Price Coordination and Consumer Behavior

Evidence from Retail Fuel

Andreas Jørgensen Tveito

Thesis for the degree of Philosophiae Doctor (PhD)
University of Bergen, Norway
2022

UNIVERSITY OF BERGEN

Price Coordination and Consumer Behavior

Evidence from Retail Fuel

Andreas Jørgensen Tveito

Thesis for the degree of Philosophiae Doctor (PhD)
at the University of Bergen

Date of defense: 08.04.2022

Year: 2022
Title: Price Coordination and Consumer Behavior

Name: Andreas Jørgensen Tveito
Print: Skipnes Kommunikasjon / University of Bergen

Acknowledgements

When I finished my master's degree at the Department of Economics at the University of Bergen (UoB) in 2007 I did not consider starting a PhD. Instead, I wanted to apply what I had learned in the "real world" and started working at the Norwegian Competition Authority. After working there for almost a decade, I was very happy to get the opportunity to apply for funds for a "Public Sector PhD" from the Research Council of Norway. Immersing myself in research on topics I had become interested in at the competition authority was tempting, and suddenly I was back at UoB working on a PhD.

Many people have contributed to making my four years as a PhD student an enjoyable experience and improving the quality of my thesis. My main supervisor, Bjørn Olav Johansen, has always been open to discuss ideas, give honest and constructive feedback, and to point me in the right direction when I hit a dead end. My co-supervisor, Morten Sæthre, has been very helpful on various econometric problems I have encountered and has also provided great insights on how to improve the introductions in my research articles. I also want to thank both my supervisors for letting me explore my own ideas rather than pushing me to pursue projects closer to their own research agendas.

I also want to thank the people at the Department of Economics at the UoB. The close integration of PhD students with the staff creates an inclusive and stimulating environment. Thanks to all the PhD students and post-docs for making the time both in and out of the office a pleasure. Thanks to Hans K. Hvide for valuable comments on my research. A special thanks to my fellow industrial organization nerds and office mates Teis Lunde Lømo and Håvard Mork Sandvik. Although they are mainly working on industrial organization theory, they patiently listened to my rants about the retail fuel market and have been great discussion partners. Teis even came up with the best possible title for one of my papers.

I also had a great stay at the University of California San Diego and wish to thank Gordon Dahl, who arranged for my visit and gave very useful feedback on my research, and the PhD students for a welcoming and stimulating research environment. A special thanks also to Giacomo Rondina and Lodovica Guidarelli and family for the warm welcome and good times at the beach and in the waves.

It has also been a pleasure to spend some time at the competition authority during the last 4 years, and I am thankful for the comments from various people at the seminars I held there. Sigurd Birkeland has been a great discussion partner for various issues regarding retail fuel markets. Magnus Friis Reitan has provided insightful comments on my research and been a great discussion partner. Kurt Richard Brekke and Mai Nguyen-Ones have also provided valuable feedback on my papers.

Jonas Gade Christensen has also taken an interest in and provided great feedback on my research. Katrine Vellesen Løken has kindly read drafts of all my papers, given great feedback, and has endured listening to my complaints about issues with the data, nasty fixed effects, and imperfect control groups, and given thoughtful responses.

My greatest thanks go to my family. I am lucky to have incredibly supportive parents—both in terms of supporting my choices and of babysitting my kids. Some may think that having kids is a burden when working on a PhD, but I rather find that Oskar, Sara, and recently also Alfred have forced me to structure my work time and have been a most welcome distraction. Spending time with them and my wife, Katrine, has been the best cure for the gloom after less successful days of research. Katrine has constantly encouraged me, and has both been understanding in periods when I have worked long hours and urged me to relax in periods when I have been unnecessarily stressed.♡.

Bergen, October 2021
Andreas Tveito

Abstract

This thesis consists of an introduction and three essays on price coordination and consumer behavior in the retail fuel market. Each essay includes one of the research articles that compose the principle part of the thesis. The essays use microeconometric methods and data from the Norwegian retail fuel market to investigate how firms use price leadership to coordinate more frequent price increases, the costs and benefits of price leadership, and long-run dynamics in consumers' response to changes in the intertemporal price pattern. The introduction summarizes the essays, discusses the merits of studying firm and consumer behavior in the retail fuel market, and elaborates on policy implications of the research in the thesis.

Price leadership—a practice involving sequential price changes whereby a leader changes price first and rivals quickly follow—is commonly observed in many retail markets. The first chapter use a unique dataset spanning 14 years with the exact timing of price changes for most Norwegian gasoline stations to study price leadership and coordination in the Norwegian retail gasoline market. The market features asymmetric price cycles where prices slowly fall for several days before being restored to a high level within a few hours. The main contribution is to show how large retail chains use price leadership to both agree on and sustain a new equilibrium with more frequent price hikes. I argue that faster price changes due to a lack of price regulations in Norway can explain why the chains in Norway end up coordinating on a different equilibrium than in other countries. By combining the price data with data on volumes and costs, I estimate that the transition to more frequent price hikes has a substantial positive effect on volume-weighted retail margins.

Price leadership can bring about higher prices for all firms in the market, but can also be costly for the leader because it loses volume to rivals in the interim period when it is the sole firm with a high price. The second chapter of my thesis studies the costs and benefits of price leadership in the Norwegian retail gasoline market. The dataset with high-frequency price and volume data coupled with a particular pricing pattern allows the estimation of the costs and benefits of leading price hikes. The main result is that the leader's volume loss from being the sole firm to raise its price until the other firms

match that price increase is small compared with the large margin increases and profit gains resulting from the price jumps. Furthermore, I find that the leader is not worse off than the non-leading firms. The results can assist in explaining why firms are willing to act as regular price leaders.

Many retail markets feature intertemporal price variation caused by promotional sales, short-run wholesale price variation, or price cycles where prices fall for several days before quickly being restored to a high level. The third chapter uses 11 years of high-frequency prices and volumes for Norwegian gas stations to study the short- and long-run consumer response to price cycles with a regular low-price period at the same time every week (the sale period). I show that diesel and gasoline consumers over time increasingly fill their tanks during the sale period. Before the transition to the new price pattern, about 21% of the weekly gasoline and diesel volumes are sold in that part of the week. In the first quarter after the transition, the sale-period volume shares increase by 1–2 percentage points. In the subsequent years, the sale-period rebates remain stable while the sale-period volume shares keep rising, to total increases of 6–9 percentage points five years later. The intertemporal price elasticity increases from about -2 immediately after the transition to -6 five years later. These findings emphasize the importance of accounting for dynamics when studying consumer responses to intertemporal price variation and suggest that non-volume-weighted prices may be a poor proxy for the prices consumers pay.

Contents

Chapter 1

Introduction

Introduction*

Markets connect buyers and sellers. In many markets, the sellers are organized in large firms—often chains with multiple outlets—while buyers are individual consumers. In such retail markets, the number of firms is often limited, and each individual customer is too small to exercise buyer power. This market structure can allow firms to exercise market power unilaterally. If the market is transparent and firms can easily monitor prices and quickly respond to competitors' price changes, firms may also be able to exercise market power collectively by colluding with the other firms in the market. Market power can result in higher prices and lower product quality, and leads to a dead-weight welfare loss for society (Tirole, 1988). Surplus is also shifted from consumers to producers.

Colluding on higher-than-competitive prices demands both that the higher prices embody a stable equilibrium, and that firms manage to agree on a common strategy—they must for example agree on the timing and level of price increases. A large literature considers the stability of collusive equilibria, while a much smaller literature investigates how firms agree on a common strategy. The easiest way to agree on a common strategy is direct communication between representatives at the different firms. Because such explicit communication between firms is unlawful, they may try to find other ways to agree on a common strategy.

The first two papers of this thesis concern a commonly observed practice that can help firms agree on a common strategy to initiate price increases: price leadership—a practice involving sequential price changes whereby a leader changes price first and rivals quickly follow. The price leader solves the problem of coordinating on a common strategy by deciding when and by how much prices should increase. The first article, "Might as Well Jump—Coordinating More Frequent Price Hikes in a Retail Gasoline Market", analyzes price leadership and price coordination in the Norwegian retail gasoline market and shows how large retail chains use price leadership to coordinate on a margin-enhancing equilibrium. I refer to this chapter to as Tveito (2021c) in the following. The equilibrium

*The views expressed in this introduction are those of the author and do not necessarily reflect the views of the Norwegian Competition Authority.

transition involves a new way to increase margins: more frequent price increases. I argue that faster price changes due to a lack of price regulation in Norway can explain why the chains in Norway coordinate on a different margin-enhancing equilibrium than that of other countries.

Price leadership can be costly for the leader because the leader loses volume to competitors in the interim period when it the sole firm with a high price. The second chapter of my thesis, “The Costs and Benefits of Price Leadership—Evidence from Retail Gasoline”, studies the costs and benefits of price leadership in the retail gasoline market, and shows that the leader’s volume loss in the interim period is small compared with the large margin increases and profit gains that result from the price increases. I refer to this chapter to as Tveito (2021a) in the following.

The third paper, “Long-Run Dynamics in Intertemporal Substitution—Evidence from Retail Fuel”, shifts the focus from the sellers’ behavior to the retail fuel buyers’ behavior. I refer to this chapter to as Tveito (2021b) in the following. During the sample period, the price pattern in the studied market changes to a cycle with predictable intertemporal price variation with a low-price period at the same time every week. I study how consumers respond to the new pricing pattern in the short and the long run and show that over time, gasoline and diesel consumers increasingly move purchases to the part of the week when prices are low, and that the intertemporal elasticity of demand increases gradually over time.

The remainder of this introduction is divided into two sections. First, I discuss the merits of studying firm and consumer behavior in the retail fuel market. Second, I discuss various possible interventions in oligopoly markets characterized by fast price changes, price leadership, and possible tacit collusion.

1 Studying the Norwegian retail fuel market

Four years is a long time to dedicate to study a single market. Would it not be more interesting to use data across many industries to reach more general conclusions about market structure, institutions, and competition? A brief history of industrial organization provides some answers.

Industrial organization is concerned with the structure of industries in the economy and the behavior of firms and individuals in these industries. Historically, industrial organization focused on how markets depart from idealized conditions with perfect competition (Einav & Levin, 2010). Modern industrial organization has mainly tried to tackle two different challenges in the early literature. The first is a lack of theoretical models for studying imperfect competition. This problem was largely reversed with the introduction of game theory and the subsequent flood of theoretical research on various forms of market imperfections such as entry barriers, information asymmetries, differentiation, and collusion (Tirole, 1988).

The second challenge concerned empirical evidence. Empirical industrial organization was lacking good data and convincing empirical strategies for evaluating hypotheses about competition and industry structure (Einav & Levin, 2010). The most active strand of empirical industrial organization into the 1980s was cross-industry regression analysis of market structure with various market outcomes—the so-called "structure–conduct–performance" paradigm. The questions being investigated were important, but the literature was riddled with problems related to small datasets and imperfect proxies for the market outcomes. However, the most serious issue in the literature was that the outcomes were "logically endogenous" and that most studies lacked convincing strategies for econometric identification of causal effects (Schmalensee, 1989).

The concerns about cross-industry regression models and the development of clearer theoretical foundations for analyzing imperfect competition set the stage for a dramatic shift in the 1980s toward what Bresnahan (1989) called the "New Empirical Industrial Organization." Underlying this approach was the idea that individual industries are sufficiently distinct, and industry details sufficiently important, that cross-industry variation was often going to be problematic as a source of identification (Einav & Levin, 2010). Instead, the new wave of research set out to understand the institutional details of particular industries and to use this knowledge to test specific hypotheses about consumer or firm behavior. The current state of empirical industrial organization reflects this development. Emphasis has shifted from the cross-industry correlations toward more focused studies of individual industries.

Under this more focused approach, it is not unusual to spend an entire PhD thesis studying a single industry. Studying the retail fuel market has a number of advantages. First, the homogeneous nature of the products makes retail fuel markets attractive for study (Eckert, 2013). As Barron et al. (2004) state, "gasoline markets appear to be nearly ideal for testing the theories because the physical attributes of regular unleaded gasoline are essentially identical across spatially differentiated sellers." Second, the retail fuel market is a large industry with substantial regulatory and antitrust scrutiny. In Norway, the industry generated 44 billion NOK of revenue in 2019—1.2% of the GDP.[1] The Norwegian retail fuel industry has also frequently been reviewed by regulators who have conducted market studies, investigations of collusion, and merger reviews.[2] Similar investigations are also common in other countries, prompting Eckert (2013) to note that "few industries have been subject to as much regulatory and antitrust scrutiny as gasoline retailing." The size of the industry and the intense scrutiny from regulators and policy makers makes research that leads to new policy recommendations valuable.

[1]Total revenue is calculated based on volume and price information from Drivkraft Norge, and GDP from Statistics Norway (2021).

[2]See e.g., Konkurransetilsynet (2010), Konkurransetilsynet (2014) Konkurransetilsynet (2015) and Konkurransetilsynet (2020).

The fast price changes and intricate pricing behavior seen in retail fuel markets also mean that they can provide insights relevant to the introduction of high-frequency pricing, sometimes using pricing algorithms, and particularly in markets where prices are posted online; see Assad et al. (2020) and Calvano et al. (2020).

A final and significant reason that I chose to study the Norwegian retail fuel market was data availability. As for many other retail fuel studies, I have a good proxy for the wholesale costs the retail chains are facing on a daily frequency. Many other studies have also obtained and used gasoline price data. However, the price data is often aggregated across firms, areas, and time—making it difficult to, for example, identify price leaders and estimate short-run elasticities. The price data I had access to for my dissertation is both completely disaggregated (exact time of price changes for individual gas stations) and spans a period of 14-years. However, the most unique feature of the data is that it includes high-frequency station-level sales volumes, giving me the opportunity to estimate volume loss when leading price increases, consumers' reactions to changes in the price cycles, and volume-weight price–cost margins.

Some may question the relevance of these types of studies, and in the following subsections I consider three other issues relevant for assessing the contribution of my thesis. First, I consider how the demand for retail fuel will develop in the coming years. Second, I consider whether letting firms collude can be an effective way to decrease greenhouse gas emissions. Third, I consider the external validity of my results—how relevant the results are for other markets and other countries.

1.1 The demand for retail fossil fuel

New electric vehicles (EVs) are indeed being developed at a record pace, but high costs (mainly related to the large batteries) mean that EVs are still more expensive to produce than comparable fossil fuel vehicles. Norway has very high taxes on fossil fuel vehicles and no taxes (not even VAT) on EVs. EVs also obtain some benefits such as free or reduced prices for using toll roads, ferries, and parking. Retail gasoline and diesel is also heavily taxed. Due to the tax benefits, Norway is the global leader in EV adoption. In 2020, 54% of new cars sold in Norway were BEVs (pure battery electric cars, excluding hybrids) (Statistics Norway, Table 11823). Nevertheless, due to the large number of existing fossil fuel cars, BEVs only made up 12% of the total Norwegian car fleet. With the current pace of BEV adoption, the market share of BEVs will clearly increase in the coming years, but the existing fossil fuel cars and the fact that a large share of new cars still have fossil fuel engines, mean that there will be demand for retail gasoline and diesel in Norway for years to come.

No other country is close to Norway when it comes to EV adoption. In 2019, the share of EVs in Norway was almost 3 times higher than the next country's figures (Iceland),

and only four other countries had a car fleet with more than a 1.5% share of electric cars (International Energy Agency, 2020). The USA in particular struggles to increase the share of electric cars: in 2020, only 2% of new cars were BEVs (International Energy Agency, 2021). Even with a predicted reduction in the cost of producing BEVs, the International Energy Agency estimates that only 17–36% of global new car sales and 8–13% of the global car fleet will be electric in 2030.

Unfortunately, the demand for retail gasoline and diesel will continue to be strong for many years to come.

1.2 Collusion with a view to reducing greenhouse gas emissions

If demand for gasoline and diesel continues to be high and we wish to reduce greenhouse gas emissions, why not let gas stations collude and set higher prices, and thus reduce demand?

In the classical economic approach, damaging side-effects of market interactions are seen as negative externalities (Schinkel & Treuren, 2021). The solution is to force market participants to internalize these externalities. The social costs of greenhouse gas emissions from retail fuel then become part of the production costs to be expressed in the product's prices. Higher prices decrease demand and thereby environmental damage. Through competition, an optimal allocation of production and consumption will take place, based on a society's preferences to favor the climate over consumption goods. The government should ensure that the social costs of production are incorporated in the private costs of suppliers. This can be achieved through taxes or emission quotas. Governments have, however, frequently failed to achieve this goal, and several scholars have in fact pushed for relaxing cartel laws as a way to fight climate change—so-called "green antitrust policy" (see, e.g., OECD (2020).)

Schinkel & Treuren (2021) warns against trying to remedy government failure to internalize emission externalities by allowing firms to collude and gain market power. There is no reason for a green corporate cooperative to invest more of its extra revenue in sustainability than it is minimally required to do: the rest it can pocket as profit. Governments, though certainly imperfect, at least strive for optimal taxation and break-even public good provision. Companies with market power instead have an incentive to maximize their margin. In addition, green antitrust policy runs the risk of exacerbating government failure. Governments' failure to guarantee the public interest has many causes, including public choice incentives ranging from regulatory laziness to outright corruption. Being able to point to industry self-regulation, in the form of sustainability agreements on the restriction of competition, can be another excuse for governments not to take up their regulatory responsibility.

Many countries, in particular Norway, have high carbon taxes on the sale of retail fuel.

Levying taxes on retail vehicle fuel seems easier than levying fuel taxes on international transport industries such as the shipping and airline industries, because motorists must buy fuel for their vehicles locally. Ships and planes that are visiting multiple countries can more easily fill the tank in the country with lower fuel taxes. Currently, the tax per liter of gasoline sold in Norway is 6.36 NOK + 25% VAT, representing more than 1 US$ total taxes per liter. Most political parties are also in favor of increasing the tax further in the coming years. As mentioned, there are also high taxes on vehicles with fossil fuel engines, while EVs are exempted from taxes. Thus, the government seems able to impose high taxes to internalize the social costs of greenhouse gases in the retail fuel market. Internalization through taxes is a better solution than allowing collusion because it produces tax revenue that can be used for sustainability projects (or other welfare-enhancing projects) that firms would be unlikely to initiate with the extra cartel profit.

1.3 External validity

As Angrist & Pischke (2010) explains, empirical evidence on any given causal effect is always local: it is derived from a particular time, place, and research design. Economic theory often suggests general principles, but extrapolation of causal effects to new settings is always speculative. Nevertheless, anyone who makes a living out of data analysis probably believes that heterogeneity is limited enough that the well-understood past can be informative about the future. External validity is the ability to generalize the relationships found in a study to other persons, times, and settings (Roe & Just, 2009). External validity depends on the relationship between the population for which internally valid estimates have been obtained and another, different population (Bo & Galiani, 2020).

The extent to which results from a particular industry in a given time period and in a particular country can be generalized to other countries, industries, or time periods is always open to debate. Markets differ greatly, and importing particular numbers across markets often does not seem compelling. Instead, if one hopes to generalize, it is often more appealing to view empirical industrial organization as building up support for principles of strategic interaction or market functioning that are broadly applicable across industries (Einav & Levin, 2010). Nevertheless, it seems likely that results are more likely to have relevance in other settings if the institutions are similar, the agents are similar, and the events of interest are similar.

The first chapter of this thesis concerns price leadership and coordination on a higher-price equilibrium in the Norwegian retail gasoline market. The fact that the organization of the Norwegian retail fuel market is similar to that of other countries (oligopoly with a few large chains that control prices of affiliated gas stations) and that the product sold is almost identical in different countries indicates that the results have relevance to retail fuel markets in other countries. An additional benefit is that there is no special regulation of prices in Norway.

The asymmetric price cycles found in the Norwegian retail fuel market are indeed a strange phenomenon. However, the cycles are not at all exclusive to the Norwegian retail fuel market. Similar cycles are found in the retail fuel markets in the USA, Canada, Australia, and multiple European countries such as Sweden and Germany. The main contribution of the paper is showing how price leadership can increase profit margins by initiating the coordination of more frequent price jumps. Price leadership is also a common practice in most retail fuel markets with price cycles, and Byrne & de Roos (2019) have shown another way in which firms use price leadership to coordinate on a high-price equilibrium in the retail gasoline market in Australia. Ultimately, external validity is established by replication in other datasets (Angrist, 2004). My paper is not the first to document that price leadership can be used to coordinate price increases, but by studying a different country with a different setting (especially one with a lack of price regulation) and documenting a different mechanism for price increases, it strengthens the evidence that large chains can use price leadership to coordinate price increases in different settings, particularly in retail fuel markets with price cycles. The results also guide regulators to be concerned with increases in the frequency of price jumps.

Asymmetric 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). Eibelshäuser & Wilhelm (2018) also argue that the recent introduction of digital price tags drastically reduces menu costs, while price comparison applications promote price transparency and increase the speed at which retailers can react to price changes by their competitors. As a result, retailers in many different industries change their prices more and more frequently, possibly making price cycles more likely to occur in other retail markets in the near future. My result, showing that large firms can act as price leaders to initiate and preserve an equilibrium with more frequent price jumps, is also relevant to other retail fuel markets with asymmetric price cycles and other industries with price cycles. Although not as directly, these results contribute to general knowledge about price leadership, showing that large chains can act as price leaders to coordinate equilibria with higher prices.

Chapter 2 of the thesis concerns the costs and benefits of acting as a price leader. As in the first chapter, the setting is the Norwegian retail gasoline market with its cycling prices. The results in the second chapter are also clearly relevant to other retail fuel markets with price cycles. Some of the results are also informative for other industries and retail fuel markets without price cycles—most notably the results that when price transparency is high, other firms can follow the leader within a very short period and lead to a very small loss of demand for the leader.

Chapter 3 of the thesis studies the development of consumers' response to changes in the intertemporal price pattern. The results are of course particularly relevant to other retail fuel markets because the option to store fuel in the fuel tank is the same in all countries and fuel consumers are probably quite similar between countries. I study the response to changes in the price cycle, and similar changes are common also in the retail fuel market in other countries. Examples include many different changes in Australia such as the recent change from price jumps on Wednesday to jumps on Tuesday in Perth (ACCC, 2020), the additional noon and afternoon price jumps in Germany (Eibelshäuser & Wilhelm, 2018), and a transition to a cycle with more frequent (daily) price jumps in multiple Canadian states (Atkinson et al., 2014).

In other industries, consumers' storage facilities may differ. Some grocery items will for example perish quickly while others can be stored several months before consumption. In some industries, like the residential electricity market, changing the consumption timing may be more relevant than changing the purchase timing.[3] The intertemporal price variation may also be more or less salient to consumers (sales may be pre-announced, or price transparency may be low). Each item may also be purchased as part of a multi-product shopping basket, meaning that sales on individual products may be less likely to trigger a shopping trip. The study showing substantial dynamics in retail fuel customers' response to intertemporal price variation does, however, show that such dynamics can exist and should be explored in other markets as well.

Changes in the intertemporal price pattern have also recently taken place in the residential electricity market in many countries and are expected to occur in more countries in the coming years. The changes occur when smart meters are installed, and real-time pricing (RTP) is introduced. Before the transition to RTP, consumers typically pay a single monthly price computed as the average monthly RTP price, adjusted according to a standard consumption profile. The transition from fixed prices through long periods to hourly price variation in the residential electricity market is similar to the transition from fixed prices to the cycling of retail fuel prices that I study. The existing evidence on the introduction of RTP suggest that consumers do not adjust their consumption to the intertemporal price variation in the short run (Fabra et al., 2021). My results suggests that it is important to study the long-run response as well because consumers may need time to learn about the new price pattern and to change their habits.

[3] Note, however, that it is possible to install household batteries like the Tesla Powerwall to store electricity. The introduction of EVs also makes it possible to purchase electricity when prices are low, store it in the car's battery, and use it later either to power the EV or even to power the household in periods when electricity prices are low.

2 Policy

The retail fuel market in both Norway and many other countries has been found to be conducive to, and subject to, tacit collusion. The public's dissatisfaction with high fuel prices and large price fluctuations due to cyclical fuel prices have put considerable pressure on competition authorities and governments in many countries to implement measures to decrease retail fuel prices. In this section, I discuss different measures policy makers could implement to lower the prices that consumers pay in retail markets with high-frequency pricing and possible tacit collusion. I focus on the retail fuel market, but the discussion is also relevant to other markets with possible tacit collusion, high-frequency price changes, price cycles, price leadership, and slow consumer adaptation to changes in pricing patterns.

As in many other countries, the Norwegian market has seen multiple equilibrium transitions over the last 20 years. This dissertation explores issues related to the transitions from 2004 to 2009, documenting a gradual shift from price cycles with non-synchronized price hikes to a cycle with price hikes every Monday and later to price hikes every Monday and Thursday. Large chains share price leadership on the different days. The pattern with hikes every Monday and Thursday continued until November 2017, when price hikes again began to increase on irregular weekdays (but never on Saturday or Sunday) and the two largest chains started to signal price hikes with changes in their online recommended prices. The Norwegian Competition Authority issued a decision in October 2020, halting signaling with recommended prices. No study has explored the pricing pattern after the authority's decision, but personal observation indicates that prices are still following a cycle with 2–3 weekly price hikes. Price hikes appear to also be carried out on Saturdays and Sundays.

Volume-weighted price–cost margins in Norway increased after the transition from 1 to 2 price hikes per week in 2009 (Tveito, 2021c), and Norwegian margins have been found to be high compared with other countries (Konkurransetilsynet, 2014). As more consumers purchase during the low-price part of the cycle over time (Tveito, 2021b), volume-weighted margins could have been decreasing in the years before the transition to non-synchronized cycles in November 2017. No studies have investigated margin development after November 2017, but the transition to irregular timing of price hikes means that the strategy of purchasing on Sunday or Monday morning is no longer a good strategy to follow for customers wanting to fill up at low prices. Slow consumer adaptation to changes in the intertemporal price pattern (Tveito, 2021b) and the fact that the timing of the bottom of the cycle becomes harder to predict, may have increased the retailers' volume-weighted margins.

2.1 Merger control and market entry

European competition authorities can challenge mergers that they can plausibly argue will "significantly impede effective competition." In practice, this means that competition authorities must prove that it is more likely than not that prices will increase, or consumers will be harmed in some other way. The Europe Commission's horizontal merger guidelines also state that prices can increase due to "the creation or the strengthening of a collective dominant position because it increases the likelihood that firms are able to coordinate their behavior in this way and raise price."(European Commission, 2004). Basically, a merger can be prohibited if the competition authority can prove that it is likely to make tacit collusion possible, or because it makes an existing tacit collusive equilibrium more stable or allows coordination on higher prices.

According to economic theory, firm size asymmetries make tacit collusion easier to sustain (Motta & Fabra, 2013), and the European Commission's merger guidelines point to size symmetry as a factor that makes tacit collusion more likely. However, the results in Byrne & de Roos (2019) indicate that mergers that create a clear market leader, and thus increase size asymmetries, may make collusion easier to *initiate* because the market leader acts as a price leader and facilitates agreement on focal points for collusion. Tveito (2021c) corroborates that the largest chain acts as a price leader, but may also suggest that mergers creating a clear runner-up in terms of market share can bring about a new price leader that initiates additional price increases at a different time than the largest firm.[4]

Adding to this, a reduction in the number of firms will make collusion easier to initiate and sustain because it is easier to agree on a common strategy, easier to monitor for deviations, and less tempting to deviate from the collusive agreement because the collusive profits are shared among fewer firms. Similarly, the Edgeworth pricing model predicts that average prices are lower with more firms involved because attempts to lead price jumps will fail more frequently (Noel, 2008).

The evidence suggests that competition authorities should have a strict merger policy in markets with price cycles and pay particular attention to the possibility that the merged firm can become a price leader and initiate more frequent price jumps.

While mergers reduce the number of firms, entry increases the number of firms. Much in the same way as mergers make tacit collusion easier to initiate and sustain, low barriers of entry and new entrants make tacit collusion harder to initiate and sustain (Ivaldi et al., 2003). Policies that reduce entry barriers could thus increase welfare in markets conducive to tacit collusion. In retail fuel markets, easing zoning restrictions on gas stations and forcing existing market players to grant entrants access to fuel depots are some entry-inducing options that can be explored.

[4]Similarly, mergers creating a new runner-up in markets with multi-product retailers may create a new price leader that can lead price increases in new product categories or in new areas.

2.2 Vertical relations

Large chains dominate both retail fuel markets and many other retail markets. The chains either own the retail outlets in their network (vertically integrated outlets) or have various kinds of franchising agreements and long-run vertical contracts with affiliated outlets that are locally owned (vertically separated outlets). In Norway, about one third of gas stations are vertically separated from the chains (Tveito, 2021a). Similar market structures have been observed in the retail fuel industry in many other countries and have been extensively studied in the academic literature.[5]

Foros & Steen (2013b) and Wang (2009) show that retail fuel chains use either de jure retail price maintenance (RPM), minimum RPM, or a combination of maximum RPM and wholesale prices to force vertically separated stations to set their pump prices at the levels suggested by headquarters.

RPM can facilitate collusion among upstream firms (or in other ways induce higher retail prices) but can also solve a free-riding problem with regard to presale services by retailers, meaning that the effect of RPM on consumer welfare is ambiguous. When wholesale prices are not easily observable, upstream firms may find it difficult to distinguish between changes in retail prices that are caused by local demand and cost fluctuations from changes that are caused by cheating on the collusive arrangement. In contrast, RPM can enhance stability by ensuring that retail prices are uniform, thereby making price cuts easier to detect and punish (Jullien & Rey, 2007). The prices that retail fuel chains charge to affiliate stations are typically not observed by competing chains, meaning that de jure or de facto RPM can facilitate tacit collusion in retail fuel markets.

Lewis (2012) also argues that chains' ability to control prices at many stations enable them to carry out a chain-wide price jump at the same time for all affiliated stations and thus facilitate coordination on price jumps by sending a strong signal to competitors that a market-wide price restoration is being initiated.

RPM can facilitate collusion in retail markets both with and without price cycles. De jure or de facto RPM can breach antitrust laws, and both the Irish and Danish competition authorities have forced the headquarters of retail fuel chains not to use price support arrangements that limit the control that independent retailers have over price decisions (Foros & Steen, 2013a). Competition authorities that are concerned about tacit collusion in retail markets can consider taking legal action against de jure or de facto RPM. Enforcement action does, however, risk being rendered irrelevant if the chains can change the contracts with retailers to so-called "agency agreements" (that are excepted from antitrust laws) where the financial and commercial risk lies with the chain.[6] Similar

[5]See Shepard (1993), Slade (1998), (Wang, 2009) and (Foros & Steen, 2013a).

[6]The European Commission's new draft guidelines for vertical relations should be commended for providing clearer and stricter requirements for agreements to be considered agency agreements exempted from the Treaty on the Functioning of the European Union TFEU 101 (European Commission, 2021).

issues arise if the chains are allowed to buy the independent retailers.

2.3 Recommended prices

Before November 2017, the price leader in the Norwegian retail fuel market would initiate chain-wide price jumps, and the other chains would follow 1–5 hours later. All stations within a chain would increase the price to the chain's publicly available national recommended price (adjusted for transportation costs). Foros & Steen (2013b) argue that such publicly recommended prices are only targeted at competitors, can facilitate horizontal collusion, and should be banned.

Because a price leader carried out price jumps first (Tveito, 2021c), the other chains could observe the leader's actual new price before changing their own price, diminishing the information value of the publicly recommended prices. It is not clear why the publicly available recommended prices in this situation should contribute to coordination between the chains.[7]

On the other hand, the recommended prices have very limited informational value for customers and may in some cases, as in Konkurransetilsynet (2020), be used to signal upcoming price increases.[8] Banning retail fuel chains from publishing recommended prices is unlikely to have any negative effects and may in some cases make it harder for firms to coordinate price increases. In Norway, the commitment decision of 2020 (See Section 2.4) has already prevented the two largest retail fuel chains from publishing recommended prices.

2.4 Outlawing price leadership

The legal framework to prevent collusion focuses on explicit communication and information exchange between firms as a means to reach a collusive agreement. Price leadership presents an alternative to explicit communication to initiating collusive equilibria and will generally not be considered to breach antitrust laws.

Changing antitrust laws to ban price leadership may thus be tempting for policy makers. There are, however, several problems with this proposition. Firms must be allowed to change prices in response to, for example, cost changes, changes in demand, or changes in the product space. The same firm may regularly be the first to change its price without trying to initiate collusion. This can occur with barometric price leadership where some firms are better informed than others. Less informed firms delay their decisions until

[7] The competition authority's 2020 commitment decision focused on the two largest chains' use of changes in the recommended prices to signal the *timing* of price increases, not the presence of publicly available recommended prices in themselves.

[8] Faber & Janssen (2019) also provide evidence indicating that publicly suggested prices have a horizontal coordinating effect in the Dutch retail gasoline market.

a better-informed firm moves, thereby providing a signal about market conditions; the leader thus acts as a "barometer" (Cooper, 1996).

Philips (1996) note that tacit collusion may be hard to distinguish from oligopolistic competition. Similarly, collusive price leadership may be difficult to separate from normal price changes that are responses to changes in the marketplace. Even when the same firm is frequently the first to implement price changes, this may be caused by innocuous reasons such as the firm being better informed than its competitors.[9] Thus, a general ban on price leadership risks restricting market operators' ability to compete and may ultimately resemble an instrument of price control.

There are, however, some activities related to price leadership that appear more suited to regulation. First, firms may act as price leaders by announcing their intent to change *future* prices. Miller et al. (in press) provide evidence suggesting that a major beer brewer in the USA acts as a leader in price announcements to coordinate prices tacitly.[10] Just as with price leadership in actual prices, pre-announcing price increases can enable a price leader to create focal points for price. However, pre-announcing price increases can help the leader avoid the demand loss that would otherwise be associated with being the first firm to raise prices because all firms can simultaneously implement the price increases (Harrington, 2017). In many cases, the pre-announcement of price changes also provides little or no informational value to consumers.

Signaling of future price jumps to avoid the cost of leading price jumps was indeed at the center of the Norwegian Competition Authority commitment decision on the retail fuel market in 2020 (Konkurransetilsynet, 2020).[11] The two largest chains used public pre-announcements of changes in recommended prices to signal that chain-wide price jumps would occur. The competition authority argued that this made it possible for the chains to carry out price jumps simultaneously and thus reduce the volume loss related to leading. The decision also considers the fact that the pre-announcements have little value for consumers, but mainly inform competing firms of future intentions. Furthermore, the fact that multiple firms pre-announce their price changes made it easier for the authority to argue that the chains' behavior was a form of coordination between undertakings rather than unilateral conduct. Andreoli-Versbach & Franck (2015) discuss an interesting problem regarding unilateral pre-announcements. They argue that, given a concentrated market prone to tacit collusion and evidence on price increases, the market leader's unilateral public commitment to a specific pricing strategy should also be considered a breach

[9] Gerlarc & Nguyen (2021) shows, in a theoretical model, how explicit cartels can use staggered price increases to reach optimal cartel prices without triggering suspicion from customers and competition authorities. Their results give some guidance to competition authorities in their assessment as to whether a given staggered price increase is potentially a sign of collusion or the outcome of normal competitive behavior.

[10] Marshall et al. (2008) also argue that firms in an explicit cartel in the vitamins industry use price announcements to make buyers accept price increases.

[11] Foros & Ones (2021) describe in detail the transition that occurred.

of antitrust laws.

Price leadership in actual prices can certainly facilitate price coordination, but a general ban on this kind of conduct is neither feasible nor desirable. However, behavior that reduces the cost of leading price increases, for example though pre-announcement of price changes or other kind of signaling of future intentions, can in some cases reasonably be prohibited

2.5 Price transparency

Gas stations in Norway post their prices on large electronic boards. Consumers can thus observe each station's price when they pass by, but driving to different stations involves time and fuel costs meaning the search is expensive for many customers. Similarly, retailers can monitor competitors' prices, but monitoring is costly. Price comparison services where users report fuel prices to a webpage exist in many markets and can reduce search costs, but as prices vary greatly between areas and through the week, the price reports for individual stations are often out of date.

To better inform retail fuel customers, Australia, Chile, Germany, Austria, France, and South Korea have implemented information disclosure policies. The retail chains are required to report up-to-date prices for all stations to a government-run database, and either the government or private firms present the price information to users through webpages or smartphone apps. Similar policies have also been introduced in several other industries such as ready-mixed concrete, supermarkets, snack foods, and restaurants (Luco, 2019). In Norway, price disclosure policies have been implemented in the residential electricity market, dentists, markets for financial and telecom services, but not in the retail fuel market.

The information disclosure policies aim to intensify competition by reducing consumer search cost. A major drawback of these policies is that they also allow firms to monitor their rivals' actions, which could facilitate coordination among firms and decrease the intensity of competition. In the end, whether information disclosure policies intensify competition or facilitate coordination crucially depends on whether the demand- or supply-side response to disclosure dominates (Luco, 2019).

The evidence on the effect of the disclosure policies is mixed. Luco (2019) finds that retail gasoline margins in Chile increased by 9% on average after the introduction of the disclosure policy in 2012. The results show significant heterogeneity across the country, and an analysis based on data on locations of smartphone users when they searched for prices through a smartphone app suggests that in areas with low local search intensity, the supply-side response to disclosure (coordination) dominates and margins increase. However, when local search intensity is higher, the disclosure policy has the potential to overcome price coordination and increase competition. Montag & Winter (2020) analyzed the introduction of a price disclosure policy in the German retail fuel market in 2013 and found that the policy decreased retail margins by 13%. They also found that the effect was greater in areas where local radio stations frequently broadcast local petrol prices.[12]

The studies in Chile and Germany only consider margin development over 1.5–2 years after the introduction of the disclosure policies. Byrne & de Roos (2019) and Tveito (2021c) show that it takes several years to coordinate on a margin-enhancing new equilibrium. A new price disclosure policy can have positive short-run effects, as it makes consumer search less costly, and the change in market conditions may trigger a breakdown in an existing collusive equilibrium. However, the lower prices may not last. Firms may need time to initiate coordination (again) under the new market conditions. Eventually, the increased transparency may facilitate tacit collusion in markets where it was previously not possible or could facilitate tacit collusion on higher prices than was previously possible.

A recent working paper by Assad et al. (2020) shows a particularly worrying development in German retail gasoline markets several years after the price disclosure policy was introduced. The price disclosure policy allows the feeding of real-time prices to algorithms that can determine each station's price. Such algorithmic pricing became widely available in the German retail fuel market in mid-2017. The authors found that in local duopoly markets where both stations adopt algorithmic prices, margins increase by 28%. The increase occurs gradually, starting about a year after adoption, suggesting that algorithms learn tacitly collusive strategies over time. Feeding real-time price information into the algorithm is unlikely to be possible without the price disclosure policy.

Prices in Germany follow a high-amplitude intra-day price cycle, and a change in the weekly cycle occurred (Eibelshäuser & Wilhelm, 2018) at about the same time as the pricing algorithms became widely available in mid-2017. The papers analyzing the German retail fuel market do not use volume-weighted prices. Tveito (2021b) shows that consumers' long-run response to changes in the intertemporal price pattern is much stronger than the short-run response, and that unweighted prices may give biased estimates of changes in the profits that firms actually earn and the prices consumers actually pay.

In Norway and many other countries in the year 2021, the smart phone penetration rate is very high – much higher than it was in the areas of low penetration in Chile in 2012. Thus, it is likely that a large proportion of consumers could utilize information from internet-based price comparison services. In this situation, the evidence from Germany and Chile suggest that Norwegian retail fuel prices would decrease in the short run if a price disclosure policy is introduced. However, the evidence showing that it may take a long time to initiate a new high-price equilibrium, and the evidence of algorithmic tacit collusion, suggest that in the longer run, prices may increase again—possibly to a higher

[12] Ater & Rigbi (2019) similarly found that in Israel, grocery prices decreased after the introduction of a price portal, and that newspapers played an important role in diffusing information to consumers.

level than without the price disclosure policy.

An alternative could be to disclose non-perfect price information that can steer consumers to purchase at low-price suppliers at the time of the week when prices are lowest, without disclosing detailed price information that could help suppliers facilitate tacit collusion. The most basic way to steer consumer to purchase at the bottom of the cycle is to inform them about the typical timing of the price cycles. With calendar-synchronized price cycles, this is as easy as diffusing information through webpages and traditional or social media about the time of the week when the bottom of the cycle occurs. If the price cycles are non-synchronized and trough occurrence varies from week to week, as in Norway in 2021, policy makers could try to release information that could help consumers predict when the next trough might occur. The Australian Competition and Consumer Commission continuously collects price data and presents up-to-date buying tips for different major cities three times a week (ACCC, 2021). The buying tips urge customers to either buy now or wait, depending on how prices are predicted to develop in the near future.

Given that the price cycle does not change, such information policies can clearly help consumers save money by buying when prices are low. However, they can also enhance welfare by lowering prices. de Roos & Smirnov (2020) present a theory of collusive intertemporal price dispersion In their model, price cycles can enable higher collusive profits because they hamper consumer search and thus decrease deviation profits. Increasing the proportion of consumers who can predict and purchase when the trough of the cycle occurs means that suppliers must accelerate price cutting during the cycle and provide a deeper sale at the trough to prevent deviations from the collusive equilibrium. Policies that enable consumers to predict the future price path can thus reduce prices both at the bottom and other parts of the cycle.

Market-wide price hikes in markets with asymmetric price cycles occur at the bottom of the cycle. Tveito (2021a) shows that the leader's volume loss is low, and argues that this may have contributed to the transition to an equilibrium with more frequent price jumps and higher margins. Steering consumers to purchase at the bottom of the cycle can increase the share of total volume that is sold in the period when the price leader is alone with a high price and thereby increase the cost of leading. A higher cost of leading can reduce the frequency of price jumps and thus increase the time spent at the low-price part of the price cycle.[13]

Policy makers can also amplify the loss of leading by providing information about when each firm typically increases prices to help consumers take advantage of the non-

[13] In Edgeworth pricing models based on the model in Maskin & Tirole (1988), the incentives to undercut in a given period depends both on current period profits and the discounted expected profit in the following periods. If the cost of leading jumps increases and firms expect that the probability of price jumps at a given price level decreases, a firm's decision to undercut or not at different parts of the cycle and the size of price cuts may change.

leaders' low prices in the period before they match the leader's price jump. In markets where price jumps are not calendar-synchronized, policy makers can send notifications through smart phone apps immediately after the leader carries out market-wide price jumps. Motorists can then purchase at rival chains' stations within the few hours before rivals raise their prices. Johnson et al. (2021) propose similar demand steering using online platforms: They simulate competing Q-learning algorithms in a market where products are displayed on online platforms and show that that competition can be improved by giving sellers that display behavior consistent with deviation from a collusive equilibrium additional exposure for a long time, to prevent other firms from punishing the deviation.

2.6 Price regulation

Dissatisfaction with high retail fuel prices puts governments under pressure from the public to act and find suitable measures to decrease prices. Several countries have responded by implementing various price regulations to lower the prices. I focus on regulating the frequency of price changes rather than regulating the price level directly.

Prices change very frequently—often multiple times per day—in both the Norwegian and other retail fuel markets. In Germany, where real-time prices are being fed to pricing algorithms, prices change on average nine times per day (Assad et al., 2020). The fast price changes cause two possible problems. First, consumers may find it expensive and difficult to compare prices at different gas stations. For example, a consumer passing multiple gas stations on the commute to and from work can check prices at all stations on her way to work. When prices change multiple times per day, she cannot, however, expect prices at the various stations to be the same on the commute home. This limits the value of the information she gathered on the way to work and likely makes it harder to choose the cheapest supplier and reduce competition even without tacit collusion. de Roos & Smirnov (2020) show that firms can use intertemporal price variation to obfuscate prices for consumers and in this way reduce the payoffs to deviation and make collusion easier to sustain. de Roos & Smirnov (2021) consider a similar setting but with a fringe competitor. Faced with a fringe competitor, the colluding firms have an additional motivation for obfuscation: to limit the ability of the fringe to undercut the collusive price and steal market share. Pennerstorfer et al. (2020) found empirical evidence that a greater proportion of informed consumers has a negative effect on retail fuel prices.

Second, the fast price changes mean that firms can respond very quickly to rivals' price increases and decreases. Fast response to price *decreases* mean that the volume gains from substantial price decreases will be small, discouraging deviation from possible collusive equilibria. Both in models of tacit collusion supported by history-dependent strategies and in Edgworth-pricing models with Markow strategies, decreasing the frequency of price adjustments relative to the discount factor leads to lower prices.[14]. Fast response to price *increases* means that the cost of leading price increases is small, making price leadership a cheap way to coordinate price increases Tveito (2021a).

The metropolitan area of Perth in Australia has implemented regulations restricting the frequency of retail fuel price changes. The regulation took effect in 2001. It requires every gas station to (1) notify the government of its next day's retail prices by 14:00 each day so that these prices can be published on a website, and (2) post the published prices on its price board at the start of the next day for a duration of at least 24 hours. The law thus forces firms to set gasoline prices simultaneously (without knowing rivals' prices) and at most once every 24 hours.

Wang (2009) finds that the pricing pattern in Australia changed after the law was enacted. Before the law, gasoline prices followed an asymmetrical cycle. Just after the change, the price cycles disappeared, but they returned 4 months later. Before the law, a single chain acted as a regular price leader to restore prices to a high level from the bottom of the cycle, and the other chains followed within a few hours, which is very similar to the way price jumps are carried out in Norway. After the change, the leader had to be alone with a high price for at least 24 hours and thus faced a higher demand loss. When the cycles began to occur again, price leadership was shared among the chains, consistent with no firm wanting to bear the higher cost of leading alone. The timing law lowered the Perth market average non-volume-weighted retail prices in the first 4 months of the law when the price cycles disappeared (consistent with the fact that the timing law disrupted the firms' price coordination in the short run) but did not have a statistically significant effect once the chains succeeded in re-establishing the price cycle equilibrium.

Some years after the law was enacted, the largest chain in Perth used price leadership to coordinate higher prices at the top of the cycle over a three-year long equilibrium transition (Byrne & de Roos, 2019). The chains eventually managed to coordinate on increasing prices simultaneously once per week and fixed simultaneous 2-cent price cuts per day in the downward-sloping part of the cycle.

Austria implemented a similar regulation in 2009, allowing retailers to increase daily fuel prices only once at the beginning of the day, but allowing them to carry out price decreases whenever they wanted. Obradovits (2014) argues, based on a theoretical model, that the law – specifically the option to lower prices at any time during the day, can increase average prices, but Becker et al. (2021) found that Austrian retail gasoline margins decreased relative to other European countries in the first two years after the law was implemented.[15]

Summing up, restricting the frequency of price changes and forcing firms to set prices

[14] See Ivaldi et al. (2003) and Noel (2008)

[15] There were intra-day price cycles in Austria in 2014 (Boehnke, 2017), but price cycles are not discussed by Becker et al. (2021).

simultaneously seems a promising way to lower prices in markets characterized by frequent price changes, price leadership, intertemporal price variation, and tacit collusion. Such regulations can improve consumer search, destabilize tacit collusion, and make it harder to use price leadership to coordinate a new high-price equilibrium. The evidence from Australia and Austria shows that such regulations can have a positive effect. However, the Australian experience, where price leadership is used to initiate coordination on a high-price equilibrium under the law, indicates that a restriction to one price per day may not be sufficient in the retail fuel market. Less frequent price changes, perhaps once per week, may be better.

A potential problem with restricting the frequency of price changes is that it makes the market more transparent for firms. If prices can only change once per week, firms can more easily monitor their competitors. The well-known problem related to higher transparency leading to swift punishment and low deviation profits for firms is not, however, relevant as long as firms have to set prices for the coming week simultaneously without knowing rivals' prices: Even though firms can swiftly detect that a rival has set a low price, they have to wait until the next week to punish them for the deviation. Similarly, firms must wait a week to follow a price leader's price increase even though the increase is swiftly detected.

Another possible problem is that the complexity of collusive equilibria can be reduced. The coordination on 2-cent daily price cuts that occurred in Perth would, for example, be harder to initiate in a market where prices can change multiple times per day. Thus, a regulation restricting price changes to a frequency of only once per week would make it very expensive to use price leadership to initiate coordination but would also reduce the complexity of the coordination problem.

Policy makers should also be aware that the price cycles can disappear if each price sticks for a week or longer, and if the cycles continue, the duration of each cycle will last several weeks. This will eradicate the gains from intertemporal substitution, eliminating the time costs related to timing purchases to the bottom of the cycle ((Noel, 2012). There is, however, no guarantee that the fixed weekly prices will be equal to or lower than prices would have been at the bottom of the cycle without the regulation.

A final problem is that wholesale costs in the retail fuel market are fairly volatile and a long fixed-price period can prevent firms from responding to cost shocks. Although wholesale costs vary greatly over time, the within-week variation is rarely more than one cent in the US dollar. A good wholesale price proxy is also readily available to both firms and regulators, making it easy to include a safeguard that allows firms extra price changes if the wholesale price changes more than a given amount.

3 Concluding remarks

Strict merger control and an entry-friendly environment should be priorities in any oligopoly market, and competition authorities should always consider whether vertical relations and signaling of future intentions restrict competition. Price disclosure policies and regulation of the timing of price changes are more novel interventions, and the effects of these policies are harder to predict. In dynamic games with sufficiently patient firms, a multitude of different equilibria are possible market outcomes (Fudenberg & Tirole, 1991). Even with extensive knowledge of a market it is difficult to predict which equilibrium will arise after a policy change.

In general, the worse a market is performing (the closer it is to the monopoly outcome), the more likely it is that new policies will be welfare-enhancing. The Norwegian retail fuel market has historically been characterized by tacit collusion and increasing margins, but a thorough investigation of the situation today would be necessary before reforms can be considered.

The goal of price disclosure policies and regulation of the timing of price changes is to 1) improve consumer search to enable consumers to purchase from a low-price retailer at a low-price time of the week, (2) make tacit collusion harder to sustain by increasing deviation payoffs, and (3) make it harder to initiate new tacit collusive equilibria by increasing the cost of leading price increases and lengthening the time it would take pricing algorithms to learn to collude.

In markets with frequent price changes, price leadership, and tacit collusion, regulating the timing and frequency of price changes is a promising intervention that speaks to all the goals mentioned above. Furthermore, implementation costs are likely to be small, and the regulation will be easy to reverse if it is not performing well. It is hard to know ex ante which frequency would be better suited, but evidence of the extensive use of price leadership and successful coordination with a daily frequency in Perth suggests a longer period may be better—perhaps one price change per week. It is also very important to ensure that prices for the upcoming week are set simultaneously without knowing rivals' future prices.

As consumers' search costs decrease with longer price duration, the value for consumers of price disclosure policies like a webpage with real-time price information would be lower if a restriction of the frequency of price changes also exists. However, as firms can easily monitor rivals' prices with a restriction of the frequency of price changes (but cannot respond quickly to price changes), price disclosure policies are unlikely to do any harm (except for the cost of implementing the policy). If a timing regulation is not implemented, measures that give customers information to help predict when prices will be low and try to steer customers to purchase from non-leaders before they match the leader's price jump may be preferable to policies giving perfect real-time price information.

Tveito (2021b) shows that over time, consumers respond more strongly to intertemporal price variation. When the cycle with a regular sale period every Sunday/Monday morning had been present for 5–10 years, a large share of customers timed their purchases to the bottom of the cycle. The best time to implement regulation of the timing of price changes is soon after a change in the pricing pattern has occurred, when most consumers have yet to learn about the new pattern and change their habits accordingly.

New policies should be evaluated to see if they work and should be reversed if it is found that they do not achieve their goals. Evaluations should take into consideration that while firms may not be able to initiate a new collusive equilibrium in the short run, they may be able to do so in the long run. Furthermore, evaluations should also take into consideration that consumers may need time to respond to changes in the price pattern caused by the policy, and that unweighted average prices and margins are poor proxies for changes in the price consumers pay and the profit firms earn (Tveito, 2021b).

