drive time of station i in week t.

Figure B.2: Margins for *no cycle* and *strong cycle* stations, January 2004–April 2005



Note: The figure plots weekly volume-weighted average margins across all *no cycle* and *strong cycle* stations respectively, and the difference between the two groups. The 13-week moving averages of the time series are also plotted. The first red vertical line marks the week when the regular Mon price jumps were initiated, the second line marks the week when the cycle reverted to the old pattern, and the third line marks the week when regular Mon price jumps were re-initiated. Take note of the following:

1. No clear break in the level or trend in margins is visible around the time Mon price jumps were initiated (first vertical red line).
2. The margins of*strong cycle* stations are higher in the period with regular Mon price jumps.

December 2008 and estimating Model B.2:

$$y_{it} = \alpha + \beta_1 Post_t + \beta_2 Rev_t + \beta_3 Study_t + \beta_4 Platts_t + \delta_{it} + \gamma_i + \theta_m + \varepsilon_{it} \tag{B.2}$$

where $Study_t$ identifies the period before the week starting April 18 2005, and θ_m represents month-of-year fixed effects.[64] Mindful of the possible problems with the control group, I also estimate the following diff-in-diff model with *no cycle* as a control group:

$$y_{it} = \alpha + \beta_1 Post_t + \beta_2 Post_t * Cyc_i + \beta_3 Rev_t + \beta_4 Rev_t * Cyc_i + \delta_{it} + \gamma_i + \tau_t + \varepsilon_{it} \tag{B.3}$$

where Cyc_i identifies *strong and weak cycle* stations and τ_t represents week fixed effects.

Table B.1 renders the results. Model B.1 gives a small positive estimate of change

[64]In specifications with seasonal variation, I also include year fixed effects for years after the period of interest (after 2005). Note also that the models with seasonal variation allow the wholesale price coefficient to be determined based on all included years, rather than just the period before April 18 2005.

in the cycling stations' retail margins after the transition to regular Monday price jumps (*Post* is 0.03/0.05 NOK), but the effect turns negative when we adjust for seasonal variation in Model B.2. The diff-in-diff model B.3 gives a fairly precise estimate of 0 (the coefficient of $Post * Cyc$ is 0.01 with a standard error of 0.01).

Table B.1: Transition to regular Monday price jumps

	(Eq.B.1)	(Eq.B.1t)	(Eq.B.2)	(Eq.B.2t)	(Eq.B.3)
Post	0.03***	0.05***	-0.09***	-0.01	
	(0.01)	(0.01)	(0.01)	(0.01)	
Rev	-0.13***	-0.11***	-0.22***	-0.14***	
	(0.01)	(0.01)	(0.02)	(0.02)	
Study			-0.03**	0.03*	
			(0.01)	(0.02)	
Cyc					-0.17**
					(0.06)
Post*Cyc					0.01
					(0.01)
Post*Rev					-0.06**
					(0.02)
Platts	0.03	-0.06***	-0.16***	-0.17***	
	(0.02)	(0.01)	(0.01)	(0.01)	
t		0.00***		0.00***	
		(0.00)		(0.00)	
Constant	0.93***	1.11***	1.58***	1.22***	1.21***
	(0.14)	(0.14)	(0.06)	(0.08)	(0.10)
Week FE	No	No	No	No	Yes
Month of year FE	No	No	Yes	Yes	No
Year FE	No	No	Yes	Yes	No
Station FE	Yes	Yes	Yes	Yes	Yes
Competitors FE	Yes	Yes	Yes	Yes	Yes
Observations	56269	56269	222746	222746	63351
R2	0.46	0.49	0.42	0.42	0.69

Notes: The first two columns of the table display results from Eq. B.1 with and without a linear time trend, the third and fourth column results from Eq. B.2, and the last column results from Eq. B.3. Estimation is carried out with Correia (2016)'s multi-level fixed effects absorbing estimator. Holiday weeks are excluded from all models. Standard errors are clustered at the municipality level and are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Controlling for the level of gasoline taxes increases the coefficient of *Post* to 0.11 in Model B.1 without a linear time trend. In all other specifications, controlling for taxes gives an effects close to zero ($Post/Post * Cyc$ coefficient are between -0.02 and 0.02 with standard errors around 0.01).

Changing the length of the period after the study period has a minor effect on the results in (B.2). The changes in *Post* are within 0.04 NOK of the baseline models when varying the end of the included period between all years from 2007 to 2017.

The short pre-period limits the robustness of the results, but overall the evidence suggests that the transition to regular Monday price jumps did not have a substantial effect on retail margins.

B.2 Transition to regular Thursday price jumps

Figure B.3 depicts average volume-weighted retail margins for the period from 2 years before to 2 years after the regular Thursday price jumps were introduced the week of March 23 2009. Visual inspection confirms that although there are short-term deviations, the margins of the *strong cycle* stations share a common trend with the margins of the *no cycle* stations. Furthermore, no longer term trends in margins are visible neither in the period before nor after the transition. After the regular Thursday price jumps are introduced, the margins of the *strong cycle* stations increase relative to the *no cycle* stations. As expected, both groups experience an increase in margins during the summer months of 2009 (see Figure 3 in the main text), but the increase is greater for *strong cycle* stations, and contrary to *no cycle* margins, *strong cycle* margins stay high after the summer. The volatility in the difference between *no cycle* and *strong cycle* stations (the volatility in the black line in Figure B.3) also decreases after March 2009. This is expected after a transition from irregular Thursday/Friday price jumps to regular Thursday jumps because margins for *strong cycle* stations become less volatile when a successful second price jump occurs every Thursday.

I employ models similar to Eq. B.1 and B.3 to quantify the effect of the transition to regular and successful Thursday price jumps.[65] $Post_t$ identifies the week starting March 23 2009 and all following weeks.

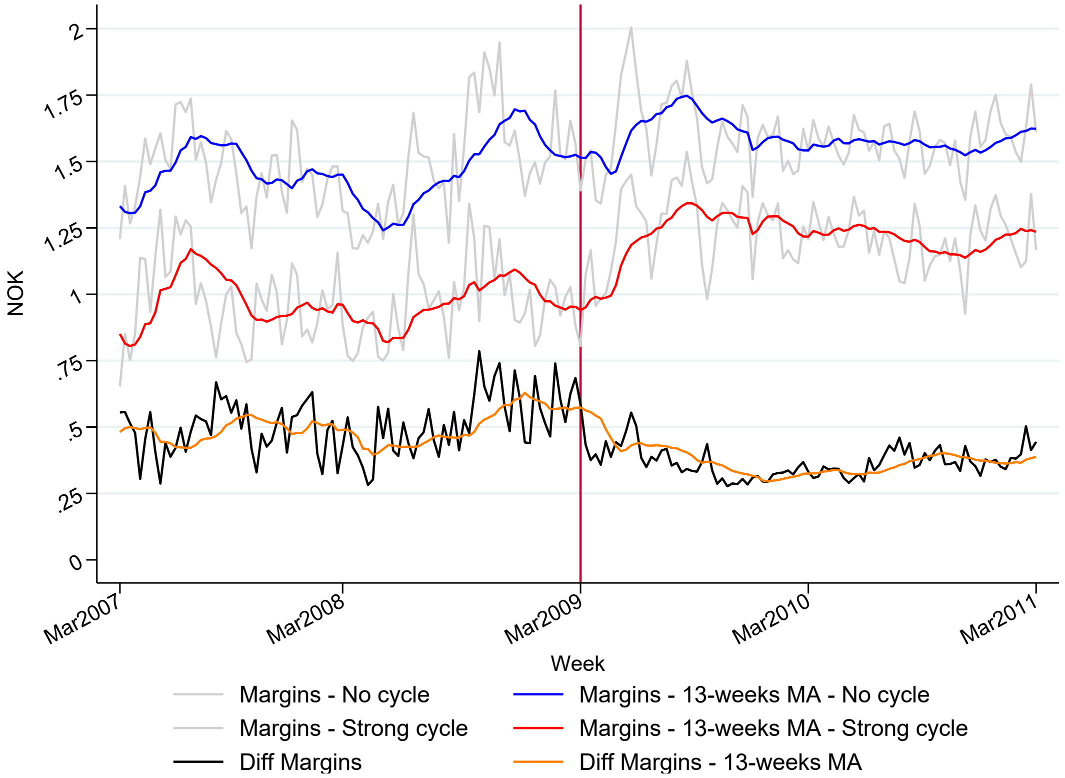
Table B.2 depicts the results. The leftmost column shows results from the fixed effect model in Eq. B.1 restricting the sample to 1 year before and after the transition. The next column shows the results for the same model and sample period with a linear time trend. Columns 3 and 4 show the results from identical models, but extend the sample period to 2 years before and after the transition. The last 2 columns show the results for difference-in-difference models as specified in Eq. B.3 for the 2008-2010 and 2007-2011 sample periods respectively.