References

ACCC. (2020). *Report on the Australian Petroleum Market - June Quarter 2020.* Retrieved 2021-05-12, from https://www.accc.gov.au/system/files/20-27RPT_Petrol%2520Quarterly%2520Report%2520-%2520June%25202020_FA.pdf

ACCC. (2021). *Petrol Price Cycles.* Retrieved 2021-08-06, from https://www.accc.gov.au/consumers/petrol-diesel-lpg/petrol-price-cycles#petrol-price-cycles-in-capital-cities/

Andreoli-Versbach, P., & Franck, J. (2015). Endogenous Price Commitment, Sticky and Leadership Pricing: Evidence from the Italian Petrol Market. *International Journal of Industrial Organization*, *40*, 32-48.

Angrist, J. D. (2004). Treatment Effect Heterogeneity in Theory and Practice. *Economic Journal*, *114*(494), C52-C83.

Angrist, J. D., & Pischke, J.-S. (2010). The Credibility Revolution in Empirical Economics: How Better Research Design is Taking the Con out of Econometrics. *Journal of Economic Perspectives*, *24*(2), 3-30.

Assad, S., Clark, R., Ershov, D., & Xu, L. (2020). Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market. *Working Paper*.

Ater, I., & Rigbi, O. (2019). Price Transparency, Media and Informative Advertising. *Working Paper*.

Atkinson, B., Eckert, A., & West, D. S. (2014). Daily Price Cycles and Constant Margins: Recent Events in Canadian Gasoline Retailing. *Energy Journal*, *35*(3), 47-69.

Barron, J. M., Taylor, B. A., & Umbeck, J. R. (2004). Number of Sellers, Average Prices and Price Dispersion. *International Journal of Industrial Organization*(8-9), 1041-1066.

Becker, M., Pfifer, G., & Schweikert, K. (2021). Price Effects of the Austrian Fuel Price Fixing Act: A Synthetic Control Study. *Energy Economics*, *97*.

Bo, H., & Galiani, S. (2020). Assessing External Validity. *Working Paper*.

Boehnke, J. (2017). Pricing Strategies and Competition: Evidence from the Austrian and German Retail Gasoline Markets. *Working Paper*.

Bresnahan, T. F. (1989). Empirical Studies of Industries with Market Power. *Handbook of Industrial Organization, vol. 2, ed. Richard Schmalensee and Robert D. Willig*, *2*, 1011–57.

Byrne, D. P., & de Roos, N. (2019). Learning to Coordinate - A Study in Retail Gasoline. *American Economic Review*, *109*(2), 591-619.

Calvano, E., Calzolari, G., Denicolò, V., & Pastorello, S. (2020). Artificial Intelligence, Algorithmic Pricing, and Collusion. *American Economic Review*, *110*(10), 3267-3297.

Cooper, D. J. (1996). Barometric Price Leadership. *International Journal of Industrial Organization*, *15*, 301-325.

de Roos, N., & Smirnov, V. (2020). Collusion with Intertemporal Price Dispersion. *RAND Journal of Economics*, *51*(1), 158-188.

de Roos, N., & Smirnov, V. (2021). Collusion, Price Dispersion, and Fringe Competition. *European Economic Review*, *132*.

Eckert, A. (2013). Empirical Studies of Gasoline Retailing: A Guide to the Literature. *Journal of Economic Surveys*, *27*(1), 140-166.

Eibelshäuser, S., & Wilhelm, S. (2018). High-Frequency Price Fluctuations in Brick-and-Mortar Retailing. *Working paper*.

Einav, L., & Levin, J. (2010). Empirical Industrial Organization: A Progress Report. *Journal of Economic Perspectives*, *24*(2), 145–162.

European Commission. (2004). Guidelines on the Assessment of Horizontal Mergers under the Council Regulation on the Control of Concentrations Between Undertakings.

European Commission. (2021). Draft Revised Guidelines on Vertical Restraints.

Faber, R. P., & Janssen, M. C. W. (2019). On the Effects of Suggested Prices in Gasoline Markets. *Scandinavian Journal of Economics*, *121*(2), 676-705.

Fabra, N., Rapson, D., Reguant, M., & Wang, J. (2021). Estimating the Elasticity to Real Time Pricing: Evidence from the Spanish Electricity Market. *AEA – Papers and Proceedings*(111), 425-429.

Foros, Ø., & Ones, M. N. (2021). Coordinate to Obfuscate? The Role of Prior Announcements of Recommended Prices. *Economics Letters*, *198*.

Foros, Ø., & Steen, F. (2013a). Retail Pricing, Vertical Control and Competition in the Swedish Gasoline Market. *Report for the Swedish Competition Authority*.

Foros, Ø., & Steen, F. (2013b). Vertical Control and Price Cycles in Gasoline Retailing. *Scandinavian Journal of Economics*, *115*(3), 640-661.

Fudenberg, D., & Tirole, J. (1991). *Game Theory*. Cambridge, MIT Press.

Fung, M. K. (2018). Deposit Rate Asymmetry and Edgeworth Cycles after Hong Kong's Interest Rate Deregulation, in (ed.) Banking and Finance Issues in Emerging Markets. *International Symposia in Economic Theory and Econometrics*, *25*, 105-121.

Gerlarc, H., & Nguyen, L. (2021). Price Staggering in Cartels. *International Journal of Industrial Organization*, *77*.

Harrington, J. E. (2017). A Theory of Collusion with Partial Mutual Understanding. *Research in Economics*, *71*, 140-158.

Hasbrouck, J. (2018). High-Frequency Quoting: Short-Term Volatility in Bids and Offers. *Journal of Financial and Quantitative Analysis*, *53*(2), 613-641.

Hauschultz, F. P., & Munk-Nielsen, A. (2017). Priscykler i Markedet for Receptpligtig Medicin efter Patentudløb (Price Cycles in the Market for Prescription Medicin after Patent Expiration). *Konkurrence- og Forbrugerstyrelsen: Velfungerende Markeder*.

International Energy Agency. (2020). Global EV Outlook.

International Energy Agency. (2021). Global EV Outlook.

Ivaldi, M., Jullien, B., Rey, P., Seabright, P., & Tirole, J. (2003). The Economics of Tacit Collusion. *Final Report for DG Competition, European Commission.*

Johnson, J. P., Rhodes, A., & Wildenbeest, M. (2021). Platform Design When Selles Use Algorithms. *Working Paper*.

Jullien, B., & Rey, P. (2007). Resale Price Maintenance and Collusion. *RAND Journal of Economics*, *38*(4), 983-1001.

Konkurransetilsynet. (2010). Det Norske Drivstoffmarkedet (The Norwegian Fuel Market).

Konkurransetilsynet. (2014). Drivstoff Markedet i Norge - Marginøkning og Ny Pristopp (The Norwegian Fuel Market – Margin increase and a New Price Peak).

Konkurransetilsynet. (2015). Vedtak V2015-29 - St1 Nordic OY - Smart Fuel AS - Konkurranseloven § 16 jf. § 20 - Inngrep mot Foretakssammenslutning (Decision V2015-29 - St1 Nordic OY - Smart Fuel AS - the Competition Act § 16 jf. § 20 - Intervention Against Merger).

Konkurransetilsynet. (2020). V2020-26 – Circle K Norge AS - Konkurranseloven § 12 Tredje Ledd, Jf. § 10 og EØS-Avtalen Artikkel 53 (Decision V2020-26 - Circle K Norge AS - the Competition act § 12 Third Paragraph Ref. Competition Act § 10 and EEA-Agreement Article 53).

Lewis, M. S. (2012). Price Leadership and Coordination in Retail Gasoline Markets with Price Cycles. *International Journal of Industrial Organization*, *30*(4), 342–351.

Luco, F. (2019). Who Benefits from Information Disclosure? The Case of Retail Gasoline. *American Economic Journal: Microeconomics*, *11*(2), 277-305.

Marshall, R. C., Marx, L. M., & Raiff, M. E. (2008). Cartel Price Announcements: The Vitamins Industry. *International Journal of Industrial Organization*, *26*, 762-802.

Maskin, E., & Tirole, J. (1988). A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles. *Econometrica*, *56*(3), 571-599.

Miller, N. H., Sheu, G., & Weinberg, M. C. (in press). Oligopolistic Price Leadership and Mergers: The United States Beer Industry. *American Economic Review*.

Montag, F., & Winter, C. (2020). Price Transparency against Market Power. *Working Paper*.

Motta, M., & Fabra, N. (2013). Coordinated Effects in Merger Cases. *Report Commissioned by the World Bank*.

Noel, M. D. (2008). Edgeworth Price Cycles and Focal Prices: Computational Dynamic Markov Equilibria. *Journal of Economics and Managment Science*, *17*(2), 345-377.

Noel, M. D. (2012). Edgeworth Price Cycles and Intertemporal Price Discrimination. *Energy Economics*, *34*(4), 942–954.

Obradovits, M. (2014). Austrian-Style Gasoline Price Regulation: How it May Backfire. *International Journal of Industrial Organization*, *32*, 33-45.

OECD. (2020). Sustainability and Competition.

Pennerstorfer, D., Schmidt-Dengler, P., Schutz, N., Weiss, C., & Yontcheva, B. (2020). Information and Price Dispersion: Theory and Evidence. *International Economic Review*, *61*(2), 871–899.

Philips, L. (1996). On the Detection of Collusion and Predation. *European Economic Review*, *40*(3-5), 495-510.

Roe, B. E., & Just, D. R. (2009). Internal and External Validity in Economics Research: Tradeoffs between Experiments, Field Experiments, Natural Experiments, and Field Data. *American Journal of Agricultural Economics*, *91*(5), 1266-1271.

Schinkel, M. P., & Treuren, L. (2021). Green Antitrust: Friendly Fire in the Fight against Climate Change. *Working Paper*.

Schmalensee, R. (1989). Inter Industry Studies of Structure and Performance. *Handbook of Industrial Organization, vol. 2, ed. Richard Schmalensee and Robert D. Willig*, *2*, 951–1010.

Seaton, J. S., & Waterson, M. (2013). Identifying and Characterising Price Leadership in British Supermarkets. *International Journal of Industrial Organization*, *115*(31), 392-403.

Shepard, A. (1993). Contractual Form, Retail Price, and Asset Characteristics in Gasoline Retailing. *RAND Journal of Economics*, *24*(1), 58-77.

Slade, M. E. (1998). Strategic Motives for Vertical Separation: Evidence from Retail Gasoline Markets. *Journal of Law, Economics, and Organization*, *14*(1), 84–113.

Statistics Norway. (2021). Nasjonalregnskap for 2020(National Accounts 2020).

Tirole, J. (1988). The Theory of Industrial Organization. *The MIT Press*.

Tveito, A. (2021a). The Costs and Benefits of Price Leadership – Evidence from Retail Gasoline. *Working Paper*.

Tveito, A. (2021b). Dynamics in Intertemporal Substitution – Evidence from Retail Fuel. *Working Paper*.

Tveito, A. (2021c). Might as Well Jump! Coordinating More Frequent Price Hikes in a Retail Gasoline Market. *Working Paper*.

Wang, Z. (2009). (Mixed) Strategy in Oligopoly Pricing: Evidence from Gasoline Price Cycles Before and Under a Timing Regulation. *Journal of Political Economy*, *117*(61), 987-1030.

Zhang, M., & Feng, J. (2011). Cyclical Bid Adjustments in Search-Engine Advertising. *Management Science*, *57*(9), 1703-1719.

Chapter 2

Might as Well Jump! Coordinating More Frequent Price Hikes in a Retail Gasoline Market

Might as Well Jump! Coordinating More Frequent Price Hikes in a Retail Gasoline Market*

Andreas Tveito†

October 7, 2021

Abstract

I use a unique dataset spanning 14 years with the exact timing of price changes for most Norwegian gas stations to study price leadership and coordination in the retail gasoline market. The market features asymmetric price cycles where prices slowly fall for several days before being restored to a high level within a few hours. The main contribution is to show how large retail chains use price leadership to both agree on and sustain a new equilibrium with more frequent price hikes. I argue that faster price changes due to a lack of price regulations in Norway can explain why the chains in Norway end up coordinating on a different equilibrium than in other countries. By combining the price data with data on volumes and costs, I estimate that the transition to more frequent price hikes has a substantial positive effect on volume-weighted retail margins.

*I would like to thank Sigurd Birkeland, Kurt Brekke, Shangrong Chen, Jonas Gade Christensen, Gordon Dahl, Joe Harrington, Bjørn Olav Johansen, Katrine V. Løken, Teis,Lunde Lømo, Ole-Andreas E. Næss, Mai N. Ones, Frode Steen, Morten Sæthre, Simen A. Ulsaker, and seminar participants at CRESSE, University of Bergen, and the Norwegian Competition Authority for helpful comments. I gratefully acknowledge financial support from the Research Council of Norway.

†Department of Economics, University of Bergen and the Norwegian Competition Authority. The views expressed in this paper are those of the author and do not necessarily reflect the views of the Norwegian Competition Authority.

1 Introduction

Collective price hikes can be difficult to implement because firms fail to initiate coordination or because the high-price outcome is not a stable equilibrium (Harrington, 2017). A large body of theoretical literature investigates the stability of collusive equilibria, and a growing body of empirical literature provides evidence of the pervasiveness of both tacit and explicit collusion.[1] However, research on the initiation of tacit collusion is sparse. Initiation demands that firms have mutual beliefs regarding the new strategy profile—they must coordinate on focal points for the timing and level of price hikes.

Direct communication using natural language could help firms coordinate on a high-price strategy, but policy makers wanting low prices have outlawed such communication.[2] Thus, firms may employ other instruments to agree on a strategy. *Price leadership*—a practice involving sequential price changes whereby a leader changes price first and rivals quickly follow—provides a natural solution to the coordination problem (Markham, 1951). Byrne & de Roos (2019) show how a retail gasoline price leader in Perth, Australia, creates focal points that facilitate price coordination and enhance profit margins.

I employ a unique dataset with the exact timing of retail gasoline price changes for almost all Norwegian gas stations from 2004 to 2017 to show that large retail chains act as price leaders, and argue that price leadership enables the chains to both agree on and sustain a new margin-enhancing equilibrium. The equilibrium transition involves a new way to increase margins: more frequent price increases. I argue that faster price changes due to a lack of price regulations in Norway can explain why the chains in Norway end up coordinating on a different margin-enhancing equilibrium than the chains in Perth. The price data combined with data on costs and volume sold allow me to present evidence suggesting that the transition to the new equilibrium increases volume-weighted price–cost margins. This paper also contributes to the literature on asymmetric price cycles by showing that, contrary to predictions in the existing literature, the size of the price jumps does not decrease when the amplitude increases.

The market is dominated by four national chains with a combined national market share of more than 90%. Unlike the market studied by (Byrne & de Roos, 2019), there are no price regulations in the Norwegian retail fuel market. During the start of the sample period, prices follow a sawtooth-like pattern in which stations carry out a large price jump once a week but on different weekdays in different weeks. Every week, one of the national chains leads by increasing prices at most of its stations almost simultaneously, and the other chains follow a few hours later. Many small price cuts follow after the large price jump before another large jump occurs in the following week. Similar price patterns

[1] See Green et al. (2014) for a discussion of the theoretical literature on collusion and Byrne & de Roos (2019) for a short review of the empirical literature on collusion.

[2] Despite the illegality of such communication, explicit cartels are not uncommon, see Wang (2008) and Clark & Houde (2013) for examples of cartels in the retail gasoline market.

have been found in retail fuel markets in 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 for several periods at the bottom of the cycle to decide who makes the next price jump to restore prices.

How can firms in an equilibrium featuring asymmetric price cycles increase margins? They could try to coordinate at a fixed high price, but this may be unattainable due to problems related to initiating or implementing this kind of equilibrium—see, e.g., de Roos & Smirnov (2020) who show that equilibria with cycling prices can sustain higher collusive profits than collusion with a fixed price. Firms could instead try to increase the price at the top of the cycle or reduce the size of the price cuts: Byrne & de Roos (2019) show how a dominant chain uses price leadership and signaling to transition the retail fuel market in Perth to an equilibrium with price jumps every Thursday, a fixed price cut per day in the undercutting phase, and a gradual increase in margins at the peak of the cycle.

Margins can also be boosted by coordinating to shorten the time between price jumps. Wang (2008) shows how explicit communication among retail gasoline stations is used to resolve the war of attrition problem at the bottom of the cycle and thus shorten the time between price jumps. Lewis (2012) documents the price leadership that 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. Foros & Steen (2013) argue that Norwegian retail gasoline chains de facto simultaneously decide to hike prices at the same time every Monday to stop the war of attrition phase and increase average margins. However, Noel (2019) argues that such "calendar synchronization" of price jumps is not necessarily anticompetitive because consumers can use the more predictable price pattern to shift purchases to low-price days. He also argues that even a transition to more frequent price jumps may not be anticompetitive because prices at the top of the cycle should competitively adjust downwards when the frequency of jumps increases.

I show how price leadership is used to first initiate calendar-synchronized price jumps once per week and then to increase the frequency of price jumps from 1 to 2 per week. The largest chain begins to initiate price jumps at the same time every Monday in April 2004. From the very first week, the other chains match the Monday jumps within a few hours. When the leader stops initiating price jumps in a short period in the fall of 2004, the other chains also stop hiking prices on Mondays. After the short break, the leader

[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).

starts to initiate Monday price jumps every week for the next 13 years.[4] The Monday jumps are stable even through periods with extreme wholesale price volatility when price cycles have been shown to break down in other countries. Contrary to Foros & Steen (2013), I find that the calendar-synchronized price jumps occur sequentially rather than simultaneously. The jumps are initiated by a regular price leader, and the other chains swiftly follow the leader.

I find that the calendar synchronization of the cycles is unlikely to have caused an immediate increase in retail margins. The regular Monday jumps do, however, prepare the ground for more frequent price jumps. The largest chain tries to initiate Thursday price jumps as well in the first weeks when the Monday price jumps are initiated, but after several failed attempts (one or more chains do not follow the Thursday price jump, and prices quickly revert to the pre-jump path), the Thursday jumps are abandoned.

In January 2005, Thursday, or (more rarely) Friday, price jumps begin to occur again in some weeks. As these are in addition to the Monday price jumps, I call them *second price jumps*. Over the next four years, second price jumps occur in 62% of the weeks, and 43% of the attempts fail.

In August–December 2008, an acquisition transferring 90 stations between two of the national chains increases one of the chains' market share, creating a clear number two 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 begins to initiate price jumps every Thursday, and the rate of failure drops to zero as all other chains follow the second price jumps. Both Monday and Thursday price jumps occur every week for the next eight years.

Using a difference-in-difference (diff-in-diff) approach in which I compare the development for cycling stations with non-cycling stations, I find that the transition from irregular to regular Thursday jumps increases volume-weighted retail margins by at least 0.10 Norwegian kroner (10%). The margin increase is driven by higher margins in the part of the week after the Thursday jumps are carried out. The downward adjustment in prices at the top of the cycle that Noel (2019) predicts should occur when the frequency of price jumps increases does not materialize. Coordinating 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.

This paper contributes to the sparse literature on how collusive equilibria are initiated. Recent research investigates the emergence of collusion with explicit secret communication (Chilet, 2018), price-matching guarantees (Cabral et al., 2021), and public announcements (Foros & Ones, 2021). As in Byrne & de Roos (2019)'s study of the retail gasoline market in Perth, I focus on price leadership in actual prices rather than secret communication or publicly pre-announced prices. However, the events leading to price coordination in

[4]The only exception is that price jumps never occur on public holidays.

Norway differ from those in Perth. Margins in Perth increase due to transitioning to regular Thursday price jumps, increasing margins at the top of the cycle, and fixing size of the daily price cut. Margins in Norway increase due to a transition to more frequent price jumps.

Different regulatory regimes provide a possible explanation for the chains in Perth and Norway ending up with different margin-enhancing equilibria. Regulation of the frequency of price changes in Perth forces the price leader to be alone with a high price for a full day, and a requirement for retailers to post prices online is likely to increase own-price elasticities. Thus, this regulatory regime is likely to increase the volume loss related to raising prices first in Perth. However, this regime limits gas stations to one price change per day and thus makes it easier to coordinate prices in the undercutting phase of the cycle. There are no price regulations in Norway, and I show in a companion paper that the volume loss related to leading second price jumps in Norway is low (Tveito, 2021a). The low cost of leading price jumps and high complexity related to coordinating prices in the undercutting phase of the cycle make a transition to more frequent price jumps an attractive way to increase margins for Norwegian gasoline retailers.

The paper also contributes to our understanding of the connection between firm size and price leadership. Byrne & de Roos (2019) show that the largest chain in Perth acts as a regular price leader over a long period where prices only change once per day. High-frequency price changes and lower frequency data limit the robustness of the previous studies on price leadership in the more typical case without price regulation, but Noel (2007), Atkinson (2009), and Lewis (2012) provide some cross-sectional evidence that price jumps in the USA and Canada are led by large retail gasoline chains. I provide evidence that size differences both between chain and within-chain changes over time suggest that having a large network of gas stations is positively correlated with being a regular price leader. Price jumps are also more frequent and more often successful when the largest chains lead.

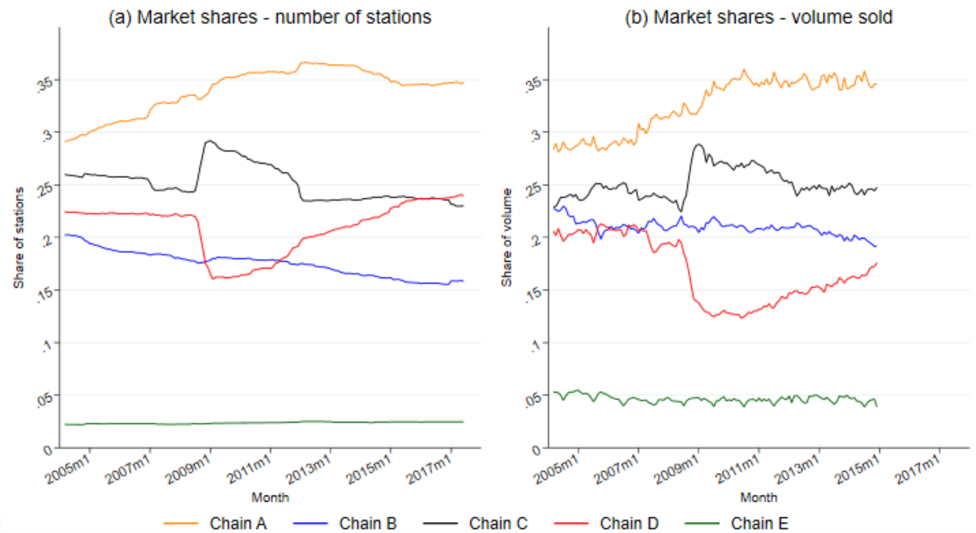
The paper is organized as follows. Section 2 presents institutional details and a description of the data. Section 3 describes the transition to more frequent price jumps. Section 4 estimates the effect of the transitions. Section 5 discusses the results emphasizing the role of price leadership in the transitions and the connection between firm size and price leadership. Section 6 concludes.

2 Institutional setting and data

2.1 Institutional setting

Four national chains with a combined market share of more than 90% dominate the retail gasoline market.[5] 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 five chains.[6] Chain A is the largest chain, with 30–35% market share. Chains B–D have about 20–25% market share each until August 2008. Between August and December 2008, Chain C begins to operate the 90 gas stations it gained control over after an agreement with Chain D. By December 2008, Chain C's market share has increased to almost 30%, while Chain D's share has fallen to less than 15%.[7] 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



[5]The same chains also sell diesel and dominate the retail diesel market. I focus on retail gasoline. However, retail diesel prices follow the same pattern as retail gasoline prices, with price jumps on the same days and generally the same chains leading price jumps.

[6]Chain A's market share also 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 (Neset, 2010). Independent stations and some small local chains are not included when market shares in the figure are calculated.

[7]Four other mergers are proposed in the sample period. Three of these are vertical, and one horizontal merger is solved with structural remedies (see Appendix B).

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 almost perfectly transparent prices. In Australia and Austria, the frequency of price changes is also regulated, and in some regions of Canada price floor regulation is implemented. Norwegian gasoline stations can change prices as often as they like and are not obliged to report prices to any price comparison website.

The chains have a combination of vertically integrated (stations owned by the chains) and vertically separated retail outlets (owned by the local dealers). About two-thirds of the gas stations are vertically integrated. The dealer-owned stations have exclusive long-term contracts (usually for five years or more) with one of the major chains. The 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 (Foros & Steen, 2013).

Each chain operates with a national "recommended price" (Foros & Steen, 2013). The chains post their recommended price online or communicate it in newsletters. The recommended prices closely trail the wholesale price of gasoline and can change multiple times each week. Station-level prices are posted on large electronic boards next to each station, and the retail chains closely monitor each other's prices at a local level (Konkurransetilsynet, 2015). The actual prices at a given chain's affiliated stations are close to the recommended price at the top of the price cycle, but otherwise prices at stations within the same chain vary between local markets with different competitive conditions (Section 3).

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 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 (Borenstein & Shepard, 1996; Bundeskartellamt, 2011; Byrne & de Roos, 2019). The Norwegian Competition Authority has also concluded that the Norwegian retail gasoline market is subject to tacit collusion (Konkurransetilsynet, 2015).

2.2 Data

Data on gasoline price and volume spells, station characteristics, and the cost of transporting gasoline are obtained from the Norwegian Competition Authority, which collects the data directly from the chains and has merged and prepared the data for analysis.[8].

The data include price and volume periods spells for most of the gas stations in Norway

[8]The data include unleaded 95-octane gasoline prices and volumes. No gas stations sold leaded gasoline during the sample period. The share of non-95 octane gasoline was low during the period, starting at 8% of retail gasoline sales in 2004 and steadily falling to 2% in 2017 (Drivkraft Norge, 2021)

from January 2004 to November 2017.[9] A price spell starts the minute a station changes its price and ends when the station next changes price. The price spells are on average 15 hours long (Table 1). The panel with to-the-minute timing of price changes makes it possible to identify price leaders even when stations change prices multiple times per day. The price spells also allow the construction of a data set with hourly prices that is used in the Figures 2–5 in Section 3 to illustrate how prices develop through the week.

Volume spells show how many liters of gasoline a given station sold during a spell. The start and end times of the volume spells usually match the price spells, but some of the price spells are also split into multiple volume spells of shorter duration. For these spells, the price is unchanged over a longer period, but volume is registered in two or more different spells. For this reason, the average volume spell is only nine hours long (Table 1). I use the high-frequency volume and price spells to create a panel with weekly station-level volume-weighted price–cost margins to estimate the effects of transitions between different market equilibria. For spells starting and ending in different weeks, I assume that volume sold is equal in every minute of the spells, and split the spell volume between the different weeks accordingly.

Similar to multiple other papers, I proxy wholesale prices with the reference wholesale price of gasoline from a price-reporting agency (see Tveito (2021a) for details). The reference price on day t is based on trades that took place during day t and therefore not known to the gasoline chains when they make pricing decisions on day t. Thus, I use the reference price on day $t-1$ as a proxy for the wholesale price on day t. The wholesale price is by far the most important component of marginal costs in gasoline retailing, averaging 3.37 NOK/liter (69% of the tax-excluded retail price) in the sample period (Table 1).

The second most important nontax marginal cost component is the cost of transporting gasoline to each individual station. 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. The chains calculate the cost of transporting gasoline to each individual station and use this information when setting retail prices Foros & Steen (2013). The average transportation cost is 0.15 NOK/liter (Table 1), and the within-station variation from year to year is very small.

There are large VAT and environmental taxes on motor fuels. The VAT increases from 24% to 25% in January 2005 and stays at 25% thereafter. The environmental taxes are

[9] There are a few periods with missing data. Spell data are 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's stations before November 2004 are missing, but daily volume sold and volume-weighted daily prices are available for most of Chain C's stations during this period. Spell data for Chain E are missing between November 2008 and June 2009. Spell volumes for Chain E are missing before 2012, but daily volumes for the chain's stations are available from 2004 to 2009. The daily prices and volumes are used to construct weekly station-level panels (see below) when spell data are not available. Some individual stations are also missing price or volume data in parts of the sample period.

CPI-adjusted January 1 every year, leading to a steady increase from 4.72 NOK/liter in 2004 to 6.23 NOK/liter in 2017.

I combine the reference wholesale price and transportation cost to make a proxy for marginal costs. I use the marginal cost proxy when calculating margins. Throughout the paper, the volume-weighted margin per liter for station i in the time period t is defined as $y_{it} = p_{it} - W_t - tax_t - c_{it}$, where y_{it} is the average volume-weighted margin/liter for station i in time period t, p_{it} is the average volume-weighted price/liter (the average price the consumer paid), W_t is the wholesale price proxy, tax_t is VAT and other taxes, and c_{it} is the station-specific transportation cost.

Price jumps never occur on weekends or any public holidays. The pricing pattern is therefore different in weeks when any of the weekdays are public holidays. In periods with regular price jumps on Monday and later also on Thursday, price jumps either take place the day before or after the holiday or not at all. 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, decreasing the probability that competitors will quickly detect and respond to attempts. Because the paper focuses on transitions between different calendar synchronized price cycles, while the price patterns in weeks with public holidays deviate from the regular patterns, the 5–8 weeks each year when one or more weekdays are public holidays are excluded from the analysis.

The sample restriction leaves us with 10.6 million price spells for 2245 individual stations located in 395 different municipalities in the period from January 2004 to November 2017. The panel with station-level average weekly margins consists of 931 000 observations. Table 1 shows descriptive statistics for the sample.

Table 1: Descriptive statistics, January 2004 to November 2017

	Mean	Std. dev.	Min.	Max.
Price excl tax/L	4.88	1.07	0.45	8.15
Wholesale price/L	3.37	0.81	1.62	5.20
Transportation costs/L	0.15	0.10	0.01	1.15
Margin/L	1.36	0.48	-1.42	4.61
Volume/Week	16674	12151	0	150071
Price spell length in hours	14.6	29.6	0	12749
Volume spell length in hours	9.2	11.9	0	720

Note: The upper five rows in the table show the mean, standard deviation, minimum, and maximum for various variables in the weekly panel. The bottom two rows show the same statistics for the length of price and volume spells.

3 Transition to more frequent price jumps

The market is characterized by asymmetric price cycles during the whole sample period. Prices slowly decrease over multiple days before all chains in quick succession initiate sudden large price jumps for most of their stations (Figure 2).

In this 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 use the following definitions.

(a) Let p_{idt} be the retail price at station i on day d and time of day t, $\boldsymbol{p_{idz}}$ be a vector of all prices at station i on day d before time t, and $\Delta p_{idt} = p_{idt} - min\{\boldsymbol{p_{idz}}\}$. A *station price jump* occurs at station i on day d and time t the first minute of the day when $\Delta p_{idt} \geq 0.25NOK$ (the first time during a given day when the price is at least 0.25 NOK higher than the lowest previous price at the station that day).

(b) I split the stations into one group with price cycles and another group with almost constant prices through the week. During most of 2004 and all years thereafter, all chains carry out Monday price jumps every week. Station i is a *cycling station* in year y if the average difference between the maximum and minimum price on Mondays when market-wide price jumps are carried out is $> 0.05NOK$, and a *non-cycling* station if the difference is $\leq 0.05NOK$.[10]

(c) In the restoration phase of the cycle, each chain carries out price jumps for most of its stations within a very short period of time (typically within 1 hour for the first 75% of the stations that carry out station price jumps, see Tveito (2021a)). A *chain price jump* for Chain C occurs on day d at time t the first minute of the day when *station price jumps* have occurred on at least 30% of Chain C's *cycling stations*.

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

The 0.25 NOK threshold strikes a balance between identifying chain-wide price jumps and excluding more random smaller station-specific price increases (Tveito, 2021a). The main results are robust to variations in the definitions of station and chain price jumps.

From 2004 to 2011, the share of non-cycling stations slowly decreases from 13% to 8% (panel (a) in Appendix Figure A.1). After 2011, the share of non-cycling stations decreases further, and only 1% of the stations are non-cycling in 2017.

[10] 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.

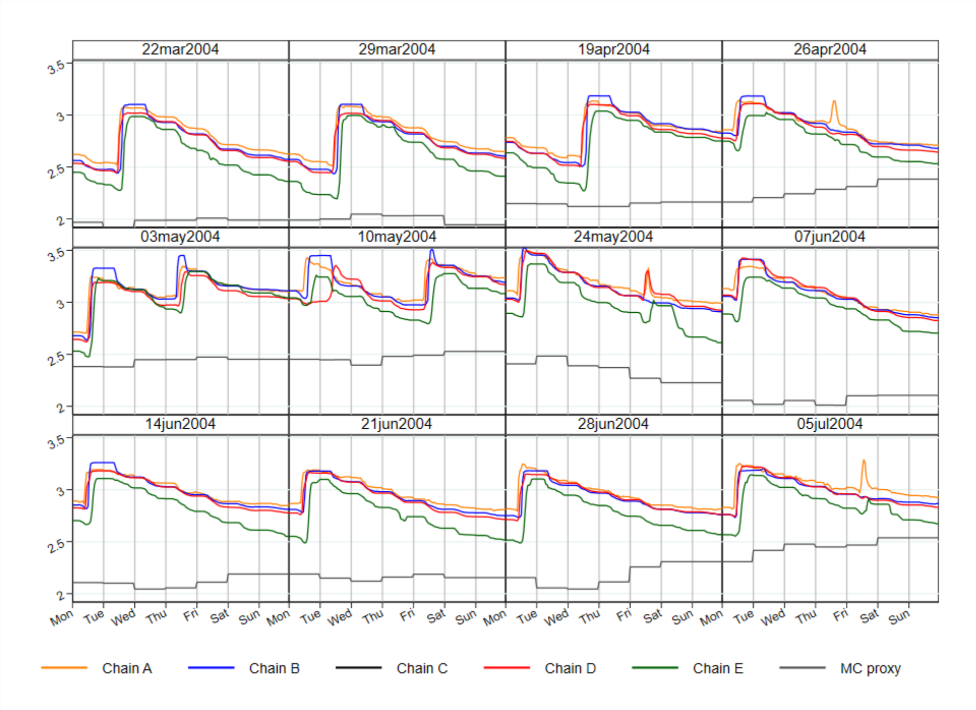
Competitive pressure and cycle amplitude are likely to be the main reasons that some stations are cycling, and some are not. Panel (b) in Figure A.1 reveals that stations with multiple competitors are more likely to be cycling. Prices fall swiftly in the undercutting phase in areas with strong local competition, while stations facing weak competition stay at or close to the recommended price for the whole week (Konkurransetilsynet, 2014). However, each chain increases prices to about the same level—the recommended price adjusted for transportation costs—for affiliated stations when large chain-wide price jumps are initiated (Foros & Steen, 2013). This means that price jumps are larger for stations facing strong local competition. Thus, 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 a cycling station. Cycle amplitude gradually increases, particularly after 2011, due to higher margins at the peak of the cycle, leading to more cycling stations.

3.1 Weekly price jumps on irregular weekdays

In the first 16 weeks of the sample period, successful price jumps occur once a week but on different weekdays—seven Tuesdays, four Wednesdays, and five Thursdays. The first three panels of Figure 2 depict price cycles for the last three of these weeks. There is no regular price leader—all national chains are leading price jumps in one or more weeks (Appendix Figure A.4).[11]

[11]Spell 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 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), making an even earlier price jump by Chain C unlikely. 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 revert to the pre-jump path after the price jumps (Figure 2). See also footnote 14.

Figure 2: Price cycles, March 2004 to July 2004



Note: The figure plots average prices excluding taxes for each chain's cycling stations during each hour of the week. The bottom grey line is the marginal cost proxy. 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 Monday starting the week of April 26.
3. Attempts at Thursday/Friday jumps start on the week of April 26. There are five such attempts in the following weeks, and three of the attempts fail.

3.2 Regular Monday price jumps

The week of April 26, 2004, is the first week in the sample period with a Monday price jump. The jump is initiated by Chain A (Figure 2 and Appendix Figure A.4).[12] The 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 (Figure A.4).

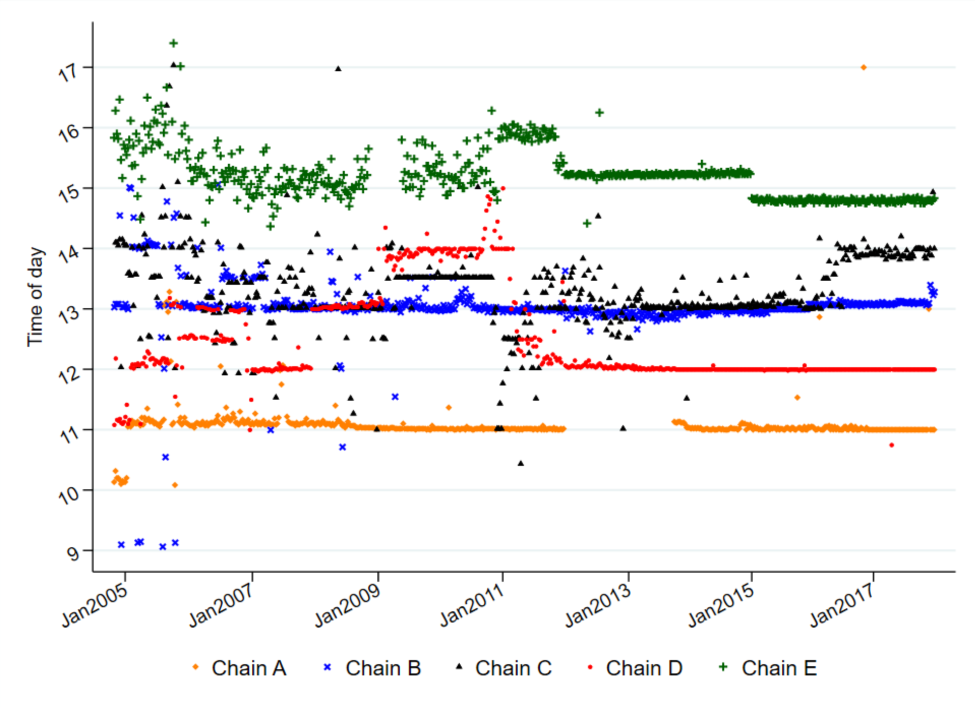
After four months of successful Monday price jumps, Chain A does not initiate a price jump on the first Monday in September 2004 (Appendix Figure A.6). Only Chain D completes a price jump this Monday. When Chain A refrains from initiating a price jump the following Monday as well, no other chains jump. In the next six weeks, price jumps

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

occur on irregular weekdays and different chains lead.

In mid-October 2004, Chain A starts to initiate Monday price jumps again. For the next 13 years, Chain A leads price jumps that are followed by all other chains every Monday. The chain initiates price jumps at 10:00 until January 2005 and at 11:00 for the remainder of the sample period (Figure 3). The three other national chains follow 1–3 hours later, and the smaller regional chain implements price jumps 4–5 hours after the leader.

Figure 3: 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 November 2017. Each dot represents the time-of-day a given chain initiates a *chain price jump*. Data are missing for Chain E from November 2008 to June 2009, and for Chain A from January 2012 to October 2013.

In late August 2005, hurricanes Katrina and Rita landed and caused large supply shocks to the world oil market and extreme volatility in the wholesale price of gasoline until mid-October. A price cycle with weekly jumps in Perth, Australia, collapsed during the supply shocks. The cycle in Perth restarts in January–March 2006 when the largest chain begins to lead price jumps every second week (Byrne & de Roos, 2018). Price cycles also temporarily broke down in a range of U.S. cities in this period (Lewis, 2009). Chain A continues to lead Monday price jumps through this period in the Norwegian market even though some of the Monday jumps are unsuccessful as one or more competitors fail to follow (Appendix Figure A.7). By the end of October, all Monday jumps are successful again.

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. Chain A continues to initiate Monday price jumps during this turbulent period too, and the Monday jumps remain successful (Appendix Figure A.8).

3.3 Transition from 1 to 2 price jumps per week

The week when Chain A introduces regular Monday price jumps is also the first week with two price jumps in the sample period. Chain A also leads a price jump on Thursday this week, but no competitors follow the Thursday jump (Figure 2). Multiple attempts at second price jumps on Thursday or Friday follow the next weeks. However, the second price jumps are mostly unsuccessful (three of five fail) and quickly vanish. Beyond these first attempts, there are no weeks with more than one jump until January 2005.

Starting in January 2005, a second price jump occurs in some weeks on Thursday or Friday. Over the next four years, such jumps happen in 62% of the weeks. 43% of the jumps fail as one or more chains do not follow the leader's price jump. All four national chains lead second price jumps during these four years. Chain A leads most of the jumps in a four-month period in 2005, and Chain B leads most of the jumps after June 2007. The price jumps occur more frequently and have a higher success rate in the periods when Chain A or Chain B provides price leadership regularly.[13]

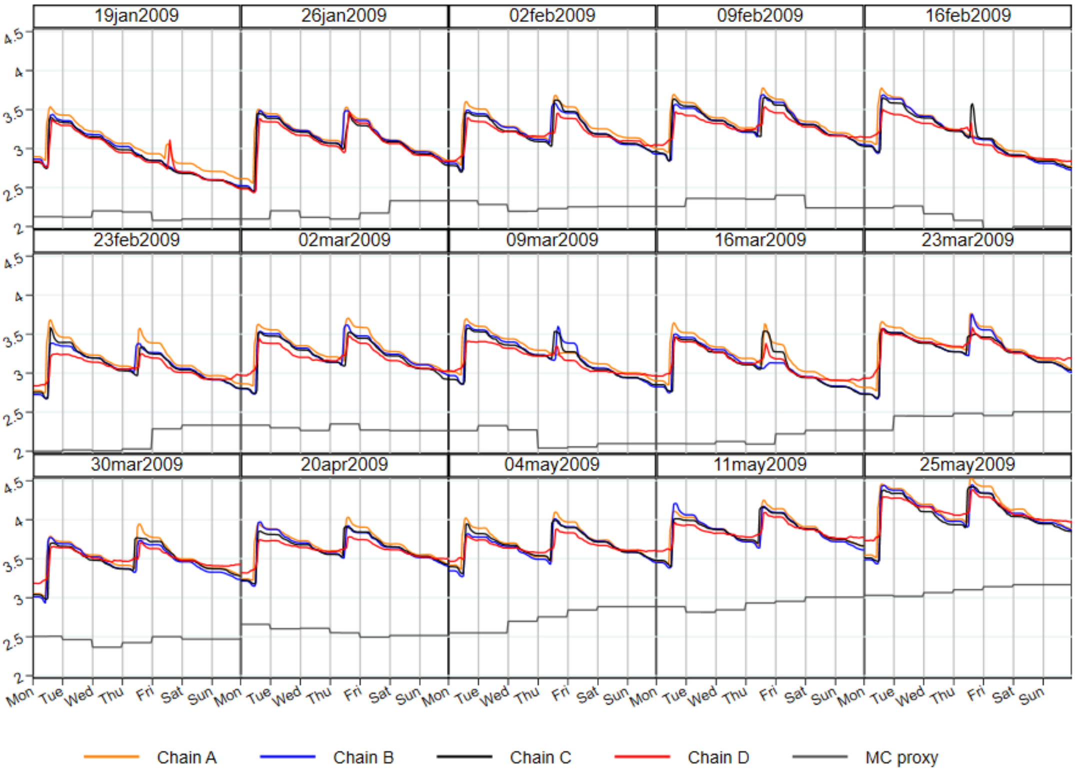
Between August and December 2008, Chain C starts operating 90 gas stations it acquired from Chain D (see Appendix B), increasing Chain C's national market share from 23% to 29% (Figure 1) and creating a clear market share runner-up. A few months later in March 2009, the period with irregular and often unsuccessful second price jumps ends when Chain C begins to initiate Thursday price jumps every week.

Second price jumps occur in all weeks from the start of January until March 16, 2009, but these price jumps frequently fail (Figure 4). After the week of March 23, 2009, price jumps occur every Thursday and are always successful. Figure 5 depicts how Chain B leads most jumps until March 2009. Chain C leads two late (12:30–13:00) jumps in the weeks of March 9, 2009, and March 16, 2009, when no other chains initiate price jumps earlier in the day. The two late jumps are not successful. The following week (March 23, 2009), Chain C initiates a Thursday jump at 11:00 that is successful and continues to do

[13]The four-year period with irregular Thursday/Friday jumps is described in depth by Tveito (2021a). In the period without a regular leader from October 2005 to June 2007, second price jumps occur in 50% of the weeks, and 38% of the jumps are successful. Jump attempts occur every week in the four months when Chain A leads second jumps in April–September 2005, and 88% of these jumps are successful. Second jumps occur in 71% of weeks when Chain B leads regularly after June 2007, and 58% of these jumps are successful.

so in the following months.[14]

Figure 4: Price cycles, January–March 2009



Note: The figure plots average prices excluding taxes for each chain from January to March 2009. The bottom grey line is the marginal cost proxy. Data are missing for Chain E. Weeks with national holidays are omitted. Take note of the following.

1. Thursday/Friday jump attempts fail in the weeks of 19Jan2009, 16Feb2009, 09March2009, and 16March2009.
2. Starting the week of 23March2009, Thursday price jumps occur every week and are always successful.

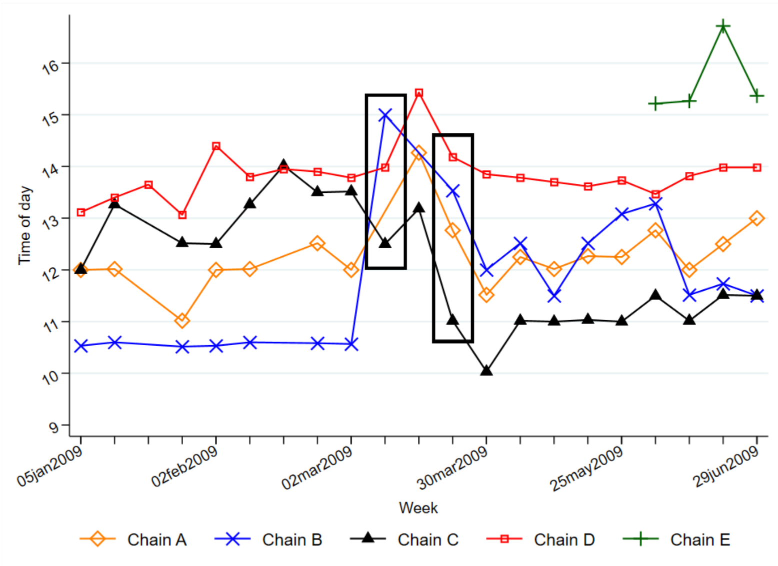
After March 2009, successful Monday and Thursday price jumps are initiated every week for more than eight years. The timing of price jumps is fairly stable once the new

[14] Data are missing for Chain E in this period. Figure 4 shows that prices quickly revert to the pre-jump path during the four weeks when one or more of the other chains do not carry out price jumps. In weeks when all the other chains carry out price jumps, 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 implements price jumps during all weeks when the other four chains implement price jumps. Chain E is almost always the last chain to initiate price jumps, making it very unlikely that the chains should start to lead price jumps in the period with missing data

equilibrium is solidified (Appendix Figure A.5), with the most important change being that Chain D starts to lead the Thursday jumps in 2014 after having experienced a slow but continuous growth in its market share since 2009 (Figure 1 and Figure A.5).

The price pattern changes in November 2017 when the largest chain publicly announces a change in its pricing policy and stops leading Monday price jumps. After this, the market immediately transitions to a new equilibrium where the two largest chains signal future price jumps with changes in their recommended prices (Foros & Ones, 2021).

Figure 5: Time of day of second chain price jumps, first half of 2009



Note: The figure depicts the time of day of Thursday/Friday 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. The jumps in the week of 19Jan2009 occur on a Friday, and all other jumps occur on Thursday. Take note of the following.

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

4 The effect of the transitions on price–cost margins

4.1 Methods

The goal of this section is to estimate the effects of both the transition to regular Monday price jumps and the transition to the additional regular Thursday price jumps.

For each of the transitions, I first estimate fixed-effects models that simply calculate the change in cycling stations' margins from the period before to the period after the transition. However, my main specification is a diff-in-diff model where I compare cycling stations with non-cycling stations to account for trends affecting all stations. I follow Byrne & de Roos (2019) in aggregating to weekly time frequency to net out the within-week price variation. Contrary to Byrne & de Roos (2019) and most other studies of the retail fuel market, I have access to station-level high-frequency volume data that allow me to estimate the development in volume-weighted margins (the margins the firms actually earn) rather than unweighted margins.[15]

The fixed-effects model is run on a sample including all cycling stations and is given by

$$y_{it} = \alpha + \beta_1 Post_t + \delta_{it} + \beta W_t + \gamma_i + \varepsilon_{it}, \tag{1}$$

where y_{it} is the average volume-weighted margin of station i in week t as defined in Section 2.2. $Post_t$ identifies all weeks after (and including) the week the transition occurs. γ_i represents station fixed effects, and δ_{it} represents fixed effects for the number of competing chains in the vicinity of station i in week t.[16] W_t is a vector of variables for the reference wholesale price of gasoline in the current week and lags of the wholesale price in each of the four previous weeks as in Andreoli-Versbach & Franck (2015). β_1 is the coefficient of interest as it gives the change in cycling stations' margins from before to after the transition.

The diff-in-diff model is given by

$$y_{it} = \alpha + \beta_1 Post_t + \beta_2 Post_t \times Cycle_i + W_t \times Cycle_i + \delta_{it} + \gamma_i + \tau_t + \varepsilon_{it}, \tag{2}$$

$Cycle_i$ identifies cycling stations, and τ_t is week fixed effects. The interaction with $Cycle_i$ allows the vector of current and lagged wholesale prices to have a different effect on cycling and non-cycling stations' margins. β_2 is the coefficient of interest as it estimates the change in cycling stations' margins relative to non-cycling stations' margins from before to after the transition.

[15] Tveito (2021b) shows that the development in unweighted margins can be a poor proxy for the development in volume-weighted margins in markets featuring intertemporal price variation.

[16] Station entry and exit gives 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.

4.2 Transition to regular Monday price jumps

The transition to regular Monday price jumps does not in itself increase the frequency of price jumps. However, it does change which days' prices are high and low. Before the transition, both the peak and the trough of the cycle occur at different times each week, but on average prices are highest on Thursday and Friday and lowest on Monday and Tuesday morning (Figure A.2).[17] After the transition, prices are always highest on Monday afternoon and the following days and lowest on Sunday and Monday morning.

Noel (2019) argues that calendar synchronization of price jumps can either increase or decrease volume-weighted margins. 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; 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.

An increase in margins after the transition to Monday jumps in Norway would be surprising as the new high-margin days are not days with particularly high sales volumes (Figure A.2). However, by comparing non-volume-weighted margins calculated based on an unbalanced sample of user-reported price observations 100 days before and after the transition, Foros & Steen (2013) find a large increase in margins (about 0.11 NOK/13.5%) after the transition.[18]

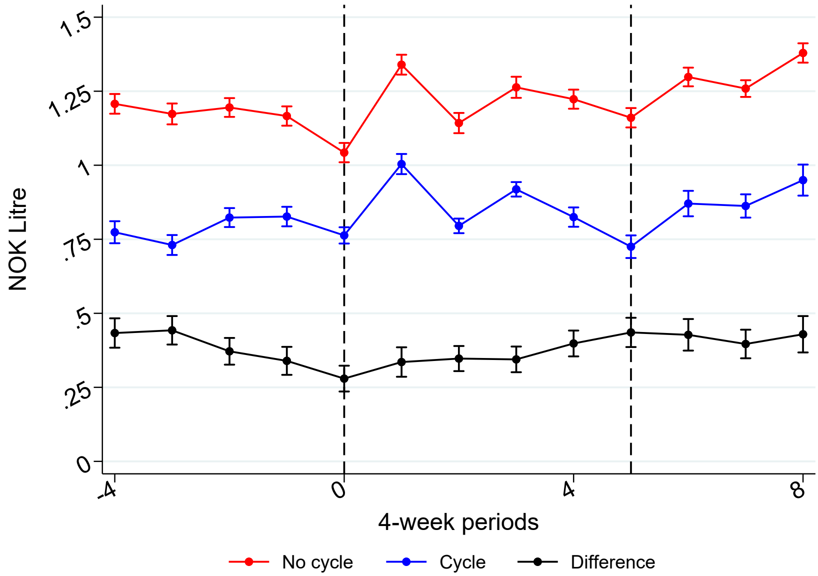
In this paper, the sample period starts only four months before the transition to regular Monday price jumps in the week of April 26, 2004. I limit the post-period to the first eight months after the transition to isolate the effect of the regular Monday jumps from the effect of additional Thursday/Friday price jumps that start to occur in January 2005.