All models give an increase of 0.1–0.25 NOK in volume-weighted retail margins for cycling stations after March 2009. Standard errors are small compared to the coefficients (≤ 0.02). The volume-weighted retail margin across *strong and weak cycle* stations is on average 1.04 NOK between March 23 2008-March 23 2009, meaning the average margin increased by 10-24% relative to its average the year before the solidification of the Thursday price jumps. As there are no clear in margins in the pre- and post-period I prefer the specifications without a linear trend — giving a baseline estimate of 0.12–0.23 NOK (12–22%).

The results of all models are largely unchanged when controlling for taxes (changes in $Post$ and $Post * Cyc$ from baseline models are within 0.04 NOK in all models, and the coefficients are never below 0.08 or above 0.28 NOK). Changing the length of the pre- and

[65] Seasonal variation is less of a concern as multiple years of observations are available both in the pre- and post-period.

Figure B.3: Margins, *no cycle* and *strong cycle* stations



Note: The figure plots weekly volume-weighted average margins across all *no cycle* and *strong cycle* stations, and the difference between the two groups. The 13-week moving averages of the time series are also plotted. The red vertical line marks the week when the regular Thu price jumps were initiated. Take note of the following:

1. The margins of *strong cycle* stations share a common trend with *no cycle* stations before the transition to regular Thu price jumps.
2. There is no clear long term trends in margins for neither *strong cycle* nor *no cycle stations*.
3. The margins of the *strong cycle* stations increase relative to the *no cycle* stations after the transition to regular Thu price jumps.
4. The short term volatility in the difference between *no cycle* stations' margins and *strong cycle* stations' margins decreases after the transition to regular Thu price jumps.

post-period does have some impact on the results, but all combinations of pre-period from 2005–2008 and post-period from 2010–2013 give $Post$ and $Post * Cyc$ coefficients between 0.08 NOK and 0.29 NOK. Similarly, including seasonal variation has some impact on the results, but the $Post$ and $Post * Cyc$ coefficients are between 0.08 NOK and 0.27 NOK in all models.

In the weeks following March 23 2009, Chain A starts to carry out small price jumps (0.15-0.30 NOK) for a small share of its stations every day (different stations on different days) in addition to the regular market-wide price jumps on Monday and Thursday.[66] The practice continues for 3-4 years. The other chains' stations located nearby do not follow

[66]Except for these small price jumps, prices very rarely increase during the undercutting phase of the cycle, and during the restoration phase prices jump to list price+transportation cost (see Section 3 in the main text.)

Table B.2: Transition to regular Thursday price jumps

	(B.1)08-10	(B.1)08-10t	(B.1)07-11	(B.1)07-11t	(B.3)08-10	(B.3)07-11
Post	0.23***	0.10***	0.23***	0.25***		
	(0.01)	(0.01)	(0.01)	(0.02)		
Platts	-0.05***	-0.02***	-0.05***	-0.05***		
	(0.01)	(0.01)	(0.01)	(0.01)		
t		0.00***		-0.00		
		(0.00)		(0.00)		
Post*Cyc					0.14***	0.12***
					(0.02)	(0.01)
Cyc					-0.12***	-0.06
					(0.03)	(0.04)
Constant	1.17***	0.43***	1.16***	1.19***	1.22***	1.17***
	(0.02)	(0.07)	(0.02)	(0.03)	(0.03)	(0.04)
Week FE	No	No	No	No	Yes	Yes
Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Comp_15min FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91650	91650	125065	125065	100864	139674
R2	0.42	0.43	0.38	0.38	0.69	0.67
F-value	241.64	160.77	226.78	151.20	47.15	36.81

Notes: The first and second columns of the table display results from Eq. B.1 including data from March 2008 to March 2010. The third and fourth columns display results from Eq. B.1 including data from March 2007 to March 2011. The last two columns display results from Eq. B.3 including data from March 2008 to March 2010 and from March 2007 to March 2011 respectively. Estimation is carried out using Correia (2016)'s multi-level fixed effects absorbing estimator. Holiday weeks are excluded from all models. Standard errors are clustered at the municipality level and are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the small price jumps, but the small price jumps could influence how fast prices decrease in the undercutting phase of the cycle. As the introduction of these small price jumps coincide with the solidification of the Thursday price jumps, the effect of the transition to regular Thursday price jumps could be overestimated for Chain A's stations and stations located near Chain A's stations. To disentangle the effect of the 'Thursday effect' from the 'small jump effect', I interact the treatment variables in Eq. B.1 and B.3 with dummy variable identifying stations that are either part of Chain A or has one or more Chain A stations within 15 minutes drive time (A_AM). The baseline consists of Non-chain A stations that do not have a Chain A station within 15 minutes drive time.

Table B.3 present results. For the baseline stations, the estimate of the change in margins after March 23 2009 is 0.04-0.06 NOK lower than the results in Table B.2, but the effect is still between 0.05-0.20 NOK and significantly different from 0 in all models. Excluding the fixed effect models with linear trends, the estimates are all between 0.08-0.19 NOK (8-18%).

Chain C acquires 90 stations from Chain D just prior to the transition to regular Thursday jumps (see Appendix C). A possible concern is that unilateral effects from the merger, rather than the transition to regular Thursday price jumps, is driving the

Table B.3: Transition to regular Thursday price jumps - A/nonA

	(B.1)08-10	(B.1)08-10t	(B.1)07-11	(B.1)07-11t	(B.3)08-10	(B.3)07-11
Post	0.18***	0.05*	0.19***	0.20***		
	(0.02)	(0.02)	(0.03)	(0.03)		
A_AM	-0.00	-0.02	0.01	0.01	0.05	0.07
	(0.06)	(0.06)	(0.04)	(0.04)	(0.05)	(0.05)
Post × A_AM	0.06*	0.06*	0.05	0.05		
	(0.02)	(0.02)	(0.03)	(0.03)		
Platts	-0.05***	-0.02***	-0.05***	-0.05***		
	(0.01)	(0.01)	(0.01)	(0.01)		
t		0.00***		-0.00		
		(0.00)		(0.00)		
Post*Cyc					0.08***	0.08**
					(0.02)	(0.03)
Post*Cyc × A_AM					0.06*	0.05
					(0.02)	(0.03)
Cyc					-0.08	-0.04
					(0.05)	(0.05)
Cyc × A_AM					-0.06	-0.05
					(0.05)	(0.05)
Constant	1.17***	0.45***	1.15***	1.18***	1.19***	1.13***
	(0.06)	(0.09)	(0.04)	(0.05)	(0.05)	(0.05)
Week FE	No	No	No	No	Yes	Yes
Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Comp_15min FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91586	91586	125055	125055	100792	139651
R2	0.42	0.43	0.38	0.38	0.69	0.67
F-value	127.57	102.07	117.98	94.46	19.79	15.65

Notes: The table presents results for models similar to B.1 and B.3, but interact the *Post*, *Cyc* and $Post * Cyc$ dummies with a dummy identifying stations belonging to Chain A and stations from other Chains located within 15 minutes drive time from one or more Chain A stations. The first and second columns of the table display results from Eq. B.1 including data from March 2008 to March 2010. The third and fourth columns display results from Eq. B.1 including data from March 2007 to March 2011. The last two columns display results from Eq. B.3 including data from March 2008 to March 2010 and from March 2007 to March 2011 respectively. Estimation is carried out using Correia (2016)'s multi-level fixed effects absorbing estimator. Holiday weeks are excluded from all models. Standard errors are clustered at the municipality level and are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

increase in margins. If this is the case, an increase in margins for the stations subject to the merger relatively to stations in other areas should be observed. However, the Norwegian Competition Authority conducted an ex-post evaluation of the merger in 2013 and found that the stations subject to the merger (and to a smaller extent, other stations in the same areas) experience a small (0-0.05 NOK) *decrease* in margins after the merger relative to stations in other areas.[67]

Overall, I find an economically large (0.08-0.18 %) and statistically significant effect of the transition to regular Thursday price jumps.

[67] See OECD (2013).

C Notable events in the sample period

In August 2007, Chain C and Chain D agreed that Chain C would control the sale of gasoline at 92 of Chain D's manned stations in Norway for a period of 10 years. The deal was approved by the Norwegian Competition Authority in February 2008 after the parties agreed to exclude two stations from the deal. The merger was consummated between August and December 2008, when Chain C gradually began operating the 90 gas stations. There is no evidence of change in management in Chain D after the merger.