Figure 6 plots average volume-weighted margins across all non-cycling and all cycling stations and the difference between the two groups in four 4-week periods before and nine 4-week periods after the transition to Monday jumps. Cycling stations' margins increase relative to non-cycling stations (the difference between the two groups decreases) in the last 4-week period before the transition to Monday jumps. In the first 4-week period with Monday jumps (period 0), there are two successful second price jumps (Figure 2). Given the positive effect second price jumps have on retail margins (see Section 4.3), it is therefore unsurprising that cycling stations' margins increase slightly relative to the non-cycling stations in period 0. After period 0, both cycling and non-cycling stations' margins are mostly slightly higher than before the transition, but cycling stations' margins do not increase relative to non-cycling stations.

[17] The figure only shows averages per day. On average, prices are lowest on Tuesday morning.

[18] The authors also refer to fixed-effects models reported in a working paper. The fixed-effects models are estimated with the same unbalanced sample of user-reported and non-volume-weighted prices but include observations one year before and after the transition. The authors also find a large positive increase in margins (about 23% increase in margins) using this approach. Note, however, that these estimates are based on a sample that also includes observations for almost four months in 2005 when successful Thursday price jumps occur in addition to the Monday jumps in about half of the weeks.

Figure 6: Margins for *non-cycling* and *cycling* stations, January 2004 to April 2005



Note: The figure depicts weekly volume-weighted average margins across all *non-cycling* and *cycling* stations. The lines plot results from the regression $y_{it} = \sum_{\tau=-4}^{8} \gamma_\tau + \sum_{\tau=-4}^{8} \gamma_\tau \times cycle_i + \varepsilon_{it}$, where y_{it} is volume-weighted margins for station i in week t, γ_τ identify the different 4-week periods, and $cycle_i$ identify cycling stations. The 95% c.i are also included. The first dashed vertical line marks the first 4-week period with regular Monday price jumps, and the second line marks the 6-week period when the cycle reverted to the old pattern with irregular price jump days (this period is expanded to six weeks, and the period before and after it is shortened to three weeks each to separate the reversion period from the other 4-week periods).

Results from the fixed-effects model without controlling for wholesale prices are reported in the first column of results in Table 2.[19] The results suggest that cycling station's margins are 0.09 NOK higher in the period after the transition to Monday jumps. When controlling for changes in the wholesale price, the effect falls to 0.05 NOK.

There is a large seasonal variation in retail margins. Margins in January–April are substantially lower than margins in the following months (Appendix Figure A.3).[20] The fact that the pre-period consists of four months when margins are normally lower than in the post-period raises concerns about Eq. 1's ability to identify the true effect of the

[19] In both the fixed-effects model and the diff-in-diff model, I also account for the 6-week period with reversion to the old pattern with irregular price jump days. I let $Post_t$ identify the weeks after the transition except for the six weeks when prices revert to the old pattern. Rev_t identifies the six reversion weeks. The fixed-effects model is then $y_{it} = \alpha + \beta_1 Post_t + \beta_2 Rev_t + \beta_3 W_t + \delta_{it} + \gamma_i + \varepsilon_{it}$, and the diff-in-diff model is $y_{it} = \alpha + \beta_1 Post_t + \beta_2 Post_t \times Cycle_i + \beta_3 Rev_t + \beta_4 Rev_t \times Cycle_i + \delta_{it} + \gamma_i + \tau_t + \varepsilon_{it}$.

[20] The seasonal variation is similar for cycling and non-cycling stations.

transition to regular Monday price jumps. I account for seasonal variation by including observations from 2004 to 2017 and including month-of-year and year fixed effects in Eq. 1.[21] Controlling for seasonal variation in the fixed-effects model further reduces the estimate of the transition to -0.02 NOK (column 3 in Table 2. The diff-in-diff models also give estimates close to zero (columns (4) and (5) in Table 2).

Table 2: Transition to regular Monday price jumps

	(1)	(2)	(3)	(4)	(5)
Post	0.09***	0.05***	-0.02		
	(0.01)	(0.01)	(0.01)		
Post × Cycle				0.03	0.02
				(0.02)	(0.01)
Constant	0.78***	0.84***	1.54***	0.86***	0.89***
	(0.01)	(0.06)	(0.02)	(0.01)	(0.02)
Week FE	No	No	No	Yes	Yes
Wholesale price+Lags	No	Yes	Yes	No	Yes
Account for seasonal variation	No	No	Yes	No	No
Account for reversion period	Yes	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes	Yes
Competitors FE	Yes	Yes	Yes	Yes	Yes
Observations	55376	52168	866149	63171	59534
R2	0.53	0.59	0.69	0.70	0.71

Notes: The 1st column displays results from the fixed-effects model in Eq. 1 accounting for the reversion period. The model in the 2nd column also adjusts for changes in the wholesale price, and the 3rd column also accounts for seasonal variation. The 4th column shows results from the diff-in-diff model in Eq. 2, and the diff-in-diff model in the 5th column also adjusts for changes in the wholesale price. Standard errors are clustered at the municipality level and are shown in parentheses. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

The short pre- and post-periods limit the robustness of the results somewhat, but overall the evidence suggests that the transition to regular Monday price jumps did not have a substantial effect on retail margins. The difference in results in this study and Foros & Steen (2013)'s study could be due to the fact that their analysis is based on an unbalanced and non-volume-weighted panel of user-reported prices, that they do not account for seasonal variation, or because the pre- and post-periods differ. When I do not account for seasonal variation, estimates in this study are closer to their results.

4.3 Transition to regular Thursday price jumps

I focus on the period from two years before to two years after the transition to regular Thursday jumps.[22] There are successful second price jumps in some of the weeks in the

[21] $Post_t$ still only identifies the weeks in the first eight months after the transition to regular Monday jumps. The result that the transition to regular Monday jumps did not have a substantial effect on retail margins is robust to changing how many years after 2004 are included in the model.

[22] The results in Table 3 are robust to decreasing the pre- and post-periods to one year before and after the transition or increasing the pre- and post-periods to three years. The estimates from the fixed-effects

pre-period. Thus, I estimate the effect of a transition from an equilibrium with regular Monday jumps and also Thursday/Friday price jumps in some weeks, to an equilibrium with successful price jumps on Monday and Thursday every week. The development in maximum margins on Monday and Thursday in Figure 8 illustrates this nicely—before the transition, maximum Thursday margins are lower than maximum Monday margins, but after the transition maximum margins on those two days are almost identical because prices are increased to the same level on both Monday and Thursday.

Given that the other characteristics of the cycle, such as the size of the jumps and how fast prices fall in the undercutting phase of the cycle, remain unchanged, it is natural to expect that the more frequent price jumps increase the chains' average margins. However, according to Noel (2019), more frequent price jumps need not be anticompetitive. The author argues that price jumps should occur only when they are competitively necessary, even if the frequency of jumps increases. With more frequent price jumps, the size of the jumps should competitively adjust downwards to compensate for fewer rounds of undercutting so that the bottom of the cycle is reached faster. Noel (2019)'s insight implies that margins at the bottom of the cycle should be the same after the jump frequency increases, but the smaller price jump size should decrease margins at the top of the cycle, i.e., the maximum margin on Monday should decrease.

Figure 7 reveals that the Monday maximum margin does not decrease after the transition—the mitigating effect related to decreasing margins at the top of the cycle that Noel (2019) predicts does not materialize. The figure also shows that the minimum margin on Monday (the margin at the bottom of the cycle) increases substantially after the transition. Contrary to Noel (2019)'s predictions, Monday price jumps are carried out as before the transition even though the pre-jump margins are higher.

Figure 8 shows that the trends in cycling and non-cycling stations' margins are fairly similar in the pre-period, but with a small gradual increase in cycling stations' margins relative to the non-cycling stations' margins.[23] Both the cycling and non-cycling stations' margins are higher in the post-period than in the pre-period. The cycling stations' margins also increase relative to the non-cycling stations' immediately after the transition (in period 0) and stay closer to the non-cycling stations' margins through the next seven 13-week periods, indicating that the transition to regular Thursday price jumps increases the cycling stations' margins.

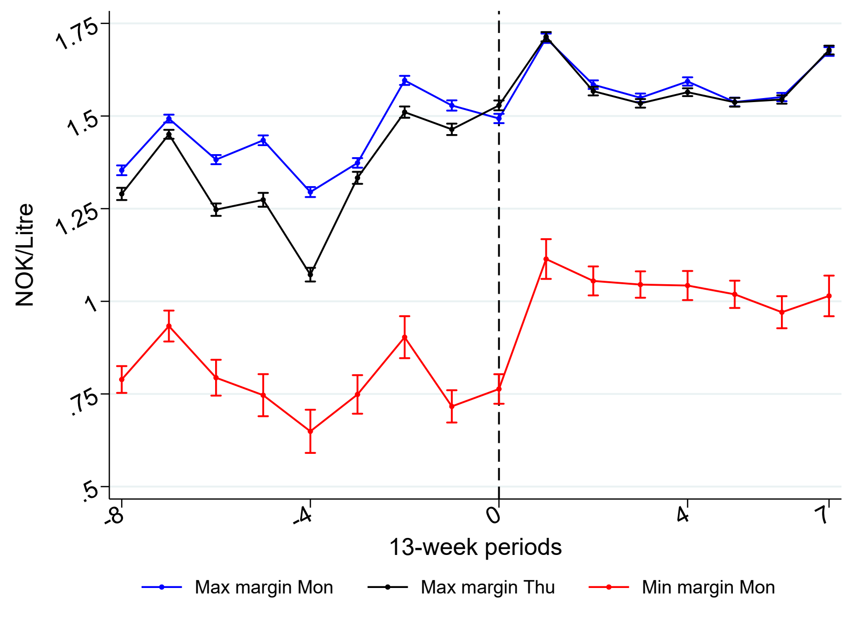
Table 3 shows a final set of results related to the transition to Thursday price jumps based on Eqs. 1 and 2.[24] In line with the development in the cycling stations' prices

model in column (1) change $\leqslant$0.04 NOK, and the diff-in-diff estimates in columns (2)–(4) change $\leqslant$0.02 NOK.

[23] I exclude the few stations that change cycling status from non-cycling to cycling or vice versa in the years 2007–2011 from the analysis. The results are robust to including the excluded stations as well.

[24] All specifications in Table 3 include controls for current and lagged wholesale prices. All results are very similar ($\leqslant$0.02 NOK difference) without the wholesale price controls.

Figure 7: Min. and max. margins

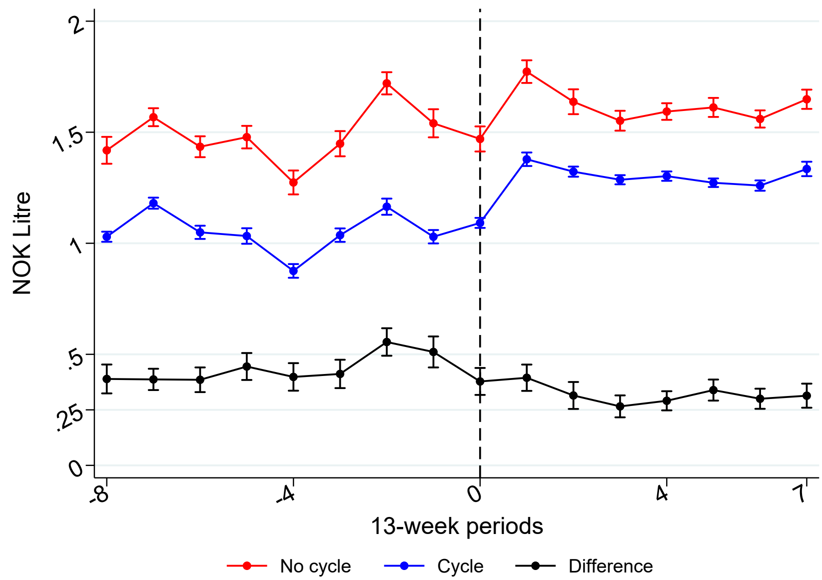


Note: The figure depicts the development in cycling stations' maximum margin on Monday, maximum margin on Thursday, and minimum margin on in the two years before and after the transition to regular Thursday price jumps. The lines plot results from the regression $y_{it} = \sum_{\tau=-8}^{7} \gamma_\tau + \varepsilon_{it}$, where y_{it} is maximum Monday margin, maximum Thursday margins, and minimum Monday margin for cycling station i in week t. γ_τ identify the different 13-week periods. The 95% c.i are also included. The dashed vertical line marks the first 13-week period with regular Thursday price jumps.

in Figure 8, the results from the fixed-effects model in the first column of the table show that average volume-weighted margins for cycling stations are 0.26 NOK higher in the two years following the transition than in the two years before the transition. This increase in volume-weighted margins does, however, include the general increase in margins experienced by the control group consisting of non-cycling stations. The results from the diff-in-diff model in column (2) show that cycling stations' margins increase by 0.10 NOK after the transition relative to the non-cycling stations. As average margins in the two years before the transition are 1.05 NOK, a 0.10 NOK increase equals an increase of about 10%.

The non-cycling stations do not provide a perfect counterfactual. Tveito (2021b) shows that the share of cycling stations' volume that is sold on Sunday and Monday morning (the time of week when prices are lowest) increases slowly from 2004 to 2009 Q1. All else equal, average weekly volume-weighted margins decrease when more consumers substitute purchases to the low-price part of the cycle. The trend towards more volume sold in the

Figure 8: Margins, cycling and non-cycling stations



Note: The figure depicts the development in volume-weighted average margins across all *non-cycling* and *cycling* stations in the two years before and after the transition to regular Thursday price jumps. The difference between cycling and non-cycling stations' margins is also plotted. The lines plot results from the regression $y_{it} = \sum_{\tau=-8}^{7} \gamma_\tau + \sum_{\tau=-8}^{7} \gamma_\tau \times Cycle_i + \varepsilon_{it}$, where y_{it} is volume-weighted margins for station i in week t, γ_τ identify the different 13-week periods, and $Cycle_i$ identify cycling stations. The 95% c.i are also included. The dashed vertical line marks the first 13-week period with regular Thursday price jumps.

low-price part of the cycle and lower average prices would probably have continued at the cycling stations in a counterfactual without regular Thursday price jumps, but the stations in the control group do not take into account this trend. Thus, the cycling stations' volume-weighted margins would probably have decreased slightly relative to the non-cycling stations without the introduction of regular Thursday jumps. This implies that results from a diff-in-diff model of cycling stations change over time in volume-weighted margins with non-cycling stations as a control group contains a slight downward bias.

The Thursday jumps increase prices around noon on Thursday, and prices stay at a higher path until around noon the next Monday. The main effect of the transition to regular Thursday jumps should thus be to increase prices on Thursday to Monday. We therefore expect the increase in average weekly margins to be driven by large margin increases in this part of the week. If other characteristics of the cycle—such as how fast prices fall in the undercutting phase—do not change after the transition, we expect to

Table 3: Transition to regular Thursday price jumps

	(1)	(2)	(3)	(4)
Post	0.26***			
	(0.01)			
Post × Cycle		0.10***	0.01	0.13***
		(0.01)	(0.01)	(0.01)
Constant	1.07***	1.15***	1.30***	1.11***
	(0.02)	(0.01)	(0.01)	(0.01)
Week FE	No	Yes	Yes	Yes
Wholesale price controls	Yes	Yes	Yes	Yes
Competitors FE	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes
Observations	205892	219740	219739	219740
R2	0.51	0.63	0.55	0.63
F-value	775.94	20.98	11.62	25.38

Note: Column (1) displays results from Eq. 1. Column (2) displays results from Eq. 2. Column (3) displays results from a model similar to Eq. 2, where y_{it} is the average volume-weighted margins over Tue and Wed for station i in week t. Column (4) displays results from a model similar to Eq. 2, but where y_{it} is the average volume-weighted margins over Monday, Thursday, Friday, Saturday, and Sunday for station i in week t. *Post* identifies all weeks after March 23, 2009. The sample period is March 2007 to March 2011. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

see no change in cycling stations' Tuesday and Wednesday margins (the two full days after the Monday jumps and before the Thursday jumps). Column (3) in Table 3 shows results from Eq. 2 with average margins across Tuesday and Wednesday as the dependent variable. Reassuringly, the cycling stations' margins on these days do not increase relative to non-cycling stations after the transition. The final column in the table shows results from Eq. 2 with average margins across Thursday–Monday as the dependent variable. As expected, cycling stations' margins on these days increase more than average weekly margins (0.13 vs 0.10 NOK).

Chain C acquired 90 stations from Chain D just prior to the transition to regular Thursday jumps (see Appendix B). A final concern is that unilateral effects from the merger, rather than the transition to regular Thursday price jumps, are driving the 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 has conducted an ex post evaluation of the merger and found, employing a diff-in-diff model, 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 (OECD, 2013).

Summing up, Noel (2019)'s prediction of lower margins at the top of the cycle when the frequency of price jumps increases does not materialize, and the evidence suggests that the transition to regular Thursday jumps increases cycling stations' volume-weighted margins by at least 0.10 NOK (10%). The effect is driven by an increase in margins in the part of the week after the Thursday jumps are initiated and before the next Monday jumps. Coordination of two weekly price jumps not only helps the chains to avoid the war of attrition game at the very bottom of the cycle but also enables them to avoid large parts of cycle trough while still reaping the benefits of high prices at the peak of the cycle.

As shown in Section 3.3, there are successful Thursday price jumps in about 40% of the weeks in the two years before the transition to regular Thursday jumps. Thus, in this section I estimate the effect of transitioning from a pattern with one price jump in some weeks and two price jumps in other weeks to a pattern with two price jumps every week. The total effect of transitioning from one to two price jumps per week is larger. Tveito (2021a) estimate that in the four years with irregular Thursday jumps, a Thursday jump increases the average weekly margins in a given week by 25% compared with a counterfactual without Thursday jumps.

5 Discussion

We have seen that the market gradually transitioned from one price jump per week on irregular weekdays to a more profitable equilibrium with two price jumps per week on regular weekdays. The calendar synchronized price jumps are remarkably stable over time. In this section, I argue that regular price leadership provided by the large retail chains played a key role in coordinating the transition to more frequent price jumps and ensuring that the price jumps continue to occur at the same time over a very long period of time. Furthermore, I highlight the connection between firms' size and price leadership.

5.1 Price leadership and transition to more frequent price jumps

The Monday price jumps emerge when the largest chain begins to initiate price jumps every Monday. From the very start, the chain's jumps are matched by all other chains. When the chain stops providing price leadership for six weeks, no other chains initiate Monday jumps, and prices revert to the old pattern with price jumps on irregular weekdays. After the six weeks without Monday jumps, the largest chain initiates Monday price jumps every week for the next 13 years. The Monday price jumps remain successful during all these years, even through periods with large wholesale price volatility when price cycles in other countries have been shown to break down.

During the four years with irregular second price jumps, both the frequency and success rate of the jumps are higher in periods when one of the chains acts as a regular leader of the second jumps. The transition to regular Thursday jumps occurs when the second-largest chain starts to lead Thursday jumps every week, and the jumps are immediately successful. The pattern with price jumps on both Monday and Thursday is stable for the next eight years until the transition to a new equilibrium is once again initiated by the largest chain.

The evidence suggests that regular price leadership was instrumental to coordinate the transition to more frequent price jumps and to keep the equilibrium with calendar synchronized jumps stable over a very long time period.

Existing empirical evidence on how firms coordinate on collusive equilibria is sparse, but in a recent paper Byrne & de Roos (2019) offer a compelling analysis of how large retail gasoline chains in Perth, Australia, use price leadership to coordinate a transition to an equilibrium with higher profit margins. There are, however, some interesting differences in the institutional settings and how the transitions occur in Norway and Perth. Perth's FuelWatch program requires gasoline retailers to submit next-day station-level prices to the government every day before 14:00, without knowing rivals' next-day prices. Prices are then posted on a webpage and are fixed at these levels the next day. Norwegian gas stations are not subject to any price regulation.

After three years of experimentation and price leadership, calendar synchronized Thursday price jumps are established as a focal point for price increases in Perth. Instead of trying to initiate price jumps on other weekdays in addition to the Thursday jumps, the leader in Perth manages to transition the market to a pricing pattern with a fixed price cut size per day in the undercutting phase of the cycle, and also greatly increases margins at the top of the cycle. This way, price–cost margins increase on all weekdays. In the Norwegian market, margins at the top of the cycle increase gradually during the whole sample period, but I find no evidence of standardization of the size of price cuts.[25] Instead, the main margin-enhancing event in Norway is the transition from one to two price jumps per week.

The different regulatory regimes provide a possible explanation of the different ways of coordinating margin-enhancing equilibria that chains in Perth and Norway ended up with. The firm providing price leadership is alone with a high price for some time until the other firms match the price increase. In this period, the leader loses volume to competitors. The volume loss related to leading imposes a cost on the leader and can thus limit incentives to lead price increases. Perth's FuelWatch regulation forces the price leader to be alone with a high price for a full day before competitors can match the price increase. In Norway, the other chains match the leader's price increase after only a few hours. The requirement in Perth to post prices online also increases price transparency, perhaps giving higher own price elasticities in Perth than in Norway. Tveito (2021a) shows that the volume loss related to leading the second price jumps in Norway is low, and that the leader does not lose profit relative to the followers. Due to the longer period alone with a high price and higher price transparency in Perth, it seems much more costly to provide price leadership

[25] Margins at the top of the cycle increase at a fairly steady pace until 2012. After 2012, margins at the top of the cycle increase at a faster pace. However, prices fall faster in the undercutting phase of the cycle after 2012, partly mitigating the effect of higher margins at the peak of the cycle.

for more frequent price jumps in Perth than in Norway.

By contrast, coordinating prices in the undercutting phase of the cycle is less complicated in Perth than in Norway. The chains in Perth only need to coordinate on the size of the daily price decrease, while coordination of prices in the undercutting phase in Norway would require firms to agree on the number of price changes per day, the timing of the price changes, and the size of the price decreases.

Summing up, I find that large retail chains use price leadership to coordinate a transition to more frequent price jumps and to sustain the new equilibrium. The absence of regulation of the timing of price changes and lack of measures to increase price transparency decrease the cost of leading and increase the complexity of coordinating prices in the undercutting phase of the cycle. In such an unregulated environment, a transition to an equilibrium with more frequent price jumps is probably easier to coordinate than transitions to other margin-enhancing equilibria that have been observed in markets with price regulations.

5.2 Firm size

The results from Section 3 also contribute to our understanding of the connection between firm size and price leadership—in particular for retail gasoline markets with price cycles. Price leadership is already comprehensibly studied in the retail gasoline market in Perth. Wang (2009) uses a combination of hourly and twice-a-day observations to show that the largest chain in this market was acting as a regular price leader in the six months before the regulation prohibiting more than one price change per day was introduced, and that just after the regulation came into effect, multiple large chains were rotating price leadership. Byrne & de Roos (2019) show that the largest chain in Perth is once again acting as a regular price leader several years later.

High-frequency price changes and data of lower frequency limit the robustness of the previous studies of price leadership in the more typical case without price regulation. Noel (2007), Atkinson (2009), and Lewis (2012) provide some evidence that price jumps in the USA and Canada are led by retail gasoline chains controlling a large number of stations, but not necessarily the largest chain. Noel (2007) and Lewis (2012)'s studies are based on observations with 12 hours and daily data frequency, meaning that the results are only a rough indicator of the retailers whose stations are most likely to jump early. Even in Atkinson (2009)'s study where prices are observed every two hours, the ability of stations to respond quickly makes it fairly difficult to identify price leaders. In addition, Atkinson (2009)'s study is based on a sample of only 26 stations and over only 103 days. Lemus & Luco (2021) find that the largest chain is the most frequent price leader in the retail gasoline market in Chile where prices only change about once per week.

With the panel of to-the-minute information on price changes for almost all Norwegian gas stations over a 14-year-long period, I provide several observations related to firm size and price leadership. First, the largest chain is the regular leader of Monday price jumps for 13 consecutive years. The chain initiates large price jumps within about an hour for affiliated stations located in all parts of Norway, and the price jumps are always followed by the other chains.

Second, the second price jumps start to occur every week and achieve a 100% success rate when Chain C starts to lead every Thursday in March 2009. The transition occurs just a few months after a transaction that made Chain C a clear runner-up in terms of national market share. The 90 stations Chain C acquired were spread out in different parts of Norway but were almost exclusively located in populous areas with other Chain C stations.[26] The local overlap with existing Chain C stations led to an increase in average local market share for Chain C's stations of the same magnitude as the increase in the national market share.[27]

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 after its market share increased over several years.

Taken together, evidence of size differences of both between-chain and within-chain changes in size shows that having a large network of gas stations is positively correlated with being a regular price leader. Price jumps are also more frequent and more often successful when the largest chains lead. The correlation between size and price leadership is consistent with theoretical models of price leadership in markets with Edgeworth cycles where firms with a large share of retail outlets earn greater profits at high prices and therefore have stronger incentives to lead price jumps (Eibelshäuser & Wilhelm, 2018; Eckert, 2003).

6 Concluding remarks

In this paper, I employ a unique data set of to-the-minute price data to show how retail gasoline chains use price leadership to both initiate and sustain a new equilibrium with price jumps every Monday and Thursday. I argue that lack of price regulation makes it easier to enhance margins by the transition to more frequent price jumps rather than by inflating margins on all days of the price cycle as in the regulated market studied by Byrne & de Roos (2019).

Contrary to what Noel (2019) postulates, the transition to more frequent price jumps

[26] 93% of the stations were located within 15 minutes' drive time of another Chain C station.

[27] The average volume-based local market share of Chain C's stations 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 market share of the center 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.

leads to a substantial increase in average volume-weighted margins. The results suggest that regulators should be concerned with increases in the frequency of price jumps.

What can regulators do to destabilize such high-margin equilibrium? Foros & Steen (2013) argue that the retail gasoline chains in Norway de facto simultaneously decide to hike prices to the recommended price. They suggest that the publication of recommended prices increases transparency among competitors, facilitates horizontal coordination, and should be banned. Due to my extremely high-frequency price data, I can show that the price hikes are sequential rather than simultaneous. A leader first hikes prices for its stations, and the other chains follow within a few hours. The non-leaders therefore observe the leader's new price level before they hike prices. Thus, the leader can create a focal point for the new price level without the publication of recommended prices. The recommended prices appear to be redundant for coordinating the price hikes.[28]

Other approaches for regulators can be to make it harder or more costly to act as a price leader. Weakening the chain headquarters' control over dealer-owned outlets' prices would make it harder to initiate chain-wide price jumps (Wang, 2009). Tveito (2021a) argues that policies that inform customers about when price jumps occur and which firms act as leaders and followers can increase the cost of leading price jumps.

Finally, I find that price leadership is provided by large chains, and the jumps are more often successful when one of the largest chains leads. The results are consistent with Byrne & de Roos (2019)'s conclusion that firm asymmetries can facilitate collusion because a dominant firm can act as a price leader and initiate price coordination. Furthermore, the solidification of Thursday price jumps after a transaction that created a clear number two in the market may indicate that mergers increasing the size of the runner-up can give rise to an additional price leader and equilibria with more frequent price increases.

[28]The publication of *future changes* in recommended prices can, however, help firms coordinate price jumps (Foros & Ones, 2021).

References

Andreoli-Versbach, P., & Franck, J. (2015). Endogenous Price Commitment, Sticky and Leadership Pricing: Evidence from the Italian Petrol Market. *International Journal of Industrial Organization*, *40*, 32-48.

Atkinson, B. (2009). Retail Gasoline Price Cycles: Evidence from Guelph, Ontario Using Bi Hourly, Station-Specific Retail Price Data. *Energy Journal*, *30*(1), 85-109.

Borenstein, S., & Shepard, A. (1996). Dynamic Pricing in Retail Gasoline Markets. *RAND Journal of Economics*, *23*(3), 429-451.

Bundeskartellamt. (2011). Fuel Sector Inquiry.

Byrne, D. P., & de Roos, N. (2018). Online Appendix: Learning to Coordinate - A Study in Retail Gasoline.

Byrne, D. P., & de Roos, N. (2019). Learning to Coordinate - A Study in Retail Gasoline. *American Economic Review*, *109*(2), 591-619.

Cabral, L., Duerr, N., Schober, D., & Voll, O. (2021). Price Matching Guarantees and Collusion: Theory and Evidence from Germany. *Working Paper*.

Chilet, J. A. (2018). Gradually Rebuilding a Relationship: The Emergence of Collusion in Retail Pharmacies in Chile. *Working Paper*.

Clark, R., & Houde, J. F. (2013). Collusion with Asymmetric Retailers: Evidence from a Gasoline Price-Fixing Case. *American Economic Journal: Microeconomics*, *5*(3), 97-123.

de Roos, N., & Smirnov, V. (2020). Collusion with Intertemporal Price Dispersion. *RAND Journal of Economics*, *51*(1), 158-188.

Drivkraft Norge. (2021). *Salg av Bransjens Hovedprodukter tilbake til 1952 (Sale of the Industries Main Products back to 1952.* Retrieved 2021-08-25, from https://www.drivkraftnorge.no/siteassets/dokumenter--filer/statistikk/salg/salg-tilbake-til-1952-til-hjemmesiden.xlsx

Eckert, A. (2003). Retail Price Cycles and the Presence of Small Firms. *International Journal of Industrial Organization*, *21*(2), 151-170.

Eckert, A. (2013). Empirical Studies of Gasoline Retailing: A Guide to the Literature. *Journal of Economic Surveys*, *27*(1), 140-166.

Eibelshäuser, S., & Wilhelm, S. (2018). High-Frequency Price Fluctuations in Brick-and-Mortar Retailing. *Working paper*.

Foros, Ø., & Ones, M. N. (2021). Coordinate to Obfuscate? The Role of Prior Announcements of Recommended Prices. *Economics Letters*, *198*.

Foros, Ø., & Steen, F. (2013). Vertical Control and Price Cycles in Gasoline Retailing. *Scandinavian Journal of Economics*, *115*(3), 640-661.

Fung, M. K. (2018). Deposit Rate Asymmetry and Edgeworth Cycles after Hong Kong's Interest Rate Deregulation, in (ed.) Banking and Finance Issues in Emerging Markets. *International Symposia in Economic Theory and Econometrics*, *25*, 105-121.

Green, E. J., Marshall, R. C., & Marx, L. M. (2014). Tacit Collusion in Oligopoly. *The Oxford Handbook of International Antitrust Economics, Volume 2, Edited by R. D. Blair and D. D. Sokol.*

Harrington, J. E. (2017). A Theory of Collusion with Partial Mutual Understanding. *Research in Economics*, *71*, 140-158.

Hasbrouck, J. (2018). High-Frequency Quoting: Short-Term Volatility in Bids and Offers. *Journal of Financial and Quantitative Analysis*, *53*(2), 613-641.

Hauschultz, F. P., & Munk-Nielsen, A. (2017). Priscykler i Markedet for Receptpligtig Medicin efter Patentudløb (Price Cycles in the Market for Prescription Medicin after Patent Expiration). *Konkurrence- og Forbrugerstyrelsen: Velfungerende Markeder*.

Konkurransetilsynet. (2014). Drivstoff Markedet i Norge - Marginøkning og Ny Pristopp (The Norwegian Fuel Market – Margin increase and a New Price Peak).

Konkurransetilsynet. (2015). Vedtak V2015-29 - St1 Nordic OY - Smart Fuel AS - Konkurranseloven § 16 jf. § 20 - Inngrep mot Foretakssammenslutning (Decision V2015-29 - St1 Nordic OY - Smart Fuel AS - the Competition Act § 16 jf. § 20 - Intervention Against Merger).

Lemus, J., & Luco, F. (2021). Price Leadership and Uncertainty about Future Costs. *Journal of Industrial Economics*, *69*(2), 305-337.

Lewis, M. S. (2009). Temporary Wholesale Gasoline Price Spikes Have Long-Lasting Retail Effects: The Aftermath of Hurricane Rita. *Journal of Law and Economics*, *52*, 581–605.

Lewis, M. S. (2012). Price Leadership and Coordination in Retail Gasoline Markets with Price Cycles. *International Journal of Industrial Organization*, *30*(4), 342–351.

Markham, J. W. (1951). The Nature and Significance of Price Leadership. *American Economic Review*, *41*(5), 891-905.

Maskin, E., & Tirole, J. (1988). A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles. *Econometrica*, *56*(3), 571-599.

Neset, G. P. (2010). Prisstøttesystemet i Bensinmarkedet (The Price Support System in the Gasoline Market).

Noel, M. D. (2007). Edgeworth Price Cycles: Evidence from the Toronto Retail Gasoline Market. *Journal of Industrial Economics*, *66*(2), 69-92.

Noel, M. D. (2019). Calendar Synchronization of Gasoline Price Increases. *Journal of Economics and Managment Science*, *28*(2), 355-370.

OECD. (2013). Competition in Road Fuel.

Seaton, J. S., & Waterson, M. (2013). Identifying and Characterising Price Leadership in British Supermarkets. *International Journal of Industrial Organization*, *115*(31), 392-403.

Tveito, A. (2021a). The Costs and Benefits of Price Leadership – Evidence from Retail Gasoline. *Working Paper*.

Tveito, A. (2021b). Dynamics in Intertemporal Substitution – Evidence from Retail Fuel. *Working Paper*.

Wang, Z. (2008). Collusive Communication and Pricing Coordination in a Retail Gasoline Market. *Review of Industrial Organization*, *32*(1), 32-52.

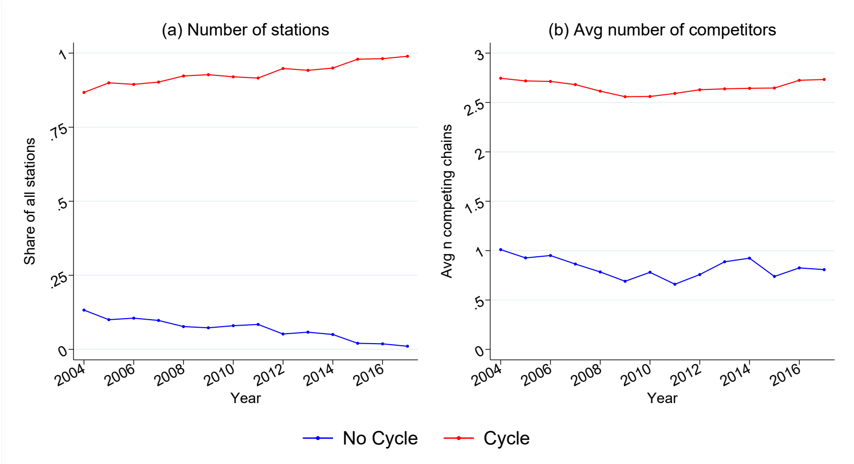
Wang, Z. (2009). (Mixed) Strategy in Oligopoly Pricing: Evidence from Gasoline Price Cycles Before and Under a Timing Regulation. *Journal of Political Economy*, *117*(61), 987-1030.

Zhang, M., & Feng, J. (2011). Cyclical Bid Adjustments in Search-Engine Advertising. *Management Science*, *57*(9), 1703-1719.

Appendices

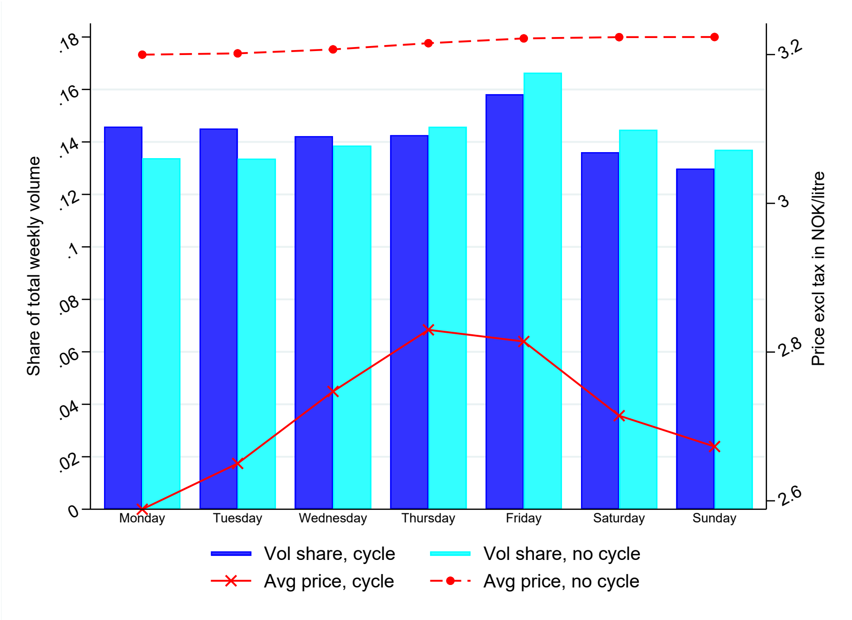
A Additional figures

Figure A.1: Cycle groups, shares and number of competitors



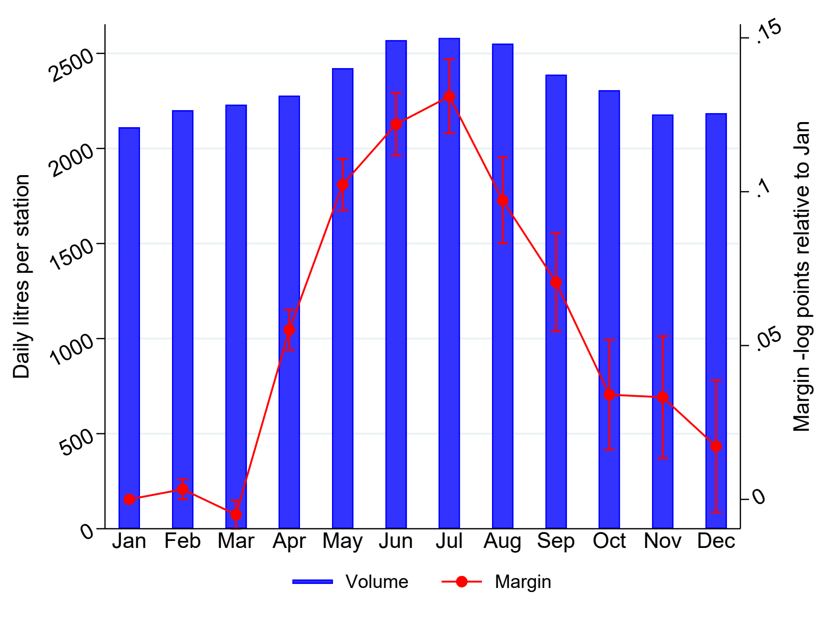
Note: Panel (a) plots the share of stations that are cycling and non-cycling each year. Panel (b) plots average number of competing chains present within 15 min drive time of each station for the same groups.

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



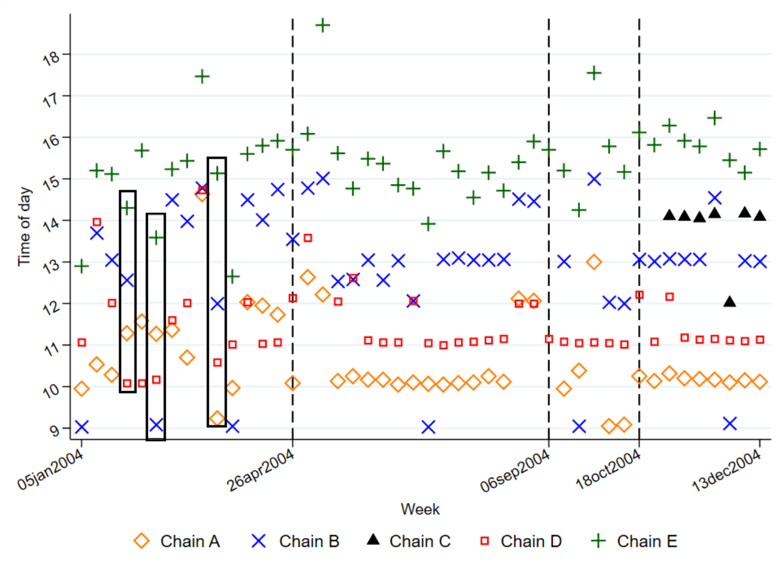
Note: The figure depicts average prices excl. taxes, and average share of weekly volume of gasoline sold on different weekdays before the regular Monday jumps are introduced. Results are split between cycling stations (prices represented by the solid red line and volume shares by the dark blue bars) and non-cycling stations (prices represented by the dashed red line and volume shares by the light blue bars). Note that both cycling and non-cycling stations experience relatively small variations in volumes on different weekdays, but sell slightly higher volume on Friday than on other days.

Figure A.3: Month of year, volume and margins



Note: The figure depicts estimated average margins per litre of gasoline for different months of the year relative to January from 2004-2017, and average volume sold per station per day in the different months over the same years.
The monthly margins results from the month of year fixed effects, τ_m in the following model: $y_{it} = \alpha + \beta W_t + \rho Holiday_t + year_j + week_t + \tau_m + \gamma_i + \varepsilon_{it}$, where y_{it} is the average weekly margin for station i in week t, τ_m is a vector of dummy variables identifying the month of year each week starts (January is the reference group), W_t is the wholesale price of gasoline, $Holiday_t$ is a dummy identifying weeks with public holidays, $year_j$ are yearly fixed effects and $week_t$ is a linear time trend and γ_i represent station fixed effects.

Figure A.4: Time of day of chain price jumps, 2004

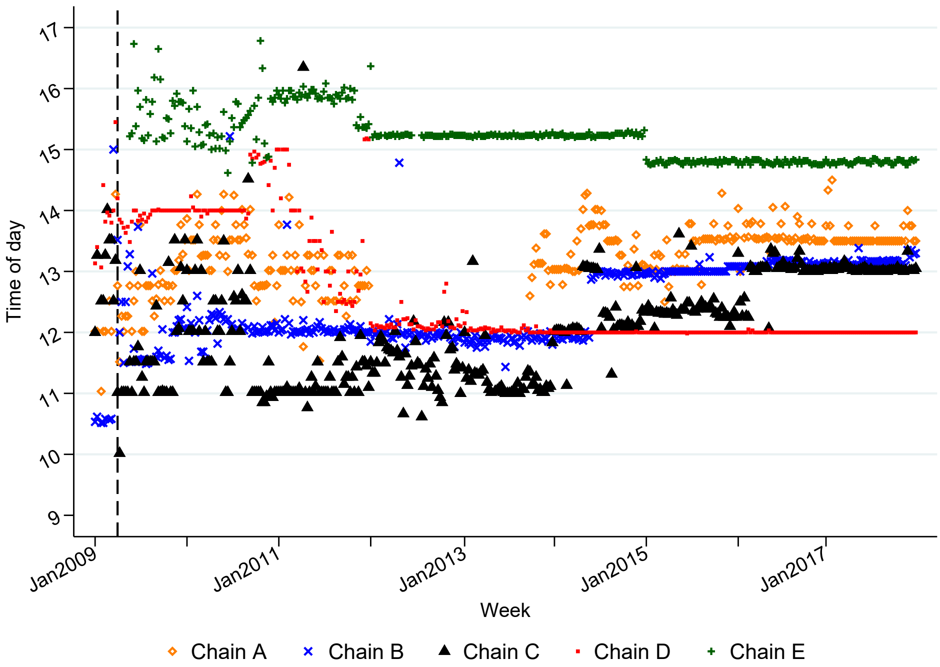


Note: The figure shows the time of *chain price jumps* for each chain for all weeks in 2004. Each dot represents the time of day a given chain initiates a *chain price jump*. Take note of the following:

1. Chain A (third black rectangle), Chain B (second black rectangle) and Chain D (first black rectangle) all lead price jumps before the week of April 26 2004.
2. On April 26 2004 (first dashed vertical line), Chain A starts to initiate price jumps every Monday. In the periods with regular Monday jumps (between the first and second dashed line and after the third dashed 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.
3. Different chains lead in the period when the pricing pattern reverts to price jumps on irregular weekdays (between the second and third dashed line).

*In the five weeks with second price jumps starting the week of April 26 2004 only the Monday price jumps are depicted.
**Data is missing for Chain C before the week of October 26 2004.

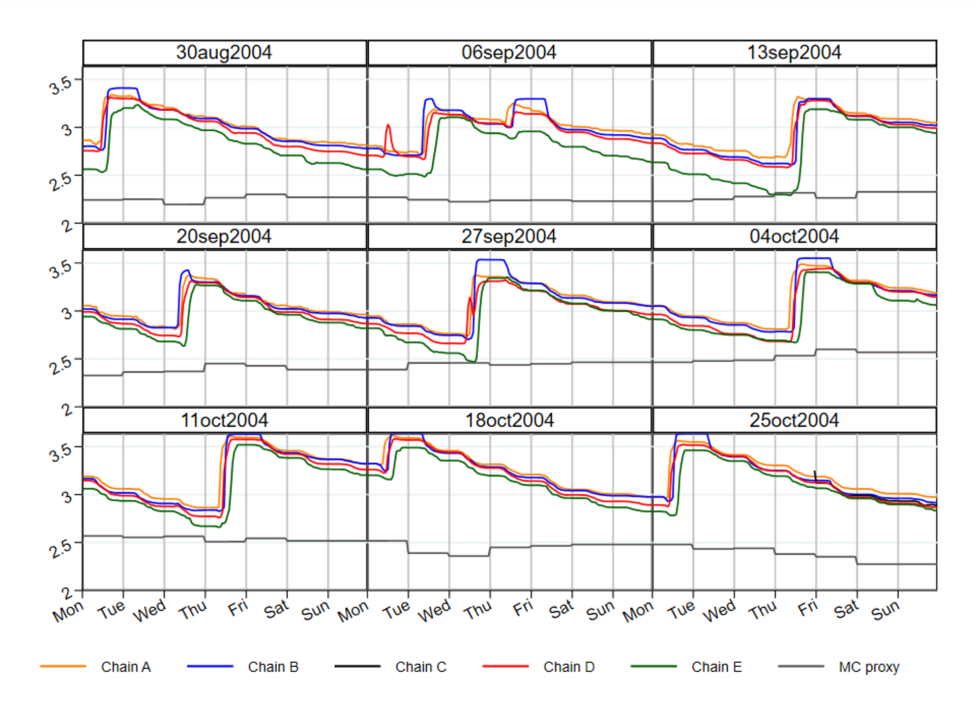
Figure A.5: Time of day of Thursday chain price jumps, 2009–2017



Note: The figure depicts the time of Thursday chain price jumps for each chain for all weeks from January 2009–November 2017. Each dot 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 Thursday price jumps are solidified. Take note of the following:

1. Chain C is first to initiate Thursday price jumps most weeks (between 11:00 and 11:30) from the week Thursday 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).

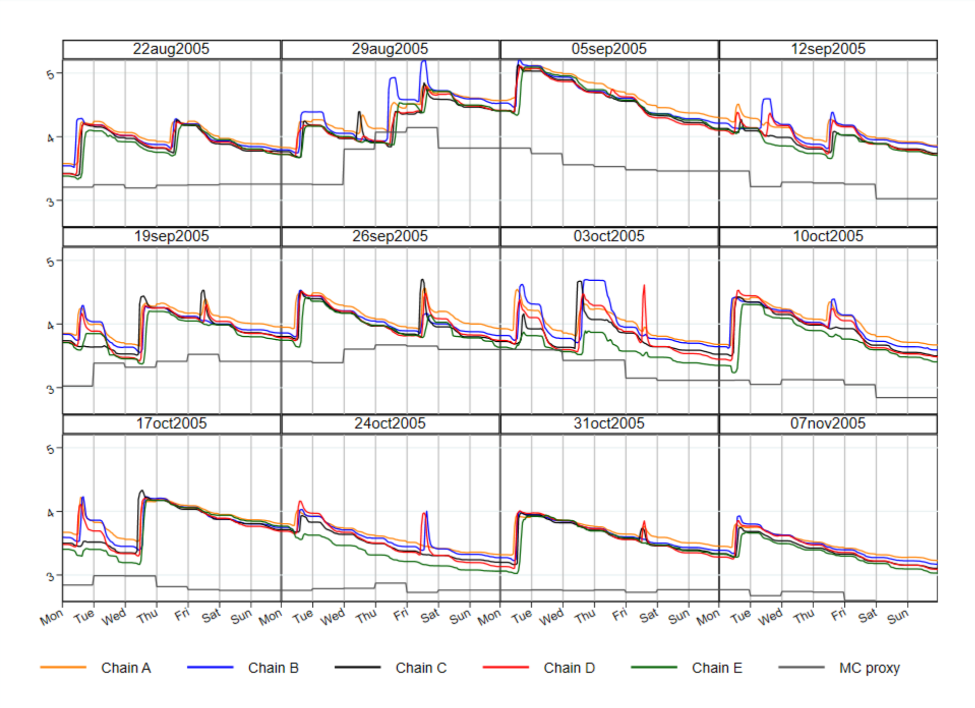
Figure A.6: Reversion to irregular jump days



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 marginal cost proxy. 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.

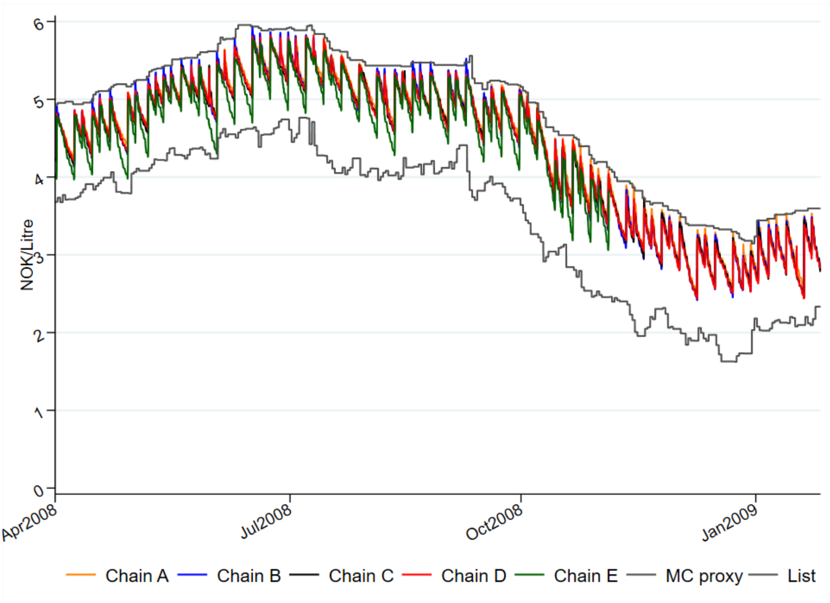
Figure A.7: Price cycles during wholesale price turbulence



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 marginal cost proxy. Take note of the following:

1. The marginal costs are very volatile 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 eight weeks, but in some of the weeks the jumps fail because one or more of the other chains do not follow.
3. In addition to the Monday jumps, jump attempts are also initiated on Tuesday, Wednesday, Thursday, and Friday.
4. When the marginal costs stabilizes after the week of October 17 2005, regular successful Monday jumps continue to occur.

Figure A.8: Price cycles during the crude oil crisis



Note: The figure depicts average hourly prices excluding taxes cycling stations from April 2008–February 2009 during a period with large wholesale price variation due to the 2008 crude oil crisis. The upper grey line is average list price, and the lower grey line is the marginal cost proxy. Note that marginal costs fall greatly during this period, but the price cycle remains stable.

B 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.

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 C 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.

Chapter 3

The Costs and Benefits of Price Leadership—Evidence from Retail Gasoline

The Costs and Benefits of Price Leadership—Evidence from Retail Gasoline*

Andreas Tveito†

October 7, 2021

Abstract

A trade-off between losing volume to rivals and gaining higher price–costs margins is central to understanding why firms may choose to act as price leaders. A unique dataset with high-frequency price, cost, and volume data allows the estimation of costs and benefits of leading price jumps in a retail gasoline market with asymmetric price cycles. The main result is that the leader's volume loss from being the sole firm to raise its price until the other firms match that price increase is small compared with the large margin increases and profit gains resulting from the price jumps. Furthermore, I find that the leader is not worse off than the non-leading firms. The results can assist in explaining why firms are willing to act as regular price leaders.