Chain E was part of a Nordic chain until October 2008 when Chain A bought the Nordic chain as part of a larger multinational merger. To remedy regulators' concerns about impediment to effective competition, Chain A sold Chain E to another Nordic fuel company with no prior activity in the Norwegian market in April 2009. In the interim period, Chain E was managed by a Hold Separate Manager under the supervision of a Monitoring Trustee.

Chain A was vertically integrated with a large oil company until April 2012, when fuel retailing was fissioned out and sold to a large international retail chain with no prior activity in Norway.

Chain B was vertically integrated with a large oil company until October 2015, when fuel retailing was fissioned out and sold to the Nordic company controlling Chain E. To remedy concerns about impediment to effective competition, the Nordic company had to sell its existing Norwegian fuel retail network (Chain E) to an independent buyer. After a lengthy process, Chain E was sold to a small Norwegian bio-fuel firm in July 2017.

D Costs and benefits of leading price jump attempts

D.1 Short-run

This appendix describes the data, explains the estimation procedure, and presents results for the analysis of how leading, following and not following *second price jumps* affects stations gasoline margins, volume and market shares, and convenience store revenue and market shares (see also Section 4 in the main text).[68] I focus on Thursday price jumps in the period from January 2005 to November 2008.[69]

[68] Convenience store revenue includes all non-fuel sales in convenience stores at manned gasoline stations.

[69] The start of the period is chosen because irregular *second price jumps* start in January 2005. The end of the period is November 2008 because we miss price/volume data from Chain E for 6 months starting November 2008, and because we do not have convenience store revenue for any chains after November 2008. Mondays (which feature regular price jumps) are removed from the sample because we want to compare outcomes on days with irregular price jumps (Thursday) with days without price jumps. Furthermore, weeks with Friday price jumps are removed from the sample so that all second price jump attempts in the sample occur on Thursdays. The results are similar (but delayed one day) for weeks with Friday price jumps. Holiday weeks are also excluded.

Because several specifications have market shares based on each urban area being a separate market as an outcome variable, stations not located in urban areas and urban areas where no other chains are active are excluded from the sample. Furthermore, stations with on average more than 1 day between each volume registration are excluded in order to increase the accuracy of daily volumes when calculating daily volumes from spell data. This leaves us with 1207 unique stations and 152 weeks.[70] Thursday price jump attempts occur in 57% of the weeks, and different chains lead price jump attempts. Of the attempts, 65% fail, and all chains are non-followers in multiple weeks.

In a given week with a Thursday price jump attempt, the chains' actions can be classified as 'leader' (the first chain to initiate a Thursday *chain price jump*), 'follower' (initiate a price jump after another chain has initiated a Thursday *chain price jump*), or 'non-follower' (not initiate a *chain price jump* after another chain has initiated a Thursday *chain price jump*.) I employ a difference-in-difference strategy in which the first difference is the change in the outcome variable for station i from Tuesday to other weekdays. The second difference is between weeks with a *second price jump* (treatment) and weeks without a second price jump (control). Different treatment groups are defined based on whether the price jump is successful or fails, and whether the chain station i belongs to is leading, following, or not following the price jump. Furthermore, I separate results for weeks with failed price jump attempts and successful price jumps. See also Section 4 in the main text.

I estimate the coefficients for the different groups using the following model:

$$\begin{aligned} y_{ijtq} = \alpha + \beta_1 DoW_j + \beta_2 Succ_t + \beta_3 Act_{it} + \beta_4 DoW_j * Succ_t + \beta_5 DoW_j * Act_{it} \\ + \beta_6 Succ_t * Act_{it} + \beta_7 DoW_j * Succ_t * Act_{it} + \theta_{jq} + \gamma_q + \delta_i + \varepsilon_{ijtq} \end{aligned} \tag{D.1}$$

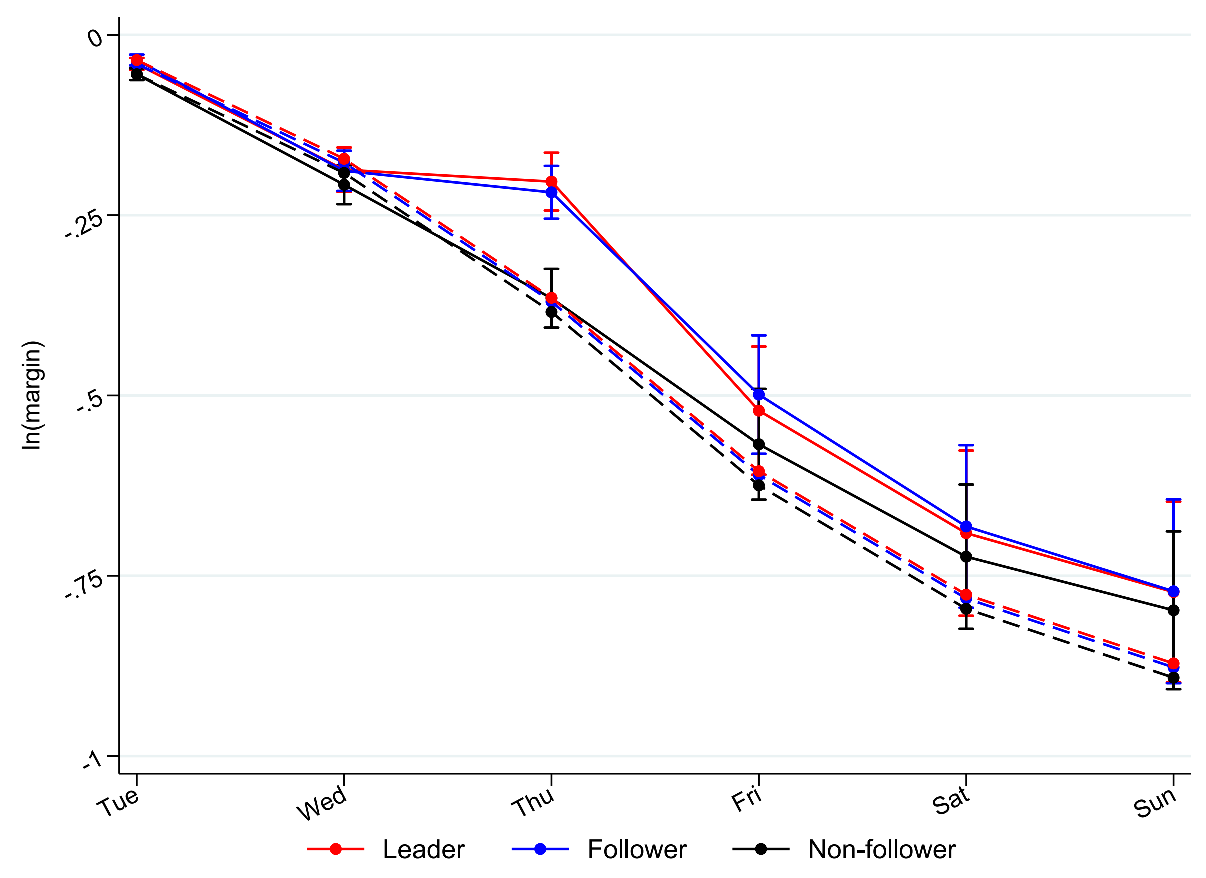
where y_{ijtq} is the outcome for station i on day of week j in week t and quarter q. DoW_j signify dummy variables for day of week with Tuesday as baseline. $Succ_t$ signify dummy variables for weeks with no *price jump attempts* (baseline), failed *price jump attempts* and *successful price jumps*. Act_{it} is a vector of dummy variables signifying whether chain i was a leader, follower, or non-follower in week t. The baseline is weeks when no price jumps occurred. θ_{qj} represent $Quarter * DoW$ fixed effects.[71] γ_q is quarter fixed effects,

[70] Some stations are not operative or are missing data in parts of the relevant period. Furthermore, in some periods we have volumes but not volume-weighted margins for some stations, meaning the number of observations is slightly larger when gasoline volume or market shares is the dependent variable. We are also missing convenience store revenue for some stations in some periods, and some stations do not have convenience stores, meaning the number of observations is lower when convenience store revenue or convenience store market shares is the dependent variable.

[71] $Quarter * DoW$ fixed effects are included to account for possible trends in the relation between the dependent variable and weekdays over time. For example, over time more customers could be purchasing gasoline on Sundays as they learn that prices are low on Sundays. By including $Quarter * DoW$ fixed effects, we use only within-quarter variation. Results are similar with $Month * DoW$ fixed effects, but

δ_i is station fixed effects and ε_{ijtq} is an error term. Table D.1 presents the results. Figure D.1, Figure D.2, Figure 14 and main text Figure 15 present results graphically.

Figure D.1: Margins, leaders, followers, and non-followers



Note: The solid red line plots the volume-weighted margins for stations belonging to the price leader in weeks with failed Thursday price jump attempts relative to margins on Tuesday in weeks without second price jumps. The dashed red line plots how the leader's margins would have developed in weeks with successful Thursday price jumps if a *second price jump* did not occur, assuming the change from Tuesday margins would be the same as in weeks with no price jumps ('the counterfactual'). The solid and dashed blue lines plot the same values for followers, and the black lines the same values for non-followers. Take note of the following:

1. In weeks with failed price jump attempts, margins for leaders, followers and non-followers are 0.03–0.04 lp lower on Tuesday and fall 0.01–0.02 lp faster from Tuesday to Wednesday relative to weeks with no price jumps.
2. On Thursday, margins for leaders are 0.17 lp higher, followers 0.15 lp higher and non-followers 0.02 lp higher than the counterfactual.
3. Leaders, followers and non-followers all have 0.06–0.11 lp higher margins on Fridays, Saturdays and Sundays than the counterfactual.

*The solid lines plots the sum of β_1 through β_7 in Eq. D.1 for leaders, followers and non-followers on different weekdays in weeks with failed price jumps. The dashed lines simply subtracts β_1 from the Tuesday value of the sum of β_1 through β_7 for leaders, followers and non-followers. All coefficients are reported in Table D.1. The standard errors for the summed coefficients are calculated using the delta method.

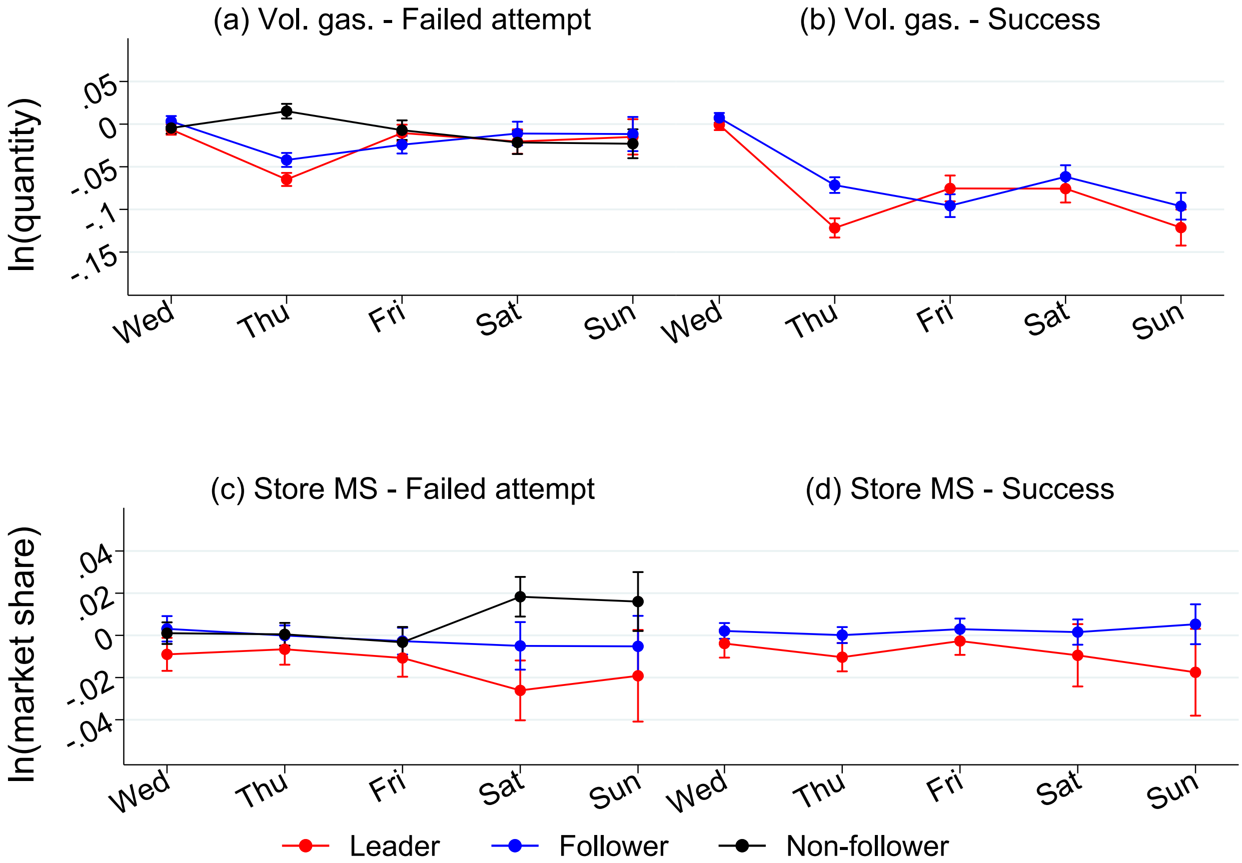
standard errors are slightly larger.

Table D.1: Effect of being a leader, follower and non-follower

	margin	quantity	ln(ms)	ln(ms_store)	nn(revenue store)
Wed	-0.14***	0.11***	0.00**	-0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Thu	-0.33***	0.21***	0.00	-0.01**	0.05***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)
Fri	-0.57***	0.36***	0.00	0.00	0.18***
	(0.04)	(0.02)	(0.00)	(0.01)	(0.01)
Sat	-0.74***	0.21***	-0.00	-0.02*	0.08***
	(0.05)	(0.03)	(0.00)	(0.01)	(0.01)
Sun	-0.84***	0.23***	-0.01*	-0.02*	0.47***
	(0.06)	(0.04)	(0.01)	(0.01)	(0.03)
leader	-0.12***	0.01*	0.03***	0.05***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
follow	-0.13***	0.00	0.01**	-0.01***	-0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
n_follow	-0.15***	0.01	-0.01	-0.02***	-0.01*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Wed × leader	-0.03***	-0.00	-0.00	-0.00	0.01*
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Wed × follow	-0.04***	0.01*	0.00	0.00	0.01***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Wed × n_follow	-0.04***	-0.00	-0.00	0.00	0.01*
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Thu × leader	0.28***	-0.12***	-0.03***	-0.01**	0.01*
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Thu × follow	0.21***	-0.07***	0.01***	0.00	0.02***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Thu × n_follow	0.08***	-0.01*	0.05***	0.00	0.01*
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Fri × leader	0.35***	-0.08***	0.01**	-0.00	0.01
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Fri × follow	0.35***	-0.10***	-0.00***	0.00	-0.00
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)
Fri × n_follow	0.31***	-0.08***	0.00	0.00	0.00
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Sat × leader	0.36***	-0.08***	-0.01**	-0.01	0.02
	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)
Sat × follow	0.35***	-0.06***	0.00	0.00	0.04***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)
Sat × n_follow	0.33***	-0.07***	-0.01	0.02**	0.06***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Sun × leader	0.37***	-0.12***	-0.01*	-0.02	-0.03*
	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)
Sun × follow	0.35***	-0.10***	-0.00	0.01	0.01
	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)
Sun × n_follow	0.34***	-0.11***	0.00	0.03*	0.00
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Failed attempt	0.09***	0.00	-0.02***	0.00	0.01**
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Wed × Failed attempt	0.03***	-0.00	0.00	0.00	-0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Thu × Failed attempt	-0.06***	0.03***	-0.02***	-0.00	-0.01
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Fri × Failed attempt	-0.25***	0.07***	0.00	-0.01	-0.00
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)
Sat × Failed attempt	-0.25***	0.05***	0.01	-0.01	-0.03***
	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)
Sun × Failed attempt	-0.25***	0.08***	0.00	-0.01	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
leader × Failed attempt	-0.01	0.01	-0.01	-0.04***	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Wed × leader × Failed attempt	-0.01*	-0.00	-0.00	-0.01	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Thu × leader × Failed attempt	-0.05***	0.03***	0.02***	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Fri × leader × Failed attempt	-0.02	-0.01	-0.00	-0.00	-0.01
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Sat × leader × Failed attempt	-0.02	0.00	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sun × leader × Failed attempt	-0.03	0.02	0.00	0.01	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.41***	7.88***	2.36***	2.72***	9.93***
	(0.05)	(0.03)	(0.00)	(0.01)	(0.01)
Station FE	Yes	Yes	Yes	Yes	Yes
Quarter X DoW FE	Yes	Yes	Yes	Yes	Yes
Observations	748592	771720	771720	552459	552459
Within R2	0.19	0.13	0.00	0.00	0.23

Note The columns display the results from Eq. D.1, with the dependent variable being ln(volume-weighted retail gasoline margins), ln(litres gasoline sold), ln(market shares based on volume gasoline), ln(market shares based on convenience store revenue) and ln(convenience store revenue) respectively. Estimation is carried out using Correia (2016)'s multi-level fixed effects absorbing estimator. Standard errors are clustered at the urban area level and are shown in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Figure D.2: Volume gasoline and market share store revenue



Note: The figure plots the difference between treatment and control with respectively ln(volume gasoline) and ln(share of convenience store revenue) as outcome variables.