*I would like to thank Sigurd Birkeland, Kurt Brekke, Gordon Dahl, Øystein Foros, Joe Harrington, Hans K. Hvide, Bjørn Olav Johansen, Katrine V. Løken, Teis Lunde Lømo, Magnus Friis Reitan and Morten Sæthre for helpful comments. I gratefully acknowledge financial support from the Research Council of Norway.

†Department of Economics, University of Bergen and the Norwegian Competition Authority. The views expressed in this paper are those of the author and do not necessarily reflect the views of the Norwegian Competition Authority.

1 Introduction

Price leadership—a practice involving sequential price changes whereby a leader changes price first and rivals quickly follow—is a common feature in retail markets.[1] Price leadership has long been considered a possible instrument to coordinate on higher prices—the leader provides focal points for the timing and level of price changes that are needed to initiate price hikes (Markham, 1951). All firms benefit from higher margins after the market-wide price hikes, but the leader suffers a cost in terms of volume transfers to rivals in the interim period before the rivals match the high price. The firms following the leader enjoy both higher demand in the interim period, and higher profits in the after period. Thus, leading price hikes is a public good from the firms' point of view and a free-rider problem regarding which firm should lead can delay the price hikes, , even if leading a price hike is better than no hike (Maskin & Tirole, 1988). Small volume transfers in the interim period and large profit increases in the after period all, make it more likely that a firm is willing to provide price leadership.

This paper uses a unique dataset of high-frequency price, cost, and volume data for Norwegian gas stations to study the costs and benefits of leading price hikes. The costs and benefits of price leadership are particularly relevant in this market because it features asymmetric price cycles with frequent market-wide price restorations led by large chains. The main results are that the leader's profit increases greatly compared with a situation without price hikes, the volume transfers from the leader to the followers in the interim period are small, and the leader does not perform worse than the followers. The results suggest that the cost of leading and the free-rider problem are not significant for the firms studied, and can assist in explaining why firms are often willing to act as regular price leaders to initiate more frequent price increases.

The Norwegian retail gasoline market is dominated by four national chains with individual market shares of 20–30% and a combined market share of more than 90%. The chains own most of their affiliated stations and control the prices of other stations through strong vertical restraints. Because each chain controls prices at all affiliated stations and carries out synchronized price hikes for affiliated stations, I focus on the effects of leading price hikes at the chain level.

As in many other countries, the Norwegian retail gasoline market features asymmetric price cycles.[2] Prices slowly decrease over several days until a nationwide price restoration occurs, with each chain quickly initiating large price jumps for affiliated stations (Figure 1). The jumps are partly "calendar synchronized" in that they occur at particular times of the week. Large chains act as "regular leaders"; the same chain leads all or most of

[1] In addition to retail gasoline markets, price leadership has been documented in grocery retailing (Seaton & Waterson, 2013), brewing (Miller et al., in press), book and CD retailing (Kauffman & Wood, 2007), and passenger transport (Bergantino et al., 2018).

[2] Asymmetric price cycles have been found in retail gasoline markets in multiple European countries, as well as in Australia, Canada, and the USA. Calendar-synchronized price jumps have been found in retail gasoline markets in the USA, Canada, Germany, and Australia (Noel, 2019).

the jumps that take place at a particular time of the week over several months or years.[3] The largest chain (Chain A) leads price jumps every Monday through the entire sample period. The three other national chains (Chains B, C, and D) and a regional chain (Chain E) always match the Monday jumps. In the 4-year period on which the main part of this analysis is based, there are also jump attempts on Thursdays (or more rarely on Fridays) in 62% of weeks. The non-leaders match most of these "midweek jumps" within a few hours. Which of the national chains leads the midweek jumps varies over time, but there are long periods in which a single chain leads almost all the midweek jumps. Immediately after the 4-year period, one of the national chains begins leading Thursday jumps every week, and both Monday and Thursday jumps take place every week for the next 8 years.

The asymmetric price cycles in retail gasoline markets are often rationalized by the "Edgeworth cycle" price commitment model first described by Edgeworth (1925), and later formalized by Maskin & Tirole (1988). The gradual price decreases over several days and the market-wide price jumps occuring within a few hours align well with the theory of Edgeworth cycles. However, several characteristics are contrary to the Edgeworth-model—the regularity of the price jumps, the same chains leading the jumps, high pre-jump margins, and the fact that the followers do not undercut the leader's price at the top of the cycle. Firm behavior in the undercutting phase of the cycle adheres well to the Edgeworth model, but the large chains appear to be using price leadership to coordinate on more frequent price jumps to avoid the cycle trough.[4]

A regular leader can solve the free-rider problem regarding who should hike prices first, thus limiting the time for which prices remain near the trough of the cycle. However, the leader must be willing to incur the cost of losing volume to rivals. Noel (2008) shows that in a price commitment model, increasing the cost of leading price jumps relative to the benefits, lowers incentives to lead and reduces the frequency of price jumps.[5]

The interim volume loss and subsequent profit increases are important determinants for firms' incentive to provide price leadership. Yet, the empirical evidence quantifying these costs and benefits is very limited. Wang (2009) argues that a new regulation in the Perth retail gasoline market increased the cost of providing price leadership, and thus caused a transition from a regular price leader to alternating price leadership. But the study does not document the actual cost of leading. Clark & Houde (2013) study a market with explicit collusion and infrequent price hikes and find large volume transfers from the cartel members who hike prices first to the members who hike prices a few hours later. However, the authors only have access to quarterly volume data, and their estimates are based on strong assumptions.

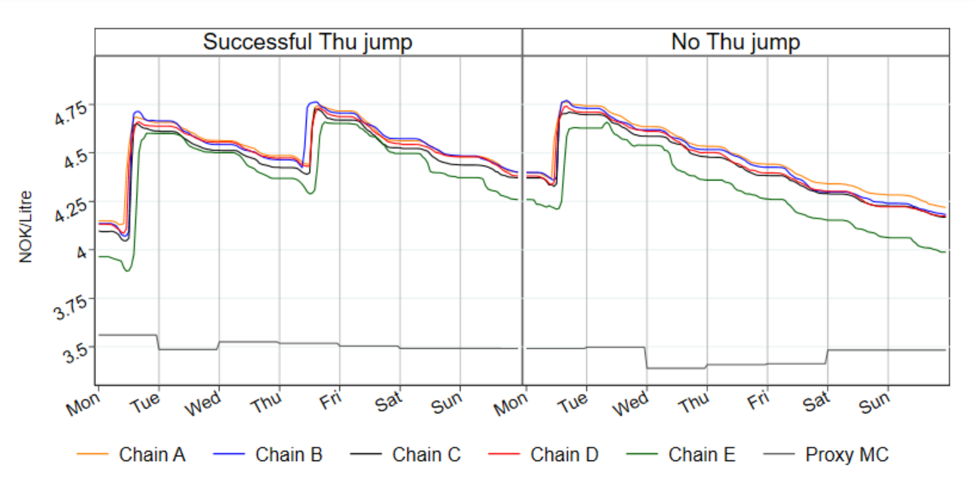
[3] Lewis (2012) (USA), Wang (2009) (Australia), and Cabral et al. (2021) (Germany) show that large chain acts as regular price leaders in other countries as well.

[4] de Roos & Smirnov (2020) show that asymmetric price cycles can be the optimal equilibrium for firms in a model with history-based strategies and tacit collusion.

[5] Both the trade-off between the cost of leading and the benefits of higher future prices, and the free-rider problem are present also in models of price leadership in repeated games with history-dependent strategies and non-cycling prices (Harrington, 2017; Harrington & Zhao, 2012).

This study has the advantage of a unique dataset that includes the exact timing of price changes, daily volume data, and data on wholesale prices and transportation costs for most Norwegian gas stations. Furthermore, the price pattern with regular Monday jumps and irregular midweek jumps provides a setting that is well suited to studying the costs and benefits of price leadership. Figure 1 provides examples of a week with a successful midweek jump and a week without a midweek jump, indicating that successful midweek jumps bring about higher prices until the next Monday jump.[6] Due to the regular Monday jumps and irregular midweek jumps, it is safe to assume that the chains anticipate that a Monday jump will occur regardless of whether a midweek occurs. Therefore, the benefits of midweek jumps last until the next Monday morning. As the followers increase prices within a few hours of the leader, the leader's immediate cost is incurred on the same day that the jumps are carried out.

Figure 1: Price cycles—with and without a midweek jump



Note: The colored lines depict the average hourly price excluding taxes in Norwegian kroner/liter for each chain for 2 weeks in November 2007. The gray line is a proxy for marginal cost, as defined in Section 2.2.

The primary challenge in estimating the effect of the price jumps is to identify the counterfactual—how the outcomes of interest would have developed if the jump had not taken place. The development in the outcome through the week in those weeks without midweek jumps provides a suitable counterfactual for weeks with midweek jumps. My baseline specification is a difference-in-difference ("diff-in-diff") model where the first difference is the development in the outcomes of interest (margins, volumes, and profits) through the week for (1) stations affiliated with the chain leading the Thursday jumps and (2) stations affiliated with the chains following the leader. The second difference is the development through the week for all stations in weeks without midweek jumps. The

[6] I focus on the Thursday jumps because 84% of the midweek jumps occur on Thursdays.

model removes biases resulting from shocks that have the same effect on the outcome on all weekdays, and accounts for trends in the outcome through the week. Except for Thursdays (the day that jumps take place), the outcomes for both the leader and the followers have a very similar development to the outcomes in weeks without midweek jumps, supporting the parallel trend assumption.

Leading a successful Thursday price jump is greatly profitable for the price leader compared with a counterfactual with no midweek jump. Across the whole week, the leader gives up only 0.5% of its market share but gains from price—cost margins—that, on average, are 25% higher, leading to a 21% increase in average weekly profit. The leader's post-jump price–cost margins increases greatly—Friday–Sunday margins increase about 45%. The higher prices trigger a close to 10% volume reduction on Friday–Sunday, but it is likely that a significant share of the volume loss stems from consumers delaying purchases, and that these losses are later recouped. Even assuming that none of the lost volume is recouped, the margin increase greatly outweighs the loss of volume and the leader's profit increases about 36% on Friday–Sunday.

As expected, the leader loses market shares only on the day of the price jumps—the leader's volume decreases 4% more than the followers' volumes on Thursday, whereas the leader and followers have similar volume losses on Friday–Sunday. However, the leader's higher margins on Thursday counteract the higher volume loss, and the leader's and the followers' profits increase by close to 20% on Thursdays compared with a counterfactual without midweek jumps.

Several factors are likely to contribute to reducing the leader's volume loss. First, the chains' strict control of prices at affiliated stations enable them to carry out price jumps very fast for all stations, reducing the delay before the followers match the high price. Second, the jumps take place in the middle of the workday when road traffic is relatively low. Third, the followers do not undercut the leader's price at the top of the cycle, meaning the leader only loses demand in the period before its rivals hike prices and not in the subsequent period. Thus, even under the extreme assumption that the price leader does not sell anything until all nearby stations have hiked prices, I find that the leader would only lose about 3% of its weekly volume.

I investigate several factors that could increase the leader's loss beyond the short-run loss on the day of the price jumps. I find no evidence of any negative spillovers to either the leader's convenience store revenue, or its gasoline volumes on days when price jumps do not occur. In addition, I examine whether the volume loss resulting from being a regular price leader increases over time. I study four different events where a single chain starts to act as a regular leader of Thursday jumps, and find no evidence that the regular leader incurs a larger volume loss over time.

The large post-jump profit relative to the small prior volume loss related to provides a strong incentive to price leadership, while the lack of a profit loss for the leader relative to the other chains indicates that the free-rider problem is not significant in this market.

Thus, the results may explain why the large chains accept the role as regular leaders. In markets with more than two firms, the free-rider problem at the bottom of the cycle can become severe, making it less likely that the asymmetric price cycles materialize (Noel, 2008). However, with regular leaders the free-rider problem is mitigated, and price restorations can occur frequently. This means that the low cost of leading may also contribute to the existence of asymmetric price cycles despite the fact that several competing chains are active in the Norwegian market.

The presence of several large chains, the timing of price hikes to match low-traffic periods, the short time span between the leader's and the followers' price hikes, and the fact that the followers do not undercut the leader, are features of retail gasoline markets in other countries as well as in Norway (Lewis, 2012; Wang, 2008; Atkinson, 2009; Cabral et al., 2021). Thus, a low cost of leading may explain to the common observation of large chains acting as regular price leaders in markets featuring asymmetric price cycles, and thus contribute to explain the very existence of asymmetric price cycles in these markets.

The rest of this article is organized as follows. Section 2 outlines some key institutional features of the market, introduces the data, and describes the observed price pattern. Section 3 presents an analysis of the short-run costs and benefits of leading price jumps. Section 4 is devoted to the long-run effects of leading price jumps. The study concludes in Section 5 where I relate the empirical results to the development in the observed price pattern with irregular midweek jumps for 4 years before the Thursday jumps start to occur every week and argue that policies that increase price transparency for consumers could decrease the frequency of price jumps.

2 Institutional setting, data and price pattern

2.1 Institutional setting

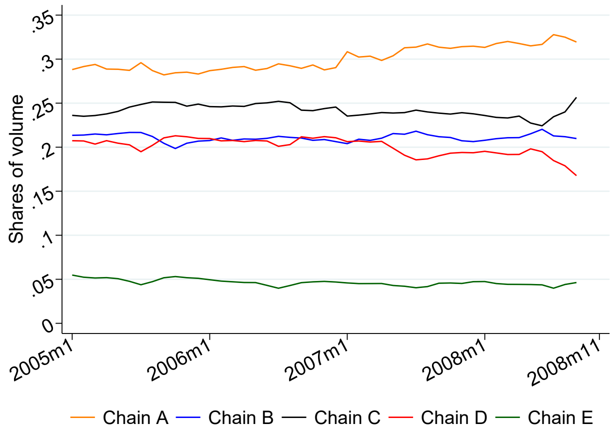
There are four national chains and one regional chain in the industry. The largest chain has a market share of about 30% (Figure 2), and the other three national chains have market shares of 20%–25%.[7]. The share of independent stations not affiliated with any of the major chains is less than 5%. All the national chains have both staffed stations with a convenience store (on average 78% of stations) and unstaffed stations where customers can only pay with credit/debit card at the pump (22% of stations), and they have stations located in all parts of Norway. The regional chain is only active in the southeastern part of Norway and has only unstaffed stations.

The chains have a combination of vertically integrated stations (owned by the chains) and vertically separated retail outlets (owned by the local dealers). About two-thirds of the stations are vertically integrated. The dealer-owned stations have exclusive long-term

[7]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 appear to be bound by the same vertical restraints as the dealer-owned stations connected to Chain A (Neset, 2010)

contracts (usually for 5 years or more) with one of the major chains. Foros & Steen (2013) document that the 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. The vertical restraints enable the chains to make vertically separated stations initiate price jumps at about the same time as vertically integrated outlets (Table 3).

Figure 2: Market shares



Norwegian gas stations can change prices as often as they want and are not obligated to report prices to any price comparison website. Prices are posted on large electronic boards next to each station, and the retail chains closely monitor each other's prices at a local level (Konkurransetilsynet, 2015b). Each chain operates with national "recommended prices" (Foros & Steen, 2013). Prices vary between local areas, and prices typically fall faster in the undercutting phase of the price cycle in areas where multiple chains are present (Konkurransetilsynet, 2014), resulting in significant price dispersion between local areas. However, each chain increases prices to about the same level (the recommended price) for affiliated stations when large chain-wide price jumps are initiated.[8] Near-uniform prices at the top of the cycle and significant price dispersion as prices fall have been observed in various other countries, see, e.g., Lewis (2012).

Both the market structure where a few large chains control prices for most outlets, and national or regional recommended prices are common in the retail gasoline industry (Foros & Steen, 2013).

[8]See Foros & Steen (2013). Prices are normally increased to the recommended price plus each station's transportation costs. Unstaffed stations increase prices to 0.1–0.2 NOK below the recommended price plus transportation costs.

2.2 Data

Data on gasoline price and volume spells, station characteristics, convenience store revenues, and the cost of transporting gasoline are obtained from the Norwegian Competition Authority, which collects the data directly from the five major retail chains in various cases. The data include the unleaded 95-octane gasoline price and volume information. No gas stations sold leaded gasoline during the sample period. The share of non-95 octane gasoline was low during the period, starting at 7% of retail gasoline sales in 2005, and falling to 5% in 2008 (Drivkraft Norge, 2021). The data have been merged and cleaned by the competition authority and include price and volume spells for more than 90% of Norwegian gas stations. Confidentiality restrictions preclude me from showing results highlighting volume-based information for individual chains; therefore, I pool results for all followers in Section 3 rather than show results for the first, second, third, and last chains to follow the leader separately, and I cannot show results from each of the events in Section 4 separately.

I use data for the period January 2005 to the first week of November 2008 for the main analysis in the paper, but also utilize data in later years for an analysis of long-run effects. The key reason that the main analysis is carried out based on data for the selected period is that irregular midweek price jumps only occur between January 2005 and March 2009. I end the sample period in November 2008 because data on price changes are missing for Chain E from November 2008 to June 2009, and because convenience store revenue is only available until November 2008.

The paper is concerned with price leadership and interaction between gas stations at a local level, meaning only stations with nearby competitors are of interest. Furthermore, I focus on price leadership in the restoration phase of asymmetric price cycles when large price jumps are carried out. Most stations located outside built-up areas or in built-up areas where only one chain is present have fixed rather than cycling prices. Therefore, I restrict the analysis to stations located in built-up areas where at least two different chains are present. built-up areas are delineated by Statistics Norway and are areas with an average population of at least 200 people, and less than 50 m between houses. The built-up areas in the sample cover $9.5km^2$ and have an average population of 18,000. Stations located outside built-up areas or in built-up areas with only one chain present constitute 11% of total volume in the sample. I drop a few noncycling stations located in built-up areas with two or more chains present from the sample because these stations are not affected by the chain-wide price jumps.[9]

A price spell commences the minute that a station changes its price and ends when the station makes a new price change. On average, the price spells in the main sample last 19 hours (Table 1). The panel with to-the-minute timing of price changes makes it

[9]Station i is a noncycling station in year y if the average difference between maximum and minimum price on Monday is $< 0.05NOK$. Noncycling stations located in built-up areas with at least two different chains constitute 3% of the volume in the sample.

possible to identify price leaders even when stations change prices multiple times per day.

Volume spells show how many liters of gasoline a given station sells during the duration of the spell. The start and end times of the volume spells often match those of the price spells, but some of the price spells are also split into volume spells of shorter duration. For these spells, the price is unchanged over a longer period, but volume is registered in two or more different spells. For this reason, the average volume spell is only 10 hours long (Table 1).

To analyze the changes in volume sold when the leader initiates price jumps, the volume spells must be transformed to a panel with station-level volume sold in fixed time periods. Although the volume spells are highly frequent, I do not know the exact volume sold for each station in each hour of the sample. When transforming the data, I assume that a station's volume sold is equal in all minutes of a given spell. For spells that start and end in the same fixed period, there is no uncertainty in relation to the fixed period in which the volume is actually sold. For spells that start and end in different fixed periods, volume is split between the fixed periods according to the share of each spell's total minutes that took place in each of the fixed periods. For example, if a station sold 2,000 liters of gasoline in a spell that started at 20:00 hours on July 1 and ended at 16:00 hours on July 2 and the fixed periods span a calendar day, then 400 liters of the spell would be credited to July 1 and 1,600 liters of the spell would be credited to July 2.

When aggregating the spell volumes to a fixed period panel, there is a trade-off between frequency and accuracy of the volume observations. Long fixed periods may average out important intra-week volume variation but are more accurate because the share of a period's volume that comes from spells spanning multiple periods is low. An hourly panel would be ideal to investigate the leader's loss in the few hours before other chains match its price increase. However, the multi-hour volume spells entail a panel with longer duration. I transform the volume spells to a panel with daily station-level volumes, meaning I can estimate, e.g., the leader's volume loss on the day it is leading.[10] The assumption of equal sales per minute in each spell allows me to create a panel with daily station-level volume-weighted prices.

I conducted a robustness check where I reproduced all results in the paper with a sample restricted to station-months combinations with an average of ≤ 24 hours between each volume registration. This sample excludes station-months with less accurate volume information, which reduces the size of the sample by 11% and reduces the average duration of the volume spells to 9.2 hours. The main results are very similar with this sample and all conclusions remain unchanged.

The data include station characteristics such as chain affiliation and location. For the period January 2005–November 2008, convenience store nonfuel revenue at the daily

[10]Daily volumes rather than spell volumes are available for some chains in part of the sample period (Tveito, 2021a). Working with a daily frequency allows me to include these observations. Some individual stations are missing price or volume data in parts of the sample period. I drop all station-weeks where one or more minute of the week involves missing information about prices or volumes.

station level is available for the 75% of stations with on-site convenience stores.

Following common practice in the existing literature, I proxy wholesale prices with the reference wholesale price of gasoline from a price-reporting agency (Foros & Steen, 2013). Norwegian retailers' wholesale prices are based on the European reference price from Platts (Konkurransetilsynet, 2015b)) which can be regarded as the opportunity cost for companies of selling their gasoline on the international wholesale market rather than to gas stations (Andreoli-Versbach & Franck, 2015).[11] The reference price on day t is based on trades that took place during day t and is therefore not known to the gasoline chains when they make pricing decisions on day t. Thus, I use the reference price on day $t-1$ as a proxy for the wholesale price on day t. The wholesale price is by far the most important component of marginal costs in gasoline retailing, averaging 3.02 NOK/liter (73% of the tax-excluded retail price) in the sample period (Table 1).

The second most important nontax marginal cost component is the cost of transporting gasoline to each individual station. 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. The chains calculate the cost of transporting gasoline to each individual station and use this information when setting retail prices (Foros & Steen, 2013). The data contain information about transport costs to each individual station. Transport costs could change over time, but for most stations only the transport cost of November 2008 is available. I use each station's transportation cost for November 2008 (or from a later date if transportation costs are not available for November 2008) as a proxy for each station's transportation costs in previous periods. For some stations where no transportation costs are available, I use the average transportation costs for other stations within the same chain and same built-up area as a proxy. For the few remaining stations without (proxy) transportation costs, I use the average transportation costs of stations in the same built-up area but affiliated with other chains as a proxy. The average transportation cost is 0.12 NOK/liter (Table 1).

There are large value-added taxes (VAT) and environmental taxes on motor fuels. The VAT is 25% during the sample period and the environmental tax is CPI-adjusted on January 1 every year, leading to a steady increase from 4.81 NOK/liter in 2005 to 5.15 NOK/liter in 2008.

I combine the reference wholesale price and transportation cost to make a proxy for marginal costs. I use the marginal cost proxy when calculating margins and profits. Throughout the paper, volume-weighted margin per liter for station i on day t is defined as $y_{it} = p_{it} - W_t - tax_t - c_{it}$, where y_{it} is the average volume-weighted margin/liter for station i on day t, p_{it} is the average volume-weighted price/liter (the average price that the consumer paid), W_t is the wholesale price proxy, tax_t is VAT and other taxes, and c_{it}

[11] KT has used the same wholesale price proxy in multiple cases and has noted that the four national chains have similar costs (Konkurransetilsynet, 2015b). Platts is a global price-reporting agency that publishes bids and offers for oil products.

is the station-specific transportation cost.

There is a 6-week period during September–October 2005 with extreme wholesale price volatility caused by the hurricanes Katrina and Rita. I exclude this period from the analysis due to a temporary disruption of the price pattern with successful Monday price jumps (Tveito, 2021b). Finally, I exclude weeks with national holidays (6–8 weeks per year) because the price pattern is different in holiday weeks (Tveito, 2021b).

The sample restrictions leave 1.1 million daily observations for 1,164 individual stations located in 196 different built-up areas in the period January 2005–November 2008. In the following, I refer to this as "the main sample" and the "the sample period". Table 1 shows descriptive statistics for the main sample.[12]

Table 1: Descriptive statistics for the main sample, Jan 2005-Nov 2008

	Mean	Std. dev.	Min.	Max.
Price excl. tax in NOK/liter	4.15	0.71	1.16	6.62
Wholesale price in NOK/liter	3.02	0.60	1.60	4.63
Transport costs in NOK/liter	0.12	0.07	0.02	0.57
Margin in NOK/liter	1.01	0.36	-1.00	2.93
Liters sold/day	3,489	2,305	0	29,753
Price spell length in hours	18.6	23.2	0	1,783
Volume spell length in hours	10.2	12.2	0	718

2.3 Price pattern

In April 2004, Chain A starts leading price jumps every Monday.[13] The other chains always follow the Monday jumps and, for the next 13 years, market-wide Monday jumps happen every week. Starting in January 2005, a second price jump occurs in some weeks on Thursdays or Fridays. Over the next 4 years, midweek jumps occur in 62% of the weeks (Figure 3). Most of the midweek jumps occurs on Thursdays (84%). A total of 43% of the midweek jumps fail, as one or more chains do not follow the leader's price jump. Just after the sample period, in March 2009, Chain C starts to lead Thursday jumps every week and for the next 8 years, market-wide jumps occur on both Monday and Thursday every week.

I use the to-the minute data on price changes for all stations to identify which chain leads price jumps in a given week. As each chain has many stations and each station does not initiate price jumps at exactly the same time, I first find the time at which each station initiates a price jump and then define a chain as initiating a price jump when a

[12]On average, 1 USD is equivalent to 6.09 NOK and 1 EUR is equivalent to 8.07 NOK during the sample period, meaning that the average price exclusive of tax/liter in the sample period is 0.68 USD and 0.52 EUR.

[13]See Tveito (2021b) for a detailed description of the different price patterns and the transitions between different price patterns.

given share of its affiliated stations have initiated price jumps. The following definitions aid the analysis:

(a) Let p_{idt} be the retail price at station i on day d and at time t, $\boldsymbol{p_{idz}}$ be a vector of all prices at station i on day d before time t, and $\Delta p_{idt} = p_{idt} - min\{\boldsymbol{p_{idz}}\}$. A*station price jump* occurs at station i on day d and at time t, the first minute of the day when $\Delta p_{idt} \geq 0.25 NOK$ (i.e., the first time during a given day when the price is at least 0.25 NOK higher than the lowest previous price at that station that day). The threshold is in 2005 NOK and is CPI-adjusted yearly.

(b) A *chain price jump* for chain c occurs on day d at time t when *station price jumps* have occurred for at least 30% of chain c's stations.

(c) The first chain to initiate a *chain price jump* on a given day is the *price leader* that day. Chains initiating *chain price jumps* the same day but after the leader are *followers*, and chains not initiating *chain price jumps* on days when one or more other chains initiate *chain price jumps* are *nonfollowers*.

(d) A *successful price jump* occurs on days when all five major chains carry out *chain price jumps*. A *failed price jump* occurs on days when one or more but not all five chains carry out a *chain price jump*.

The 0.25 NOK threshold is similar to the threshold of 0.06 AUD/liter in Byrne & de Roos (2019) (0.06 AUD = 0.29 NOK) and about half of the average Thursday price jump (0.47 NOK) and one quarter of the average retail margin (1.01 NOK). It strikes a balance between identifying chain-wide price jumps and excluding more random smaller station-specific price increases. The main results are robust to variations in the definitions of station price jumps and chain price jumps.

In the restoration phase of the cycle, each chain carries out price jumps for most of its stations within a very short period. On average, it takes only 1.07 hours between the time at which the first 10% of a chain's stations have carried out midweek price jumps to the time at which 75% of the chain's stations have carried out price jumps (Table 2). The variations in the within-chain timing of price jumps can largely be attributed to differences between staffed and unstaffed stations; within the same chain (and within the same chain and the same built-up area), unstaffed stations typically carry out price jumps a few hours after staffed stations—they occur about 1.7 hours later for the chain that is leading and 0.9 hours later when including observations from chain-wide price jumps for both the leader and the followers (Table 3). Consistent with strict vertical price control, the results show that within the same chain, chain-owned stations carry out price jumps at about the same time as vertically separated stations.

Both the leader and the followers restore prices to the recommended price adjusted for transportation costs, except for unstaffed stations, which restore prices to 0.1–0.2

NOK less than staffed stations (Section 2.1). See also Appendix Table A.1, which shows that stations associated with the leader hike prices to about the same level as stations associated with the followers. This means that the followers typically do not undercut the leader's price at the top of the cycle.

Table 2: Within-chain timing of midweek price jumps, by chain

	10% to 30%	10% to 50%	10% to 75%
Chain A	0.13	0.30	0.96
Chain B	0.12	0.22	0.46
Chain C	0.28	0.36	0.64
Chain D	0.19	0.46	1.40
Chain E	0.78	1.31	2.01
Mean of all chains	0.27	0.49	1.07

Note: The table shows the average time in hours from which the first 10% of each chain's stations carried out *station price jumps* until the times at which 30%, 50%, and 75% of the chain's stations had carried out *station price jumps*. The statistics in the table are based on observations from days with midweek *chain price jumps* in the main sample period.

Table 3: Within-chain timing of midweek price jumps, by characteristics

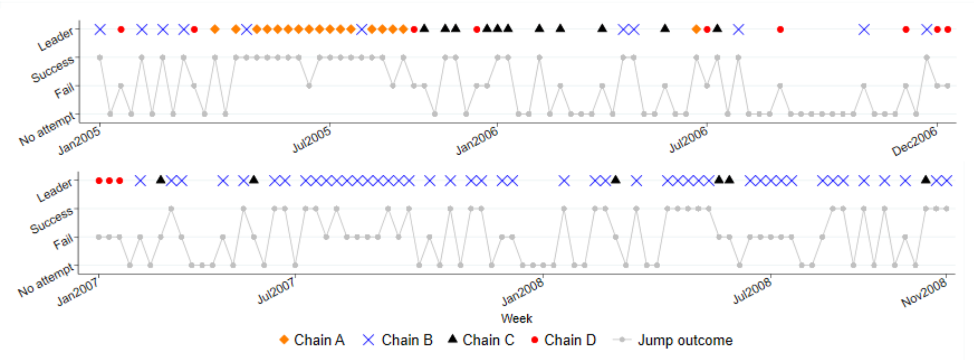
	All	All—Built-up FE	Leader	Leader—Built-up FE
Staffed	-0.89***	-0.90***	-1.56***	-1.75***
	(0.08)	(0.11)	(0.23)	(0.32)
Chain-owned	-0.04	0.02	-0.19***	-0.11
	(0.04)	(0.06)	(0.05)	(0.13)
Constant	13.35***	13.32***	12.63***	12.73***
	(0.09)	(0.12)	(0.25)	(0.35)
Chain FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Built-up FE	No	Yes	No	Yes
Observations	68030	68022	18505	18488
R2	0.29	0.31	0.33	0.42

Note: The table shows the results from the regression model $y_{iw} = \alpha + \beta_1 Staffed_i + \beta_2 CO_i + \gamma_i + \theta_i + \delta_w + \varepsilon_{iw}$. y_{iw} is the time of day that station i carried out a midweek price jump in week w. $Staffed$ is a dummy identifying stations with a staffed convenience store. CO is a dummy identifying stations that are chain owned. θ_i represent chain fixed effects and δ_w represents week fixed effects. Results are shown both with and without built-up area fixed effects, γ_i. The first two columns of results include all station-weeks where the chain with which station i is affiliated carries out a midweek chain price jump. The last two columns only include station-weeks where the chain with which station i is affiliated is a price leader of a midweek jump. Observations in the main sample are included, except for 12% of stations that are missing information about whether they are chain-owned.

All four national chains lead midweek price jumps in multiple weeks in the sample period (Figure 3). Chain A leads most of the jumps in a 4-month period in 2005, and Chain B leads most of the jumps after June 2007.

Regardless of which chain is leading, the leader typically initiates price jumps between 10:00 and 11:00. As we see in Table 4, the first follower carries out a chain price jump

Figure 3: Midweek price jumps, Jan 2005–Nov 2008



Note: The figure shows the prevalence and success of midweek price jumps in the sample period. The coloured symbols in the upper row indicate which chain (if any) leads the midweek jump attempt in a given week. The connected gray dots indicate whether the jumps were successful.

about 1.5 hours after the leader. All chains except one have carried out price jumps within 3 hours of the leader doing so, and all chains have carried out price jumps 5 hours after the leader. The regional chain with only around 40 gas stations is always the last chain to restore prices (Tveito, 2021b); thus, in most areas, all stations have carried out price jumps within 3 hours of the leader doing so. The delay from the leader to the followers is fairly stable over time for the period 2005–2008 (Appendix Figure A.1).

Table 4: Between-chain timing of midweek price jumps, Jan 2005–Nov 2008

	Hours after leader
1. Follower	1.45
2. Follower	2.22
3. Follower	3.10
4. Follower	5.25
Mean of all followers	3.01

Note: The table shows the average time in hours from the time that the leader carries out a midweek chain price jump until the other chains follow, from the first to the fourth chain following, for the weeks with successful midweek chain price jumps.

The leader carries out price jumps in the middle of the workday, and most rivals increase prices before the afternoon rush starts. Road traffic—which is likely to be a good proxy for fuel demand—is 17% lower in the period from 10:00 to 15:00 than in the morning rush period of 08:00–10:00, and 25% lower than in the afternoon rush from 15:00 to 18:00 (see Appendix Figure A.2, which is based on 3 years of data of traffic counts from nine tracker stations). Travel demand is even lower during the night, but the lack of personnel at head offices and gas stations would make it difficult to carry out price jumps during these hours. This may also explain why price jumps never occur on weekends or public holidays.

The asymmetric price cycles in retail gasoline markets are often rationalized by the

Edgeworth cycle price commitment model first described by Edgeworth (1925) and later formalized by Maskin & Tirole (1988). The observed gradual price decreases over several days and the market-wide price jumps occurring within a few hours align well with the Edgeworth model. However, according to the Edgeworth model, the time between price jumps should be stochastic and different firms should lead price jumps.[14] This is not the case in the sample market where price jumps occur at the same time every Monday and on some Thursdays/Fridays, and the same firms repeatedly lead the price jumps. According to the Edgeworth model, price jumps should only occur when margins approach marginal costs. Lower midweek margins increase the chance of midweek price jumps (Appendix F), but the pre-midweek-jump margins are still far above marginal costs, and well above the pre-Monday jump margins.[15] Finally, followers hike prices to the same level as the leader rather than undercutting the leader as (Maskin & Tirole, 1988)'s model predicts. Firm behavior in the undercutting phase of the cycle aligns with the Edgeworth model, but the large chains appear to use price leadership to coordinate on more frequent price jumps to avoid the cyclical trough.[16]

3 Short-run costs and benefits of price leadership

In this section, I investigate the short-run effect of midweek price jumps on the leader's and nonleaders' margins, the volume of gasoline sold, the gasoline market share, convenience store revenue, and profits. I focus on Thursday jumps because they make up 84% of the midweek jumps. Friday jumps have very similar effects, as can be seen in Appendix C.

The period when the leader is in danger of losing volume to competitors starts when it increases its prices and ends when all competitors have matched the price increases.[17] We have seen that the leader of midweek jumps remains the sole competitor with a higher price for only 1.5 hours before the first competitor follows, and it takes about 5 hours before all competitors have followed suit. Therefore, the potential volume loss related to leading midweek jumps is limited to the same day that the price jumps are carried out.

The period when the benefits of price jumps are reaped is typically difficult to delineate

[14] Noel (2008) extends Maskin & Tirole (1988)'s model to include firm asymmetries and shows that asymmetries can lead to a situation where the same firm leads all jumps. However, this model cannot explain the situation where one chain leads all Monday jumps while other firms act as regular leaders of the Thursday jumps.

[15] In weeks with Thursday jumps, the average pre-Monday-jump margins (average minimum margins on Monday) are NOK 0.72 and the average pre-Thursday margins are NOK 0.94.

[16] See also Tveito (2021b), who studies the transition to the equilibrium with two price jumps per week. An alternative explanation for the cycles is that they result from intertemporal price discrimination, as in Conlisk et al. (1984). However, Noel (2012) argues that expectations about falling prices come well after the cycle has been established and do not create the cycle in the first place, as is required in a price discrimination story. He also argues that the low long-run elasticity of demand for retail gasoline makes volume gains from intertemporal price discrimination small compared with the necessary slash in margins. Foros & Steen (2013) also note that Norwegian gas stations without nearby competitors have fixed prices, which contrasts with the price discrimination explanation.

[17] I discuss possible spillover effects to other periods in Section 4.

because it is hard to say how long the higher prices last. The regular Monday jumps and irregular midweek jumps provide a suitable setting to overcome this problem. The chains know that a price jump will occur the next Monday morning regardless of whether a midweek jump is carried out. Thus, the benefits of a successful midweek jump last until the next Monday morning. The effect of the midweek jumps on the outcome of interest the following Monday is difficult to separate from the effect of the Monday price jump the same day (the chains increase prices at different times on Mondays). Therefore, I exclude Mondays from most of the analysis.

3.1 Empirical strategy

The primary challenge in estimating the effect of the Thursday jumps is to identify the correct counterfactual; how would the outcome of interest have developed if no Thursday jump attempt occurred? The jumps are not exogenous events, and it is not random which weeks they take place in, nor which chain leads the jump. For example, margins on Tuesdays and Wednesdays are lower in weeks with Thursday jumps than in weeks without Thursday jumps. Therefore, simply comparing the outcome of interest in weeks with jumps to weeks without jumps can lead to biased estimates. Furthermore, there are clear trends in both demand and prices/margins through the week, making a simple comparison of the outcome of interest in the pre-jump days to the post-jump days infeasible.

Therefore, my baseline specification is a diff-in-diff model that accounts for differences between the treatment and control groups in terms of both pre-period differences and trends through the week. Consider a simplified setting in which only the effect of leading successful Thursday jumps on the leader's outcome of interest is estimated. The treatment group consists of the leader's stations in weeks with successful Thursday jumps and the control group of all chains' stations in weeks without midweek jump attempts. The first difference is the change in the treatment group's outcome from Wednesday to weekdays later in the week, and the second difference is the same change in the control group's outcome. Tuesdays are also included to see how the outcome changes from Tuesday to Wednesday ("pre-trends"), whereas Mondays are dropped because another price jump takes place this day. With both failed and successful jumps and with a leader, followers, and nonfollowers, there are five different treatment groups: "Leader in failed weeks", "Followers in failed weeks", "Nonfollowers in failed weeks", "Leader in successful weeks", and "Followers in successful weeks". The five treatment groups are compared with the control group consisting of all stations in weeks without midweek jumps.[18]

I estimate the effects of Thursday price jumps with the following model:

$$ln(y_{iwt}) = \alpha + \boldsymbol{\beta_1} Treat_{iw} + \boldsymbol{\beta_2} D_t + \boldsymbol{\beta_3} Treat_{iw} \times D_t + \rho W_{wt} + \theta^D_{iw} + \lambda_{wt} + \gamma_w + \delta_i + \varepsilon_{iwt} \quad (1)$$

[18]Weeks with Friday price jumps are removed from the sample when estimating the effects of Thursday jumps to ensure that the baseline only includes weeks without price jumps.

where y_{iwt} is the outcome of interest for station i in week w and on weekday t. D_t is a vector of day-of-week indicators with Wednesday as baseline. $Treat_{iw}$ is a vector of indicators for the five treatment groups and weeks without midweek jumps as baseline.

The main specification includes various controls. W_{wt} is the European reference wholesale price of gasoline, and θ^D_{iw} is a vector of three sets of indicators interacted with day-of-week indicators. The first set of indicators is the chain affiliation. Stations affiliated with a given chain can change $Treat_{iw}$-group from week to week depending on whether price jumps take place and whether the chain they are affiliated with is a leader, follower, or nonfollower in a given week. The $Chain \times D$ fixed effects control for differences in the development in the outcome variable through the week for different chains. The second set is the number of chains present in week w in the built-up area where station i is located, and the third set identifies if a given station is staffed or unstaffed. The second and third sets control for possible differences in the development in the outcome variable for stations located in areas with different numbers of competing chains and for differences between staffed and unstaffed stations. λ_{wt} represents $Month \times D$ fixed effects to account for changes in how the outcomes develop through the week over time. Week fixed effects, γ_w, are included to remove overall differences in the outcomes between different weeks. δ_i represents station fixed effects and ε_{iwt} is an error term.

Standard errors are clustered at the built-up area level. Two-way clustering by built-up area and week increases standard errors slightly, but the main results hold (Appendix Figure A.4).

The diff-in-diff model removes bias resulting from unobserved shocks that have the same effect on the outcome on all weekdays (such as demand shocks with the same effect on all weekdays) and accounts for trends through the week. The possible remaining biases are related to unobservables correlated with both Thursday price jumps and the development of the outcome through the week. The identifying assumption is that, in the absence of the Thursday jumps, the outcome of interest would have followed the same trend through the week as in weeks without midweek jump attempts (conditional on the control variables).[19]

Appendix Figures B.1–B.5 show trends through the weeks conditional on the control variables for the leader and followers in weeks with successful Thursday jumps and for all stations in weeks without midweek jumps (the counterfactual). Conditional on the control variables, all the outcomes follow a very similar trend from Tuesday to Wednesday in weeks with successful jumps as in weeks without price jumps. In the period after successful Thursday jumps are carried out (Friday–Sunday), the level of the outcomes is different, but the day-to-day changes are similar to the counterfactual. It should be noted that, except for Thursdays, the development through the week is almost identical for the

[19] The dependent variable is ln(outcome). Therefore, the identifying assumption is that in the absence of the Thursday jump, the log-change in the outcome variable from Wednesday to other weekdays would have been the same as in weeks without midweek jumps.

leader and the followers. The similar trends both before and after Thursday support the identifying assumption.

However, without controlling for changes in the wholesale price and the $Month \times D$ fixed effects, the price–cost margins fall faster from Tuesday to Wednesday (panel (a) in Appendix Figure A.3).[20] This is likely due to selection into Thursday price jumps when margins are low. As the wholesale price (and obviously the $Month \times D$) indicators are plausibly exogenous (see Appendix D), and controlling for these removes the pre-period trend differences, I am less concerned that selection into Thursday jumps biases the results. Note also that the developments through the week for the leader and the followers are almost identical (except for Thursdays) without the control variables, and that the main results are very similar with and without the controls (compare Appendix Figure A.3 with Figure 4).

Nevertheless, the common trend assumption in the diff-in-diff model could be violated if the Thursday price jumps are correlated with unobserved variables that are also correlated with the development of the outcome variable through the week. For example, the diff-in-diff estimate of the effect of Thursday jumps on volume-weighted margins can be biased if the chains can predict how fast margins will fall through the week and are more likely to initiate Thursday jumps if they expect faster than normal margin reductions from Thursday to Sunday. In this case, the counterfactual margin in the diff-in-diff model is too high (margins would have fallen faster than in the control group consisting of weeks without midweek price jumps) and the diff-in-diff estimate would be biased downwards.[21]

I estimate similar diff-in-diff models as Eq. 1 in Appendix D but use the Wednesday European reference wholesale price as an instrument for Thursday jumps to account for possible selection bias. The Wednesday reference wholesale price is a valid instrument because it is strongly correlated with the probability of Thursday price jumps. The exclusion restriction would be violated if the wholesale price is correlated with the outcome of interest through other channels than the Thursday price jumps. I argue that the European wholesale price is unlikely to be affected by shocks in the Norwegian gasoline market. In addition, I argue—based on out-of-sample testing—that the higher average prices in weeks with high wholesale prices are unlikely to bias results through an increase in the intertemporal demand elasticity.

The diff-in-diff and the instrumental variable (IV) models assume the same counterfactual development through the week for both the leader and followers. However, the chains could be selecting into leading price jumps based on unobservables that are cor-

[20] θ_{iw}^{D}, the three sets of indicators interacted with the day-of-week indicators are dropped in the model estimated for Figure A.3. However, these indicators have a very small impact on the results.

[21] Similarly, the diff-in-diff estimate of the effect on the volume sold from Friday to Sunday can be biased if the chains can both predict how demand will develop through the week and Thursday jumps are more likely if they expect demand to be high in the period after all chains have carried out a price jump (Friday–Sunday). The estimate of the counterfactual Friday–Sunday volume sold that I use in the diff-in-diff model would then be too low, giving an upward bias in the estimated effect that Thursday jumps have on the Friday–Sunday volume.

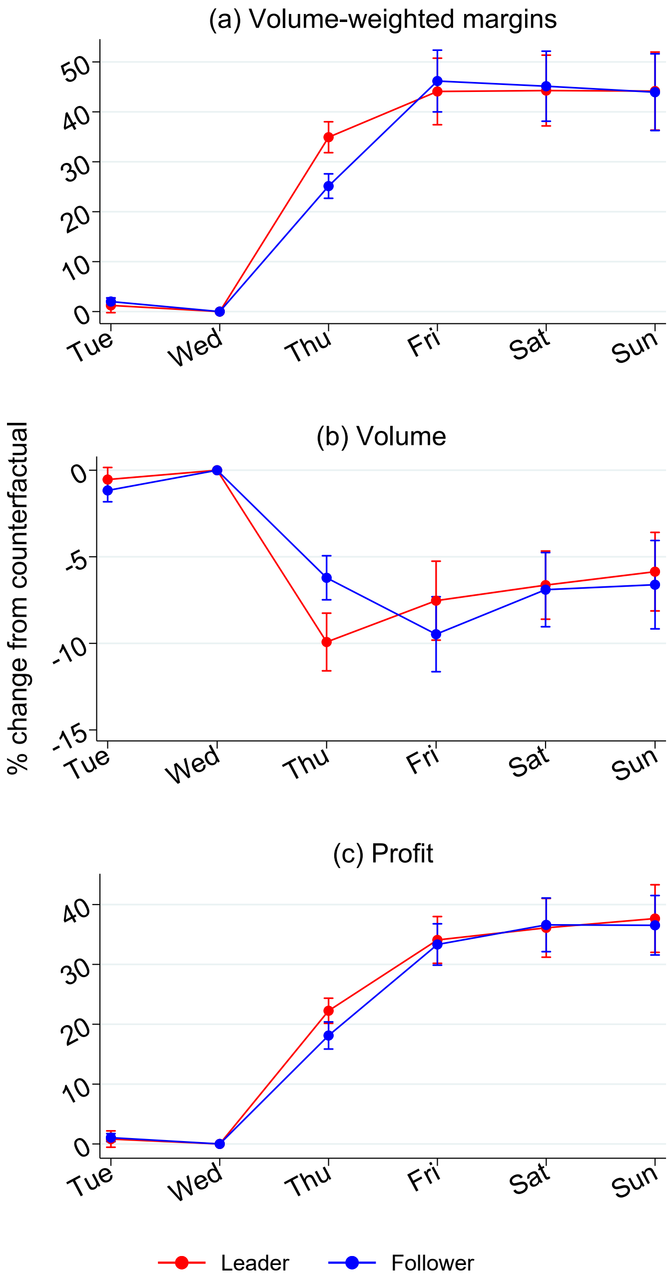
related with the outcome of interest. Even if the models are well suited to estimating the average effect of Thursday jumps across both the leader and the followers, selection into leading may make it difficult to separate effects for the leader and the followers. For example, a chain with a lower own-price demand elasticity on midday Thursday relative to other chains would have a lower cost of leading and therefore a greater incentive to lead. In this case, the loss of volume on Thursday for the leader relative to the followers would be overestimated.

Even so, I argue that selection into leading is unlikely to bias the results. Recall first that both the diff-in-diff and the IV models remove bias caused by unobservable shocks that have the same effect on all weekdays. $Chain \times D$ fixed effects also remove time-invariant chain-specific differences in Δy_{iwt}. Nevertheless, selection into leading could be a problem if Δy_{iwt} develops differently over time for different chains. Apart from spatial differentiation, retail gasoline is a very homogeneous product, and all four national chains have stations in all parts of Norway and quite stable market shares, suggesting that unobserved firm-specific factors that influence Δy_{iwt} are unlikely to exist.

3.2 Results—Successful price jumps

Figure 4 presents the main results from the diff-in-diff model. The red lines plot the difference in the development through the week in the outcome of interest between stations affiliated with the leader in weeks with successful Thursday jumps and all stations in weeks without midweek jumps (counterfactual). The blue lines plot the same for stations affiliated with the followers. Figures with the development through the week for both the treatment and control groups are presented in Appendix B. Appendix Table A.2 displays all coefficients. Results from the IV model are presented in Tables D.3–D.7 in Appendix D.

Figure 4: Successful price jumps



Note: The figure plots results from Eq. 1 with volume-weighted margins, volume sold, and profit as outcome of interest. The lines plot $(exp(\boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) \times 100$ over different weekdays for the treatment groups "Leader in successful weeks" and "Followers in successful weeks". The red lines plot the difference in the outcome through the week between stations affiliated with the leader in weeks with successful Thursday jumps and all stations in weeks without midweek jumps (counterfactual). The blue lines plot the same for stations affiliated with the followers. The 95% confidence intervals are shown.

3.2.1 Margins

Of course, the primary effect of the price jumps is to increase prices, and we expect successful jumps to result in large increases in price–cost margins.

Panel (a) in Figure 4 plots the diff-in-diff estimates of the effect that successful Thursday price jumps have on the leader's and followers' volume-weighted margins. The leader experiences a larger increase in margins on Thursday than the followers do (35% vs 25%). The higher average margins for the leader result from the leader moving early rather than the leader having higher prices at the top of the cycle (Section 2.3). Margins stay at the higher path through the rest of the week, and both the leader's and the followers' margins are 44%–46% higher than the counterfactual on Friday–Sunday. Overall, in weeks with successful Thursday jumps, the leader's volume-weighted margins are 25% higher than they would have been in the counterfactual.[22]

The IV model also indicates large positive effects of the Thursday price jumps (Appendix Table D.3). For Friday–Sunday, the IV model predicts margin increases about twice as large as those of the diff-in-diff model. The IV estimates are less accurate, making it difficult to identify differences between the leader and the followers.

3.2.2 Volume and market shares

Panel (b) in Figure 4 plots the results from the diff-in-diff model with liters of gasoline sold per day as the outcome of interest. As expected, volume sold falls after successful price jumps. Both the leader and followers sell 6%–9% less gasoline on the weekdays after the jump. On Thursday, the leader loses 10% of volume sold, whereas the followers lose only 6%. Losing 4% more volume on Thursday corresponds to losing 0.5% more of total weekly volume. The estimates from the IV model are similar to those from the diff-in-diff model (Appendix Table D.4).

The results suggest that in the very short run (1–4 days), the market demand elasticity is high and successful price jumps lead to a substantial volume loss for both the leader and followers. However, Levin et al. (2017) find that although there is a large response in the amount of gasoline purchased in the first days following a price change, the response results almost entirely from a temporary change in the probability of making a purchase rather than a change in gasoline usage. As in multiple other studies, Levin et al. (2017) find that the longer-run market demand elasticity is much lower than in the very short run. Consistent with this, I find that both the leader and followers experience a 3% increase in volume on Tuesdays and Wednesdays in the first week after a week featuring a successful midweek jump (Appendix E). The total effect that the price jumps have on

[22]The overall change in the weekly volume-weighted margin is the difference between the average volume-weighted margin across all weekdays in weeks with successful jumps, and the average volume-weighted margins across all weekdays in the counterfactual. I assume that 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.

gasoline demand is likely to be negative, but it is smaller than the decline in volumes seen on Thursday–Sunday in weeks with midweek jumps.

The leader's volume falls by 4% more than the followers' volume on the day of the price jump. As the leader's volume loss relative to the followers is central to the free-rider problem related to leading price jumps, I also show results from models with market share as the outcome of interest.[23] Panel (a) in Appendix Figure A.5 shows that the leader loses 3.4% market share on Thursday, whereas the followers gain 1.3%. Results from the IV model are similar (Appendix Table A.5). Losing 3.4% market share on Thursday reduces the weekly market share by about 0.5%.

The results support Wang (2009)'s prediction of a small volume loss for the leader when the delay between the leader and followers is short. The delay is comparably long in my study and Clark & Houde (2013)'s study of volume transfers between early and late movers in a Canadian retail gasoline cartel, but my results imply much smaller volume transfers from the early movers to the late movers than their estimate of an at least 2.5% loss of volume in restoration weeks for the early movers and at least 12.5% gains for the late movers.[24]

The main reason for the diverging results is likely to be that the share of total weekly volume sold in the few hours when the leader stands alone with a high price in my study is much smaller than the 14% of total weekly volume that Clark & Houde (2013) assume. Using the traffic flow data as a proxy for hourly fuel demand (Section 2.3), I estimate that total volume sold in the few hours from the time that the leader's stations increase prices until all other stations have increased prices is about 2.8% of total weekly volume.[25]

Clark & Houde (2013) base their assumption of a very high volume share in the restoration period on a stockpiling effect, whereby consumers time their purchases to the restoration period because prices are lowest during these hours. Stockpiling effects are certainly present in the market that I study, but prices are lower on Sundays and on Monday mornings than in the Thursday restoration period. Consumers shift their purchases to Sundays or Monday mornings rather than the Thursday restoration period (Tveito, 2021a).[26] Transforming the spell volumes to hourly volumes carries a risk of measure-

[23]The market share of station i is defined as the station's share of total volume sold in the built-up area where the station is located.

[24]Clark & Houde (2013) estimate that the late movers' total volume increases about 5% compared with simultaneous price changes and that the early movers' volume decreases about 1%. This includes both transfers from price increases and price decreases, but the authors mention that the transfers occur mostly during price restorations. Price restorations occur in only 20% of weeks. Assuming that 50% of the volume transfers are related to price increases, the authors' method provides an estimate of late movers' volume increase of $0.5 \times 0.05 \times (1/0.2) = 0.125 = 12.5\%$ in weeks with price restorations and the early movers' weekly volume decrease of $0.5 \times (-0.01) \times (1/0.2) = -0.025 = -2.5\%$.

[25]I assume that the leader increases prices at 11:00, that all stations affiliated with the followers have increased prices by 14:00 in built-up areas where the regional Chain E is not present (59% of stations), and that all stations have increased prices by 16:00 in built-up areas where Chain E is present (41% of the stations). Based on these assumptions, 2.8% of weekly traffic takes place during the hours before all other stations have increased their prices.

[26]Tveito (2021a) does not find evidence of a large share of volume sold in the Monday restoration period, estimating that the share of weekly volume sold on Mondays between 11:00 and 16:00 is about

ment error (Section 2.1); nevertheless, I find a similar Thursday restoration volume share (3.1% vs 2.8%) by converting the spell volumes to hourly data as I do with the traffic flow data.

I argue in Section 3.1 that selection into leading is unlikely to bias my results concerning the leader's volume loss. However, I provide an estimate of an extreme lower bound of the leader's loss. Even under the assumption of perfectly elastic demand, where the leader's stations sell no gasoline before all other stations in the same built-up area have jumped prices, the low share of volume sold in the Thursday restoration period implies that the leader only suffers a modest volume loss relative to the followers: the leader's weekly volume would fall 2.8%, and the followers' volumes would rise by on average about 0.7%. Various market imperfections imply that the own-price elasticity of demand is far from perfectly elastic. For example, Chandra & Tappata (2011) find that search costs deter gasoline consumers from price shopping. MacKey & Remer (2021) find that 62% of gasoline consumers become affiliated to the brand from which they have previously purchased. These consumers have an average own-price (brand-level) elasticity of only –0.55 and the average own-price elasticity across all consumers is –3.4.

The timing of price restorations to midday, when many people are at work and demand is likely quite low, probably lowers the volume loss for the leader. Price restorations typically occur around noon in retail gasoline markets with price cycles in Canada, the USA, Australia, and Germany (Atkinson, 2009; Lewis, 2012; Wang, 2009; Cabral et al., 2021).

It is likely that several other factors contribute to reducing the leader's loss of volume to its rivals. First, the followers match the leader's price increase very quickly, limiting the period when the leader stands alone with a high price. A high share of chain-owned stations and the headquarters' strict control of vertically separated station prices (Section 2.3) may contribute to the fast price jumps—the leader can increase prices at all affiliated station at about the same time and thus send a strong signal to rival chains that a market-wide price restoration has been initiated (Lewis, 2012), and the rivals can quickly match the price jump. Strong vertical price control is common in retail gasoline markets in other countries as well, and price restorations typically occur within a few hours (Wang, 2009; Lewis, 2012; Atkinson, 2009).

Second, the followers do not undercut the leader's price at the top of the cycle (Section 2.3) as Maskin & Tirole (1988)'s theory of Edgeworth cycles predicts. Thus, the leader only loses demand in the period before rivals match the price increase, and not in the subsequent period as it would if followers were undercutting the leader at the top of the cycle. Again, this result is not unique to the Norwegian retail fuel market—Atkinson (2009), Lewis (2012), and Wang (2009) show that the leader and the followers restore prices to about the same level in Canada, the USA, and Australia, respectively.

4% for the period 2005–2009.

3.2.3 Convenience store revenue

Gasoline price jumps could also have spillover effects on the co-located convenience stores' revenue. However, the baseline diff-in-diff model does not point to any clear effect of Thursday price jumps on convenience store revenue. For both the leader and the followers, the development in convenience store revenue through weeks with successful Thursday price jumps is about the same as in weeks without midweek price jumps (Appendix Figure B.4). The lack of an effect on convenience store revenue can be explained by a low share of convenience store sales coming from customers who also purchase gasoline. In a 2015 survey, the Norwegian Competition Authority found that only 14% of convenience store customers also purchased gasoline (Konkurransetilsynet, 2015a). Customers who avoid purchasing gasoline due to high gasoline prices could be more price sensitive and less inclined to shop at convenience stores where prices are higher than in grocery stores.

The IV model points to no effect on convenience store revenue for both the leader and followers on Thursday, but an 11% increase for the leader on Friday–Sunday (Appendix Table A.6). However, if there were an effect on convenience store revenue, we would expect it to be negative rather than positive in the period after the Thursday jumps were carried out.

Overall, there is no indication that Thursday price jumps have a negative effect on convenience store sales for the leader.

3.2.4 Profit

We have seen that successful Thursday price jumps bring about large increases in Thursday–Sunday margins and a lower volume sold for both the leader and the followers. As expected, on Thursday, the leader has a higher margin than the followers but it loses volume relative to the followers. In this section, I combine the margin and volume data to consider how the jumps affect firm profits.

I define daily profit for station i on day t as $\Pi_{it} = m_{it} \times v_{it}$, where m is volume-weighted margin and v is volume sold. Then, I estimate the diff-in-diff model in Eq. 1 and the IV model in Eq. D.2 with Π_{it} as the outcome of interest to determine how Thursday jumps affect profit.

In weeks with successful Thursday jumps, both the leader and the followers experience a close to 20% increase in profit on Thursday relative to the counterfactual (panel (c) in Figure 4). On Friday–Sunday, profits are 33–38% higher than the counterfactual. Overall, in weeks with successful Thursday jumps, the leader's profit increases 21% compared with a counterfactual without midweek jumps.[27] The IV model gives lower estimates of the Thursday profit increases than the diff-in-diff-model, and estimates that are more than twice as the large profit increases for Friday–Sunday (Appendix Table D.7).

[27]The overall change in weekly volume-weighted profit is the difference between the average profit across all weekdays (weighted by volume sold per weekday) in weeks with successful price jumps, and average profit across all weekdays in the counterfactual.

The results suggest that successful Thursday price jumps greatly increase the leader's profit. However, pre-jump margins are higher in weeks without a midweek jump than in weeks with a successful midweek jump (Appendix F). Could this mean that leading successful Thursday jumps would not have been profitable in weeks when no midweek jump occurred because margins would be quite high even without midweek jumps? I estimate a lower bound of the profitability of leading Thursday price jumps in no-midweek-jump weeks by assuming both that margins would increase to the same level and the leader's volume loss would be the same as in weeks with successful Thursday jumps. It is likely that this approach underestimates the profitability of price jumps because it both assumes a smaller price increase than in weeks with successful jumps (the leader's margin increases from a higher pre-jump level to the same post-jump level), and that the leader's volume loss is equally large as in weeks with successful jumps. Even with these conservative assumptions, I find that leading successful Thursday jumps in the weeks when they do not occur would have increased the leader's profit by 5% on Thursday and on average by 10% across Thursday–Sunday.

The results suggest that the leader does not lose profits relative to the followers—likely because the leader sells some volume during the short period before rivals match the high price and the leader's higher margins in this period counteracts the loss of volume to rivals. Even in the extreme scenario where the leader sells no gasoline in the restoration period, the leader's weekly profit only falls modestly by about 3%. If Thursday price jumps are profitable for the leader, and the leader is unlikely to be worse off than the followers, why do the jumps not occur every week? In the first quarter of 2009, after 4 years with irregular Thursday jumps, the jumps do in fact start to occur every week. I discuss the slow transition to regular Thursday jumps in Section 5.

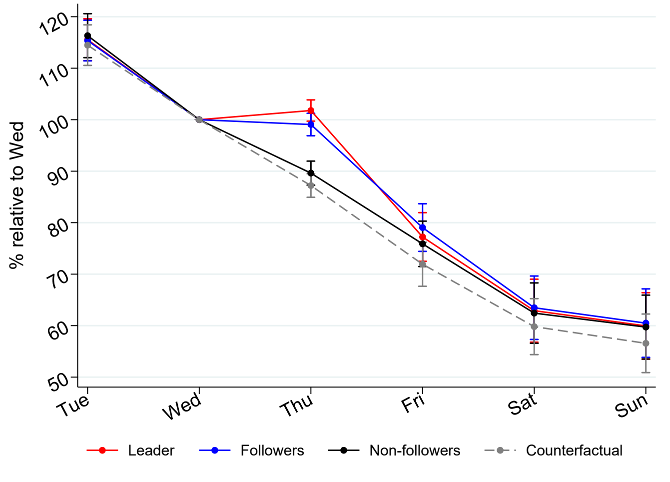
3.3 Failed price jumps

A total of 43% of all midweek price jumps fail because one or more chains do not follow the leader's price increase. Thursday jumps fail slightly less often (38%). Figure 5 shows the margin development through the week for the leader, followers, nonfollowers, and the counterfactual in weeks with failed Thursday jumps. The leader and followers experience a large increase in margins as they increase prices on Thursdays, whereas the nonfollowers stay at the same path as the counterfactual. The leader and followers quickly decrease prices again after observing that some chains do not follow, and margins converge down to about the same level as the nonfollowers' level over Friday–Sunday.[28]

The leader loses 5% volume on Thursdays with failed price jumps, whereas the followers lose 4% and the nonfollowers gain 1% (panel (a) in Appendix Figure A.6). In terms of Thursday market share, the leader loses 3%, the followers lose 1%, and the nonfollowers

[28] Margins for all chains stay slightly above the counterfactual on Friday–Sunday. This is likely because the distinction between failed and successful price jumps is not perfect. In some weeks categorized as failed price jumps, a small share of the stations keep prices high through the rest of the week.

Figure 5: Margins—Failed weeks



Note: The red line plots the development in volume-weighted margins through the week for stations affiliated with the leader in weeks with failed Thursday jumps. The blue line is for followers and the black for nonfollowers. The dashed gray line plots the development through the week for all stations in weeks without midweek jumps. The lines plot $(exp(\boldsymbol{\beta_2} D_t + \boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) \times 100$ in Eq. 1 with volume-weighted margins as the outcome of interest on different weekdays for the different treatment groups. The 95% confidence intervals are shown. Standard errors for the combined coefficients are calculated using the delta method.

gain 3% (panel (b) in Appendix Figure A.6).

The leader's margins are slightly larger than the followers' on Thursdays with failed jumps (Figure 5). The higher margins offset the leader's small market share loss, and the leader does not lose profit on Thursday relative to the other chains (panel (c) in Appendix Figure A.6).

4 Spillovers and long-run costs of price leadership

Consumer affiliation arising from search costs, habit formation, or brand loyalty may make consumers more likely to repurchase from a retailer from which they have previously purchased.[29] Such affiliations can result in negative spillover effects on the price leader's demand in the period after the followers have increased prices because loyal or poorly informed consumers are less likely to choose the leader after the price jumps when all firm have similar prices. Furthermore, if the same firm provides price leadership over a long period, the regular leader's volume loss can increase over time as consumers become better informed and change their habits to avoid buying from the leader when it stands

[29] See MacKey & Remer (2021) who find evidence of state dependence in the retail gasoline market.

alone with a high price.[30]

4.1 Spillovers

The presence of demand spillovers related to leading Thursday jumps should decrease the leader's volume relative to the nonleaders on other weekdays. I consider such possible spillovers in both the short run and the long run.

In the short run, spillovers would decrease the leader's volume relative to the nonleaders' on the days following the price jumps. As can be seen in panel (b) in Figure 4, the volume change on Friday–Sunday after successful Thursday jumps is almost identical for the leader and the followers, and market shares return to pre-jump levels (Appendix Figure A.5). The leader and followers experience a very similar volume increase on Tuesday and Wednesday in the week after successful price jumps (Appendix Table E.1).

There are multiple events where a chain starts to act as a regular leader of Thursday price jumps. Below, I exploit these events to examine how the regular leader's volume on the price jump day develops in the long run, but similar models can uncover spillovers. Spillovers to other weekdays could reduce the regular leader's volume on no-jump days over time. Column 4 in Appendix Table G.1 shows the volume development for the regular leader relative to the nonleaders on Wednesdays and column 4 shows the same for total volume over Tuesday, Friday, Saturday, and Sunday. There are no indications that the regular leaders lose volume relative to nonleaders on no-jump days in the period after taking up regular price leadership.

The short period in which the leader is the sole retailer with a high price and the small volume loss in this period suggest that relatively few customers notice that the leader has a higher price than the nonleaders. In this light, the lack of spillover effects is perhaps unsurprising.

4.2 Long-run effects

Price leadership is often provided by a single firm that leads most price increases over a long period (Lewis, 2012), and there are multiple episodes where a single chain leads almost all Thursday jumps over a long time period in the sample market. A gradually decreasing Thursday volume for the regular leader after it starts leading Thursday jumps would suggest that the volume loss of leading increases over time. To investigate such possible long-run effects, I conduct an event study into how the Thursday volume sold for stations affiliated with a chain acting as a regular leader of Thursday jumps develops in the weeks before ("pre-periods") and after ("post-periods") the chain starts to lead regularly.

[30] See e.g., Deryugina et al. (2020), who show that the residential price elasticity of electricity demand increases over time.

There are only two events where a chain starts to regularly lead Thursday jumps in the main sample period—Chain A leads for 4 months in 2005 and Chain B leads for 1.5 years during 2007–2009 (Figure 3). Therefore, I also include two events occurring later, when Thursday price jumps occur every week, when Chain C leads for 1.5 years in 2009–2010 and Chain D leads for a little for than a year in 2014–2015; see Appendix Figure G.1 for a summary of the different events.

The treatment group consists of stations affiliated with the chain that takes up regular Thursday price leadership in each event. To account for trends affecting both the regular leader and the other chains, the treatment group is compared with a control group of stations affiliated with the other chains in the market.[31] The control group is also affected by the events—they follow the leader's Thursday price jumps in the post-period.[32] Thus, the estimated treatment effect is the effect of leading price jumps relative to following a leader's jumps. Our main interest is not in the average treatment effect across all weeks in the post-period, but rather how the effect evolves over time in the post-period.

Unobserved shocks could affect the volume of the treatment and control groups differently and bias estimates. For example, an advertising campaign carried out by the regular price leader could increase demand on all weekdays for the leader's stations relative to other stations. To minimize the risk of bias, I use the change in volume from Wednesday to Thursday as the dependent variable. This essentially makes the analysis a triple diff-in-diff. The third difference is the change in the volume from Wednesday to Thursday. The first difference is the change in the treatment group's volume development from Wednesday to Thursday in the baseline period compared with other periods. The second difference is the change in the control group's volume development from Wednesday to Thursday in the baseline period compared with the other periods. This approach eliminates bias caused by unobserved factors that have a differential effect on the overall

[31] Observations from stations affiliated with the chain that is a regular leader in the pre-period in each event are excluded from the control group. This means that Chain B is removed from Event 3, and Chain C is removed from Event 4. No chain is excluded from Event 1 or 2 as there were few Thursday jumps and no regular Thursday leader in the pre-period in these events.

[32] Ideally, there would be no Thursday price jumps in the pre-period of the events and Thursday jumps led by the regular leader in every week in the post-period. However, in the pre-period of the first three events, there are Thursday jumps in a little more than half of the weeks and different chains lead the jumps. This gives some week-to-week variation in the Thursday prices and volumes between the different chains. Therefore, I only retain the weeks without Thursday jumps in the pre-periods of these three events. In the last event, Thursday jumps occur in all weeks in the pre-period and the same chain leads almost all these jumps. As Thursday jumps always occur and the same chain leads, there is little week-to-week variation in Thursday prices and volumes, and I keep all weeks in the pre-period in this event.

In the post-periods, the regular leader leads Thursday jumps in 81% of weeks, there are no Thursday jumps in 7% of weeks, and there are Thursday jumps led by a chain that is not a regular leader in 12% of the weeks. Almost all post-period weeks without Thursday jumps occur in Event 2. The results in this section are robust to removing Event 2 from the sample. Almost all post-period Thursday jumps led by a chain that is not a regular leader occur over a few months in Event 3 when the regular leader delays its price jumps a few hours. The results in this section are robust to removing Event 3 from the sample. I limit the post-period sample to the 81% of weeks when the regular leader leads Thursday jumps because the Thursday price difference between the regular leader and the other chains is obviously different in weeks when the regular leader does not lead.

weekly demand of the treatment and control groups. In the example with the leader's advertising campaign, the campaign is unlikely to change Thursday demand relative to Wednesday demand and therefore unlikely to bias the triple diff-in-diff estimates.

The estimation is carried out with the following model:

The estimation is carried out with the following model:

$$\Delta y_{ijw} = \alpha + \beta L_{ij} + \sum_{\tau=-10}^{19} \gamma_\tau \times L_{ij} + \theta_w + \delta_{ij} + \varepsilon_{ijw} \tag{2}$$

where $\Delta y_{ijw} = ln(y_{ijw4}) - ln(y_{ijw3})$ is the log difference in the outcome of interest from Wednesday to Thursday for station i in event j and week w. L_{ij} identifies the treatment group in each event. $\sum_{\tau=-10}^{19} \gamma_\tau$ represents the indicator variables for the last 10 weeks before and the first 20 weeks after each event. $\tau = 0$ is the first week with treatment and $\tau = -1$ is the reference week.

I follow the recommendation in (Baker et al., 2021) and include event-saturated station fixed effects, δ_{ij}, and event-saturated event-time fixed effects, θ_{iw}. ε_{ijw} is an error term.[33] Standard errors are clustered at the built-up area level.

To consider even longer-run trends and to smooth out week-to-week variations, I estimate a similar model but include 48 weeks pre and post the events and let τ represent 4-week periods ($\tau = 0$ represents the first 4 weeks with treatment).

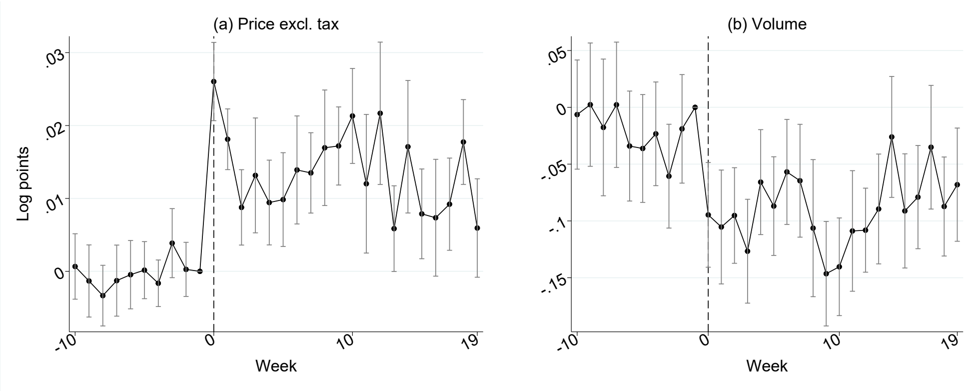
As explained in Section 3.1), the price leader in a given week could be selected based on unobservables. The same problem could be present when considering the effects of being a regular price leader. Using Δy_{ijw} rather than just y_{ijw4} as the dependent variable removes bias caused by selection on unobservables that affect demand in the same way on all weekdays, and δ_{ij} removes selection based on unobserved event-invariant station-specific differences in Δy_{ijw}. The treatment estimate could still be biased if the selection of a given chain as a regular leader is influenced by differing expectations about the development over time in Δy_{ijw} among the chains.[34] For example, a chain could become a regular leader because it expects its Thursday volume to gradually fall relative to volume on other weekdays during the next year, whereas the other chains expect no change. Selection into price leadership cannot be ruled out, but the homogeneous nature of the retail gasoline industry (see Section 3.1), having Δy_{ijw} rather than y_{ijw4} as dependent variable, and including *station* $\times$ *event* fixed effects make selection unlikely to have a large impact on the estimates. Adding to this, the pre-trends do not point to any changes in Thursday demand for the forthcoming regular leader relative to the other chains (panels (b) in Figure 6 and Appendix Figure G.2).

Post-period changes in relative prices between the treatment and control groups pose a final threat to identification. The chains could respond to changes in Thursday demand

[33] The main results are robust to including calendar month fixed effects to account for seasonality and various controls to account for changes in the number of competitors that each station faces.

[34] Recall that the main interest in this section is the volume development over time for the leader after it starts to lead, not the difference between the pre- and the post-period.

Figure 6: Long-run event study - weekly



Note: The figure shows results from Eq. 2. Panel (a) plots γ_τ from –10 to 19 with volume-weighted daily gasoline prices as the outcome of interest. Panel (b) plots the same with daily volume gasoline as the outcome of interest. The 95% confidence intervals are also included. The results in tabular form are presented in Appendix Table G.1.

by changing Thursday prices. Thus, changes in the regular leader's prices relative to the other chains' prices over time in the post-period could be indicative of long-run demand effects but would also complicate the analysis of long-run demand changes because the price changes would impact the observed post-period volumes. Panels (a) in Figure 6 and Appendix Figure G.2 show that the only notable change occurs when the regular leader's Δp_{ijw} (Thursday price minus Wednesday price) increases 1–2 log points relative to that of the control group in period $\tau = 0$. Otherwise, the difference in prices is fairly stable in both the pre- and the post-period

Panel (b) in Figure 6 depicts results from Eq. 2 with volume as the outcome of interest. As expected, the regular leader experiences a downward shift in Δv_{ijw} relative to the control group in week $\tau = 0$. The regular leader's volume relative to the other chains' volumes vary somewhat over the next 20 weeks, but the volume difference does not increase over time.[35] Appendix Figure G.2 depicts results from a model similar to Eq. 2, but with τ representing 4-week periods and with 12 such periods before and after each event included. As can be seen in the figure, there is no evidence of increasing volume loss. The midday timing of price restorations masking the timing of price restorations for many customers might be part of the reason why the leader does not experience an increasing demand loss over time.

[35]The results are similar to the Thursday volume rather than to the difference from Wednesday to Thursday as the dependent variable (Appendix Table G.1).

5 Concluding remarks

High-frequency price and volume data coupled with a particular price pattern have allowed me to estimate the costs and benefits of leading price jumps in a retail gasoline market. The evidence suggests that rivals follow the leader's price jump within a few hours and that the leader's volume loss is low both in weeks when price jumps fail and in weeks when they succeed. Successful jumps bring about large margin and profit increases for both the leader and followers. Regardless of whether price jumps succeed or fail, the leader does not lose profit relative to the other chains, indicating that the free-rider problem is of little importance in this market.

Given the profitability of leading price jumps and the apparent unimportance of the free-rider problem, it is perhaps surprising that Thursday jumps do not happen every week. However, Thursday jumps become a regular occurrence just after the sample period ends when one of the chains starts to lead Thursday jumps every week. Successful Thursday jumps are then carried out every week over the next 8 years. During the sample period, each individual chain did not have access to the 4 years of price and volume data from all chains that I use in this paper. Uncertainty about the costs and benefits of leading and following price jumps may have contributed to what appear, in retrospect, to be suboptimal strategies in the sample period. Slow equilibrium transitions are not unique to the Norwegian retail fuel market—Byrne & de Roos (2019) show that Australian gasoline retailers took 3 years to coordinate on a collusive equilibrium.

Providing price leadership to coordinate price increases is not illegal per se. Changing this would risk unduly restricting firms' ability to compete. Policy makers wanting to decrease average prices could instead implement regulations aimed at increasing the leader's volume loss to make it less attractive to lead and thus possibly decrease the frequency of price jumps. Regulating how often firms can change their prices can increase the time for which the leader is the sole chain to implement a high price and thus increase the volume loss (Wang, 2009), but such regulation risks limiting competition in the undercutting phase (Byrne & de Roos, 2019). Regulations mandating that gas stations post prices on government webpages can increase the leader's volume loss by helping consumers time their purchases to the bottom of the cycle and take advantage of the nonleaders' lower prices. However, such measures can also facilitate collusion by helping firms monitor their rivals' actions and have been shown to increase retail gasoline margins (Luco, 2019).

In recent years, some policy makers have focused on enabling customers to time their purchases to the bottom of the price cycle. For example, both the Australian and the Norwegian Competition Authorities frequently collect price data from the retail chains and issue updates online, in reports or press releases focusing on when prices are lowest (ACCC, 2021; Konkurransetilsynet, 2014). An additional benefit of these measures could be increasing the share of total volume that is sold in the period when the leader only has a high price, thereby increasing the cost of leading. Policy makers could also identify the price leader and provide information about when each firm typically increases prices to help consumers take advantage of the nonleaders' low prices in the period before they match the leader's price jump. Such limited information disclosure measures could increase the cost of being a price leader and thus possibly decrease the frequency of price jumps, but would not temper firms' capacity to price freely and would largely avoid improving firms' ability to monitor their rivals' actions.

References

ACCC. (2021). *Petrol Price Cycles.* Retrieved 2021-08-06, from https://www.accc.gov.au/consumers/petrol-diesel-lpg/petrol-price-cycles#petrol-price-cycles-in-capital-cities/

Andreoli-Versbach, P., & Franck, J. (2015). Endogenous Price Commitment, Sticky and Leadership Pricing: Evidence from the Italian Petrol Market. *International Journal of Industrial Organization*, *40*, 32-48.

Atkinson, B. (2009). Retail Gasoline Price Cycles: Evidence from Guelph, Ontario Using Bi Hourly, Station-Specific Retail Price Data. *Energy Journal*, *30*(1), 85-109.

Bachmeier, L. J., & Griffin, J. M. (2003). New Evidence on Asymmetric Gasoline Price Responses. *Review of Economics and Statistics*, *85*(3), 772-776.

Baker, A., Larcker, D., & Wang, C. (2021). How Much Should We Trust Staggered Difference-In-Differences Estimates? *Working Paper*.

Bergantino, A. S., Capozza, C., & Capurso, M. (2018). Follow the Leader: Price Change Timing in Internet-Based Selling. *Managerial and Decision Economics*, *50*(46), 4937-4953.

Byrne, D. P., & de Roos, N. (2019). Learning to Coordinate - A Study in Retail Gasoline. *American Economic Review*, *109*(2), 591-619.

Cabral, L., Duerr, N., Schober, D., & Voll, O. (2021). Price Matching Guarantees and Collusion: Theory and Evidence from Germany. *Working Paper*.

Chandra, A., & Tappata, M. (2011). Consumer search and dynamic price dispersion: an application to gasoline markets. *RAND Journal of Economics*, *42*(4), 681-7043.

Clark, R., & Houde, J. F. (2013). Collusion with Asymmetric Retailers: Evidence from a Gasoline Price-Fixing Case. *American Economic Journal: Microeconomics*, *5*(3), 97-123.

Conlisk, J., Gerstner, E., & Sobel, J. (1984). Cyclic Pricing by a Durable Goods Monopolist. *Quarterly Journal of Economics*, *38*(2), 291-313.

de Roos, N., & Smirnov, V. (2020). Collusion with Intertemporal Price Dispersion. *RAND Journal of Economics*, *51*(1), 158-188.

Deryugina, T., MacKay, A., & Reif, J. (2020). The Long-Run Dynamics of Electricity Demand: Evidence from Municipal Aggregation. *American Economic Journal: Applied Economics*, *12*(1), 86-114.

Drivkraft Norge. (2021). *Salg av Bransjens Hovedprodukter tilbake til 1952 (Sale of the Industries Main Products back to 1952.* Retrieved 2021-08-25, from https://www.drivkraftnorge.no/siteassets/dokumenter--filer/statistikk/salg/salg-tilbake-til-1952-til-hjemmesiden.xlsx

Edgeworth, F. Y. (1925). *'The Pure Theory Economy' in Papers Relating to Political Economy, Volume 1.* MacMillan.

Foros, Ø., & Steen, F. (2013). Vertical Control and Price Cycles in Gasoline Retailing. *Scandinavian Journal of Economics*, *115*(3), 640-661.

Harrington, J. E. (2017). A Theory of Collusion with Partial Mutual Understanding. *Research in Economics*, *71*, 140-158.

Harrington, J. E., & Zhao, W. (2012). Signaling and Tacit Collusion in an Infinitely Repeated Prisoners' Dilemma. *Mathematical Social Sciences*, *64*, 277-289.

Hastings, J. S., & Shapiro, J. M. (2013). Fungibility and Consumer Choice: Evidence from Commodity Price Shocks. *Quarterly Journal of Economics*, *128*(4), 1449-1498.

Kauffman, R. J., & Wood, C. A. (2007). Follow the Leader: Price Change Timing in Internet-Based Selling. *Managerial and Decision Economics*, *28*(7), 679-700.

Konkurransetilsynet. (2014). Drivstoff Markedet i Norge - Marginøkning og Ny Pristopp (The Norwegian Fuel Market – Margin increase and a New Price Peak).

Konkurransetilsynet. (2015a). Varsel - NorgesGruppen ASA - Tiger AS/Esso Norge AS - Konkurranseloven § 16 jf. § 20 - Inngrep mot Foretakssammenslutning (Statement of Objection - Tiger AS/Esso Norge AS - the Competition act § 16 jf. § 20 - Intervention Against Merger).

Konkurransetilsynet. (2015b). Vedtak V2015-29 - St1 Nordic OY - Smart Fuel AS - Konkurranseloven § 16 jf. § 20 - Inngrep mot Foretakssammenslutning (Decision V2015-29 - St1 Nordic OY - Smart Fuel AS - the Competition Act § 16 jf. § 20 - Intervention Against Merger).

Levin, L., Lewis, M. S., & Wolak, F. A. (2017). High Frequency Evidence on the Demand for Gasoline. *American Economic Journal: Economic Policy*, *9*(3), 314–347.

Lewis, M. S. (2012). Price Leadership and Coordination in Retail Gasoline Markets with Price Cycles. *International Journal of Industrial Organization*, *30*(4), 342–351.

Liu, W. (2016). Estimating the Elasticities of Gasoline Demand: an Instrumental Variable Approach. *Applied Economics Letters*, *23*(16), 1153-1156.

Luco, F. (2019). Who Benefits from Information Disclosure? The Case of Retail Gasoline. *American Economic Journal: Microeconomics*, *11*(2), 277-305.

MacKey, A., & Remer, M. (2021). Consumer Inertia and Market Power. *Working Paper*.

Markham, J. W. (1951). The Nature and Significance of Price Leadership. *American Economic Review*, *41*(5), 891-905.

Maskin, E., & Tirole, J. (1988). A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles. *Econometrica*, *56*(3), 571-599.

Miller, N. H., Sheu, G., & Weinberg, M. C. (in press). Oligopolistic Price Leadership and Mergers: The United States Beer Industry. *American Economic Review.*

Neset, G. P. (2010). Prisstøttesystemet i Bensinmarkedet (The Price Support System in the Gasoline Market).

Noel, M. D. (2008). Edgeworth Price Cycles and Focal Prices: Computational Dynamic Markov Equilibria. *Journal of Economics and Managment Science*, *17*(2), 345-377.

Noel, M. D. (2012). Edgeworth Price Cycles and Intertemporal Price Discrimination. *Energy Economics*, *34*(4), 942–954.

Noel, M. D. (2019). Calendar Synchronization of Gasoline Price Increases. *Journal of Economics and Managment Science*, *28*(2), 355-370.

Sanderson, E., & Windmeijer, F. (2016). A Weak Instrument F-test in Linear IV models with Multiple Endogenous Variables. *Journal of Econometrics*, *190*(2), 212-221.

Seaton, J. S., & Waterson, M. (2013). Identifying and Characterising Price Leadership in British Supermarkets. *International Journal of Industrial Organization*, *115*(31), 392-403.

Tveito, A. (2021a). Dynamics in Intertemporal Substitution – Evidence from Retail Fuel. *Working Paper*.

Tveito, A. (2021b). Might as Well Jump! Coordinating More Frequent Price Hikes in a Retail Gasoline Market. *Working Paper*.

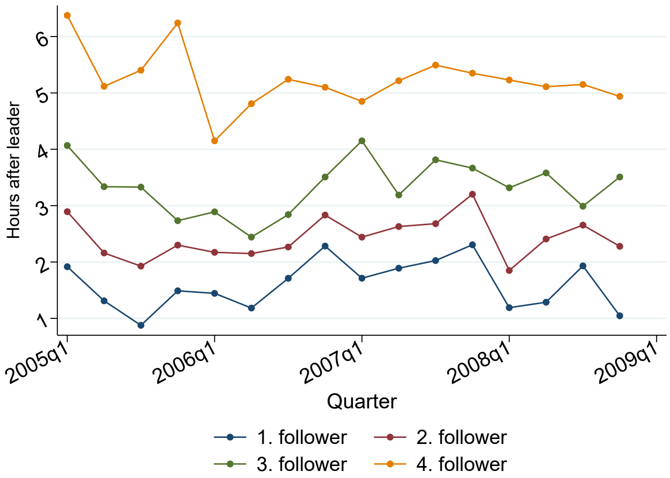
Wang, Z. (2008). Collusive Communication and Pricing Coordination in a Retail Gasoline Market. *Review of Industrial Organization*, *32*(1), 32-52.

Wang, Z. (2009). (Mixed) Strategy in Oligopoly Pricing: Evidence from Gasoline Price Cycles Before and Under a Timing Regulation. *Journal of Political Economy*, *117*(61), 987-1030.

Appendices

A Additional figures and tables

Figure A.1: Follower delay after leader, Jan 2005–Nov 2008



Note: The figure depicts the quarterly development in average duration from the leader carried out a *chain price jump* until the first to fourth follower carried out a *chain price jump*. The figure is based on successful midweek price jumps.

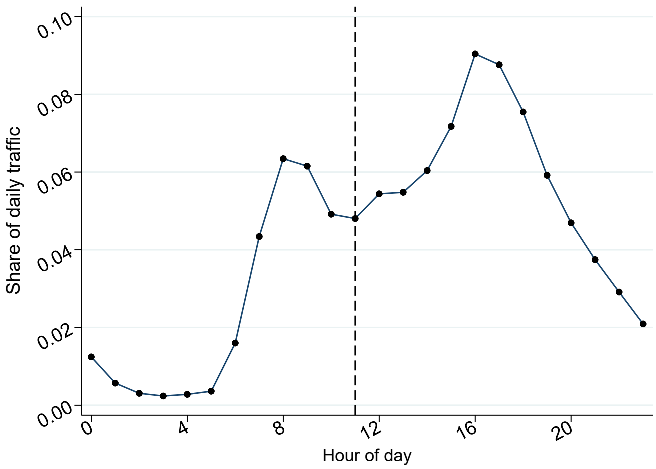
Table A.1: Prices at the top of the cycle

	Within Station	Within Built-up Area
Leader	0.0002	0.0008**
	(0.0004)	(0.0003)
Staffed		0.0122***
		(0.0005)
Constant	2.4668***	2.4575***
	(0.0001)	(0.0004)
Week FE	Yes	Yes
Station FE	Yes	No
Built-up area FE	No	Yes
Observations	95329	95270
R2	0.98	0.97

Note: The first column shows results from the regression model $ln(y_{iw}) = \beta_1 Leader_{iw} + \gamma_i + \delta_w + \varepsilon_{iw}$. y_{iw} is the maximum price of station i on the day the chain it is affiliated with carries out a Thursday price jump in week w. $Leader_{iw}$ identifies stations affiliated with the chain that is leading the midweek price jump in week w. δ_w represents week-fixed-effects and γ_i represents station-fixed-effects. The second column shows results from the regression $ln(y_{iw}) = \beta_1 Leader_{iw} + \beta_2 Staffed_i + \gamma_i + \delta_w + \varepsilon_{iw}$, where $Staffed$ identifies stations with a staffed convenience store, and θ_i represent built-up area-fixed-effects. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Take note of the following:

1. The first column of results shows that a station's maximum price on days with Thursday jumps is 0.02% higher (and not significantly different from zero) in weeks when the chain they are associated with is leading a Thursday jumps than in weeks when the chain is following.
2. The second column of results shows that, after controlling for whether stations are staffed or not, stations in a given built-up area associated with the leader have 0.08% higher maximum prices on days with Thursday jumps than station in the same built-up area associated with the followers.
3. Both models point to the leader and followers having very similar maximum prices on days with Thursday jumps. In levels the difference is NOK 0.002–0.009. 0.01 NOK is the smallest possible price increment and the average size of price cuts in the sample is NOK 0.15.

Figure A.2: Hourly share of Thursday traffic counts



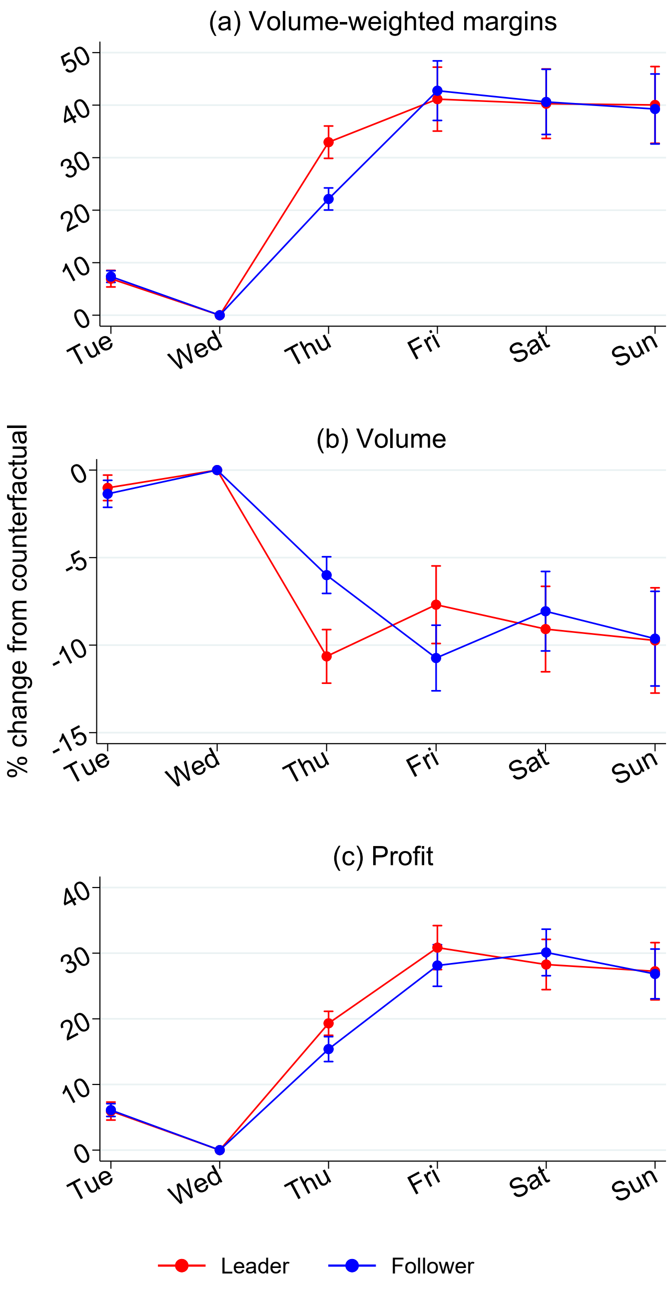
Note: The figure shows the average hourly share of the total daily count of cars on Thursdays. The sample consists of all cars passing tracker stations run by The Norwegian Public Roads Administration at 9 roads in the county of Vestfold in Norway on Thursdays in the period March 2014–December 2017. Observations from vehicles longer than 7.5 meters, and observations in weeks with public holidays are excluded. The dashed line marks the hour from 11:00 to 12:00.

Table A.2: Thursday price jumps

	M	V	MS	CSR	Pro
Wholesale price	0.34***	0.97***	1.00	0.95***	0.32***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Tue	1.14***	0.88***	0.96***	0.99	1.00
	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)
Thu	0.87***	1.10***	1.00	1.04***	0.96***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Fri	0.72***	1.33***	1.03**	1.23***	0.96
	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)
Sat	0.60***	1.25***	1.07***	1.06	0.73***
	(0.03)	(0.04)	(0.01)	(0.04)	(0.02)
Sun	0.57***	1.29***	1.13***	1.47***	0.70***
	(0.03)	(0.06)	(0.03)	(0.10)	(0.03)
Fail - Leader	1.00	1.00	1.00	0.97***	1.01
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Fail - Follower	0.99	0.99	1.00	0.98**	0.99*
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
Success - Leader	1.01	0.99*	0.99**	1.00	1.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Tue × Fail - Leader	1.01**	0.99	1.01**	1.00	1.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Tue × Fail - Follower	1.01**	0.98***	0.99***	0.99**	0.99***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Tue × Fail - Non-Follower	1.02***	0.98***	1.00	0.99*	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Tue × Success - Leader	1.01	0.99	1.00	1.00	1.01
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Tue × Success - Follower	1.02***	0.99***	1.00	0.99***	1.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Thu × Fail - Leader	1.17***	0.95***	0.97***	1.01	1.11***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Thu × Fail - Follower	1.14***	0.96***	0.99***	1.01***	1.10***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Thu × Fail - Non-Follower	1.03***	1.01**	1.03***	1.00	1.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Thu × Success - Leader	1.35***	0.90***	0.97***	1.00	1.22***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)
Thu × Success - Follower	1.25***	0.94***	1.01***	1.00	1.18***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Fri × Fail - Leader	1.07***	1.00	1.02***	1.01	1.07***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Fri × Fail - Follower	1.10***	0.97***	0.99***	0.99	1.06***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Fri × Fail - Non-Follower	1.06***	0.98***	1.00	0.99*	1.04***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Fri × Success - Leader	1.44***	0.92***	1.02***	1.00	1.34***
	(0.03)	(0.01)	(0.00)	(0.00)	(0.02)
Fri × Success - Follower	1.46***	0.91***	1.00**	0.98***	1.33***
	(0.03)	(0.01)	(0.00)	(0.00)	(0.02)
Sat × Fail - Leader	1.05***	0.99*	1.00	1.01	1.04***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Sat × Fail - Follower	1.06***	0.98***	1.00	1.01*	1.05***
	(0.02)	(0.00)	(0.00)	(0.00)	(0.01)
Sat × Fail - Non-Follower	1.04***	0.98***	1.00	1.01*	1.02**
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Sat × Success - Leader	1.44***	0.93***	1.00	1.03***	1.36***
	(0.04)	(0.01)	(0.00)	(0.00)	(0.03)
Sat × Success - Follower	1.45***	0.93***	1.00	1.00	1.37***
	(0.04)	(0.01)	(0.00)	(0.00)	(0.02)
Sun × Fail - Leader	1.06**	1.00	1.01*	1.06***	1.06**
	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)
Sun × Fail - Follower	1.07**	0.98**	0.99**	1.01	1.05**
	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)
Sun × Fail - Non-Follower	1.06***	0.97***	1.00	1.00	1.03*
	(0.02)	(0.00)	(0.00)	(0.00)	(0.01)
Sun × Success - Leader	1.44***	0.94***	1.00	1.02***	1.38***
	(0.04)	(0.01)	(0.00)	(0.01)	(0.03)
Sun × Success - Follower	1.44***	0.93***	1.00	0.98***	1.37***
	(0.04)	(0.01)	(0.00)	(0.00)	(0.03)
Week FE	Yes	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes	Yes
Chain X DoW FE	Yes	Yes	Yes	Yes	Yes
N Chain X DoW FE	Yes	Yes	Yes	Yes	Yes
Staffed X DoW FE	Yes	Yes	Yes	Yes	Yes
Month X DoW FE	Yes	Yes	Yes	Yes	Yes
Observations	836004	844277	844277	582597	836004
R2	0.22	0.13	0.05	0.25	0.13

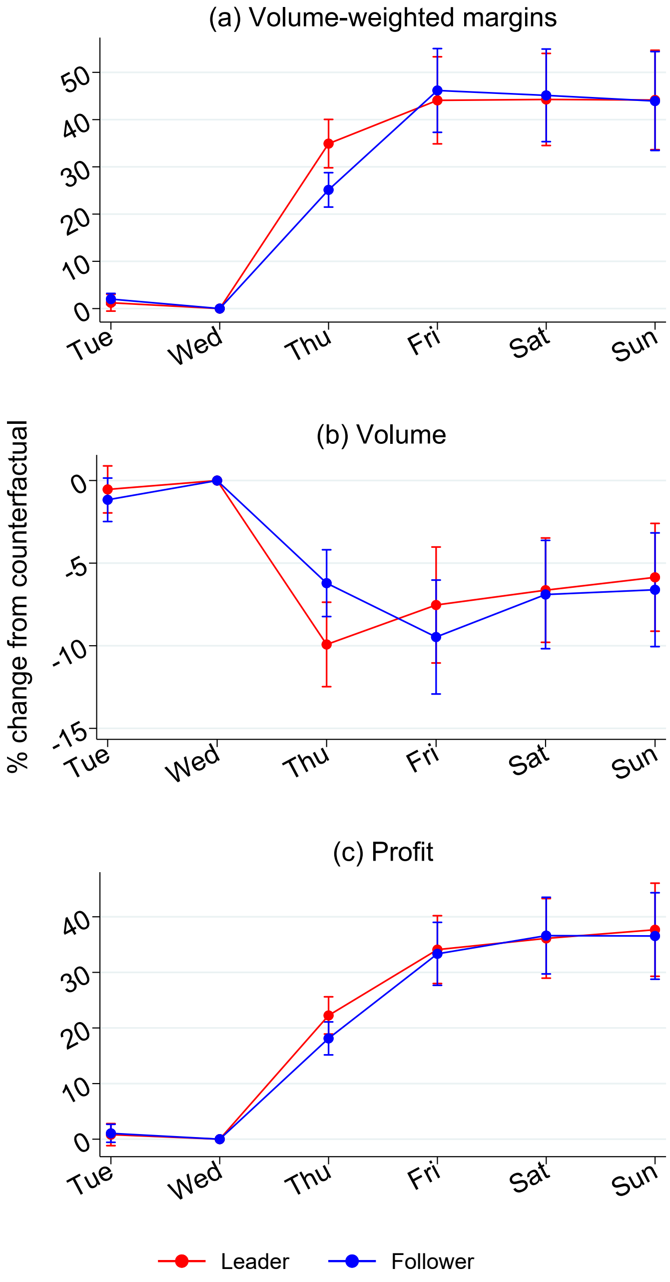
Note: The table shows the results from Eq. 1 for Thursday price jumps with the outcome of interest being volume-weighted retail gasoline margins, liters of gasoline sold per day, market shares based on volume gasoline, convenience store revenue, and profits, respectively. The coefficients are exponentiated. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Figure A.3: Successful price jumps, less controls



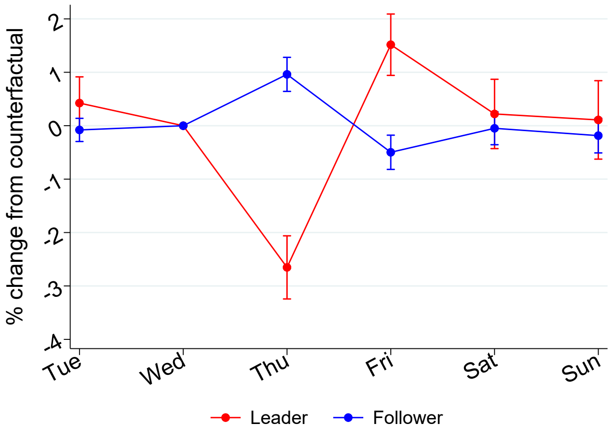
Note: The figure plots results from a model similar to Eq. 1, but with less control variables. ρW_{wt}, θ^D_{iw} and λ_{wt} are not included. Volume-weighted margins, volume sold, and profits are outcomes of interest. The lines plot $(exp(\boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) \times 100$ over different weekdays for the treatment groups "leader in successful weeks" and "followers in successful weeks". 95% confidence intervals are shown.

Figure A.4: Successful price jumps, two-way clustering



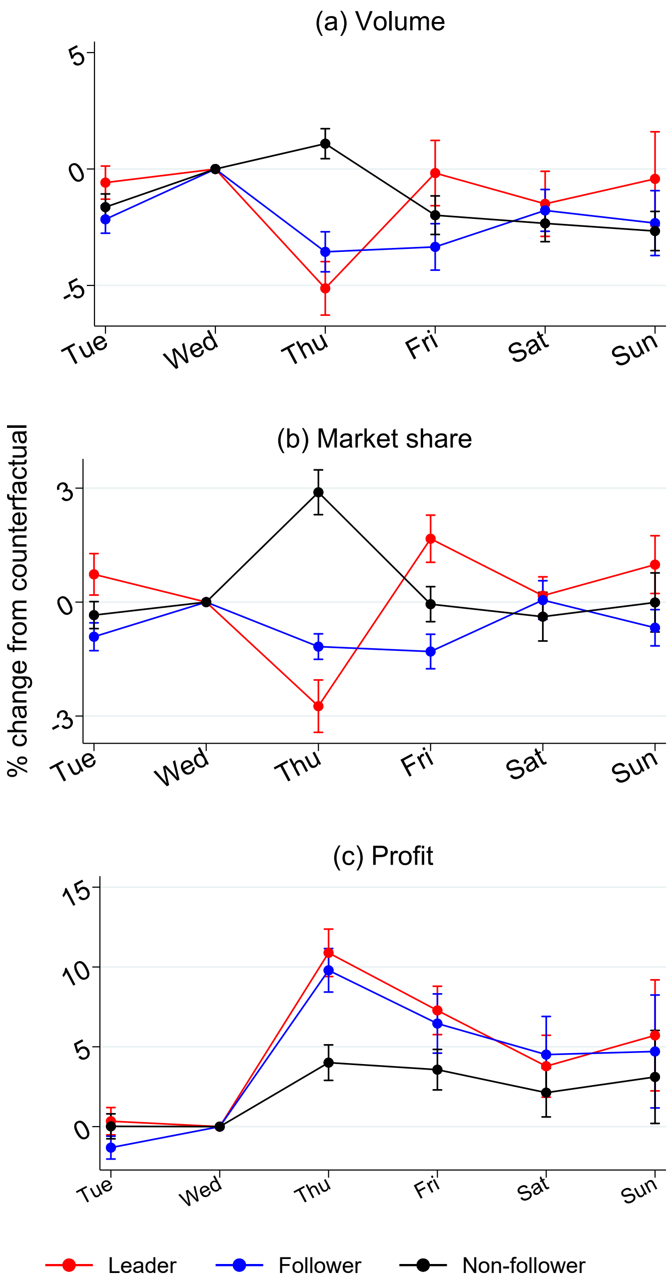
Note: The figure plots results from Eq. 1, but with two-way clustering of standard errors on built-up area and week. Volume-weighted margins, volume sold, and profits are outcomes of interest. The lines plot $(exp(\boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) \times 100$ over different weekdays for the treatment groups "leader in successful weeks" and "followers in successful weeks". 95% confidence intervals are shown.

Figure A.5: Successful Thursday jumps, market share



Note: The figure plots results from Eq. 1 with gasoline market share as outcome of interest. The lines plot $(exp(\boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) \times 100$ over different weekdays for the treatment groups "leader in failed weeks" and "followers in failed weeks". 95% confidence intervals are shown.