1. In all the panels, the difference in the change between treatment and control from Tue to Wed is <1%.
2. Panel (a) shows that the leader loses 6% gasoline volume, followers lose 4% volume, and non-followers gain 2% volume on Thu in failed weeks. Panel (b) shows that on Thu in successful weeks, the leader loses 12% volume and the followers lose 7% volume.
3. Panel (a) shows that in failed weeks, Fri–Sun gasoline volume changes with <2% for leaders, followers and non-followers. Panel (b) shows that Fri-Sun volume falls 6-12% for both leaders and followers in successful weeks.
4. Panels (c)/(d) show that being a leader has no clear effect on Thu c-store revenue.

*The lines plot the sum of coefficients from Eq. D.1. Only coefficients varying over weekdays are included when the plotted values are calculated. β_1 is common to both treatment and control and is negated. The values plotted are therefore $\beta_4 + \beta_5 + \beta_7$. The coefficients are reported in Table D.1. 95% confidence intervals are shown. Standard errors for the combined coefficients are calculated using the delta method.

D.2 Longer-run

To investigate possible longer-run effects of being a price leader, I compare price and outcomes in a week (t) following a week featuring a successful or failed *second price jump* ($t-1$) to the outcomes in weeks without *second price jumps*. I restrict the sample to only Tuesdays and Wednesdays because Mondays are contaminated due to the regular Monday price jumps, and Thursdays–Sundays are contaminated by possible *second price jumps* in week t. I separate results for leaders, followers and non-followers in failed and successful weeks using the following model:

$$y_{ijtm} = \alpha + \beta_1 DoW_j + \beta_2 Succ_{t-1} + \beta_3 Act_{i,t-1} + \beta_4 Succ_{t-1} * Act_{i,t-1} + \theta_m + \delta_i + \varepsilon_{ijtm} \quad \text{(D.2)}$$

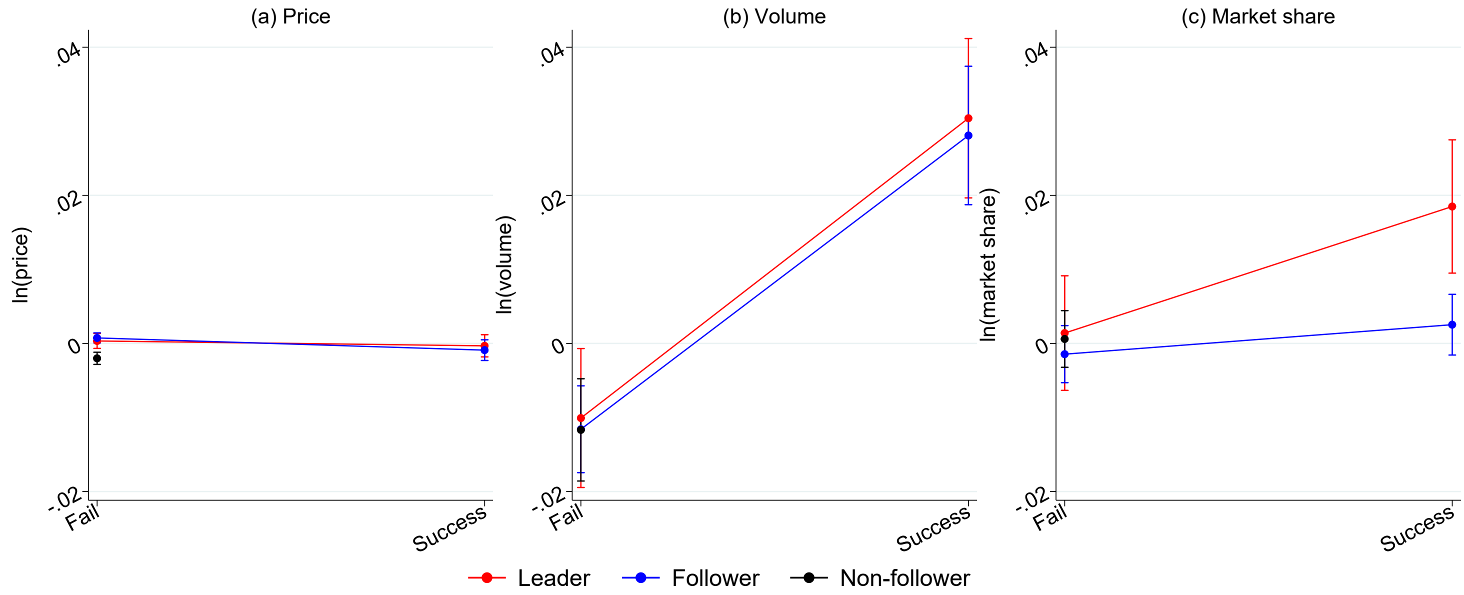
where y_{ijtm} is the outcome for station i on day of week j in week t and month m. DoW_j signify dummy variables for day of week with Tuesday as baseline. $Succ_{t-1}$ signify dummy variables for weeks following a week with no *price jump attempts* (baseline), failed *price jump attempts* and *successful price jumps*. $Act_{i,t-1}$ is a vector of dummy variables signifying whether chain i was a leader, follower, or non-follower in week $t-1$. The baseline is weeks when no price jumps occurred. γ_q is quarter fixed effects, δ_i is station fixed effects and ε_{ijtm} is an error term. Table D.2 presents the results in table form and Figure D.3 presents the results graphically.

Table D.2: Long-run effects of price jumps

	Price	Quantity	Market share
Failed attempt	-0.002***	-0.012**	0.001
	(0.000)	(0.004)	(0.002)
Success	-0.004***	0.028***	0.005
	(0.001)	(0.006)	(0.004)
leader	0.003***	0.002	0.014*
	(0.001)	(0.005)	(0.007)
follow	0.003***	0.000	-0.002
	(0.000)	(0.003)	(0.003)
Failed attempt × leader	-0.001	-0.001	-0.013*
	(0.001)	(0.005)	(0.005)
Wed	-0.013***	0.099***	0.003***
	(0.001)	(0.003)	(0.001)
Constant	2.455***	7.778***	2.360***
	(0.000)	(0.003)	(0.001)
Station FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	277093	286105	286105
Within R2	0.07	0.03	0.00

Note The columns displays results from Eq. D.2 with the dependent variable being ln(volume-weighted retail gasoline prices), ln(litres gasoline sold), and ln(market shares based on volume gasoline) respectively. Estimation is carried out using Correia (2016)'s multi-level fixed effects absorbing estimator. Standard errors are clustered at urban area level, and are shown in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Figure D.3: Long-run effect of price jumps



Note: The figure plots the difference in the outcome variable in weeks following a week featuring a failed or successful *second price jump* compared to weeks following a week without a *second price jump*. Outcome variables are respectively ln(price of gasoline), ln(volume gasoline) and ln(market share). Results are separated for being a leader, follower and non-follower in the previous week, and between week following a week featuring a failed or successful Thursday price jump respectively. Take note of the following:

1. There is a precisely estimated null-effect on prices for all groups, suggesting that that prices in week t are not correlated with second price jumps in week $t-1$ and that supply side responses are not driving the results in panel (b) and panel (c).
2. Volume is 3.0 log points (lp) higher for leaders and 2.8 lp higher for followers in weeks following a week featuring a successful *second price jump*. Volume is 0.7–0.9 lp lower for leaders, followers and non-followers in weeks following a week featuring a failed *second price jump*.
3. The difference in market shares is similar and close to zero for leaders, followers and non-followers in weeks following weeks featuring failed *second price jumps*. The difference in market shares is close to zero for followers in weeks following weeks featuring failed *second price jumps*, while the leaders market share increases 1.6 lp.