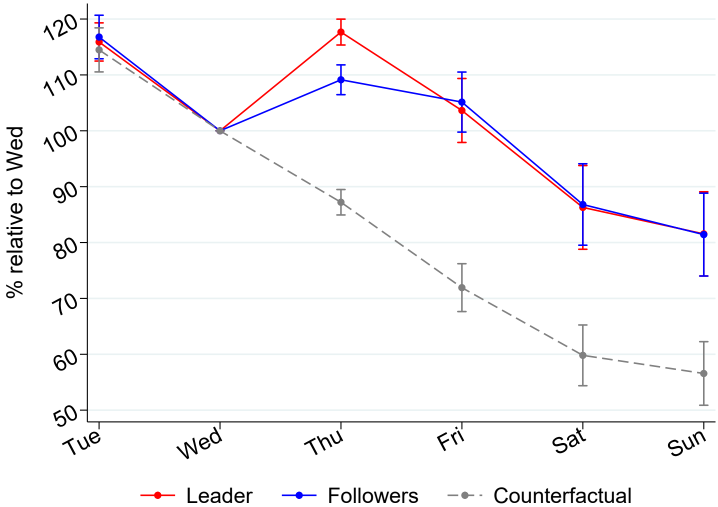
Figure A.6: Failed Thursday price jumps



Note: The figure plots results from Eq. 1 with volume-weighted margins, volume sold and profit as outcome of interest. The lines plot $(exp(\boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) \times 100$ over different weekdays for the treatment groups “leader in failed weeks”, “followers in failed weeks” and “non-followers in failed weeks”. 95% confidence intervals are shown.

B Trends through the week

Figure B.1: Margins trends, success

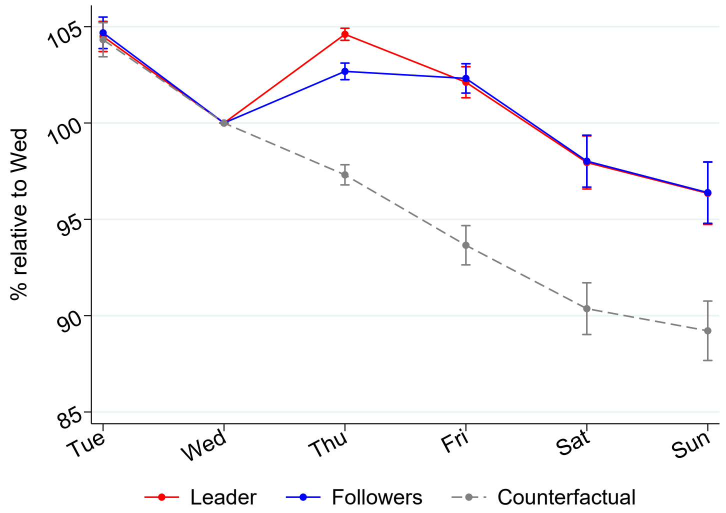


Note: The red line plots the development in volume-weighted margins through the week for stations affiliated with the price leader in weeks with successful Thursday jumps. The blue line for the followers. The dashed gray line plots the development through the week for all stations in weeks without midweek jumps. Take note of the following:

1. The leader's and followers' margins have a very similar development from Tuesday to Wednesday compared with weeks without midweek jumps.
2. After the Thursday jumps, the leader's and followers' margins stay at a higher level but have a very similar development compared with weeks without midweek jumps.

*The lines plot $(exp(\boldsymbol{\beta_2} D_t + \boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) * 100$ in Eq. 1 with volume-weighted margins as outcome of interest over different weekdays for the treatment groups "leader in successful weeks", "followers in successful weeks" and the counterfactual. 95% confidence intervals are shown. Standard errors for the combined coefficients are calculated using the delta method.

Figure B.2: Price trends, success

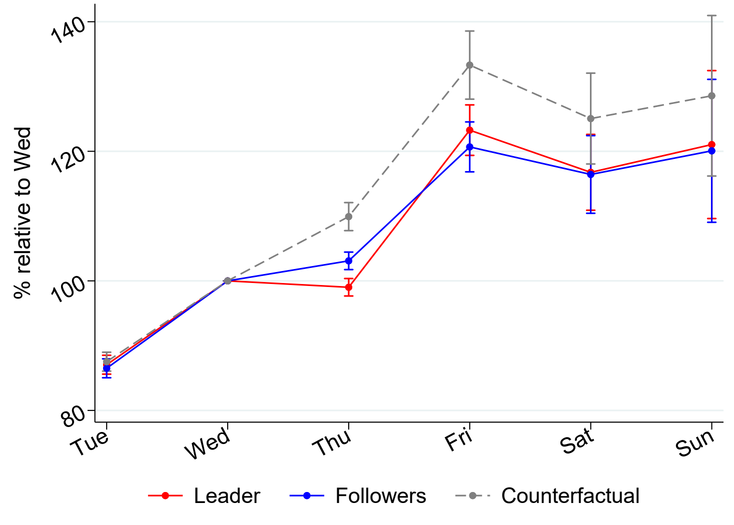


Note: The red line plots the development in volume-weighted prices through the week for stations affiliated with the price leader in weeks with successful Thursday jumps. The blue line for followers. The dashed gray line plots the development through the week for all stations in weeks without midweek jumps (the counterfactual). Take note of the following:

1. The leader's and followers' prices have a very similar development from Tuesday to Wednesday compared with weeks without midweek jumps.
2. After the Thursday jumps, both the leader's and followers' prices stay at a higher level but have a very similar development compared with weeks without midweek jumps.

*The lines plot $(exp(\boldsymbol{\beta_2} D_t + \boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) * 100$ in Eq. 1 with volume-weighted prices as outcome of interest on different weekdays for the treatment groups "leader in successful weeks", "followers in successful weeks" and the counterfactual. 95% confidence intervals are shown. Standard errors for the combined coefficients are calculated using the delta method.

Figure B.3: Volume trends, success

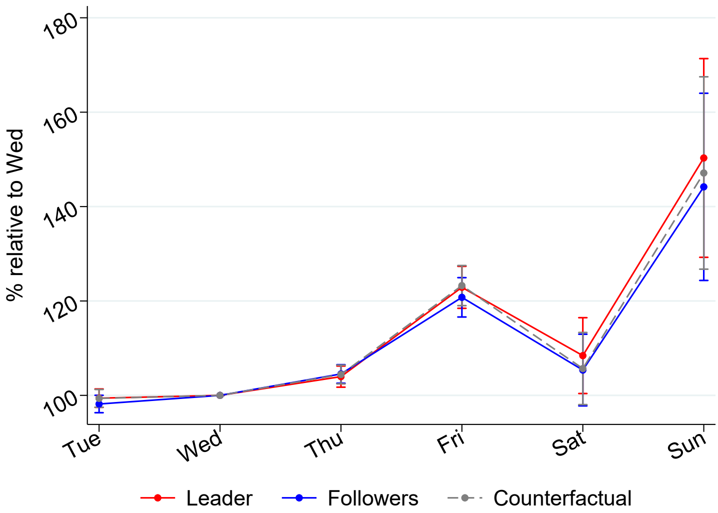


Note: The red line plots the development in volume gasoline sold through the week for stations affiliated with the price leader in weeks with successful Thursday jumps. The blue line for followers. The dashed gray line plots the development through the week for all stations in weeks without midweek jumps (the counterfactual). Take note of the following:

1. The leader's and followers' volume sold have a very similar development from Tuesday to Wednesday compared with weeks without midweek jumps.
2. After the Thursday jumps, the leader's and followers' volume stay at a lower level but have a very similar development compared with weeks without midweek jumps.

*The lines plot $(exp(\boldsymbol{\beta_2} D_t + \boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) * 100$ in Eq. 1 with volume gasoline sold as outcome of interest on different weekdays for the treatment groups "leader in successful weeks", "followers in successful weeks" and the counterfactual. 95% confidence intervals are shown. Standard errors for the combined coefficients are calculated using the delta method.

Figure B.4: Store revenue trends, success

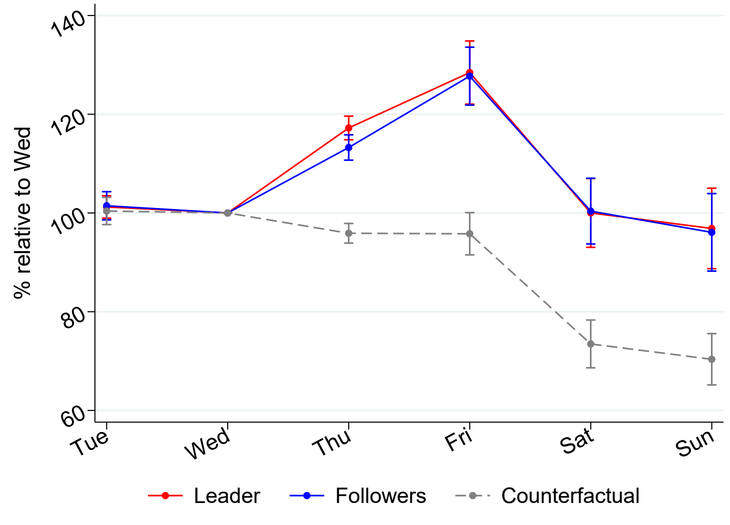


Note: The red line plots the development in store revenue through the week for stations affiliated with the price leader in weeks with successful Thursday jumps. The blue line for followers. The dashed gray line plots the development through the week for all stations in weeks without midweek jumps (the counterfactual). Take note of the following:

1. The leader's and followers' store revenue follow a similar development through the whole week as in weeks without midweek jumps.

*The lines plot $(exp(\boldsymbol{\beta_2} D_t + \boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) * 100$ in Eq. 1 with store revenue as outcome of interest on different weekdays for the treatment groups "leader in successful weeks", "followers in successful weeks" and the counterfactual. 95% confidence intervals are shown. Standard errors for the combined coefficients are calculated using the delta method.

Figure B.5: Profits trends, success



Note: The red line plots the development in gasoline profits through the week for stations affiliated with the price leader in weeks with successful Thursday jumps. The blue line for followers. The dashed gray line plots the development through the week for all stations in weeks without midweek jumps (the counterfactual). Take note of the following:

1. The leader's and followers' profits have a similar development from Tuesday to Wednesday compared with weeks without midweek jumps.
2. After the Thursday jumps, the leader's and followers' profits have a very similar development compared with weeks without midweek jumps.

*The lines plot $(exp(\boldsymbol{\beta_2} D_t + \boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) * 100$ in Eq. 1 with profit as outcome of interest on different weekdays for the treatment groups "leader in successful weeks", "followers in successful weeks" and the counterfactual. 95% confidence intervals are shown. Standard errors for the combined coefficients are calculated using the delta method.

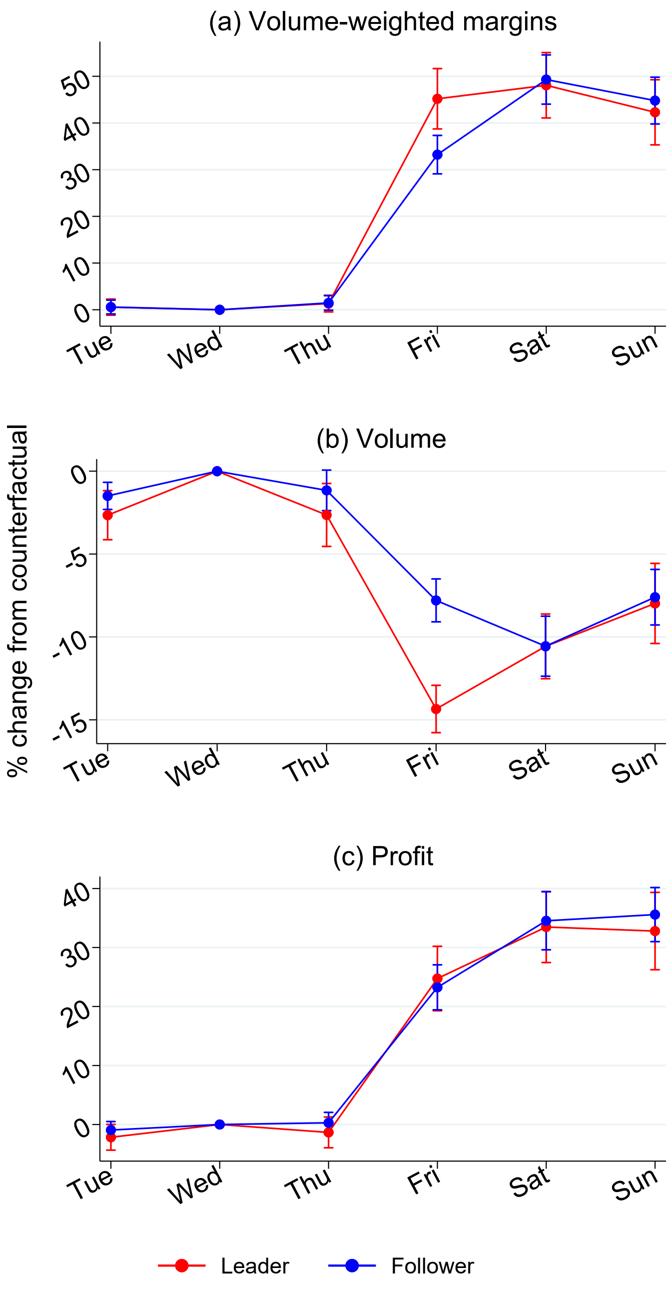
C Friday price jumps

Table C.1: Friday price jumps

	M	V	MSG	CSR	Pro
Wholesale price	0.39***	0.95*	1.00	0.99	0.37***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Tue	1.17***	0.88***	0.97***	0.99	1.03*
	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)
Thu	0.84***	1.10***	1.02**	1.06***	0.92***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Fri	0.65***	1.34***	1.04***	1.24***	0.87**
	(0.03)	(0.03)	(0.01)	(0.02)	(0.04)
Sat	0.54***	1.23***	1.07***	1.07	0.65***
	(0.04)	(0.04)	(0.02)	(0.04)	(0.03)
Sun	0.51***	1.26***	1.14***	1.47***	0.62***
	(0.03)	(0.07)	(0.03)	(0.11)	(0.03)
Fail - Leader	0.99	1.02**	1.02**	1.05***	1.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fail - Follower	1.01	0.98*	0.98*	1.04***	0.99
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Success - Leader	0.99	1.03***	1.03***	1.02	1.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tue × Fail - Leader	1.00	0.95***	0.97***	1.02	0.95***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tue × Fail - Follower	0.99	0.98*	1.00	1.01	0.97*
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Tue × Fail - Non-Follower	1.01	0.99*	1.00	1.01	1.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Tue × Success - Leader	1.01	0.97***	0.99*	0.96***	0.98
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tue × Success - Follower	1.01	0.99***	1.00	0.98**	0.99
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Thu × Fail - Leader	0.99	0.94***	0.98***	0.97***	0.93***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Thu × Fail - Follower	0.99	0.95***	1.00	0.97**	0.95***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Thu × Fail - Non-Follower	0.99	0.95***	0.99	0.97**	0.94***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Thu × Success - Leader	1.01	0.97**	0.99*	1.00	0.99
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Thu × Success - Follower	1.01	0.99	1.01*	1.02*	1.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Fri × Fail - Leader	1.17***	0.91***	0.97***	0.95***	1.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fri × Fail - Follower	1.12***	0.92***	0.98**	0.96***	1.03*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fri × Fail - Non-Follower	0.99	0.96***	1.01*	0.97***	0.95***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Fri × Success - Leader	1.45***	0.86***	0.95***	0.96***	1.25***
	(0.03)	(0.01)	(0.01)	(0.01)	(0.03)
Fri × Success - Follower	1.33***	0.92***	1.01***	1.00	1.23***
	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)
Sat × Fail - Leader	1.03	0.91***	0.98**	0.97***	0.93**
	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
Sat × Fail - Follower	1.01	0.90***	0.98**	0.92***	0.91***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Sat × Fail - Non-Follower	0.97	0.94***	1.01	0.97***	0.91***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Sat × Success - Leader	1.48***	0.89***	0.99	0.98	1.33***
	(0.04)	(0.01)	(0.01)	(0.01)	(0.03)
Sat × Success - Follower	1.49***	0.89***	0.99	0.99	1.35***
	(0.03)	(0.01)	(0.00)	(0.01)	(0.03)
Sun × Fail - Leader	1.03	0.90***	1.00	0.93***	0.92**
	(0.03)	(0.01)	(0.01)	(0.01)	(0.03)
Sun × Fail - Follower	1.00	0.90***	0.99	0.91***	0.90***
	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
Sun × Fail - Non-Follower	0.98	0.90***	0.99	0.95***	0.89***
	(0.04)	(0.01)	(0.01)	(0.01)	(0.03)
Sun × Success - Leader	1.42***	0.92***	0.99	0.99	1.33***
	(0.04)	(0.01)	(0.01)	(0.01)	(0.03)
Sun × Success - Follower	1.45***	0.92***	1.00	0.99	1.36***
	(0.03)	(0.01)	(0.00)	(0.01)	(0.02)
Week FE	Yes	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes	Yes
Chain X DoW FE	Yes	Yes	Yes	Yes	Yes
N Chain X DoW FE	Yes	Yes	Yes	Yes	Yes
Staffed X DoW FE	Yes	Yes	Yes	Yes	Yes
Month X DoW FE	Yes	Yes	Yes	Yes	Yes
Observations	450032	455851	455851	314766	450032
R2	0.25	0.15	0.04	0.24	0.14

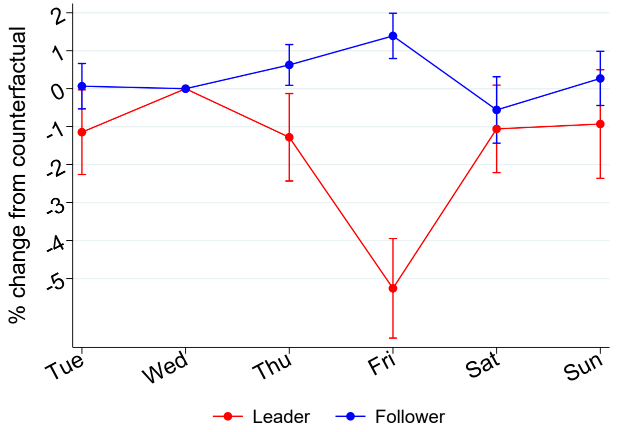
Note: The table displays the results from Eq. 1 for Friday price jumps with the outcome of interest being volume-weighted retail gasoline margins, daily volume gasoline, market shares based on volume gasoline, convenience store revenue, and profits. The coefficients are exponentiated. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Figure C.1: Successful Friday price jumps - margins, volume, and profits



Note: The figure plots results from Eq. 1 with volume-weighted margins, daily volume gasoline and profits as outcomes of interest. The lines plot $(exp(\boldsymbol{\beta_3} Treat_{iw} \times D_t) - 1) \times 100$ over different weekdays for the treatment groups “leader in successful weeks” and “followers in successful weeks
. 95% confidence intervals are shown.

Figure C.2: Successful Friday jumps, market shares



Note: The figure plots results from Eq. 1 with market shares as outcome of interest. The lines plot $(exp(\boldsymbol{\beta_3}Treat_{iw} \times D_t) - 1) \times 100$ over different weekdays for the treatment groups "leader in successful weeks" and "followers in successful weeks". 95% confidence intervals are shown.

D Diff-in-diff+IV

In this appendix, I estimate similar diff-in-diff models as Eq. 1, but use the Wednesday European reference wholesale price, w, W_w^W, as an instrument for Thursday jumps.[36] To be a suitable instrument, W_w^W must be strongly correlated with Thursday jumps (validity), but not influence the change in the outcome from Wednesday to later weekdays, Δy_{iwt}, aside from its effects on Thursday jumps (exclusion restriction).[37] I first show that the instrument is valid, and then discuss the exclusion restriction.

Figure D.1 reveals that there is a lot of variation in W_w^W. The average within-month standard deviation of W_w^W, given by $\bar{\sigma}$, is 0.13 NOK.[38] The figure also shows a strong correlation between W_w^W and the average Wednesday retail price. However, the short-run pass-through of W_w^W is less than 100%; a $\bar{\sigma}$ increase in W_w^W gives 6% lower Wednesday margins (Table D.1). The theory of Edgeworth Cycles predicts that price jumps should

[36]The leader initiates price jumps around 11:00 on Thursday and likely decides on implementation at least a few hours earlier, meaning the Thursday wholesale price (an average through all hours on Thu) is not known when Thursday jumps are initiated. The Wednesday wholesale price is a proxy for the wholesale price at the time when the chains decide whether to carry out a price jump or not.

[37]The reference wholesale price of gasoline is strongly correlated with the European crude oil price (Figure D.1). The crude oil price has been used as an instrument to estimate price elasticities (Liu, 2016) and been assumed to be exogenous to retail gasoline prices in multiple studies estimating asymmetric cost pass-through in the gasoline industry (Bachmeier & Griffin, 2003). I instrument price jumps with the reference wholesale price rather than the crude oil price because the reference wholesale price is a more relevant cost measure for gasoline retailers and hence a stronger instrument. Results are similar, but less precise, when instrumenting with the crude oil price.

[38]$\bar{\sigma}$ is defined as $\bar{\sigma} = 1/M \sum_{m=1}^{M} (\sigma_m)$, where σ_m is the standard deviation of W_w^W in month m.

occur more frequently when margins are low (Noel, 2008). In accordance with this, the first-stage regression of W_w^W on the probability of successful Thursday jumps, reveals that a $\bar{\sigma}$ increase in W_w^W increases the probability of a successful price jump with 16%, indicating that the instrument has some bite. The F-statistic (calculated with the method proposed by Sanderson & Windmeijer (2016)) is over 1500 for all IV-models, rejecting the hypothesis that the second-stage equation is weakly identified.

Figure D.1: Reference wholesale price, Brent crude oil and Wednesday margins

Note: The figure plots the weekly Wednesday reference price for wholesale gasoline (W_w^W), the Wednesday European Brent crude oil price, and the average Wednesday retail gasoline price exclusive taxes across all stations in the main sample.

The exclusion restriction would be violated if W_w^W is correlated with the outcome of interest through other channels than the Thursday price jumps. The Norwegian retail gasoline market is small compared with the rest of Europe, meaning that demand shocks specific to Norway are unlikely to affect W_w^W. But W_w^W could be correlated with demand through seasonal demand variation or macro shocks that are transmitted to demand for retail gasoline. The monthly fixed effects eliminate the main channels through which such correlation could emerge.

Even if W_w^W was correlated with overall demand, it would not necessarily be correlated with the within-week development of demand, Δy_{iwt}. However, wholesale prices are higher in weeks when W_w^W is high, leading to higher average retail gasoline prices in these weeks. This could increase consumers' inter-temporal demand elasticity, thereby increasing demand in periods of the week with low prices.[39] This would violate the exclu-

[39] The inter-temporal demand elasticity could increase due to income effects, or category budgeting as in Hastings & Shapiro (2013).

Table D.1: Within-month pass-through of W_w^W

	PT WED
Wednesday wholesale price	-0.42***
	(0.03)
Month FE	Yes
Station FE	Yes
Observations	139261
R2	0.35
F-value	200.56

Note: The within-month pass-through of W_w^W to Wednesday margins is estimated with the model $y_{iw} = \alpha + \beta_1 W_w^W + \theta_m + \delta_i + \varepsilon_{iw}$, where y_{iw} is the volume-weighted margin of station i in week w, W_w^W is the reference wholesale price on Wednesday in week w. θ_m and δ_i signify month and station fixed effects. The table shows that a 1 NOK increase in W_w^W decreases the Wednesday margin with 0.42 NOK. A $\bar{\sigma}$ increase in W_w^W reduces the Wednesday margin by $0.42 \times 0.13 = 0.06$ NOK.

sion restriction. Out-of-sample testing of this potential violation is possible in the period when Thursday price jumps occur every week (after March 2009). Table D.2 shows how W_w^W affects the change in different outcomes through the week after March 2009. Depending on how many years after March 2009 is included, W_w^W can have a statistically significant effect. However, the economic impact of a $\bar{\sigma}$ change in W_w^W is very small compared with the effects of Thursday price jumps, suggesting that potential bias working through changes in the inter-temporal elasticity is small—a $\bar{\sigma}$ change in W_w^W never give more than 1.3 % change in Δy_{iwt} with volume-weighted margins as outcome, and never more than 1.0% change in Δy_{iwt} with volume as outcome. These effects are very small compared with the diff-in-diff estimates in Section 3.2 and the IV estimates reported in this appendix.

The IV-models are estimated by 2SLS. In the first stage (Eq. D.1), the possibly endogenous Thursday price jumps, S_w, are independently regressed on the excluded instrument, W_w^W, and the included instruments, θ_{iw}^D, δ_i and γ_m. θ_{iw}^D, γ_m, and δ_i are defined as in Eq. 1.

$$S_{iw} = \alpha_1 + \delta W_w^W + \theta_{iw}^D + \gamma_m + \delta_i + \varepsilon_{iw} \tag{D.1}$$

The IV estimates are then obtained in the second stage by estimating a slightly altered version of the diff-in-diff model in Eq. 1 using the predicted instead of the observed values of the Thursday price jumps.[40]

$$\Delta y_{iwt} = \alpha_2 + \pi \hat{S}_{iw} + \theta_{iw}^D + \gamma_m + \delta_i + u_{iwt} \tag{D.2}$$

Δy_{iwt} is given by $ln(y_{iwt}) - ln(y_{iw3})$; the difference between the outcome of interest

[40]Note that in the diff-in-diff model $y_i = \beta_0 + \beta_1 TREAT + \beta_2 POST + \beta_3 TREAT \times POST + e_i$ the POST-period values are $y_i = \beta_0 + \beta_1 TREAT + \beta_2 + \beta_3 TREAT + e_i$, and the pre-period values are $y_i = \beta_0 + \beta_1 TREAT + e_i$. Post minus Pre is then given by $\Delta y_i = \beta_2 + \beta_3 TREAT + u_i$.

Table D.2: Out of sample testing of the exclusion restriction

	M_09_10	M_09_11	M_09_12	V_09_10	V_09_11	V_09_12
Thu × platts_wed	1.07***	1.00	1.01***	1.00	0.99*	1.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
Fri × platts_wed	1.07***	0.99	1.02**	1.07***	1.01	1.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sat × platts_wed	1.09***	0.94**	0.99	0.99	0.98*	1.00
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Sun × platts_wed	1.09***	0.90***	0.94***	0.92***	1.03	1.08***
	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)	(0.02)
Observations	193355	400485	597224	193856	401126	598021
R2	0.16	0.18	0.20	0.11	0.10	0.11

Note: The table shows results from the model $\Delta y_{iwt} = \alpha + \beta_1 W_w^W \times D + \theta_{iw}^D + \gamma_m + \delta_i + \varepsilon_{iwt}$, where $\Delta y_{iwt} = ln(y_{iwt}) - ln(y_{iw3})$ is the log difference in the outcome of interest from Wednesday to the later weekdays. θ_{iw}^D, γ_m and δ_i are defined as in Eq. D.2. The first 3 columns show results with volume-weighted margins as outcome and include observations from April 2009-March 2010, April 2009-March 2011, and April 2009-March 2012. The last 3 columns show results with volume sold per day as outcome for the same periods.
The results vary quite a bit depending on which years are included, but a 1 NOK change in W_w^W never give more than 10% change in Δy_{iwt} for any weekdays with volume-weighted margins as outcome and never more than 8% change in Δy_{iwt} with volume sold at outcome. This means a $\bar{\sigma}$ change in W_w^W never give more than $10\% \times 0.13 = 1.3\%$ change in volume-weighed margins, and never more than $8\% \times 0.13 = 1.0\%$ change in volume sold.
*The coefficients are exponentiated. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

on weekday t and the outcome of interest on Wednesday. The effect of Thursday price jumps on the outcome of interest is given by π. I estimate the model separately for different weekdays and separately for the leader and the followers. For example, to estimate the effect of successful Thursday jumps on the leader's Thursday margins, I keep only Thursday observations so that Δy_{iwt} is given by the difference in the outcome between Thursday and Wednesday, $ln(y_{iw4}) - ln(y_{iw3})$. Furthermore, I only keep observations for the leader's stations in weeks with successful Thursday jumps (treatment) and observations for all stations in weeks without midweek jumps (control). Fridays, Saturdays, and Sundays are pooled together to increase accuracy.

Tables D.3–D.7 show results from the IV model with different outcome variables.

Table D.3: IV, volume-weighted margins

	Leader Thu	Followers Thu	Leader FriSun	Followers FriSun
Success × *Thu*	1.19***	1.19***		
	(0.04)	(0.03)		
Success × *FriSun*			2.05***	1.69***
			(0.15)	(0.08)
Observations	70282	96087	207978	284641
SW F-value	1609	13147	1593	11634

Note: The table shows results from the IV model in Eq. D.2 with volume-weighted margins as outcome of interest. From left to right the columns show estimates of the effect of successful Thursday jumps on the leader's Thursday margins, the followers' Thursday margins, the leader's margins on Friday–Sunday and the followers' margins on Friday–Sunday. The coefficients are exponentiated.

Table D.4: IV, volume

	Leader Thu	Followers Thu	Leader FriSun	Followers FriSun
Success × *Thu*	0.90***	0.94***		
	(0.02)	(0.01)		
Success × *FriSun*			0.94	0.93***
			(0.03)	(0.02)
Observations	70682	96841	212046	290520
SW F-value	1579	13100	1579	13084

Note: The table shows results from the IV model in Eq. D.2 with volume sold as outcome of interest. From left to right the columns show estimates of the effect of successful Thursday jumps on the leader's Thursday volume, the followers' Thursday volume, the leader's volume on Friday–Sunday and the followers' volume on Friday–Sunday. The coefficients are exponentiated.

Table D.5: IV, market shares

	Leader Thu	Followers Thu	Leader FriSun	Followers FriSun
Success × *Thu*	0.959**	1.012*		
	(0.014)	(0.006)		
Success × *FriSun*			1.002	0.990
			(0.016)	(0.007)
Observations	70682	96841	212046	290520
SW F-value	1579	13100	1579	13084

Note: The table shows results from Eq. D.2 with market shares as outcome of interest. From left to right the columns show estimates of the effect of successful Thursday jumps on the leader's Thursday market share, the followers' Thursday market share, the leader's market share on Friday–Sunday and the followers' market share on Friday–Sunday. The coefficients are exponentiated.

Table D.6: IV - convenience store revenue

	Leader Thu	Followers Thu	Leader FriSun	Followers FriSun
$Success \times Thu$	1.009	0.989		
	(0.030)	(0.012)		
$Success \times FriSun$			1.112***	1.016
			(0.033)	(0.013)
Observations	51361	65396	151372	192088
SW F-value	1701	11426	1763	10873

Note: The table shows results from Eq. D.2 with convenience store revenue as outcome of interest. From left to right the columns show estimates of the effect of successful Thursday jumps on the leader's Thursday convenience store revenue, the followers' Thursday convenience store revenue, the leader's convenience store revenue on Friday–Sunday and the followers' convenience store revenue on Friday–Sunday. The coefficients are exponentiated.

Table D.7: IV, profits

	Leader Thu	Followers Thu	Leader FriSun	Followers FriSun
$Success \times Thu$	1.07**	1.12***		
	(0.03)	(0.02)		
$Success \times FriSun$			1.94***	1.58***
			(0.12)	(0.05)
Observations	70282	96087	207978	284641
SW F-value	1609	13147	1593	11634

Note: The table shows results from the IV model in Eq. D.2 with Π_{iwt} as the outcome of interest. From left to right the columns show estimates of the effect of successful Thursday jumps on the leader's Thursday profits, the followers' Thursday profits, the leader's profits on Friday–Sunday and the followers' profits on Friday–Sunday. The coefficients are exponentiated.

E Delayed purchasing

I compare price and volume in week (t) following a week featuring a successful or failed midweek price jump ($t-1$) with weeks following weeks without midweek price jumps. I restrict the sample to only Tuesdays and Wednesdays because Mondays are contaminated due to the regular Monday jumps, and Thursdays–Sundays are contaminated by possible midweek jumps in week t. I separate results for the leader, the followers and the non-followers after failed and successful weeks using the following model:

$$ln(y_{iwt}) = \alpha + \boldsymbol{\beta_2} Price_{iwt} + \boldsymbol{\beta_3} Treat_{i,t-1} + \lambda_t + \theta_m + \delta_i + \varepsilon_{iwt} \tag{E.1}$$

where y_{iwt} is volume sold for station i on day of week t in week w. λ_t represents day-of-week fixed effects and $Price_{iwt}$ is the daily average price. $Treat_{t-1}$ is a vector of dummy variables identifying weeks following the five different treatments as described in Section 3.1. The baseline is weeks when no midweek jump occurred. θ_m is month fixed effects, δ_i is station fixed effects and ε_{iwt} is an error term. Table E.1 presents the results.

Table E.1: Week after midweek jumps

	Ln(v)
Fail - Leader	0.008
	(0.004)
Fail - Follower	0.002
	(0.005)
Fail - Non-Follower	-0.005
	(0.004)
Success - Leader	0.033***
	(0.006)
Success - Follower	0.032***
	(0.005)
Station FE	Yes
Month FE	Yes
Day-of-week FE	Yes
Observations	311003
R2	0.83

Note The table displays results from Eq. E.1. Standard errors are clustered at built-up area level and are shown in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

The leader's and the followers' volumes are is slightly more than 3% higher on Tuesday and Wednesday in the first week after a week featuring a successful midweek price jumps compared with the first week after a week without any midweek price jump. The leader's, the followers', and the non-followers' volumes are about the same in the first week after a week with failed midweek price jumps as in the first week after a week without any midweek price. Effects sizes are almost identical for the leader and the followers.

F Pre-jump margins

I employ the following model to find the difference in pre-jump margins in weeks without midweek jumps, failed midweek jumps and successful midweek jumps.

$$ln(y_{iw}) = \alpha + \beta_1 Attempt_w + \beta_2 Success_w + \gamma_m + \delta_i + \varepsilon_{iw} \tag{F.1}$$

where y_{iw} is volume-weighted Wednesday margins for station i in week w, $Attempt_w$ is dummy variable identifying weeks with Thursday price jump jumps attempts and $Success_w$ is a dummy variable identifying weeks with successful price jump attempts. γ_m signify monthly fixed effects, δ_i signify station fixed effects and ε_{iw} is an error term. Table F.1 shows results.

Table F.1: Wednesday margins

	Thu_Jump
Attempt	0.95***
	(0.00)
Success	0.91***
	(0.01)
Month FE	Yes
Station FE	Yes
Observations	156289
R2	0.03

Note: The table shows results from Eq. F.1. Take note of the following:

1. In weeks with failed Thursday price jump attempts, Wednesday margins are 5% lower than in weeks without midweek price jumps.
2. In weeks with successful Thursday price jump, Wednesday margins are 9% lower than in weeks with failed Thursday price jump and 14 % lower than in weeks without midweek price jumps.

The coefficients are exponentiated. Standard errors are clustered at built-up area level. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

G Long-run effects of regular price leadership - Additional figures and tables

Figure G.1: Overview of events

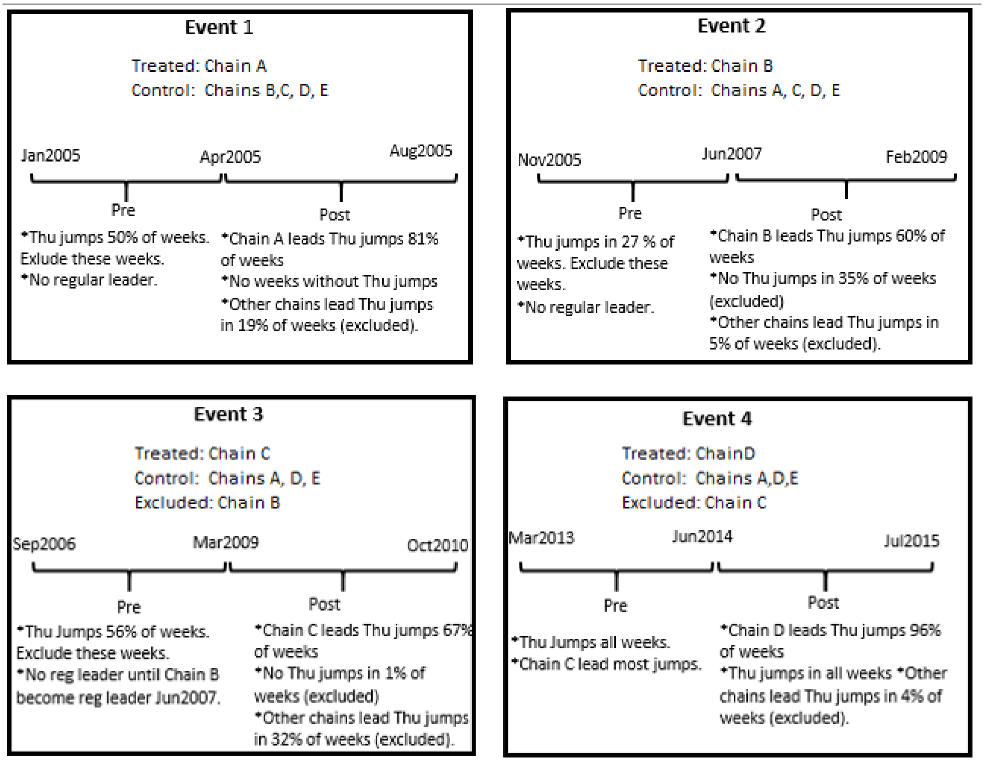
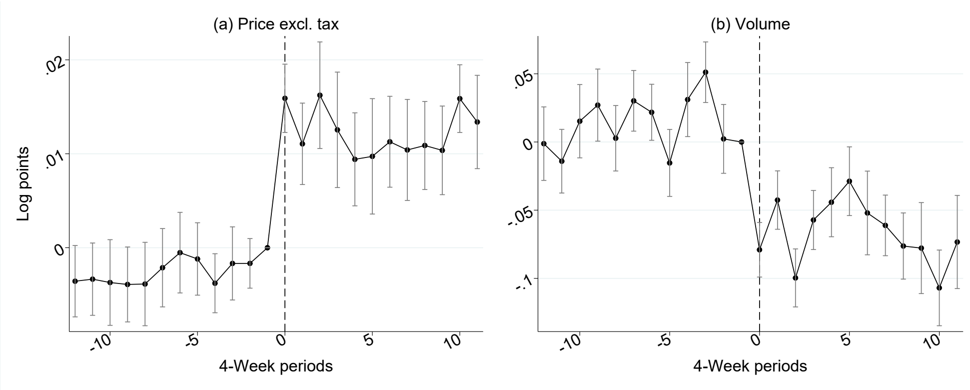


Figure G.2: Long-run event study, 4-week periods



Note: The figure shows results from a model similar to Eq. 2, but with τ representing 4-week periods. Panel (a) plots γ_τ from -12 to 11 with volume-weighted daily gasoline prices as the outcome of interest. Panel (b) plots the same for daily gasoline volumes. 95% confidence intervals are included.

Table G.1: Long-run event study

	DD-P	DD-V	WED-V	THU-V	TFSS-V
$\gamma_{-10} \times L$	0.001	-0.006	0.008	0.002	0.023
	(0.002)	(0.025)	(0.022)	(0.021)	(0.018)
$\gamma_{-9} \times L$	-0.001	0.002	-0.009	-0.006	-0.015
	(0.003)	(0.028)	(0.029)	(0.020)	(0.014)
$\gamma_{-8} \times L$	-0.003	-0.018	-0.016	-0.034	-0.019
	(0.002)	(0.031)	(0.021)	(0.021)	(0.015)
$\gamma_{-7} \times L$	-0.001	0.002	-0.002	-0.000	-0.009
	(0.002)	(0.028)	(0.022)	(0.017)	(0.012)
$\gamma_{-6} \times L$	-0.000	-0.034	0.026	-0.008	0.009
	(0.002)	(0.025)	(0.019)	(0.016)	(0.013)
$\gamma_{-5} \times L$	0.000	-0.036	0.021	-0.015	0.012
	(0.002)	(0.024)	(0.022)	(0.017)	(0.013)
$\gamma_{-4} \times L$	-0.002	-0.023	0.019	-0.005	-0.013
	(0.002)	(0.023)	(0.019)	(0.014)	(0.011)
$\gamma_{-3} \times L$	0.004	-0.061*	0.034	-0.026	0.009
	(0.002)	(0.023)	(0.020)	(0.017)	(0.010)
$\gamma_{-2} \times L$	0.000	-0.019	0.020	0.001	0.016
	(0.002)	(0.024)	(0.019)	(0.016)	(0.010)
$\gamma_{0} \times L$	0.026***	-0.095***	0.020	-0.074***	0.008
	(0.003)	(0.024)	(0.021)	(0.016)	(0.011)
$\gamma_{1} \times L$	0.018***	-0.105***	0.027	-0.078***	0.034**
	(0.002)	(0.026)	(0.018)	(0.016)	(0.012)
$\gamma_{2} \times L$	0.009**	-0.095***	0.064***	-0.031*	0.005
	(0.003)	(0.021)	(0.018)	(0.013)	(0.012)
$\gamma_{3} \times L$	0.013**	-0.127***	0.051**	-0.076***	0.033**
	(0.004)	(0.023)	(0.017)	(0.017)	(0.012)
$\gamma_{4} \times L$	0.009**	-0.066**	0.036	-0.030	0.010
	(0.003)	(0.024)	(0.018)	(0.016)	(0.014)
$\gamma_{5} \times L$	0.010**	-0.087***	0.038	-0.049***	0.019
	(0.003)	(0.022)	(0.021)	(0.015)	(0.014)
$\gamma_{6} \times L$	0.014***	-0.057*	0.018	-0.039*	0.036**
	(0.004)	(0.024)	(0.017)	(0.019)	(0.013)
$\gamma_{7} \times L$	0.014***	-0.065*	0.019	-0.045*	0.016
	(0.003)	(0.025)	(0.020)	(0.020)	(0.013)
$\gamma_{8} \times L$	0.017***	-0.106***	0.035	-0.071***	0.020
	(0.004)	(0.031)	(0.024)	(0.016)	(0.014)
$\gamma_{9} \times L$	0.017***	-0.146***	0.046	-0.101***	0.018
	(0.003)	(0.023)	(0.024)	(0.019)	(0.014)
$\gamma_{10} \times L$	0.021***	-0.140***	0.049*	-0.091***	0.020
	(0.003)	(0.022)	(0.022)	(0.017)	(0.014)
$\gamma_{11} \times L$	0.012*	-0.109***	0.013	-0.096***	0.005
	(0.005)	(0.027)	(0.025)	(0.019)	(0.016)
$\gamma_{12} \times L$	0.022***	-0.108***	0.006	-0.102***	-0.003
	(0.005)	(0.019)	(0.021)	(0.018)	(0.017)
$\gamma_{13} \times L$	0.006	-0.089***	-0.006	-0.095***	-0.005
	(0.003)	(0.025)	(0.025)	(0.020)	(0.015)
$\gamma_{14} \times L$	0.017***	-0.026	0.007	-0.019	0.025
	(0.005)	(0.027)	(0.020)	(0.018)	(0.013)
$\gamma_{15} \times L$	0.008*	-0.091***	0.023	-0.068**	-0.005
	(0.003)	(0.026)	(0.023)	(0.023)	(0.016)
$\gamma_{16} \times L$	0.007	-0.079***	-0.011	-0.090***	0.004
	(0.004)	(0.023)	(0.021)	(0.023)	(0.015)
$\gamma_{17} \times L$	0.009**	-0.035	-0.029	-0.064**	0.003
	(0.003)	(0.028)	(0.028)	(0.022)	(0.015)
$\gamma_{18} \times L$	0.018***	-0.087***	-0.002	-0.090***	-0.012
	(0.003)	(0.022)	(0.029)	(0.021)	(0.014)
$\gamma_{19} \times L$	0.006	-0.068**	-0.006	-0.074***	-0.019
	(0.003)	(0.025)	(0.025)	(0.021)	(0.017)
Observations	85916	85916	85918	85916	85918
R2	0.44	0.13	0.85	0.87	0.94

Note: The table shows results from Eq. 2 and similar specifications. The 2nd column displays results from Eq. 2 with Δv_{ijw} (Thursday minus Wednesday volumes) as dependent variable. The 3rd column displays results from Eq. 2 with Δp_{ijw} (Thursday minus Wednesday price) as dependent variable. The 4th column displays results from a similar specification as Eq. 2 but with Wednesday volume as dependent variable. The 5th column displays results with total volume across Tuesday, Friday, Saturday, and Sunday ("TFSS") as dependent variable. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. Take note of the following:

1. Results for the 1st and 3rd column are displayed in Figure 6.
2. In the pre-period, the treatment group's Thursday volumes are similar to the control group's volumes. The treatment group's Thursday volumes are 0.04-0.10 log points lower in the post-period relative to the control group. No downward or upward trend is visible in the post-period.
3. In both the pre- and post-periods, the treatment groups Wednesday volume is fairly stable relative to the control group's Wednesday volume and there is no sign of a negative trend. The same is true for TFSS volume.

Chapter 4

Long-Run Dynamics in Intertemporal Substitution—Evidence from Retail Fuel

Long-Run Dynamics in Intertemporal Substitution—Evidence from Retail Fuel*

Andreas Tveito†

October 7, 2021

Abstract

Many retail markets feature intertemporal price variation caused by promotional sales, wholesale price variation, or price cycles where prices fall for several days before quickly being restored to a high level. I use 11 years of high-frequency prices and volumes for Norwegian gas stations to study the short- and long-run consumer response to price cycles with a regular low-price period at the same time every week (the sale period). I show that diesel and gasoline consumers over time increasingly fill their tanks during the sale period. Before the transition to the new price pattern, about 21% of the weekly gasoline and diesel volumes are sold in that part of the week. In the first quarter after the transition, the sale-period volume shares increase by 1–2 percentage points. In the subsequent years, the sale-period rebates remain stable while the sale-period volume shares keep rising, to total increases of 6–9 percentage points five years later. The intertemporal price elasticity increases from about -2 immediately after the transition to -6 five years later. These findings emphasize the importance of accounting for dynamics when studying consumer responses to intertemporal price variation and suggest that non-volume-weighted prices may be a poor proxy for the prices consumers pay.

*I would like to thank Sigurd Birkeland, Kurt Brekke, Bjørn Olav Johansen, Katrine V. Løken, Teis Lunde Lømo, Magnus Friis Reitan, Morten Sæthre, and seminar participants at CBE (NHH) for helpful comments. I gratefully acknowledge financial support from the Research Council of Norway.

†Department of Economics, University of Bergen and the Norwegian Competition Authority. The views expressed in this paper are those of the author and do not necessarily reflect the views of the Norwegian Competition Authority.

1 Introduction

Theoretical models and empirical studies both frequently assume that consumer responses to price changes or changes in the product space are static. However, consumers may need time to adjust to price changes because of learning, slow habit formation, or switching costs (e.g., from brand loyalty or consumer inertia). As a result, as consumers gradually learn about the price or product changes and slowly change their habits, demand may be more elastic in the long run. For example, Deryugina et al. (2020) provide evidence of dynamics in the residential electricity demand to changes in the overall price level. By exploiting lasting changes in the overall price level in an electricity market, they show that demand is some three times more elastic 2 years after the change. Similarly, Hortaçsu et al. (2017) find that an incumbent electricity provider's brand advantage decreases over time as consumers update their beliefs about the quality of entrants' products, thereby contributing to a gradual substitution toward the entrants.

Prices can exhibit systematic *intertemporal* variation caused by the promotional sales common to many retail markets (Hendel & Nevo, 2006), the intraday wholesale price variation often prevailing in residential electricity markets (Fabra et al., 2021), and the asymmetric price cycles frequently observed in retail fuel markets (Eckert, 2013). Intertemporal price variation gives consumers the option to purchase at different times with different prices, like a menu of products with different prices. Purchasing when prices are low may involve time costs related to both predicting when prices are low and travelling to the retail location during the low-price period. Over time, consumers may become better informed about when prices are low. They may also need time to update their beliefs about the costs and benefits of purchasing at different times and habit formation may be slow. Thus, there can also be dynamics in consumers' intertemporal substitution patterns because consumers over time increasingly purchase when prices are low.

This study uses 11 years of high-frequency retail fuel prices and volumes to investigate the consumer response to intertemporal price variation caused by asymmetric price cycles. Exploiting changes in the price pattern that lead to a sale at Sundays and Monday mornings every week, I show that diesel and gasoline consumers over time increasingly fill up their tanks during this sale period, even though the price rebates in the sale period are quite stable. Before the regular sale, about 21% of the weekly gasoline and diesel volumes are sold on Sundays/Monday mornings. The first quarter with the sale, the Sundays/Monday morning volume shares increase 1–2 percentage points (pp) (6%–11% of the Sundays/Mondays morning volume share before the sale). Five years later, the total increase in the Sundays/Monday mornings volume shares are 6–9 pp (28%–43%). The intertemporal price elasticity increases from about -2 immediately after the introduction of the regular sale to -6 five years later. These findings emphasize the importance of accounting for dynamics when studying consumer responses to intertemporal price variation and suggest that non-volume-weighted prices may be a poor proxy for the prices consumers pay.

The context for the analysis is the Norwegian retail fuel market. It features asymmetric price cycles where prices increase sharply and then slowly fall until another sharp increase. In 2004, the price pattern changes from a sharp price hike at a different time each week ("irregular cycles") to a cycle with a regular price trough on Sundays and Monday mornings and sharp price hikes around noon on Monday ("regular cycles"). Both regular and irregular price cycles are frequently observed in retail fuel markets.[1] Such cycles have been extensively studied using station-level prices, but as discussed by Eckert (2013), few studies employ high-frequency volume data to investigate the demand response to the cycles. The cycles are often rationalized by the Edgeworth price commitment model formalized by (Maskin & Tirole, 1988), but recent work suggests they may also result from of tacit collusion (de Roos & Smirnov, 2020; Byrne & de Roos, 2019). In this analysis, I take retailer behavior as given and consider only the consumer response to the intertemporal price variation.

However, cycling prices are not universal in the Norwegian retail fuel market. In 2004, 13% of gas stations (mostly near-monopoly stations) set fixed gasoline and diesel prices that only change occasionally, i.e., from wholesale price variation. At different times, mainly between 2005 and 2008, most of these suddenly transition to a regular cycle with Monday price hikes every week. When a station transitions to the regular cycle, it hikes prices every Monday around noon with its lowest prices on Sundays and Monday mornings (the "sale period") throughout the remainder of the sample period. The "sale-period rebates" (prices on Sundays and Monday mornings relative to the weekly average price) are fairly stable over time.

In terms of the consumer response, most consumers purchase fuel less frequently than once a week and thus have the option to fill their tank during the sale period and consume fuel already in the tank during the high-price part of the cycle. Filling 45 liters during the sale period then yields modest savings of about 18 Norwegian kroner (NOK) (about US$ 2.95) compared with purchasing at a random time during the week — about the price of 1.5 liters of gasoline or a little more than the price of a liter of milk. On the other hand, purchasing during the sale period incurs time costs associated with additional trips to the gas station, purchasing at an inconvenient time, and possibly queuing at the pumps.

In the first analysis, I exploit 76 (71) events where individual gas stations transition from fixed gasoline (diesel) prices to regular price cycles. Consumers at these stations thus face a sudden change from stable prices to systematic intertemporal price variation with a regular sale taking place every Sunday/Monday morning. Each treated station is

[1] Irregular price cycles have been observed in retail gasoline markets in parts of Australia, the US, Norway, and Canada. Regular price cycles have been found in parts of Australia, the US, Canada, Germany, and Norway (Noel, 2019).

linked to a group of control stations that continue to set fixed prices. To investigate the development in the share of volume sold in the sale period, I implement an event study difference-in-differences design and estimate the share of total weekly volume that is sold in the sale period each quarter 5 years prior to these events and 7 years after.

The identifying assumption is that the average observed differences in the sale-period volume share between treated and control stations in the post-sale adoption period are caused only by the transition to a regular price cycle. Parallel trends in the pre-sale adoption period and no change in the sale-period volume share in the quarters immediately preceding the transition suggest that stations did not self-select into changing their price pattern based on expected changes in the intra-week demand pattern. I also show that the sale-period rebates are stable after the transition and therefore unlikely to cause the observed dynamics in the sale-period volume shares.