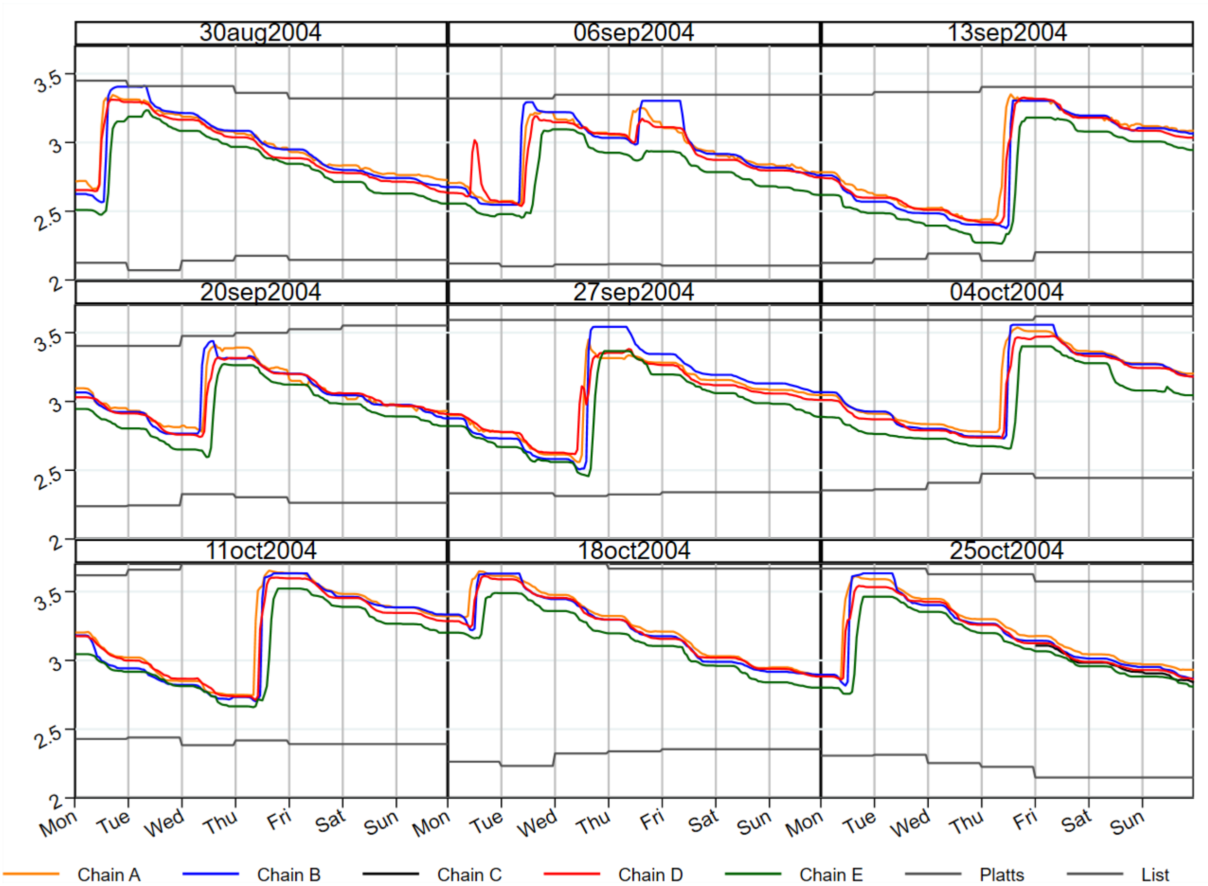
*Only Tuesdays and Wednesdays are included in the sample.
**The lines plot the sum of coefficients from Eq. D.2. The values plotted are $\beta_2 + \beta_3 + \beta_4$. The coefficients are reported in Table D.2. 95% confidence intervals are shown. Standard errors for the combined coefficients are calculated using the delta method.

E Cycle interruptions

E.1 Reversion to irregular price jumps

After 4 months of successful Monday price jumps, Chain A does not initiate a price jump the first Monday in September 2004 (cp. Figure E.1). Only Chain D completes a price jump this Monday. When Chain A refrains from initiating a price jump the following Monday as well, no other chains jump prices. In these 2 weeks and the following 4 weeks, the market reverts to the old price pattern, in which price jumps are initiated by different chains on Tuesdays, Wednesdays or Thursdays. On Monday October 18, Chain A again initiates a Monday price jump attempt that is followed by all other chains. Foros & Steen (2013) argue that the big four companies have established an arrangement whereby they de facto simultaneously decide to increase prices on Mondays (without knowledge of their rivals' prices). However, the absence of Monday price jumps when Chain A does not lead indicates that price leadership is important to keep the new equilibrium stable and that firms – at least in the first period of a new equilibrium – make sequential rather than simultaneous decisions when market-wide price jumps are initiated.[72]

Figure E.1: Price cycles - reversion to old pattern



Note: The figure plots average prices excluding taxes for each chain during each hour of the week of August 30 2004 to the week of October 25 2004. The bottom grey line is the wholesale price (Platts) and the upper grey line is the average list price. Take note of the following:

1. When Chain A suddenly stops initiating Monday price jumps the week of September 6, only Chain D carries out a price jump. The next Monday, no chains implement a Monday price jump.
2. Price jumps take place on Tuesdays, Wednesdays, and Thursdays in the weeks when Chain A does not initiate Monday price jumps (September 6-October 11).
3. When Chain A re-initiates Monday price jumps, all other chains immediately follow.

*Only *competitive stations* are included when average prices are calculated.

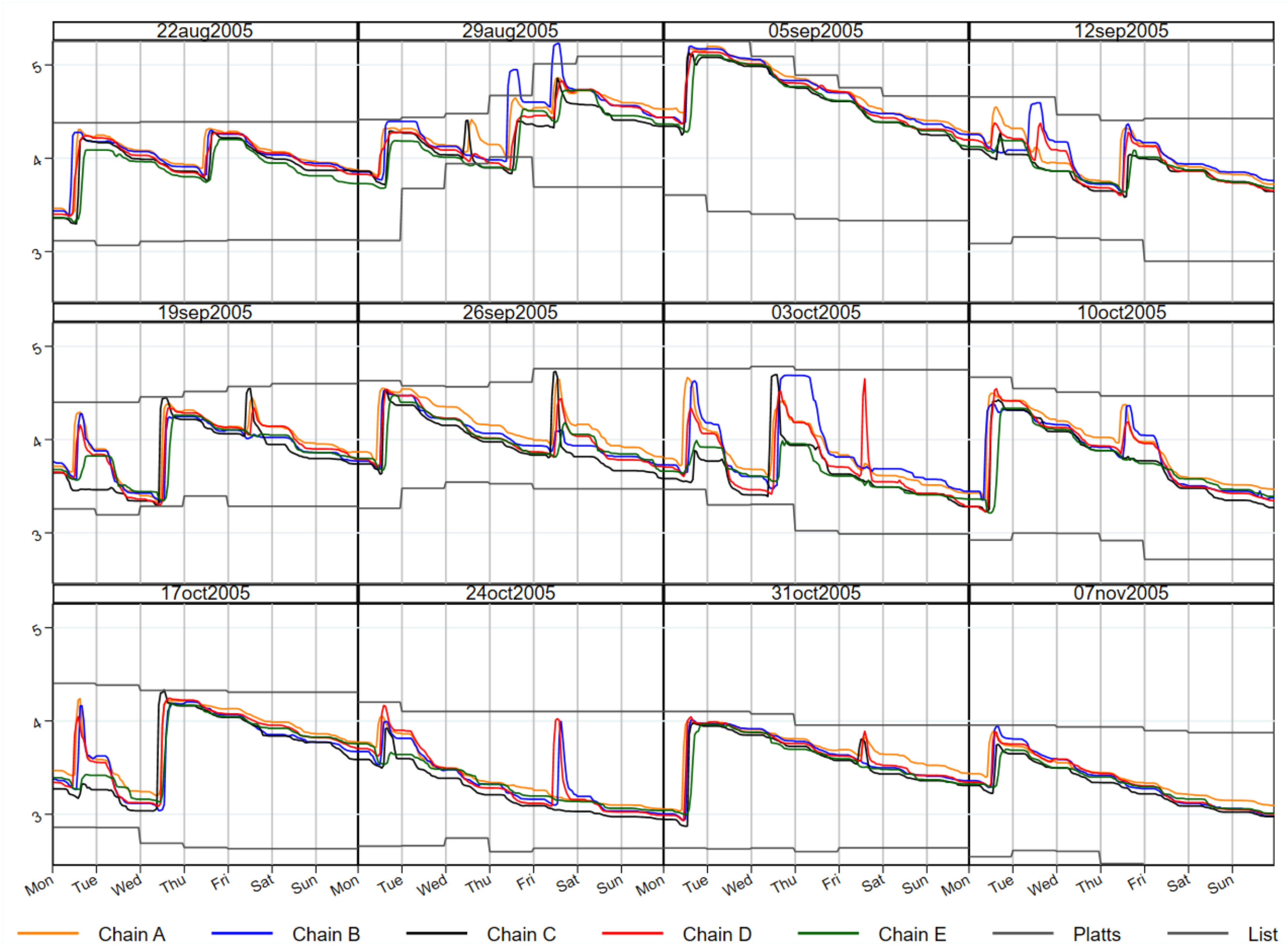
[72]The importance of price leadership and evidence of sequential decision-making are also evident when irregular Thursday and Friday price jumps occur (see Section 3.3).

E.2 Wholesale price volatility

Hurricanes Katrina and Rita land August 25 2005, and September 15 2005 respectively, causing large supply shocks to the world oil market and extreme volatility in the wholesale price of gasoline (Platts) until the week of October 17 2005. As Figure E.2 depicts, the pattern of successful price jumps both Monday and Thursday, breaks down during the period of extreme volatility. Price jumps occur on different weekdays, and many price jumps are unsuccessful. Chain A stops initiating Thursday price jumps, but continues to lead Monday price jumps through the period with extreme wholesale price volatility. The other major chains follow most of Chain A's Monday price jumps even in this period, and beginning October 31 2005, all Monday price jumps are successful again, while the regular Thursday price jumps are gone.

The hurricane related supply shocks hit gasoline retailers in the rest of the world as well. Weekly price cycles in Perth, Australia collapsed during the supply shocks, and several attempts at re-initiating the cycle failed before a few infrequent but successful price jumps occurred in December 2005-February 2006, and finally a two-week cycle materialized in March 2006; see Byrne & de Roos (2018) and de Roos & Katayama (2013). Price cycles also temporarily broke down in a range of U.S. cities; see Lewis (2009). The cycle in Perth also collapsed in April 2008 during a period with large wholesale price variation caused by a global crude oil price shock. In Norway, Chain A continued to initiate Monday price jump also during this period, and the weekly price cycle remained stable (see Figure E.3).

Figure E.2: Price cycles during wholesale price turbulence

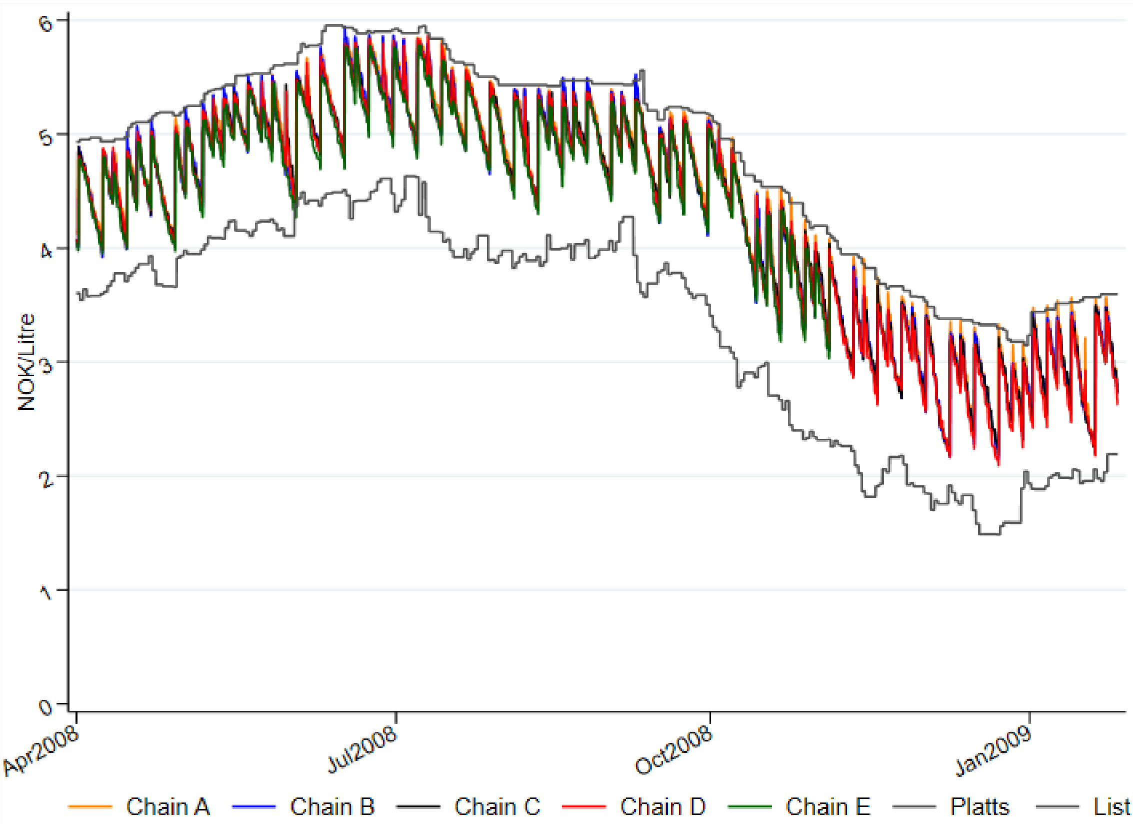


Note: The figure plots average prices excluding taxes for each chain during each hour of the week of August 22 2005, to the week of November 7 2005. The bottom grey line is the wholesale price (Platts) and the upper grey line is the average list price. Take note of the following:

1. The volatility in Platts is very large from the week of August 29 to the week of October 17.
2. Chain A continues to initiate Monday price jumps every week during these 8 weeks, but in 5 of the weeks the price jumps fail because one or more of the other chains do not follow.
3. In addition to the Monday price jumps, price jump attempts are also initiated on Tuesday, Wednesday, Thursday, and Friday. In some weeks more than 2 attempts are initiated. The *second price jumps* often fail.
4. When Platts stabilizes after the week of October 17 2005, regular successful Monday price jumps remain, but the regular Thursday price jumps have vanished.

*Only *competitive stations* are included when average prices are calculated.

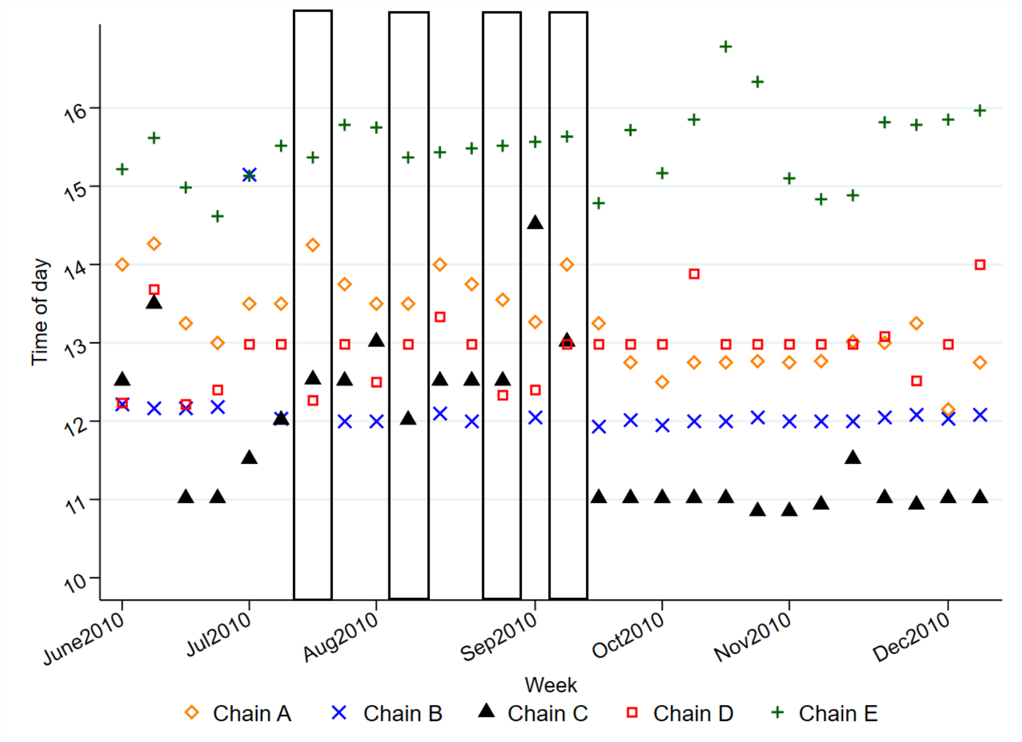
Figure E.3: Price cycles during the crude oil crisis



Note: The figure depicts average hourly prices excluding taxes for *competitive* stations from April 2008-February 2009. The upper grey line is average list price, and the lower grey line is the wholesale price (Platts). Note that the price cycle is stable through the period, with large wholesale price fluctuations during the 2008 crude oil crisis.