The results reveal substantial dynamics in the consumer response to the new price pattern. Prior to the transitions, about 22% (20%) of the total weekly gasoline (diesel) volume is sold during the sale period. The sale-period volume shares then increase 1.9 (2.2) pp in the first full quarter after the transitions, gradually rising to a total increase of 6.2 pp (7.0 pp) after 5 years. As the sale-period rebates are quite stable, these results suggest that demand becomes more elastic to the intertemporal price variation over time.

I also consider the event where most of the stations in the market undergo a transition from irregular to regular cycles in 2004. Consumers then face a sudden change from a cycle where the cycle trough (the sale) take place on different days in different weeks to a cycle with Monday hikes and a regular Sundays/Monday mornings sale period. The irregular cycles commenced 2–3 years before the transition to regular cycles, meaning consumers have had some time to learn that prices vary intertemporally at the time when the transition to regular cycles take place. The results from this transition also point to substantial dynamics in the consumer response: both gasoline and diesel Sundays and Monday mornings volume shares immediately increase by 1.3 pp after the transition. The sale-period volume shares then gradually grow through the initial years with quite stable sale-period rebates, ending some 9 pp higher 5 years after the transition.

Very high-frequency volume data for the stations during the irregular-to-regular-cycles event also allow me to estimate the developments in the intertemporal elasticity of demand in response to the temporary price variation caused by the price cycles. The intertemporal elasticity is -2.4 in the only full quarter of the 2004 with irregular cycles, suggesting that some consumers adjust their purchases to the temporary price variation even when it is difficult to predict when prices would be low. The elasticity then decreases slightly to about -2 immediately after the transition to a regular cycle. It then start to increase gradually and triples to -6 after 5 years. Another way to illustrate this is that consumers' actual savings (the actual price paid relative to not adjusting to the intertemporal price variation) are 9–17% of the potential savings (always filling the tank during the sale period) immediately after the transition and 31% 5 years after the transition. Over time, consumers thus realize a greater share of the potential savings offered by the pricing cycle.

Long-run dynamics in consumers' intertemporal substitution patterns were previously unexplored, but a substantial literature documents that consumers respond to intertemporal price variation.[2] For example, Levin et al. (2017) find evidence of stockpiling activity in the retail gasoline market in the US—the amount of gasoline purchased changes markedly in the first few days after a price change, but this response results almost entirely from a temporary change in the likelihood of consumers making a purchase rather than a change in gasoline usage. Elsewhere, Hendel & Nevo (2006) show that consumers of storable grocery goods also engage in stockpiling by anticipating the intertemporal price variation, substituting purchases into the sale period, and consuming from their inventory when prices are high, while Jessoe & Rapson (2014) reveal that informed retail electricity customers are more responsive to temporary price increases.

There is also some evidence on how consumers respond to irregular and regular retail fuel price cycles. Noel (2012) uses survey evidence to argue that gasoline consumers in Toronto are poorly informed about the irregular cycles present in the market, and that few consumers then attempt to fill their tank during the cycle trough. But then Byrne et al. (2015) demonstrate that price-reporting consumers in Ontario report more frequently during the troughs of an irregular cycle and on this basis argue that a stockpiling model best explains the reporting pattern. Noel (2019) conclude that the intertemporal elasticity of demand is high (-6.3 to -6.8) in Australian cities with regular retail gasoline price cycles.

My results show that after both a transition from fixed prices to a cycle with a regular sale and that from an irregular cycle to a cycle with a regular sale, consumers increasingly substitute fuel purchases into the sale period. These findings are consistent with both learning and slow habit formation, such that consumers may need time to learn that prices vary throughout the week and to learn when prices will be at their lowest. Informed consumers may also need time to change their habits, such as starting their day earlier on Monday to provide time to fill up the tank on the way to work or to make a regular trip each Sunday afternoon specifically to fill up the tank. Surveys conducted at two gas stations after the transition to regular cycles certainly indicate that learning matters: only 35% of the surveyed fuel customers thought prices increased on specific days of the week 1 year after the transition to regular cycles, whereas 81% thought the same 10 years later (Foros et al., 2021).

Regardless of the underlying mechanism, my results have important implications for evaluating the consumer response to intertemporal price variation. Previous studies estimate intertemporal substitution at a fixed point in time (e.g., over a 1-year period) and

[2]However, the Norwegian Competition Authority briefly reports that a larger share of retail gasoline volume was sold during the low-priced parts of the price cycle in 2011 than in 2006 (Konkurransetilsynet, 2014).

do not account for dynamics. My results suggest that this approach can yield different conclusions depending on how long the price pattern at issue has been present. For example, studies relying exclusively on short-run data to evaluate the effects of changes in the price pattern may underestimate the consumer response in the long run. This may be of particular interest in the residential electricity market where several countries are currently in the process of switching to smart meters and real-time pricing. The existing evidence, based on data from less than 2 years after a transition, indicates that consumers fail to adjust their consumption to the intertemporal price variation (Fabra et al., 2021). However, my results suggest that it is important to also examine the long-run response because consumers may need time to learn about the new price pattern and then to change their habits.

I also show that the increasing consumer sensitivity to intertemporal price variation causes volume-weighted price–cost margins to decrease over time relative to their unweighted counterparts, even with stable sale-period rebates. The increasing sale-period rebates in the last few years of the sample period exacerbate these differences. Thus, the unweighted prices and margins that are commonly used to estimate welfare effects can provide biased estimates of the actual changes in profits that firms earn and the actual prices that consumers pay.[3]

The remainder of the paper is organized as follows. Section 2 presents some institutional details and provides a description of the data. Section 3 details the development in the price pattern and the underlying intra-week demand pattern. Section 4 investigates the consumer response to the transition from fixed to regular price cycles, while Section 5 studies the consumer response to the transition from irregular to regular cycles. Lastly, Section 6 discusses the implications of the results, and Section 7 concludes.

2 Institutional setting and data

2.1 Institutional setting

In the sample period, Norway has a population of almost five million people distributed across some 385 203 km^2. Some 80% of the population live in urban areas but spread over about 430 separate municipalities. Each municipality cover a moderately large area (on average 710 km^2) and the population density varied greatly from 1,565 inhabitants/km^2 in Oslo to less than one inhabitant/km^2 in some of the more remote rural municipalities. Nearly all municipalities accommodate one or more gas stations.

[3]Wang (2009) use unweighted prices to estimate the effect of regulation causing a change in the price cycles in Perth, Foros & Steen (2013) use unweighted prices to estimate the effect of the change from irregular to regular price cycles in Norway, Noel (2015) use unweighted prices to estimate the effect of a refinery fire that halted the price cycles in parts of Canada, Assad et al. (2020) use unweigted prices to estimate the effect of retailers' adoption of algorithmic-pricing software in the German market.

Four national chains dominate the Norwegian retail fuel market with a combined market share of more than 90% throughout the sample period. Two smaller chains mainly control the remainder. These chains own about two-thirds of their affiliated stations and control the prices of the other third through vertical restraints.[4]

The gas stations sell both gasoline and diesel, with 95 octane gasoline being by far the most common type of gasoline.[5] I exclude truck stations where large commercial vehicles fill their tanks from the sample. Smaller commercial vehicles filling their tanks at regular gas stations are more likely to have a diesel engine, and private vehicles are more likely to have a gas engine.[6]

The total retail fuel volume (both gasoline and diesel) sold in Norway is quite stable over the sample period, but there is a large shift from gasoline to diesel over time. This shift resulted from lower taxes for diesel cars, thereby encouraging customers to change from gasoline to diesel vehicles during the sample period (Pilskog, 2018). The gasoline share of total fuel volume sold at the stations in the sample fall from 68% in 2004 to 47% in 2009 and 33% in 2014, while the diesel volume share increases correspondingly (Appendix Figure A.1).

Economic growth is quite stable in Norway over most of the sample period (0.5–3% yearly GDP increase in all years except 2009). The global financial crisis had a much smaller impact on Norway compared with other European countries and only invoked a 1.5% decrease in GDP in 2009 and a 1.5 pp increase in the unemployment rate (Finanskriseutvalget, 2011). Together with the stable development of total retail fuel sale, this suggests that there were no major macro demand shocks affecting the Norwegian retail fuel market during the sample period.

2.2 Data

I obtain data on gasoline and diesel price and volume spells and station characteristics from the Norwegian Competition Authority (Konkurransetilsynet), which collects the data directly from the chains. The available data span the period 2004—-2017 but owing to confidentiality restrictions, I end the sample period in December 2014.

The data include price and volume spells for gas stations affiliated with the four national chains and the two smaller chains supplying more than 90% of retail fuel in Norway. A gasoline price spell starts the minute a station changes its gasoline price and

[4] Tveito (2021a), partly drawing on evidence and reports from Foros & Steen (2013) and the Norwegian Competition Authority, provides a more detailed description of the supply side.

[5] The only other gasoline type, 98 octane, constitutes a very small share of the market through the sample period, starting at 5% of total retail fuel volume in 2004 and steadily declining to less than 1% in 2014 (Drivkraft Norge, 2021).

[6] In 2008, 73% of private vehicles in Norway had gasoline engines, decreasing to 52% in 2014. Some 83–92% of smaller commercial vehicles (such as vans without rear seating) and taxis have diesel engines in all years throughout 2008–2014. The share of vehicles with electric engines is 1% or less in all years of the sample period (Statistics Norway, 2021a).

ends when the station makes a new gasoline price change. The gasoline (diesel) price spells are on average 18.0 (17.8) hours in duration. These price spells allow the construction of a panel with station-level hourly (or longer) diesel and gasoline prices that I employ to analyze the intra-week price patterns.[7] All prices are CPI-adjusted to the 2009 level.

The gasoline volume spells show how many liters of gasoline at a given station are sold during the duration of the spell. The start and end times of the volume spells often match the price spells, but some of the price spells are also split into multiple volume spells of shorter duration. For these spells, the price is unchanged over a longer period, but volume is registered in two or more different spells. For this reason, the average gasoline (diesel) volume spell is only 10.3 (10.4) hours. As we are most interested in intra-week volume changes, I restrict the sample to station-month combinations with on average less than 24 hours between each volume registration. This sample restriction removes station-months with long volume spells that would provide inaccurate intra-week volume observations and reduces the number of gasoline (diesel) station-weeks to 19% (22%) of the full sample and the average duration of the gasoline (diesel) volume spells to 9.2 (9.4) hours. All conclusions in the paper are robust to retaining observations with less-accurate volume information in the sample.

To analyze the consumer response to changes in the intertemporal price pattern, I need to transform the volume spells to a panel with station-level volume sold in fixed time periods. Although the volume spells are of a high frequency, I do not know the exact volume sold for each station in each hour of the sample. When transforming the data, I assume that a station's volume sold is equal for all minutes of a given spell. For spells that start and end in the same fixed period, there is no uncertainty related to which fixed period the volume is sold in. For spells that start and end in different fixed periods, volume is split between the fixed periods according to the share of each spell's total minutes that took place in each of the fixed periods. For example, if a station sold 2 000 liters of gasoline in a spell that commenced at 20:00 hours on July 1 and ended at 16:00 hours on July 2 and the fixed periods span a calendar day, then 400 liters of the spell would be credited to July 1 and the remaining 1 600 liters to July 2.

When aggregating the spell volumes into a fixed-period panel, there is a trade-off between the frequency and accuracy of the volume observations: long fixed periods may average out important intra-week volume variation but are more accurate because the share of a period's volume that comes from spells spanning multiple periods is low. In most of Section 5, I use long fixed periods: each week is split into only three periods. However, when calculating the intertemporal elasticities, I split each week into 21 periods.

[7] Spell price and volume data are missing for the largest national chain between January 2012 and September 2013. Spell volume data are also mostly missing for one of the other national chains before 2006. Some individual stations are also missing price or volume data in parts of the sample period, particularly in the first 2 years. If a station is missing price or volume data in a spell covering part of a given week, then the whole station-week is treated as missing data.

For one of the national chains, daily-level volumes rather than spell volumes are available before 2006 and for another national and one of the smaller chains the same is true for the period 2012–2013q3. The other small chain has daily-level volumes rather than spell volumes in the years 2005–2008. To maximize the number of events in Section 4 and the number of observations in the pre- and post-periods for each event, I aggregate the spell data to the daily level for the analysis in Section 4 and combine it with the daily-level volumes from the chain-periods with missing spell volumes. Some individual stations are also missing price or volume data in parts of the sample period. I drop all station-weeks where one or more minutes of the week have missing information about prices or volume.

This paper focuses on the consumer response to changes in the intra-week price pattern. Because of this, I drop 6–8 weeks each year with one or more public holidays from the sample because prices follow a slightly different pattern in these weeks and because the intra-week demand pattern differs in weeks with holidays.[8]

These sample restrictions leave me with 631 000 station-weeks with intra-week gasoline price and volume observations from 2 135 individual stations, and 611 000 station-weeks with intra-week diesel price and volume observations from 2 119 individual stations. The stations are in 394 different municipalities.

3 Price pattern and underlying demand

3.1 Price pattern

Retail motor fuel prices in Norway follow a sawtooth-like pattern, where market-wide price hikes arise within a few hours (the "restoration phase") and many small price cuts follow over the next several days (the "undercutting phase") before another large price hike again takes place. Tveito (2021a) provide a detailed description of the price pattern and find that firm behaviour in the undercutting phase of the cycle adheres well with the Edgeworth cycle equilibrium in Maskin & Tirole (1988)'s price commitment model, but the large chains appears to use price leadership to coordinate on more frequent price hikes to avoid the cycle-trough.[9] The pattern is almost identical for diesel and gasoline prices. During the whole sample period, price restorations always occur once or twice per week, but the day of the week restorations take place change over time.

Most of the stations in the sample set cycling prices throughout the entire sample period. But a significant number of stations set fixed prices through the week and only change prices occasionally in response to, e.g., wholesale price changes. As shown later, stations with cycling prices carried out price restorations every Monday for most of 2004

[8]The price pattern is very similar in weeks with public holidays, but price restoration never takes place on holidays. For example, if a price restoration would normally occur on a Monday and a given Monday is a public holiday, the restoration will normally be postponed to Tuesday.

[9]See also Tveito (2021b) studying the transition to the equilibrium with two price jumps per week.

and in all years thereafter. As in Tveito (2021b), I use the Monday restorations to separate stations into *cycling stations* and *non-cycling stations*. I consider a station to be a *cycling station* in a given year if that station's average difference between the maximum and minimum price on Mondays when price restorations are carried out is $> NOK0.05$, and a *non-cycling station* if the difference is $NOK \leq 0.05$.

At the start of the sample period, 13% of all stations are non-cycling (Figure A.2). The share of non-cycling stations decreases over time because many transition to setting cycling prices, such that by 2014 only 4% of stations are non-cycling. These transitions constitute the events I explore in Section 4. In the rest of this section, I focus on how the price cycles develop over time.

In the first four months of 2004, price restorations take place once a week but on different weekdays. Thus, it vary from week to week when prices are lowest. On average, prices are lowest late Monday and Tuesday morning, and highest on Thursday afternoon and Friday (Appendix Figure A.3). Employing a sample of user-reported prices, Foros & Steen (2013) identify a similar price pattern in 2003, suggesting that the pattern with restorations on different weekdays was also present then. It is unknown exactly when the pattern of cyclical prices started, but a thorough search through Norwegian news outlets reveals that intra-week price variation was first mentioned in March 2002 in an article reporting on an analysis of user-reported prices from March 2001 to March 2002.[10]

The restoration phase only lasts a few hours: the first chain hikes prices for affiliated stations around 11:00 hours and the other chains follow between 12:00 and 16:00 the same day.[11] At a given time in the undercutting phase, the price difference between stations in the same area is small as the stations in the area are only slowly undercutting each other. But in the restoration phase, prices vary greatly between stations that have hiked prices and those that are still at the bottom of the cycle.

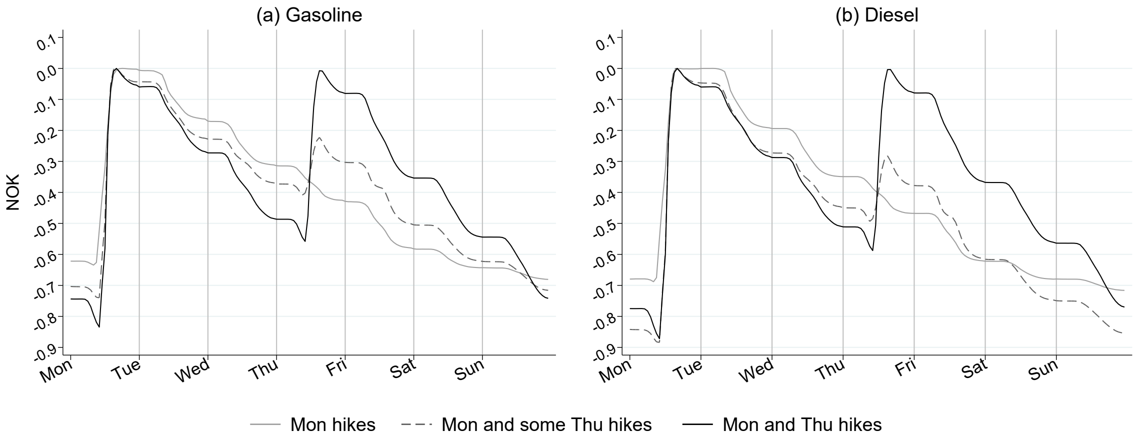
During the week starting April 26, 2004, the price hikes begin to occur exclusively on Monday. These hikes arise when the largest chains in the market begins to hike prices for affiliated stations every Monday.[12] After four months with Monday hikes, there are six weeks in September/October when prices revert to the pattern with hikes on irregular weekdays. From mid-October 2004, hikes again occur every Monday and continue to do so throughout the remaining sample period. The transition from price hikes on irregular weekdays to hikes at the same time every week is the starting point for the analysis

[10] The analysis was based on 32,000 prices reported to a price comparison website. It found that prices on the weekday with the lowest average prices were NOK0.18 lower than the weekday with the highest average prices (Hvitved-Jacobsen, 2002).

[11] In the first year of the sample period, the first chain typically hikes prices at around 10:00, but in all subsequent years, the first chain hikes prices at around 11:00.

[12] The reason why the chain begins to initiate Monday hikes is unknown. Noel (2019) suggests that a leader may initiate calendar-synchronized price hikes to make the hikes more predictable for other firms, potentially reducing both the time it takes before the other firms follow and the frequency of failed price hikes.

Figure 1: Price cycles



Note: The figure splits the sample into three different periods and plots the average gasoline and diesel prices in each hour of the week relative to the hour with the highest average price in each period. The gray lines plot averages across all cycling stations and all weeks in the period when price hikes occur exclusively on Monday. The dashed dark gray lines plot the same for the period with hikes on every Monday and on some Thursdays, and the black lines for the period with hikes every Monday and Thursday.

in Section 5. When hikes exclusively occur on Monday, prices peak Monday afternoon, and fall toward a trough on Sundays and Monday mornings (the gray lines in Figure 1). Restorations continue to occur every Monday between 11:00 and 16:00 through the rest of the sample period.

Starting in January 2005, an additional price restoration take place in some weeks on Thursday. Over the next 4 years, such restorations arise in 35% of weeks.[13] The dashed lines in Figure 1 show that average prices, except for a modest increase after Thursday afternoon, follow a similar development through the week in this period as in the period when restorations exclusively happen on Monday. In March 2009, the Thursday restorations start to occur every week and continue to do so throughout the remaining sample period. Prices are equally high on Monday afternoon and Thursday afternoon and fall between the two restorations (the solid black lines in Figure 1).

The transition to Monday restorations changes the intertemporal menu of prices consumers choose from. In periods with irregular restoration days, it varies from week to week when prices are lowest, and the prices are never lowest on Sunday and Monday morning

[13] 84% of the additional restorations are on Thursday, while 16% are on Friday. Such attempts at additional restoration are in 62% of weeks, but 43% of the attempts fail as one or more chains do not follow the leader's price hikes. When a restoration attempt fails, prices quickly return to their pre-hike path.

(Figure A.5). After the transition to Monday restorations, prices are always (even in weeks with Thursday restorations) lowest on Sundays and Monday mornings (Figure 2). This is because there are only three days with price cuts from Monday to Thursday but four days from Thursday to Monday.

The low prices on Sundays and Monday mornings are comparable to a regular sale of retail fuel every week. In the following, I call the part of the week consisting of Sunday and Monday before 16:00 the *sale period*. Thus, the Monday restoration period (11:00–16:00) is in the sale period, even though its average prices are above the weekly average (Figure 2), because some stations still have low prices in this period.[14] In what follows, I discuss the development in sale-period prices relative to prices in other parts of the week. I compare prices in the different parts of the sale period to the average weekly price and refer to these as *sale-period rebates*.[15] I refer to the sale-period rebates as rising when prices in the sale-period fall relative to the weekly average prices.

Prices fall slightly faster in the undercutting phase of the cycle in the period with an additional Thursday restoration in some weeks than in the period with only Monday restorations, and even faster in the period with Thursday restorations every week (Figure 1). Without the Thursday restorations, the sale-period rebates would increase over time. But the Thursday restorations counteract the more rapid undercutting, meaning the rebates are mostly stable after the transition to Monday restorations. As shown in Figure 2, the rebates are fairly stable until 2009q2 when Thursday restorations begin to occur every week, and these serve to compress the price cycle. The rebates remain at this lower level from 2009q2 and through 2010. In 2013 and 2014, the Sunday night and Monday morning rebates rise to a level well above the pre-2009q2 level.

The two vertical lines in Figure 2 mark two quarters with very similar sale-period rebates (2004q4 and 2009q1). I use these quarters as reference points when studying the effect of the transition from irregular to regular cycles in Section 5.

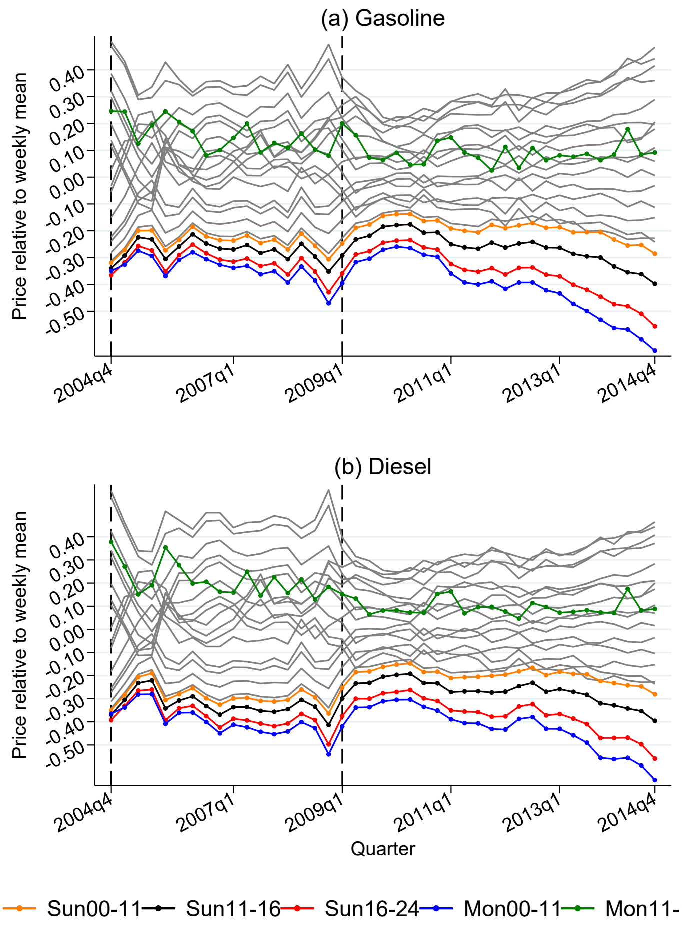
The ability and incentive of fuel consumers to time purchases to the troughs of the cycle depend on how often they need to fill their tanks and the magnitude of the savings they can earn by timing their purchases with these troughs. The average consumer needs to make about 21 trips to gas stations each year—less than one trip every second week.[16]

[14] Figure A.10 depicts the development over time in both the share of volume sold in the restoration period and the other parts of the sale-period.

[15] The rebate for station i in week w across hours $s = 1$ to $s = S$ is given by $\frac{\sum_{s=1}^{S} P_{siw}}{S} - \frac{\sum_{h=1}^{168} P_{hiw}}{168}$, where P_{siw} is station i's price in hours s of the sale period in week w and P_{hiw} is station i's price in hours h of week w (the unweighted average price). The figure could also be constructed by weighting the weekly average price according to the underlying demand pattern (Section 6). The figure would look almost identical, but the sale-period rebates would be NOK0–0.03 larger.

[16] The average car in Norway was driven 13 200 km/year in the sample period (Statistics Norway, 2021b) and the average fuel efficiency of the European Union car fleet in the same period was 7.1 km/L (European Commission, 2016), meaning, the average car consumes about 939 liters of gasoline per year. Assuming an average tank capacity of 60 liters with consumers filling their tanks whenever the tank

Figure 2: Sale-period prices vs other prices, 2004q4-2014



Note: The figure plots the quarterly development in average prices for different parts of the week relative to the unweighted weekly average price. The averages are calculated across all cycling stations. The colored lines represent different parts of the sale-period; Sunday morning, Sunday midday, Sunday night, Monday morning, and Monday midday, and the gray lines represent the other 17 intra-week periods as defined in Section 5.2. Take note of the following:

1. Both Gasoline and diesel prices are always lowest in the sale period.
2. In 2004q4 (1st vertical line), gasoline (diesel) sale-period rebates are on average NOK0.35 (0.37).
3. Sale-period rebates are fairly stable until 2009q1. In 2009q1 (2nd vertical line), the Monday morning rebates are NOK0.05 larger than in 2004q4, while the Sunday rebates are NOK0.01–0.07 smaller than in 2004q4.
4. In 2009q2, the sale-period rebates fall to NOK0.20–0.30 and stay at this level throughout 2010.
5. In 2013 and 2014, the Sunday night/Monday morning rebates rise to NOK0.50–0.60.

reaches 25% of capacity, consumers then fill up their tanks 21 times per year.

Thus, many consumers have the option to use fuel stored in the fuel tank during the high-price part of the price cycle, and to fill the tank during the low-price part of the cycle.

On average across all cycling stations and all weeks in the sample, gasoline (diesel) prices at the top of the cycle are NOK0.39 (0.42)/liter higher than average prices across the whole week, and prices at the bottom of the cycle NOK0.34 (0.38)/liter lower than average weekly prices. A consumer filling 45 liters of gasoline will then save about NOK18 if they fill up at the bottom of the cycle compared with filling up at the average weekly price and NOK26 relative to the top. To put this into perspective, 1 liter of milk cost about NOK13 during the same period. Over a year, the average consumer can then save nearly NOK400 by filling up in the low-price period.

There is of course substantial heterogeneity in how much fuel different consumers use, and the cycle amplitude (the difference between the top and bottom of the cycle) also varies across different areas (Figure A.15). A consumer with a large SUV with a 100-liter tank using four times more fuel per year than the average consumer can still fill up once per week in the low-price period. If the consumer lives in an area with large cycle amplitude, they can save NOK40 every time they fill the tank or about NOK2 000 every year. For most consumers, timing purchases to the trough of the cycle provides notable but not overwhelming savings.

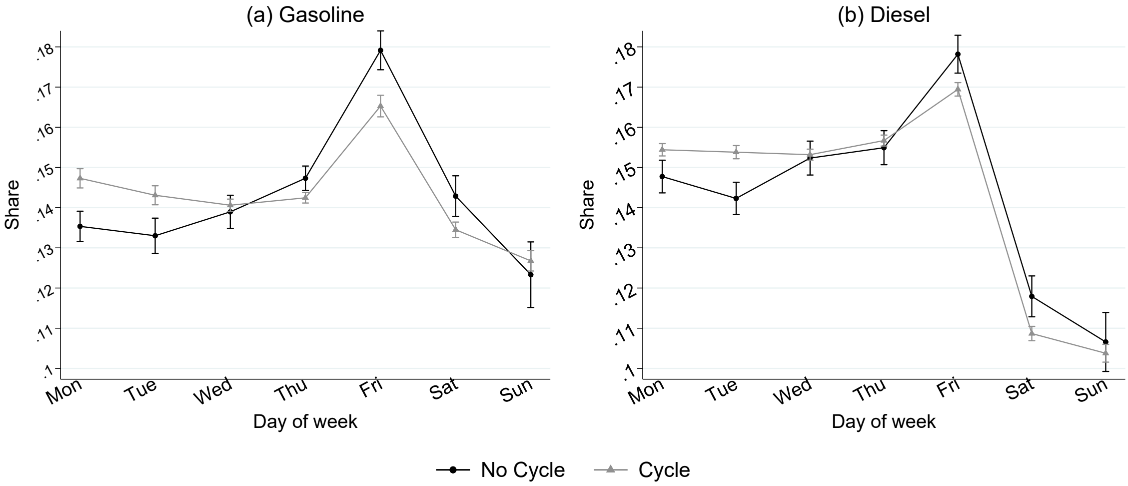
3.2 Underlying intra-week demand

Volumes normally differ across different parts of the week even in the absence of any price differences. The underlying intra-week demand pattern shows how demand would differ in different parts of the week in the absence of intra-week price differences. Owing to the intra-week price variation from the cycles, the underlying intra-week demand pattern for cycling stations is not readily available. I do, however, observe intra-week volumes for non-cycling stations. I also observe intra-week volumes for cycling stations for four months of 2004 when price restorations arose on irregular weekdays. Some parts of the week do on average have lower prices also in this period, but the average variation between weekdays is smaller than when the cycles are regular (Figures 1 and A.3).

Figure 3 depicts the results of four different regressions of the daily share of the total weekly volume of gasoline and diesel sold for cycling and non-cycling stations on indicator variables representing different days of the week. The black lines are the results based on observations for non-cycling stations in the first four months of 2004, and the gray lines are the results for cycling stations for the same four months. Standard errors are clustered at the municipality level.

For both gasoline and diesel, volumes sold on different weekdays are similar for non-cycling and cycling stations. Cycling stations sell a slightly larger share of their total

Figure 3: Underlying intra-week demand



weekly volume in the part of the week when cycling stations on average have low prices (Monday night and Tuesday), consistent with some consumers changing their purchases to the trough of the irregular cycle. As in other countries, the volume of gasoline sold is highest on Friday and lowest on Sunday (Levin et al., 2017). Diesel has a similar intra-week demand pattern to gasoline, but an even lower share of diesel is sold on weekends, likely because diesel engines are more common among commercial vehicles.

4 Fixed prices to regular price cycles

In this section, I analyze events where stations at different points in time transition from fixed (noncyclical) prices to regular price cycles. The development in the share of total weekly volume that is sold in the sale period then shows how well consumers adapt their purchases to the price cycles. Thus, the main outcomes are sale-period rebates and the share of total weekly volume that is sold in the sale period.

An event occurs where a station has fixed prices ($\leq NOK0.05$ average difference between the maximum and minimum price on price restoration days) in at least four consecutive quarters followed by cycling prices ($> NOK0.05$ average difference between the maximum and minimum price on restoration days) for at least the next eight consecutive quarters.

This means that I have data for each treated station for at least four quarters preceding the transition and at least the first eight quarters after. A requirement of at least four pre-period quarters is suitable because it ensures that all events take place in 2005 or later, the period when cycling prices are always lowest on Sundays/Monday mornings. Furthermore, it ensures that the stations in the treatment group do not have cycling prices in the year prior to the event. The requirement of at least eight post-period quarters with cycling prices ensures that the treated stations continue to have cycling prices for at least 2 years after the transition, thereby allowing sufficient time to observe any potential dynamic effects.[17] Extending the required pre- or post-event quarters with cycling prices provides similar results, but with fewer events and less precision.

The event definition yields 76 (71) transitions from fixed to cycling gasoline (diesel) prices. Most of the events (86 of 147) occur when a station simultaneously starts setting cyclical prices for both gasoline and diesel. The events take place in 64 (57) different municipalities. Some 80% of the events occur between 2005 and 2008, giving long post-event periods. On average, I have data for 12.8 (7.4) quarters before and 22.7 (21.9) quarters after each event.

I link each treated station to a group of "clean" control stations that have yet to experience a material change in price pattern in the sample period and create a stacked panel including all the event-specific treatment and control stations in relative time. A station is only included in the control group in quarter q if it has had fixed prices in all operative quarters in the sample period up to and including quarter q. For example, a station with fixed prices in all quarters during the period 2004–2006 but cycling prices in 2007q1, is included in the control group in 2004–2006, but dropped in 2007q1 and all following quarters regardless of whether the station's prices are fixed or cycling after 2007q1.

On average, each treated station is linked to 19.6 (24.8) control stations in each quarter. The number of control stations decreases over time as more stations transition to cycling prices. Both the treatment and control stations are primarily in rural areas and have few competing stations nearby. Both treated and control stations are on average located about 15 minutes' drive time from the nearest alternative station.[18]

Recent advances in econometric theory show that the two-way fixed-effects regression model that has traditionally been employed to estimate difference-in-differences models with staggered treatment can be biased in the presence of treatment effect heterogeneity (Baker et al., 2021). The stringent criteria for admissible control stations and the stacked panel-approach I use is more robust to possible problems with a staggered treatment design in the presence of heterogeneous treatment effects (Cengiz et al., 2019).

I use observations from the entire sample period but drop observations more than 5

[17] There are some occasions where a station has non-cycling pricing in a period after it has had at least eight consecutive quarters with cycling prices. Because the return to fixed prices normally only lasts one or two quarters before prices begin to cycle again, I do not drop these stations from the sample.

[18] I use the price/volume data to determine which stations are operative at a given point in time and calculate drive times with ArcGIS using the Elveg road network dataset from the Norwegian Public Roads Administration.

years prior to and 7 years after each event for reasons of low precision. The results are almost identical if all observations are included. Gasoline and diesel events are analysed separately. I conduct an event study difference-in-differences event study to identify the development in the outcome of interest for the treated stations by estimating the following regression:

$$Y_{iwg} = \sum_{\tau=-20}^{27} \gamma_\tau \times Treat_{ig} + \theta_{ig} + \delta_{\tau g} + \varepsilon_{iwg} \tag{1}$$

where Y_{iwg} is the outcome of interest (prices and volumes in the sale period) for station i in week w and event g. I follow the recommendation in Baker et al. (2021) and include event-saturated station fixed effects, θ_{ig}, and event-saturated event-time fixed effects, $\delta_{\tau g}$. These fixed effects account for station-specific changes in the outcome between the different events, and shocks with the same effect on all stations in each event quarter.

$Treat_{ig}$ identifies the treated stations in each event. $\sum_{\tau=-20}^{27} \gamma_\tau$ represent indicator variables for the last 20 quarters before and first 27 quarters after each event. Treatment occurs during $\tau = 0$ and $\tau = -1$ is the reference quarter. ε_{iwg} is the error term. Standard errors are clustered at the municipality level.

My primary interest lies in the development of the share of total weekly volume that is sold in the sale period (Sunday and Monday before 16:00) after the transitions. Because the data are at the daily level (Section 2.2), I specify the share of total weekly volume sold on Sunday and Monday as outcome. Any increase in the Sunday/Monday volume share after the transitions likely comes from the sale period. The share of volume sold in the last 8 hours of each Monday likely decreases after the transitions, as this becomes the most expensive time of the week to fill the tank. Thus, the estimated changes in Sunday/Monday volume shares are likely slightly lower than the volume changes in the Sundays/Monday mornings sale period. In the discussion of results below, I use evidence from the higher frequency volume data in Section 5 to approximate the actual changes in the sale-period volume shares.

My identifying assumption is that the average observed differences in the Sunday/Monday volume share between the treated and control stations in the post period are caused only by the transition to regular price cycles. I do not know why the transitions take place. As price cycles are more common in areas where stations from multiple chains are present, a natural explanation for the transitions could be entry from a competing chain in the area surrounding a transitioning station. I have, however, not found any evidence that entry triggers the transitions.[19] My finding of parallel trends in the pre-period and no effect on the sale-period volume share in the quarters immediately preceding each tran-

[19] I have estimated Eq. 1 with various entry-related dependent variables such as the number of stations within 5, 10, and 15 minutes' drive time, the number of stations from competing chains within 5, 10, and 15 minutes' drive time, and indicator variables for having one or more stations within 5, 10, and 15 minutes' drive time. I have not found any conclusive evidence of entry in the quarters around the events.

sition, suggest that stations did not select into changing their price pattern based on expected changes in the intra-week demand pattern and that the identifying assumption is reasonable.

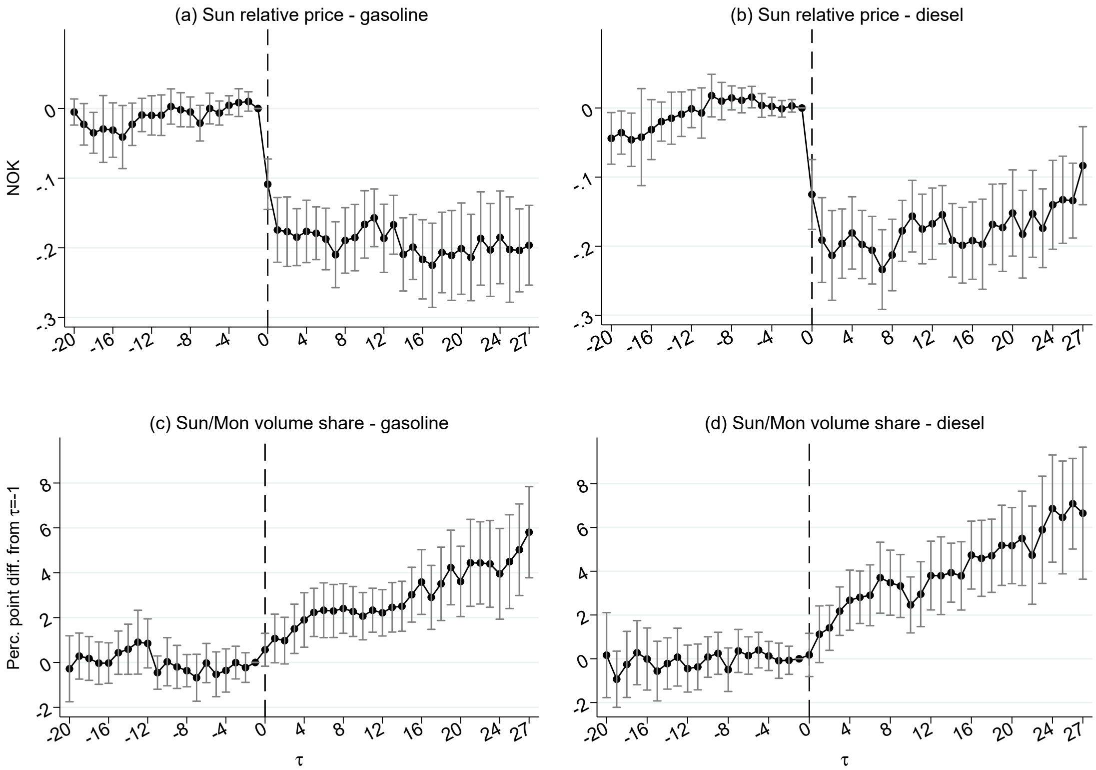
Post-period changes in the sale-period rebates could threaten identification of the dynamics in consumer response to the regular sale period. In particular, larger sale-period rebates over time in the post period could be an alternative explanation for why the sale-period shares increase over time in the post period. As the average Monday price is an average of price at the bottom and top of the cycle, I use the average price on Sunday relative to the weekly average price as a proxy for the sale-period rebates. I estimate Eq. 1 with the Sunday rebate (the average price on Sunday minus the average price over the entire week) as the dependent variable to see how the sale-period rebates develop over time.[20]

Panels (a) and (b) in Figure 4 plot the results from Eq. 1 with the sale-period rebate proxy specified as the dependent variable for gasoline and then diesel. Panels (c) and (d) in Figure 4 show the results from Eq. 1 with the Sunday/Monday volume share as the dependent variable for gasoline and then diesel. Each point represents the difference between the treatment and control group normalized so the quarter before the transitions ($\tau = -1$) is equal to zero. The stations in the control group also have fixed prices in the post period, and the sale-period rebate is therefore about zero in all pre- and post-period quarters for the control group (Panels (a) and (b) in Figure A.6). The control stations' sale-period volume shares are also stable over all pre-and post-period quarters (Panels (c) and (d) in Figure A.6). Thus, the post-period changes in Figure 4 are driven by changes in the outcomes of the treated stations.

Prior to the transitions, the difference between the treatment and control stations' sale-period rebates is stable and rarely significantly different from zero. The treated stations' gasoline (diesel) sale-period rebates increase by NOK0.11 (0.13) relative to control stations in the quarter the transition begins and increase further to about NOK0.17 (0.19) in the next quarter. The gasoline treatment group's sale-period rebates are stable at NOK0.17–0.18 in the first 14 quarters after the transition and then rise slightly to about NOK0.20 for the remaining post period. The diesel treatment group's sale-period rebates vary more but are stationary around NOK0.19 for the first 18 quarters after the transition and then fall gradually to about NOK0.13 less than the control. Overall, the sale-period rebates are quite stable over time, and the fall in the sale-period diesel rebate in the second part of the post period should decrease rather than increase the volume sold in the sale period.

[20] The results are very similar when using the average price across Sundays/Monday mornings relative to the weekly average as the dependent variable: also including the Monday morning would increase the rebates by NOK0.01–0.03. Nonetheless, I prefer the Sunday relative price because I do not have the spell prices needed to calculate the Sundays/Monday mornings average price for all station-weeks, meaning the price sample would be different from the volume sample if I used the Sundays/Mondays morning prices.

Figure 4: Transition from fixed to regular price cycles



Note: The figure shows results from Eq. 1. Panel (a) plots γ_τ from -20 to 27 with the difference between the Sun average price and the weekly average price as dependant variable. Panel (b) plots the same for diesel. Panel (c) plots γ_τ from -20 to 27 with the share of total weekly gasoline volume that sold on Sun and Mon as dependant variable. Panel (d) plots the same for diesel. 95% confidence intervals are also included. Results are also available in tabular form in Appendix Table A.1.

The rebates are about 40% lower than the rebates of the stations that have cycling prices through the whole sample period depicted in Figure 2.

The pre-period difference between the treatment and control stations' Sunday/Monday volume shares is stable and never significantly different from zero. The treated stations' gasoline Sunday/Monday volume share only increases 1.1 pp relative to the control stations in the first full quarter after the transitions. The gasoline Sun/Mon share gradually increases through post-period quarters $\tau = 2$ to $\tau = 21$ ending with a 4.5–5.0 pp increase in $\tau = 21 - 27$. The post-period development in the diesel Sunday/Monday volume share is similar with a 1.1 pp increase in the first full quarter and a gradual increase through the post-period quarters. At $\tau = 21$, the diesel sale-period share has increased 5.5 pp, and it continues to increase ending at 6.5–7.0 pp in $\tau = 24$ to $\tau = 27$.

The Sunday/Monday gasoline (diesel) volume shares (including the 8 hours after prices are restored to the high level) for the treated stations in this section are on average 27% (25%) of the weekly volume before the transitions. The high-frequency data in Section 5 reveal that 22% (20%) of the cycling stations' volume is sold in the sale period (excluding the last 8 hours of Monday) before the transition to regular cycles. The higher frequency data also reveal that cycling stations' volume sold in the last 8 hours of each Monday do indeed gradually fall after the transition to a cycle with regular Monday restorations, starting 0.08 (0.11) pp down in the first quarter with regular cycles and ending at 1.7 (1.5) pp below the pre-transition level after about 5 years.[21]

To calculate the approximate percentage changes in the sale-period volume shares after the transitions from fixed prices to regular cycles, I assume that the pre-transition sale-period volume shares are the same as the cycling stations' sale-period volume shares before the transition to a regular cycle, and that the volume share of the last 8 hours of Monday follow the same development as after the transition from irregular to regular cycles. With this approach, the gasoline (diesel) sale-period volume shares increase 1.9 (2.2) pp in $\tau = 1$, and after growing gradually over 5 years are 6.2 pp (7.0 pp) higher in $\tau = 21$ than before the transition. This corresponds to an 8.6% (10.9%) increase in $\tau = 1$ and a 28% (35%) increase in $\tau = 21$.[22] Without adjusting for the decrease in the Monday night volume share, the estimates of the increase in the sale-period volume shares in the first quarter after the transition are 5.9% (6.4%) and 20.4% (27.2%) in $\tau = 21$. With and without adjusting for changes in the Monday night volume, the increase in the sale-period share is more than three times larger after 5 years than immediately after the transition.

The treated stations are typically located far from other stations but are not true mo-

[21]The Monday 16:00–midnight volume share is 0.08 (0.11) pp lower in the first quarter in 2004 with Monday restorations. This gradually decreases over the next 4.5–5.0 years when the sale-period rebates are stable, ending 1.7 (1.5) pp below the pre-transition level in 2009q1. It then increases slightly when the sale-period prices increase in 2009q2 and finally return to their 2009q1 level in 2013–2014.

[22]For example, the change in the gasoline sale-period volume share in $\tau = 21$ is calculated by $(4.44 + 1.7)/22 = 0.28$.

nopolists. Thus, the treated stations' lower prices in the sale period could steal consumers from other stations, and part of the increase in the share of the treated stations' volume that is sold on Sunday and Monday could be driven by these new consumers. If the stealing effect is important, the sale-period volume share should increase more at treated stations with another station close by than at treated stations with greater distance to the closest station. To address this, I split the treated stations into two groups – less than and more than the median distance to the nearest station—and re-estimate Eq. 1 for each of the groups. In the less (more) than group, the average distance from a treated station to the nearest station is 3 (25) minutes' drive time.

Figure A.7 renders the results. For both gasoline and diesel, the development in the Sunday/Monday volume share is very similar for those stations with another station nearby and the stations with a greater distance to the closest station. This suggests that the stealing effect is not driving the results. The potential for stealing consumers from other stations in the sale period is very limited in the analysis in Section 5 because all stations with cycling prices (87% of all stations) are treated at the same time. The results in Section 5 are like the results in this section, consistent with the stealing effect being comparatively unimportant.

A higher price level can induce consumers to switch to a lower quality product given income effects or category budgeting (Hastings & Shapiro, 2013). Similarly, a higher fuel price level can potentially induce consumers to switch to purchasing when prices are low. Figure A.8 illustrates the quarterly development in the diesel and gasoline treated stations' average weekly prices before and after the transition. As shown, the average prices do increase over time but are stationary for the first 2–3 years after the transitions. The stable average price level and gradual increase in the sale-period volume shares in the first few years after the transitions suggests that increasing average prices are not causing the increasing sale-period volume shares. Furthermore, a price-level-based explanation for the gradual increase in the volume share cannot explain why the sale-period volume share does not decrease in quarters such as 2009q1 when average prices are much lower than in previous quarters (Figures 5 and A.4).

The market-wide substitution from cars with gasoline engines to cars with diesel engines (Section 2.1) could also be correlated with the sale-period volume share. For example, it is possible for price-sensitive consumers to be more likely to both substitute to diesel cars and to purchase in the sale period. This could bias the analysis of the development in the sale-period volume share of gasoline or diesel over time. The similar gradual increase in the sale-period volume share for gasoline and diesel suggests that any such bias is not important. As both are gradually increasing, consumers in the retail fuel market are clearly increasingly filling their tanks during the sale period. The gradual change in engine types would, however, frustrate attempts at quantifying the difference in the response of gasoline and diesel consumers to the price pattern changes.

Summing up, the share of fuel sold in the sale period increases over time after the transition from fixed prices to regular price cycles. The gradual increase occurs even though the treated stations' sale-period rebates are quite stable, suggesting that demand becomes more responsive to the intra-week price variation over time. The treated stations' increase in the sale-period volume share also appears driven by existing consumers filling up at a different time of the week, rather than by an influx of new consumers. Increasing average prices are also unlikely to have a material impact on these results.

5 Irregular to regular price cycles

This section considers the consumer response to the transition from irregular to regular price cycles that occur in 2004. This happens at the same time for all stations with cycling prices. Thus, I have a group of treated stations but not a control group of stations that were not treated but that had a similar pre-treatment price pattern. The only stations unaffected by the transition are stations with fixed prices through both the weeks before and after the other stations' price pattern changed. Stations with fixed prices have a different pre-period price pattern than stations with cycling prices. But they have a similar pre-period intra-week demand pattern to stations with price cycles (Section 3.2).

The different pre-period price pattern means that stations with fixed prices are not a valid control group for a difference-in-differences analysis of the development in the sale-period volume share, but they are useful as a placebo group in being a group of untreated stations where we do not expect to see systematic changes over time in the share of volume that is sold in the sale period. I estimate the development in the sale-period volume share separately for the treated stations and the placebo stations. The confidence that changes in the intra-week demand pattern for the treated stations was the result of the change in the price pattern, would be undermined if I identify similar changes for the placebo stations.

I use the definitions in Section 3.1 to categorize stations as cycling or non-cycling each year. I drop stations that start out with cycling prices but that at some point switch to fixed prices or vice versa. Thus, the stations in the treatment group have cycling prices in all operative years in the sample period.[23] I define the placebo group of non-cycling stations similarly to the control group in Section 4: that is, a station is only included in the placebo group in year y if it has been a non-cycling station in all operative years up to and including year y. Thus, the placebo group stations have non-cycling prices in all the years they are included in the sample.

The clear majority, about 1 200 stations, have cycling prices in all operative years

[23]The treated stations in Section 4 all have fixed prices at some point in the sample period, while none of the treated stations in this section have fixed prices at any point in the sample period. Thus, the treatment group in this section comprises a different set of stations than in the previous section.

in the sample period and are included in the treatment group. There are more than 100 stations in the placebo group in the first few years of the sample period, but this gradually decreases as more stations start to set cycling prices over time. In 2012, less than 10 stations are left in the placebo group. Due to issues with poor precision and confidentiality, I do not present the results for the placebo group after 2011.

The stationary development in the placebo groups' sale-period volume share (Figure 5) suggests that the underlying intra-week demand pattern is unchanged after the transition. But as the price cycles were a relatively new phenomenon at the time of the transition (Section 3.1), consumers at cycling stations could still have been learning and adjusting to the cyclical prices and could have become more responsive to the cyclical prices even without the transition to a regular cycle. Thus, the development in intra-week volume shares and intertemporal elasticities can show whether consumers' short- and long-run responses to the regular cycles differ, but not whether the transition to regular cycles improves consumers' response to the cycles compared with a situation where the irregular cycles had continued.

The analysis in this section adds to the event study in Section 4 in several ways. First, higher frequency volume data available for the treated stations in this section allow me to estimate the volume sold in finer detail over the week, and to estimate the intertemporal price elasticity of demand in both the period with irregular cycles before the transition and the development in the intertemporal elasticity in the period after the transition to regular price cycles. Second, the cycling stations' consumers have had 2–3 years to learn that prices are cyclical before the transition, and the development in the sale-period volume share after the transition to regular cycles could therefore differ from the transition from fixed prices to regular cycles. Third, as the transition occurs at the same time for the clear majority of the stations in the market, the potential effect of stealing customers from other stations in the sale period is very limited. Finally, as the treatment group is much larger than in the event analysis in Section 4, it is also possible to look at heterogeneous treatment effects across stations with different cycle amplitudes.

5.1 Estimating intra-week volume shares

I estimate the development in intra-week volume shares separately for the treatment group (cycling stations) and the placebo group (non-cycling stations), and separately for gasoline and diesel. I estimate the following regression model to uncover the share of volume sold in different parts of the week:

$$Y_{iwn} = \sum_{n=1}^{N} \beta_n + \sum_{\tau=1}^{T} \theta_\tau + \sum_{\tau=1}^{T} \sum_{n=1}^{N} \gamma_{\tau n} + \varepsilon_{iwn} \tag{2}$$

where Y_{iwn} is the outcome variable for station i in intra-week period n in week w. In the main text, I provide the results from a dataset where the week is split into $n = 3$ periods: Monday 16:00–Thursday 16:00, Thursday 16:00–Saturday 24:00, and Sunday 00:00–Monday 16:00 (the sale period). $\sum_{n=1}^{N} \beta_n$ represents indicator variables for each intra-week period. θ represents indicator variables for all quarters in the sample period. $\sum_{\tau=1}^{T} \sum_{n=1}^{N} \gamma_{\tau n}$ represents the intra-week period-by-quarter indicator variables.