E.3 Signalling by not following price jumps

Figure E.4: Timing of day - Thursday price jumps 2010



Note: The figure depicts the time of second *chain price jumps* for each chain for all weeks from the June 2010 to December 2010. Each dot in the figure represents the time of day a given chain initiates a *chain price jump*. The 4 black rectangles highlight weeks when Chain B do not initiate price jumps. Take note of the following:

1. Except for the 4 weeks when Chain B do not follow, all chains carry out *chain price jumps* every week.
2. Chain B carries out chain price jumps 12:00 all weeks except the 4 weeks between mid July and mid September when the chain does not initiate price jumps.
3. Chain C mostly carries out *chain price jumps* after 11:00 until the second week of September (the fourth black rectangle).
4. Chain C starts to carries out price jumps 11:00 the third week of September.

F Determinants of second price jumps

I employ various survival models to investigate the determinants of *second price jumps*. Survival models are well suited to describing the probability of irregular price jumps because they flexibly accommodate the absorbent nature of price jumps (there is at most one second price jump per week), right censoring (not all weeks have second price jumps), and time varying covariates (margins vary through the week). I first investigate which factors are associated with *second price jump attempts*. 'Price decline spells' are defined as the number of hours s from a *successful Monday price jump* is carried out to when a

Table F.1: Hazard model for second price jump attempts

	A1	A2	A3	A4	S1	S2	S3	S4
Chain B	2.577***	2.501***	2.574***	2.591***				
	(0.013)	(0.025)	(0.018)	(0.025)				
Chain C	1.424***	1.208***	1.409***	1.466***				
	(0.023)	(0.065)	(0.024)	(0.107)				
Chain D	1.036***	0.915***	1.028***	1.060***				
	(0.014)	(0.040)	(0.014)	(0.055)				
m_L4	-0.037***	-0.076***	-0.039***	-0.028				
	(0.002)	(0.010)	(0.004)	(0.023)				
uhat		0.042***		-0.013		0.001		0.007
		(0.011)		(0.025)		(0.053)		(0.036)
m_agg_L12					-0.061***	-0.062	-0.053***	-0.058
					(0.011)	(0.049)	(0.013)	(0.030)
Quarterly FE	Yes	Yes	No	No	Yes	Yes	No	No
Month FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	47897	47897	47897	47897	12361	12361	12361	12361
Log pseudolikelihood	-524.14	-523.21	-513.35	-513.16	-179.24	-179.24	-163.74	-163.72

Note: The table displays results from hazard models (Eq. F.1) for the probability of price jump attempts and successful price jumps. *ChainB/C/D* are chain fixed effects. *m_L4* is the average margin of Chain c lagged 4 hours. *m_agg_L12* is the average margin across all chains lagged 12 hours. *uhat* is the residuals from a regression of margin on Platts.
*Estimation is carried out with maximum likelihood.
**Margins are in øre (NOK*100) to make the coefficients easier to interpret.
***Standard errors are clustered at chain level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
**** Standard errors for the models in which the control function method is employed are not adjusted to account for the 2-stage estimation procedure.

second price jump attempt occurs. Weeks when no second price jump occurs are treated as right censored.[73]

The hazard function $h(s)$ measures the probability of a *price jump attempt* in period s. We estimate $h(s)$ using an extended Cox model for chain c in week t where:

$$h(s \mid X_{ct}\beta) = \lambda_0(s) \times exp(X_c'\beta + Z_{ct}(s)\gamma + \Psi) \qquad \text{(F.1)}$$

The baseline hazard $\lambda_0(s)$ is a function of s alone. X_c' is a vector of chain fixed effects (Chain A is baseline) and Ψ represents either month or quarter fixed effects. $Z_{ct}(s)$ includes average margin for chain c's stations during hour $s-4$ of the price decline spell of week t.[74]

Table F.1 column A1 and column A3 show the results with monthly and quarterly

[73] I use an hourly panel for the analyses, meaning that the duration of each price decline spell is rounded to the number of hours between the hour the successful Monday price jump occurs and the hour the *second price jump attempt* occurs. Successful Monday price jumps occur every week, normally at 15:00 (124/145 weeks and always between 13:00 and 17:00.)

[74] Margins are defined as in Section 2.2 in the main text, and are lagged 4 hours both to allow some time from when the leading chain decides to initiate a price jump to when the price jump is carried out, and to avoid contamination of margins as some of the leader's stations will jump prices before the 30% threshold is reached. Results are robust to increasing and decreasing the lag.

fixed effects, respectively. All else equal, a 1 øre (0.01 NOK) increase in margins decreases the probability of a price jump attempt in a given hour by 4%.[75]

Margins and price jumps could be jointly determined. Firms can, for example, decide at the start of the week that they will initiate a price jump on Thursday, and price more or less aggressively than in other weeks because they know a price jump will be initiated on that day. I estimate hazard models using the control function approach (CFA), using the wholesale price of gasoline as an instrument to deal with this possible endogeneity problem.[76] Because the wholesale price is determined in a European market and the Norwegian retail gasoline market is small compared to the rest of Europe, the European wholesale price for retail gasoline is likely exogenous to the price of Norwegian retail gasoline.[77] The following first stage model is estimated:

$$y_{cts} = \alpha + \beta_1 * Platts_{ts} + X_c + \Psi + \varepsilon_{cts} \tag{F.2}$$

where y_{cts} is the average volume-weighted margin for chain c's stations in hour s of week t, $Platts_{ts}$ is the wholesale price of gasoline (one observations per day), X_c represents chain fixed effects and Ψ represent monthly or quarterly fixed effects.

The results from the first-stage regressions in table F.2 show that the wholesale price is strongly correlated with retail margins. I add the residuals (uhat) from the first-stage regressions as a control variable in the hazard model. Results from the CFA model with quarterly fixed effects (A2 in Table F.1) suggest that a 1 øre lower margin causes a 7% higher probability of price jumps attempts, while the margin coefficient in the CFA model with monthly fixed effects (A4) is similar to the margin coefficients in the non-CFA models (A1 and A3) but is insignificant. The non-significant result in model A4 could be caused by insufficient within-month variation in the wholesale price.

Restricting the sample to include only weeks with *price jump attempts*, and considering average aggregate margins (1 observation per hour rather than 1 observation per chain per hour), I employ models similar to Eq. F.1 to investigate the association between margins and *successful price jumps*, where the hazard function measures the probability of a *successful price jump* in period s.[78] I also estimate models where I include the residuals from a first stage, with the wholesale price as instrument. Both the non-CFA models (S1 and S3 in Table F.1) and the CFA models (S2 and S4) suggest that a 1 øre increase in margins reduce the probability that a price jump attempt is successful by 5–6%.[79] The

[75] $(1 - exp(-0,037)) * 100 = 4$ and $(1 - exp(-0,039)) * 100 = 4$.

[76] The CFA is applied rather than IV because the extended Cox model is non-linear in parameters.

[77] Similarly, Bachmeier & Griffin (2003) argue that simultaneity between crude oil prices and gasoline prices is unlikely to be a problem because crude oil prices are determined in world markets.

[78] Margins are lagged 12 hours because a few hours pass from when the first chain starts to increase prices to when the last chain has carried out its *chain price jumps*. Results are robust to increasing and decreasing the lag.

[79] $(1 - exp(-0,061)) * 100 \approx 6$, $(1 - exp(-0,052)) * 100 \approx 6$, $(1 - exp(-0,053)) * 100 \approx 5$ and $(1 - exp(-0,058)) * 100 \approx 6$.

Table F.2: First-stage regressions

	FA2	FA4	FS2	FS4
Platts	-0.14***	-0.46***	-0.24***	-0.51***
	(0.00)	(0.01)	(0.01)	(0.01)
Constant	136.02***	231.76***	163.77***	244.38***
	(0.89)	(1.66)	(1.74)	(2.91)
Quarterly FE	Yes	No	Yes	No
Month FE	No	Yes	No	Yes
Chain FE	Yes	Yes	No	No
Observations	47944	47944	11730	11730
R2	0.31	0.46	0.38	0.52

Note: The table displays the results from Eq. F.2. The first, second, third and fourth columns show results for the first stage regression for model A2, A4, S2 and S4 respectively. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

margin coefficients are not significant in the CFA models.

Taken together, the results in Table F.1 suggest that lower margins increase both the probability of *second price jump* attempts and the probability that the *second price jumps* attempts are successful.

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