The 2004 quarters are adjusted to separate the periods with and without regular restoration days. The 1st "quarter" lasts until the week before the transition to Monday restorations (April 19, 2004). The 2nd "quarter" starts the first week with Monday restorations and ends the week before the reversion to irregular restoration days (August 30, 2004). The 3rd "quarter" includes only the 6-week reversion period. The 4th "quarter" includes the remaining weeks of 2004 (starting October 18, 2004) when restorations once again occur on Mondays. After 2004, quarters are defined as normal.

5.2 Estimating the intertemporal price elasticity of demand

The intertemporal price elasticity illustrates how well consumers time their purchases to the temporary price variation caused by the price cycles. This is a different type of elasticity than the more commonly estimated price elasticity of demand in response to a *permanent* change in price. The intertemporal elasticity takes into account that intra-week prices can vary from week to week, even in periods with regular cycles.

The placebo group without cycling prices experiences some more random price changes in some weeks due to, e.g., changes in wholesale prices. These price changes are not comparable to the predictable intra-week price changes of stations with price cycles. The development in the intertemporal elasticity of the non-cycling stations is therefore not a relevant comparator for the cycling stations' development.

The increasing share of cars with diesel engines (Section 2.1) could be correlated with the intertemporal demand elasticity. For example, price-sensitive consumers are more likely to both switch to cheaper diesel cars and have a high intertemporal demand elasticity. This could bias the analysis of the development in the intertemporal elasticity of gasoline or diesel over time. Thus, I consider gasoline and diesel as segments of an overall retail fuel market and estimate the development in the intertemporal elasticity for this market, but also display the results for diesel and gasoline separately. Figure A.13 shows that the development in the intertemporal elasticity is similar for diesel and gasoline when estimated separately rather than as segments of an overall retail fuel market.

Week-by-station fixed effects would remove variation arising from stations that have different average prices in each week. However, stations could have the same average price across the whole week but still have different prices in different parts of the week, and consumers could respond to these intra-week differences. To abstract from such crossprice effects, I aggregate the data to the municipality level. The volume sold of a given fuel type, municipality, and time period is the sum of the volume sold of the fuel type across all stations in the municipality and time period, and price is the simple average price across all stations.[24] Except for very short restoration periods, prices at stations in the same area follow a similar pattern through the week, and Appendix Figure A.14 shows that the main results are very similar if I redo the analysis at the station level.

When estimating elasticities based on volume and price spells aggregated to a set of intra-week periods, I must assume that consumers do not respond to price differences within each period. Aggregating over long periods certainly increases the accuracy of the data, but decreases the frequency of observations (Section 2.2). Aggregating over long periods when prices vary could remove important variations in prices and volume. As prices vary around price restorations, I want to separate the periods before and after restorations. Restorations occur one or two times per week between 11:00 and 16:00. Thus, I split each day in three parts, 00:00–11:00, 11:00–16:00, and 16:00–24:00, giving 21 intra-week periods. Prices vary substantially between stations during the midday period (11:00–16:00) on restoration days, but the share of total weekly volume sold in this time span is small and thus unlikely to have a substantial influence on the intertemporal elasticity.[25] The main results also hold with shorter or longer intra-week periods.

The potential endogeneity of fuel prices can bias the intertemporal elasticities. When estimating regular price elasticities, such bias can arise, e. g., if fuel prices increase in response to high demand in a week. When estimating intertemporal elasticities, the municipality-by-week fixed effects remove demand variation across weeks and areas. Only shocks that have a differential effect on demand in different parts of the week can then bias the estimates. The typical long-run demand shocks relating to macroeconomic developments affect demand similarly in all parts of the week and are thus unlikely to bias the estimated intertemporal elasticities. intra-week fuel prices could also be endogenous to the gradual change in the overall intra-week demand pattern after the transition to Monday restorations. However, Eq. 3 only employs variation within quarter τ to estimate the intertemporal elasticity in quarter τ. Changes in the intra-week demand pattern within a given quarter are then negligible. I cannot rule out that price endogeneity biases the intertemporal elasticities, but bias due to unobserved shocks that differentially affect different parts of the week seem less likely than the typical bias arising from shocks affecting overall demand throughout the entire week.

I estimate the unadjusted intertemporal price elasticity of demand in each quarter of the sample period with the following model:

[24] I also estimate the intertemporal elasticities using different types of volume-weighted prices. The results are almost identical to those with simple average prices.

[25] Figure A.10 shows that the share of total volume sold in the Monday restoration period is between 3.5% and 4.8% over 2004–2009q1 and increases to around 7% in 2014. The volume share in the Thursday restoration period is around 4% for the entire sample period.

$$ln(Y_{fiwn}) = \alpha + \sum_{\tau=1}^{T} \beta_\tau ln(P_{fiwn}) + \lambda_i \theta_w \gamma_f + \varepsilon_{fiwn} \tag{3}$$

where the outcome, Y_{fiwn}, is the total volume sold of fuel type f in municipality i in week w and intra-week period n, and P_{fiwn} is the average price of fuel type f across all stations in municipality i in week w and intra-week period n.[26] $\lambda_i \theta_w \gamma_f$ represent indicator variables for each municipality, fuel type, and weeks, and all possible interactions of these indicators.[27] The fixed effects ensure that the only variation remaining is the intra-week variation in prices and volumes in each municipality. $\sum_{\tau=1}^{T} \beta_\tau$ are the coefficients of interest and give the unadjusted intertemporal price elasticity resulting from the intra-week price variation in each quarter τ.

Nonetheless, the unadjusted elasticities do contain a bias in that they do not control for the fact that volume sold would normally differ across different parts of the week even in the absence of intra-week price variation (Noel, 2019). The usual fix would be to include fixed effects for each of the intra-week periods, but this is infeasible as the troughs and peaks near perfectly correlate with the intra-week periods with regular cycles. Noel (2019) argues that the underlying intra-week demand pattern in an area can be approximated by the average volume sold in different parts of the week in a period with irregular restoration days. He then proposes that the bias in the unadjusted elasticities can be removed by subtracting the underlying demand from the actual volume sold in each intra-week period.

Data from the first four months before the transition to regular cycles permit me to find the average volume sold for cycling stations in different parts of the week in a period with irregular cycles. However, average prices differ through the week in this period (Figure 1), so the average volumes in different parts of the week do not perfectly identify the underlying intra-week demand. I also observe the intra-week volumes sold for non-cycling stations that do not have cycling prices. These stations are typically located in more rural areas than cycling stations, and their intra-week demand could then differ from that of the cycling stations. Nevertheless, given the fixed prices, I elect to use the average intra-week demand pattern from the non-cycling stations as a proxy for the underlying intra-week demand pattern for cycling stations. Figure 3 shows that the differences in the intra-week demand pattern between the two groups of stations is relatively small, and the main results are very similar, regardless of how I proxy the underlying demand pattern.[28]

[26] P_{fiwn} is weighted by the volume sold of fuel type f of each station in the relevant week/intra-week period.

[27] $\lambda_i \theta_w \gamma_f$ represents the following fixed effects: $\lambda_i + \theta_\tau + \gamma_f + \lambda_i \times \gamma_f + \lambda_i \times \theta_\tau + \theta_\tau \times \gamma_f + \lambda_i \times \theta_\tau \times \gamma_f$. When I estimate the elasticity for gasoline and diesel separately, γ_f and other indicators interacting with γ_f are dropped.

[28] As the change over time in the intertemporal elasticity after the transition to Monday restorations is driven by a shift in volume to the sale period from all other periods of the week, the possible bias in the intertemporal elasticity caused by an imperfect estimate of the underlying intra-week demand will be similar in all years after the transition. The development in the intertemporal elasticity in the years after the transition to Monday restorations is therefore similar, regardless of the proxy for underlying demand

I calculate the adjusted intra-week volumes with the following formula:

$$ADJ\_V_{iwn} = V_{iwn} - TOT\_V_{iw} \times S_n + \overline{V_{iw}} \tag{4}$$

where V_{iwt} is total volume sold in municipality i in week w and intra-week period n. TOT_V_{iw} is the total volume sold in municipality i in week w. S_n is the average share of total weekly volume sold in intra-week period n across all non-cycling stations and all weeks in the first 4 months of 2004. $\overline{V_{iw}}$ is the average intra-week period volume in municipality i in week w, and is needed to avoid exaggerating volume changes when expressed as percentages and to avoid negative values (Noel, 2019). About 0.6% of the adjusted volume observations are zero or negative and are dropped from the analysis. My main specification use the adjusted volumes but I also show that results are similar with the unadjusted volumes as dependant variable.

5.3 Results

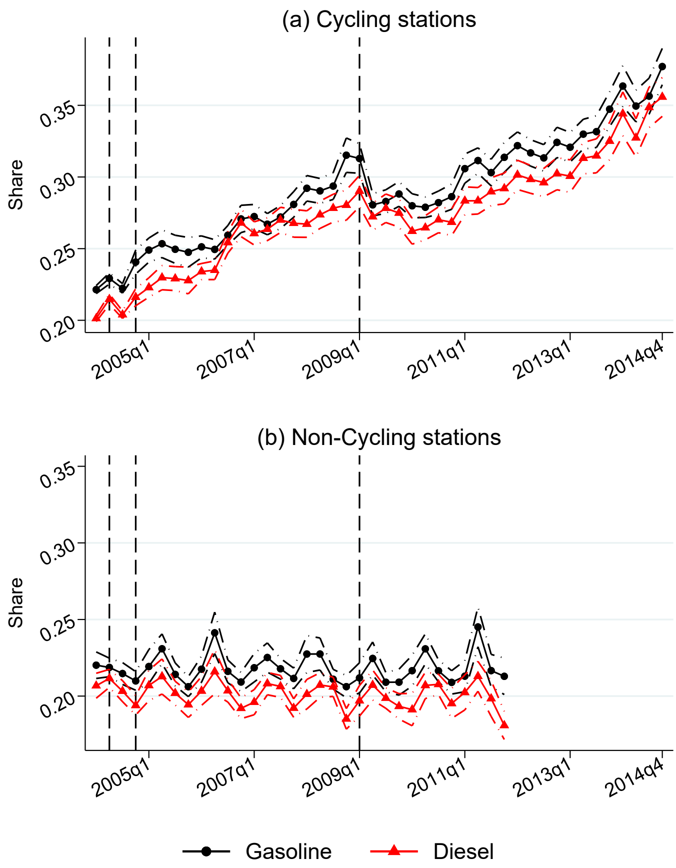
Figure 5 depicts the results from the estimation of the sale-period volume share based on Eq. 2.[29] The results are also available in tabular form in Appendix Table A.2. The first thing to note is that cycling and non-cycling stations' sale-period volume shares are very similar in 2004q1 and 2004q3, being the two "quarters" of 2004 when price restorations arise on irregular weekdays. Furthermore, the non-cycling stations' sale-period shares remains at this level over the next 7 years. Thus, there is no indication that the placebo group experiences any change in the intra-week demand pattern.

The Sundays/Monday mornings volume share gasoline (diesel) volume share is on average 22.2% (20.3%) of total weekly volume in those parts of 2004 with irregular restoration days. The initial response to the new price pattern is weak—cycling stations' diesel and gasoline Sundays/Monday mornings (the sale period) shares are only 1.3 pp higher in the parts of 2004 when restorations occur on Monday. But even with moderately stable sale-period rebates (Figure 2), both the gasoline and diesel sale-period volume shares grow by about 0.5 pp per quarter, becoming much stronger over time to 31.3% (29.0%) in 2009q1—a 9.2 (8.8) pp total increase over 5 years. In percentage terms, the sale-period volume shares increase 5.9% (6.4)% in those parts of 2004 with Monday restorations. In 2009q1, the sale-period volume share is 40.3% (43.2%) higher than in the parts of 2004 with irregular restoration days. Thus, the main takeaway from Figure 5 is that neither

pattern used.

[29] From 2012q1 to 2013q2, volume data are missing for the largest and smallest chains with a combined market share of about 35%. intra-week volume shares for stations affiliated with these chains in this period are imputed based on a model where I keep data for each station in the year before and after the period with missing data, then run a fractional response regression (to ensure that the shares sum to one) of the intra-week volume share on a set of station-by-intra-week-period indicator variables and a linear and quadratic time trend interacted with intra-week-period indicator variables, and finally predict the missing volume shares with the regression coefficients.

Figure 5: Intra-week volume shares, sale period



Note: The figure depicts the development in the share of gasoline and diesel volume sold in the sale period. Take note of the following:

1. The sale-period gasoline (diesel) volume shares are 22% (20%) for both cycling and non-cycling stations when restorations occur on irregular days (2004q1 and 2004q3).
2. The sale-period volume shares are stationary at about 22% (20%) for non-cycling stations from 2004 through 2011.
3. The sale shares of cycling stations are 1.3 pp higher in the two quarters of 2004 (1st and 2nd vertical lines) with Monday restorations. Figure A.9 zooms in on these periods.
4. The sale shares of cycling stations rise gradually to 31% (29%) in 2009q1 (3rd dashed line), then fall to 28–29% (26–28%) in 2009q2–2010q4, and finally rise to 38% (36%) in 2014q4.

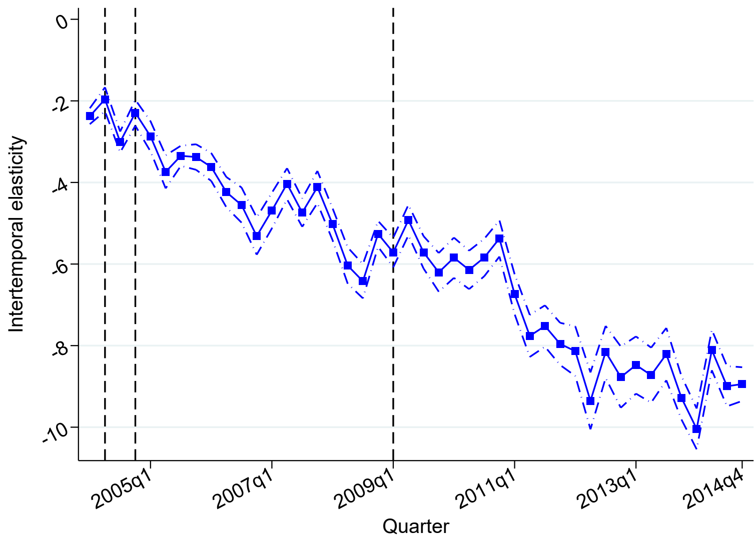
*Point estimates are based on the coefficients from Eq. 2. Each point is the sum of β_n, θ_τ, and $\gamma_{\tau n}$. The 95% confidence intervals are based on standard errors calculated with the delta method.

diesel nor gasoline consumers respond fully to the new price pattern in the short run. Rather, the share of volume purchased in the sale period grows steadily through the first

5 years after the transition to regular cycles. The increase in the sale-period share is then about seven times larger after 5 years than it was immediately after the transition.

Figure 6 plots $\sum_{\tau=1}^{T} \hat{\beta}_\tau$, the intertemporal elasticity in each quarter of the sample period resulting from estimating Eq. 3 on cycling stations with $ln(ADJ\_V_{iwn})$ as the outcome variable. The intertemporal elasticity is -2.4 to -3.0 in the parts of 2004 with irregular cycles, suggesting that some consumers adjust their purchases to the temporary price variation, even when it is difficult to predict when prices will be low. The intertemporal elasticity does not increase immediately after the transition to regular cycles. Instead, it falls slightly to -2.0 to -2.3 in the two quarters of 2004 with Monday restorations. After this, its development reflects that in the sale-period volume share: the intertemporal elasticity increases slightly in 2005 and continues to increase gradually to about -6 in 2008. It is still -6 in the reference quarter 2009q1 when sale-period rebates are about the same as in 2004q4.

Figure 6: Intertemporal elasticity, cycling stations



Note: The figure depicts the development in the adjusted intertemporal elasticity for cycling stations in the overall retail fuel market. The line plots the β_τ from Eq. 3. The 95% confidence intervals are shown. The 1st and 2nd vertical lines mark the two periods in 2004 with Monday restorations and the 3rd line marks the reference quarter 2009q1. The results are also available in tabular form in Appendix Table A.3.

The regular Thursday restorations beginning in 2009q2 decrease the sale-period rebates. The sale-period volume shares immediately fall 2–4 pp when the rebates decrease. The lost sale-period volume is shifted to Monday night–midday Thursday—that part of the week that experiences a decrease in prices after the transition to regular Thursday restorations (Appendix Figure A.11). The sale-period volume share remains sensitive to changes in the sale-period prices, even after a long period with a regular weekly sale. It appears that after the decrease in the sale-period rebate, some consumers no longer find it worthwhile to incur the time cost of timing purchases to a specific time of the week.

Even with low sale-period rebates in 2009q2–2010q4, the sale-period volume shares stay at a level well above what it was just after the transition to Monday restorations (Figure 5). When the sale-period rebates increase substantially in 2013 and 2014, the sale-period volume shares increase even further and end at 36–38%—about 75% above their pre-transition level. The intertemporal elasticity stays at around -6 in the first few years after the Thursday restorations start to occur every week in 2009q2. In 2011, the elasticity increases to about about -9 in 2012–2014.

Variation in cycle amplitude across different parts of Norway could affect consumer response to the cycles. To consider the potentially heterogeneous effects for stations with different amplitude, I split both the treated diesel and gasoline stations into the four quartiles according to each station's average cycle amplitude. For both diesel and gasoline, the quartile with the greatest amplitude has average sale-period rebates of almost NOK0.40 and the quartile with the smallest amplitude has rebates of only about NOK0.14 (Panels (a) and (b) in Figure A.15). Sale-period shares for all the quartiles start at about the same level, but the share only increases 2—-3 pp from 2004 to 2009q1 for the quartile with the smallest amplitude compared with 12 pp for the quartile with the greatest amplitude (Panels (c) and (d) in Figure A.15). In 2014, the sale-period shares in the smallest amplitude quartile have increased 6 pp from 2004 while the greatest amplitude quartile has increased 23 pp (more than a 100% increase since 2004). The sale-period volume shares increase gradually for all quartiles, but the larger amplitude is associated with a faster increase in the sale-period volume share and the total increase is much greater.

6 Discussion

Having established that consumers respond to regular price cycles and that there are significant dynamics in their responses, it is pertinent to ask how much consumers save with this behavior and how it impacts firms' price–cost margins. I now compare the average price consumers actually pay, i.e., the weekly volume-weighted price ("vwp") to two different benchmarks.[30] The first benchmark only weights each price according to

[30] I use the same panel as in Sections 3.1 and 5.2 with 21 intra-week periods for the analysis in this section. The vwp of station i in week w is given by $\sum_{n=1}^{21} P_{iwn} \times S_{iwn}$, where P_{iwn} is the unweighted average price for station i in week w and intra-week period n, and S_{iwn} is the share of station i's total weekly volume in week w that is sold in period n.

the number of hours it was active each week. This price measure would in expectation be equal to the vwp if consumers purchase at a random time of the week, and is equivalent to the unweighted average price that is often used when estimating welfare effects (typically the change in unweighted price–cost margins) in retail fuel studies. Comparing the development in margins based on vws with margins based on unweighted prices can highlight potential bias in the commonly used unweighted margins.

The second benchmark weights prices according to the underlying intra-week demand pattern.[31] Comparing the vwp to this benchmark illustrates how much consumers save by purchasing when prices are low compared with purchasing according to the underlying demand pattern without adjusting to the intra-week price variation.

Figure 7 plots the difference between the vwp and the benchmarks. The gasoline (diesel) vwp is on average NOK0.062 (0.047) lower than the unweighted prices, meaning that price–cost margins based on unweighted prices overestimate the profit that firms truly earn on each liter sold. The differences between the unweighted and volume-weighted prices are significant compared with the average unweighted price-cost margin of NOK1.22/liter sold.[32] If the difference is constant over time, this may not be a problem for studies using unweighted prices to estimate *changes* in firms' price–cost margins. The novel problem identified in Figure 7 is that the differences between the volume-weighted prices and the unweighted prices is not stable over time, increasing from NOK0.048 to 0.074 (0.006 to 0.052)/liter from 2004q4 to 2009q1. As the sale-period rebates are about the same, the increasing difference between the margin measures in this period is caused by consumers purchasing more fuel in the sale period over time.

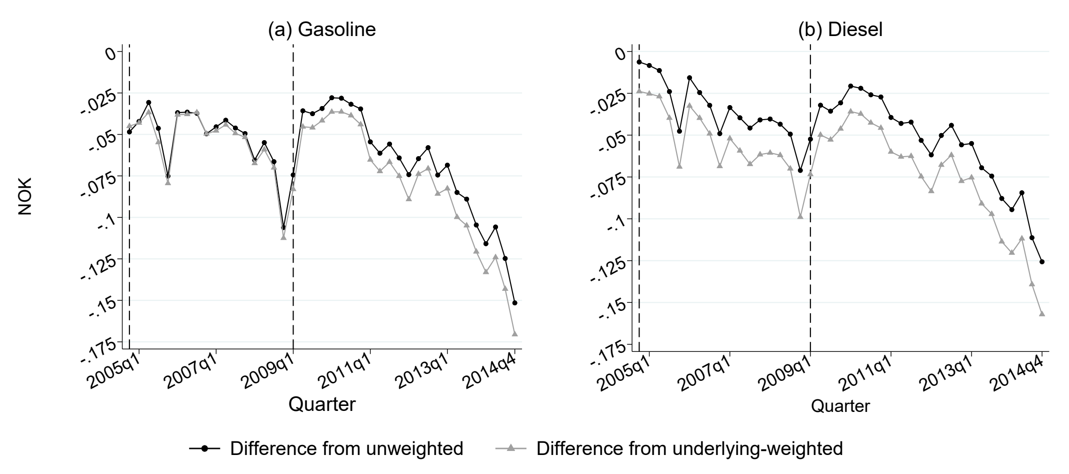
The difference between the volume-weighted and unweighted prices decreases in 2009q2–2010q4 when the sale-period rebates fall, but increase significantly again (about a NOK0.11 increase from 2010q4 to 2014q4) in the last 4 years of the sample period when the sale-period rebates rise substantially. In periods with increasing intertemporal price differences, consumers purchase more fuel when prices are low, and the difference between the unweighted and volume-weighted prices increase.

Consider a situation where the average unweighted gasoline and diesel margins are constant at NOK1.22/liter through the entire sample period, and the difference between the

[31]The underlying demand-weighted price of station i in week w is given by $\sum_{n=1}^{21} P_{iwn} \times S_n$, where P_{iwn} is the unweighted average price for station i in week w and intra-week period n, and S_n is the average share of total weekly volume sold in intra-week period n across all non-cycling stations and all weeks in the first 4 months of 2004.

[32]The average unweighted margin is calculated across all cycling stations and the entire period with regular price cycles. The unweighted margins per liter gasoline for station i in week w is defined as $Y_{iw} = P_{iw} - WS_w - TAX_w - C_{iw}$, where Y_{iw} is the average unweighted margin/liter for station i in week w, P_{iw} is the average unweighted price, WS_w is the reference wholesale from a price-reporting agency, TAX_w is VAT and other taxes, and C_{iw} is the cost of transporting gasoline to station i. See Tveito (2021a) for details about the different components of the price–cost margins. I do not have a good proxy for diesel wholesale costs and assume average diesel margins are equal to average gasoline margins.

Figure 7: Volume-weighted prices versus benchmark prices



Note: The figure depicts the development in the difference between the vwp and the unweighted prices and the difference between the vwp and the underlying demand-weighted prices across cycling stations. Only the period after the transition to regular price cycles is included.

unweighted and volume-weighted prices follow the same development as in Figure 7. As consumers adjust better to the intra-week price variation over time, the volume-weighted gasoline (diesel) margins would decrease 2.3% (3.9)% from 2004q4 to 2009q1 without changes in the intra-week price pattern and the unweighted margins. The consumer response to the increasing sale-period rebates in the last years of the sample exacerbate the difference and the volume-weighted margins would be 9.7% (11.0%) lower in 2014q4 than in 2004q4. Thus, price–cost margins based on unweighted prices may give biased estimates of changes in the profits firms really earn if consumers become more responsive to intertemporal price variation over time, or if the intertemporal price pattern changes over time.

Recall from Figure 2 that in both 2004q4 and 2009q1 the per liter gasoline and diesel rebates—or in other words, the *potential* savings per liter—for consumers purchasing in the sale-period are about NOK0.35/liter.[33] The gray lines in Figure 7 show how much consumers *actually* save relative to purchasing according to the underlying intra-week demand pattern. In 2004q4—just after the introduction of the regular cycles—gasoline (diesel) consumers save on average NOK0.045 (0.025)/liter relative to purchasing

[33] I use average prices across the entire sale period relative to the weekly average prices as a measure of potential consumer savings. Using prices at the very bottom of the cycle yields slightly (about NOK0.05) higher potential savings. Figure 2 shows the potential savings relative to purchasing at the unweighted weekly average price. The potential savings relative to purchasing according to the underlying demand pattern are marginally (<NOK0.03) larger.

according to the underlying demand pattern. These savings gradually grow over the next 4.5 years, and in 2009q1 consumers save NOK0.080 (0.075)/liter. Even with the same sale-period rebates, the actual savings increase from 13% to 24% (7% to 22%) of the potential savings from 2004q4 to 2009q1. In 2014q4, the potential savings have increased to NOK0.48 (0.48)/liter while the actual savings have increased to 0.17 (0.16); the actual savings are 35% (33%) of the potential savings.

With about 4 billion liters of retail fuel sold each year in Norway in the sample period, total consumer savings from the intertemporal demand substitution would increase from NOK133 million (US$22 million) in 2004q4 to NOK295 million (US$48 million) in 2009q1 and NOK627 million (US$103 million) in 2014q4.[34] The change in the total consumer savings over time is substantial.

7 Concluding remarks

In this study, I use high-frequency retail fuel price and volume data over an 11-year period to examine dynamics in consumers' response to price cycles with a sale occurring at the same time every week. Consumers can make modest savings by purchasing in the sale period. The main results are that fuel consumers' initial response is quite weak, but that they gradually adapt better by filling up their vehicles with fuel more in the sale period. The same development with a gradually stronger response over several years occurs both after a transition from fixed prices to price cycles with price restorations the same day every week, and after a transition from price cycles with restorations on irregular weekdays to price cycles with restorations on the same weekday. After both transitions, the sale-period volume shares of both gasoline and diesel immediately increase 1–2 pp. Five years after the transitions, the sale-period volume shares are 6–9 pp higher than before the transition. The intertemporal elasticity of demand triples over the first 5 years after the transition from irregular to regular price cycles.

These results suggest that studies investigating markets with intertemporal price variation should account for dynamics in the consumer response to intertemporal price patterns. I also show that unweighted prices can be a poor proxy for the price consumers pay, and that using price–cost margins based on unweighted prices may provide biased estimates of changes in the profits firms earn if consumers become more responsive to intertemporal price variation over time, or if the intertemporal price pattern changes over time.

When consumers increasingly purchase in the recurring sale period of regular price cycles, retailers may have an incentive to initiate changes in the cycles to frustrate their

[34] Statistics Norway Table 11185 has data on total gasoline and diesel sales for the period 2009–2014. I assume the diesel and gasoline volume are the same as in 2009 in the entire sample period, and that 95% of retail fuel is sold at gas stations setting cycling prices.

attempts to purchase when prices are low. Norway, Perth in Australia, and Germany have all had regular fuel price cycles over many years and have recently seen changes in these cycles. In Norway, the largest retail chain initiated a transition to irregular restoration days in 2017 (Foros & Ones, 2021); in Perth, the restoration day changed from Tuesday to Wednesday in 2020 (ACCC, 2020); and in Germany, new price restorations around noon and in the afternoon were introduced in 2015 and 2017 (Eibelshäuser & Wilhelm, 2018). Future research could investigate if a stronger consumer response to price cycles was contributing to these transitions.

Price cycles as well as other types of retail sales invoke intertemporal price variation. Other retail sales may be more salient for consumers because they are often advertised and often entail a large discount on an otherwise stable price. Even so, consumers may become better informed about sales activity over time and may also be slow to change their habits. Thus, dynamics may also be present in the response of consumers to various other types of sales. Future research should then investigate the possible dynamics and implications for firms determining the type and frequency of sales.

References

ACCC. (2020). *Report on the Australian Petroleum Market - June Quarter 2020.* Retrieved 2021-05-12, from https://www.accc.gov.au/system/files/20-27RPT_Petrol%2520Quarterly%2520Report%2520-%2520June%25202020_FA.pdf

Assad, S., Clark, R., Ershov, D., & Xu, L. (2020). Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market. *Working Paper*.

Baker, A., Larcker, D., & Wang, C. (2021). How Much Should We Trust Staggered Difference-In-Differences Estimates? *Working Paper*.

Byrne, D. P., & de Roos, N. (2019). Learning to Coordinate - A Study in Retail Gasoline. *American Economic Review*, *109*(2), 591-619.

Byrne, D. P., Leslie, G. W., & Ware, L. R. (2015). How do Consumers Respond to Gasoline Price Cycles? *Energy Journal*, *36*(1), 115-147.

Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs. *Quarterly Journal of Economics*, *134*(3), 1405-1454.

de Roos, N., & Smirnov, V. (2020). Collusion with Intertemporal Price Dispersion. *RAND Journal of Economics*, *51*(1), 158-188.

Deryugina, T., MacKay, A., & Reif, J. (2020). The Long-Run Dynamics of Electricity Demand: Evidence from Municipal Aggregation. *American Economic Journal: Applied Economics*, *12*(1), 86-114.

Drivkraft Norge. (2021). *Salg av Bransjens Hovedprodukter tilbake til 1952 (Sale of the Industries Main Products back to 1952.* Retrieved 2021-08-25, from https://www.drivkraftnorge.no/siteassets/dokumenter--filer/statistikk/salg/salg-tilbake-til-1952-til-hjemmesiden.xlsx

Eckert, A. (2013). Empirical Studies of Gasoline Retailing: A Guide to the Literature. *Journal of Economic Surveys*, *27*(1), 140-166.

Eibelshäuser, S., & Wilhelm, S. (2018). High-Frequency Price Fluctuations in Brick-and-Mortar Retailing. *Working paper*.

European Commission. (2016). A European Strategy for Low-Emission Mobility.

Fabra, N., Rapson, D., Reguant, M., & Wang, J. (2021). Estimating the Elasticity to Real Time Pricing: Evidence from the Spanish Electricity Market. *AEA – Papers and Proceedings*(111), 425-429.

Finanskriseutvalget. (2011). NOU 2011:1 Bedre Rustet mot Finanskriser (Better Prepared Against Financial Crises).

Foros, Ø., & Ones, M. N. (2021). Coordinate to Obfuscate? The Role of Prior Announcements of Recommended Prices. *Economics Letters*, *198*.

Foros, Ø., & Steen, F. (2013). Vertical Control and Price Cycles in Gasoline Retailing. *Scandinavian Journal of Economics*, *115*(3), 640-661.

Foros, Ø., Steen, F., & Nguyen-Ones, M. (2021). The Effects of a Day off from Retail Price Competition: Evidence on Consumer Behavior and Firm Performance in Gasoline Retailing. *International Journal of the Economics of Business*, *28*(1), 49-87.

Hastings, J. S., & Shapiro, J. M. (2013). Fungibility and Consumer Choice: Evidence from Commodity Price Shocks. *Quarterly Journal of Economics*, *128*(4), 1449-1498.

Hendel, I., & Nevo, A. (2006). Sales and Consumer Inventorties. *RAND Journal of Economics*, *37*(3), 543-561.

Hortaçsu, A., Madanizadeh, S. A., & Puller, S. L. (2017). Power to Choose? An Analysis of Consumer Inertia in the Residential Electricity Market. *American Economic Journal: Economic Policy*, *9*(4), 192-226.

Hvitved-Jacobsen, K. (2002). *Tank på tirsdager.* Retrieved 2021-02-15, from https://dinside.dagbladet.no/okonomi/tank-pa-tirsdager/62540851

Jessoe, K., & Rapson, D. (2014). Knowledge Is (Less) Power: Experimental Evidence from Residential Energy Use. *American Economic Review*, *104*(4), 1417-1438.

Konkurransetilsynet. (2014). Drivstoff Markedet i Norge - Marginøkning og Ny Pristopp (The Norwegian Fuel Market – Margin increase and a New Price Peak).

Levin, L., Lewis, M. S., & Wolak, F. A. (2017). High Frequency Evidence on the Demand for Gasoline. *American Economic Journal: Economic Policy*, *9*(3), 314–347.

Maskin, E., & Tirole, J. (1988). A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles. *Econometrica*, *56*(3), 571-599.

Noel, M. D. (2012). Edgeworth Price Cycles and Intertemporal Price Discrimination. *Energy Economics*, *34*(4), 942–954.

Noel, M. D. (2015). Do Edgeworth Price Cycles Lead to Higher or Lower Prices? . *International Journal of Industrial Organization*, *42*(1), 81-93.

Noel, M. D. (2019). Calendar Synchronization of Gasoline Price Increases. *Journal of Economics and Managment Science*, *28*(2), 355-370.

Pilskog, G. M. (2018). Frå Global Klimavinnar til Lokal Forureinar (From Global Climate Winner to Local Polluter).

Statistics Norway. (2021a). *07849: Registered vehicles, by type of transport and type of fuel (M) 2008 - 2020.* Retrieved 2021-09-8, from https://www.ssb.no/en/statbank/table/07849

Statistics Norway. (2021b). *12575: Kjørelengder, etter Kjøretøytype og Alder 2005 - 2019 (Drive Distances, by Type of Vehicle and Age 2005 - 2019.* Retrieved 2021-03-9, from https://www.ssb.no/statbank/table/12575/

Tveito, A. (2021a). The Costs and Benefits of Price Leadership – Evidence from Retail Gasoline. *Working Paper*.

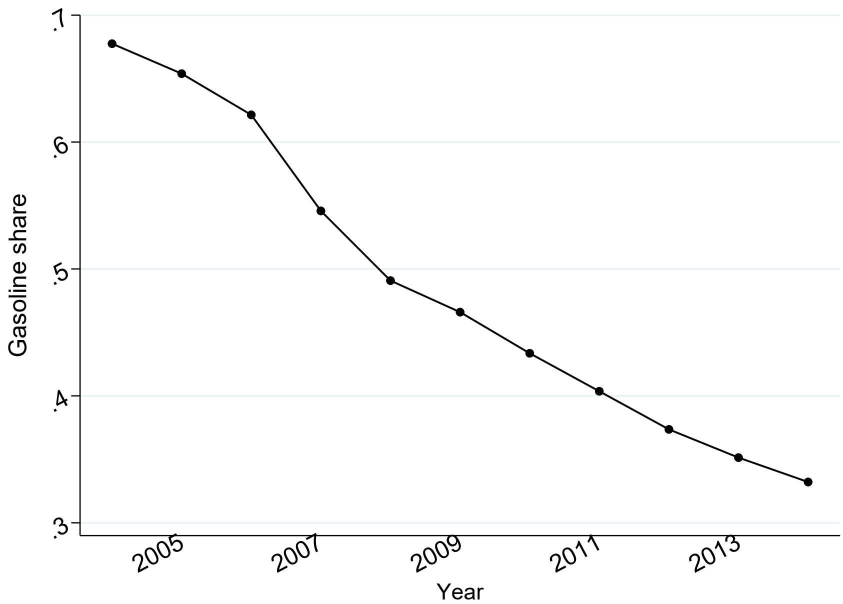
Tveito, A. (2021b). Might as Well Jump! Coordinating More Frequent Price Hikes in a Retail Gasoline Market. *Working Paper*.

Wang, Z. (2009). (Mixed) Strategy in Oligopoly Pricing: Evidence from Gasoline Price Cycles Before and Under a Timing Regulation. *Journal of Political Economy*, *117*(61), 987-1030.

Appendices

A Additional figures

Figure A.1: Gasoline share of total retail fuel volume



Note: The figure shows the average gasoline share of total retail fuel volume each year in the sample period. Station-days when either gasoline or diesel volume are missing are dropped before the averages are calculated.

Figure A.2: Number of cycling and non-cycling stations

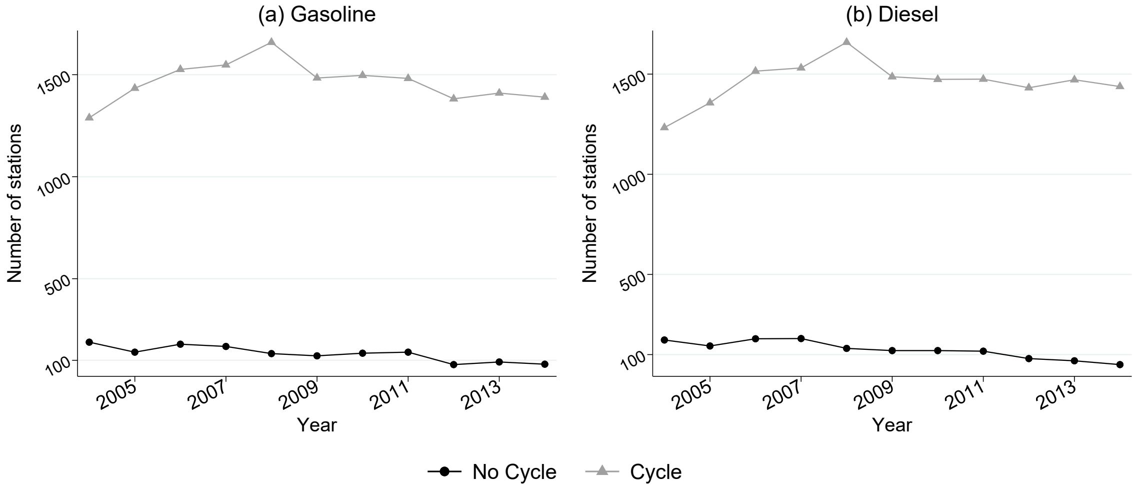
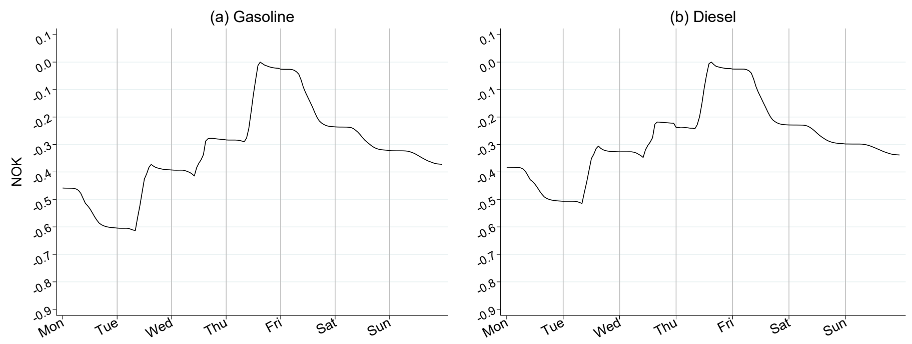
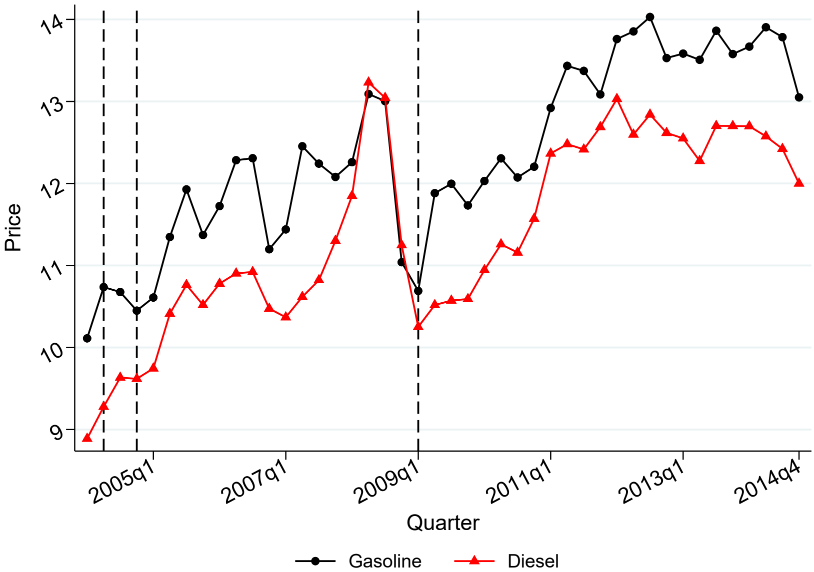


Figure A.3: Average prices through the week with irregular cycle



Note: The figure shows average gasoline and diesel prices in each hour of the week relative to the hour with the highest average price in the period when price hikes occur on irregular weekdays.

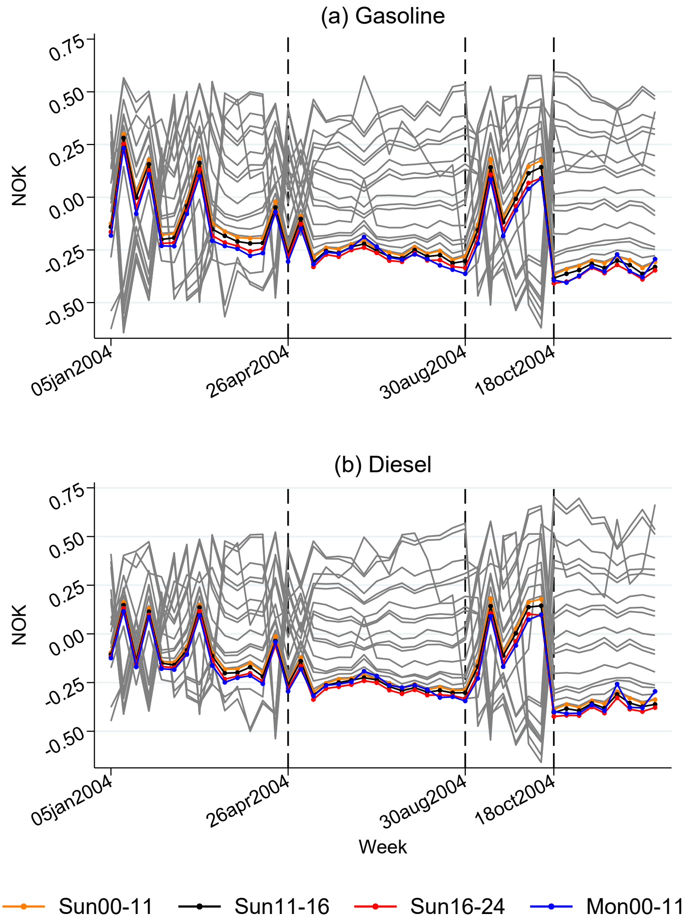
Figure A.4: Average prices



Note: The figure depicts the quarterly average price of gasoline and diesel across all cycling stations. The first and second vertical lines mark the two periods in 2004 with Monday restorations, 2004q2 and 2004q4. The third vertical line marks 2009q1. Prices include taxes. Take note of the following:

1. Gasoline and diesel prices both generally increase over the sample period.
2. After large price decreases, both the gasoline and diesel prices are at about the same level in the start of 2009 as they where in 2005.

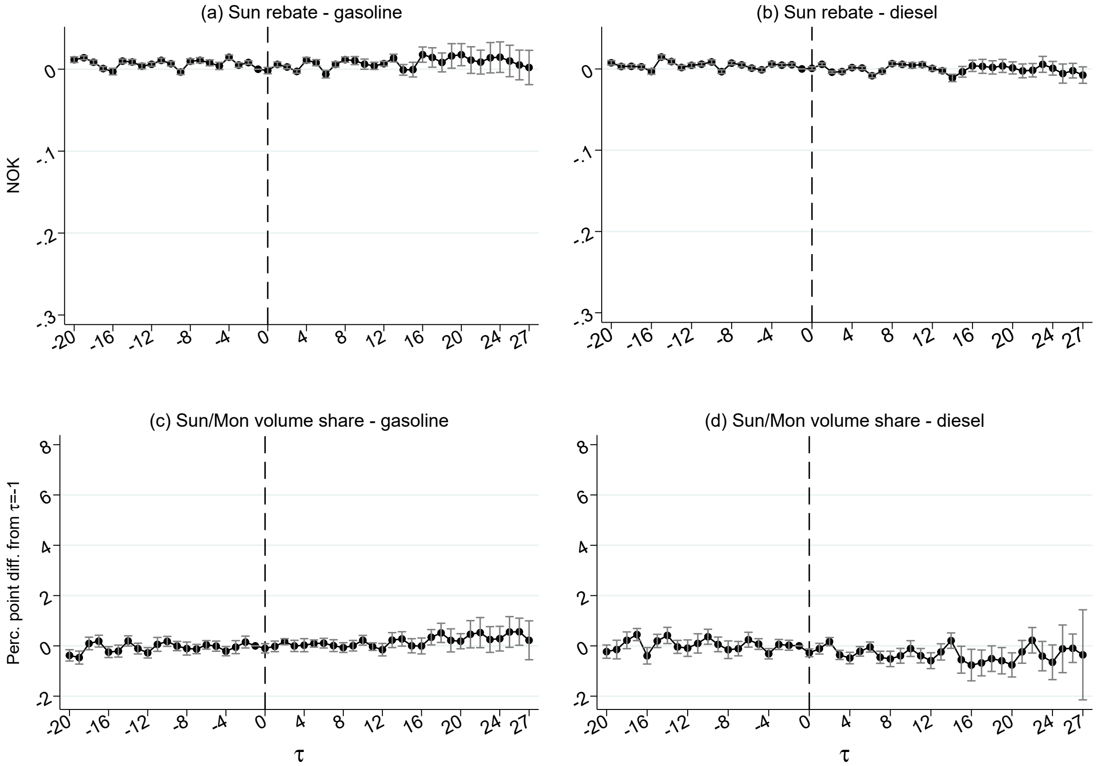
Figure A.5: Sale-period prices vs other prices, 2004



Note: The figure shows the week to week development in average prices in different parts of the week relative to the weekly average for the year 2004. The averages are calculated across all cycling stations. Each line represents the relative price in 1 of the 21 intra-week periods as defined in Section 5.2. The colored lines represent prices in different parts of Sunday and Monday morning and the gray lines other parts of the week. The first vertical line marks the change from irregular restoration days to Monday restorations. The second and third dashed lines mark the start and end of the 6-week reversion to irregular restoration days. Take note of the following:

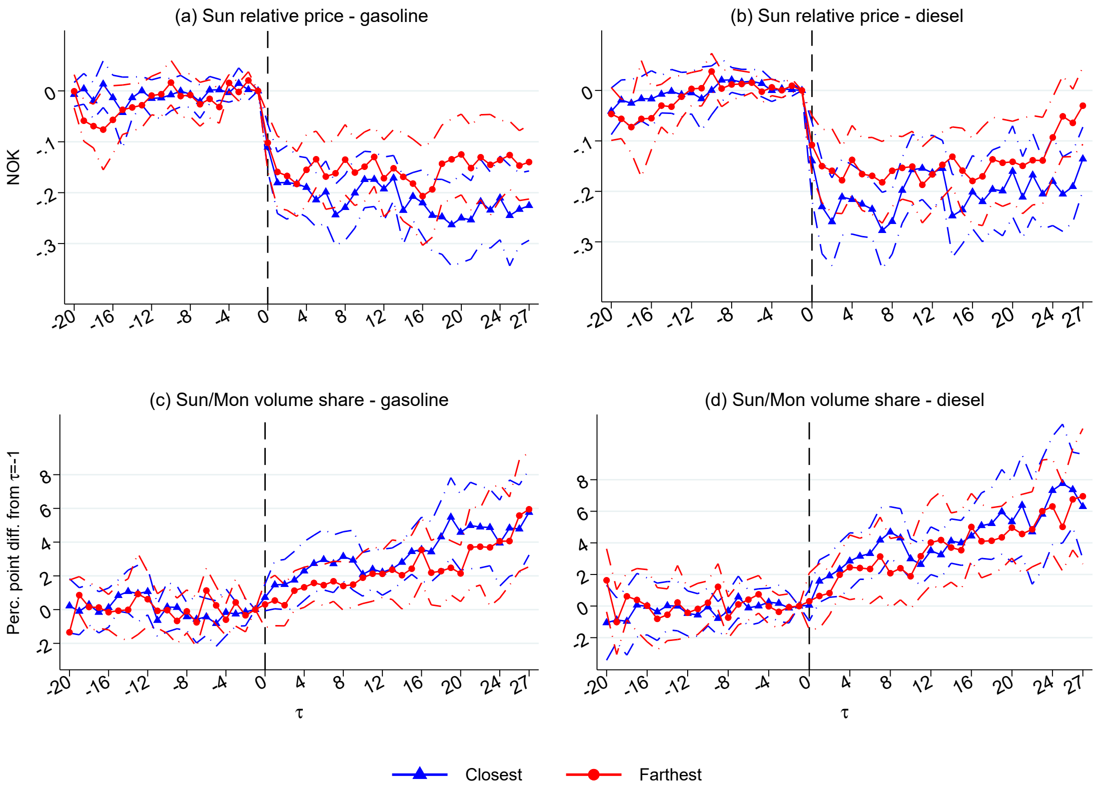
1. Prices are never lowest on Sundays/Monday mornings in weeks with irregular restoration days.
2. Prices are always lowest on Sundays/Monday mornings in weeks when restorations occur on Monday.

Figure A.6: Control stations



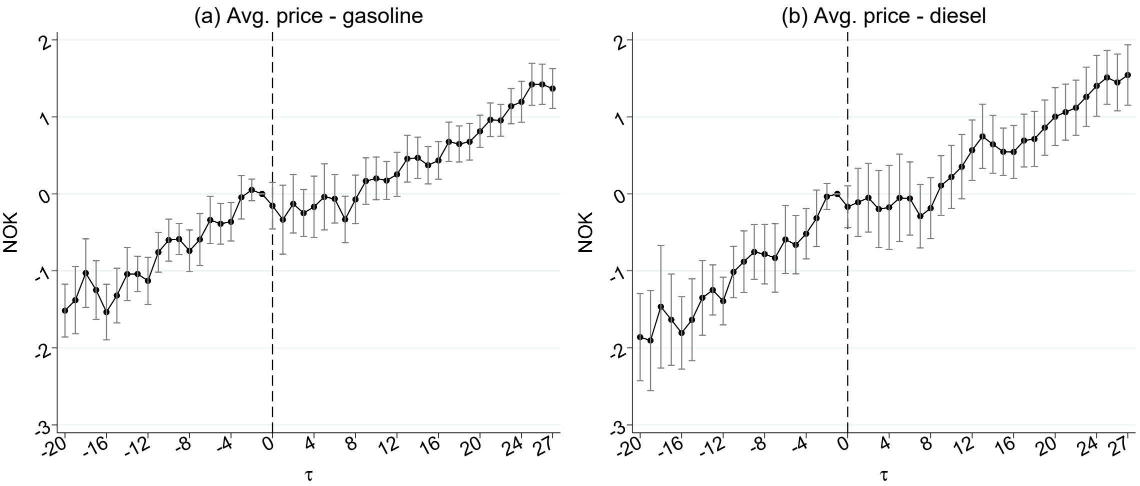
Note: The figure shows results from the regression $Y_{iwg} = \sum_{\tau=-20}^{27} \gamma_\tau + \theta_i + \varepsilon_{iwg}$ on a sample including only control stations, where Y_{iwg} is the outcome of interest for control station i in week w and event g. θ_i represent station fixed-effects.
$\sum_{\tau=-20}^{27} \gamma_\tau$ represent indicator variables for the last 20 quarters before and first 27 quarters after each event. $\tau = 0$ is the first quarter with treatment and $\tau = -1$ is the reference week. ε_{iwg} is an error term. Standard errors are clustered at the municipality level.
Panel (a) plots γ_τ from -20 to 27 with the difference between the Sunday average price and the weekly average price as dependant variable. Panel (b) plots the same for diesel. Panel (c) plots γ_τ from -20 to 27 with the share of total weekly gasoline volume sold on Sunday and Monday as dependant variable. Panel (d) plots the same for diesel. 95% confidence intervals are also included.

Figure A.7: Above/below median distance to nearest station



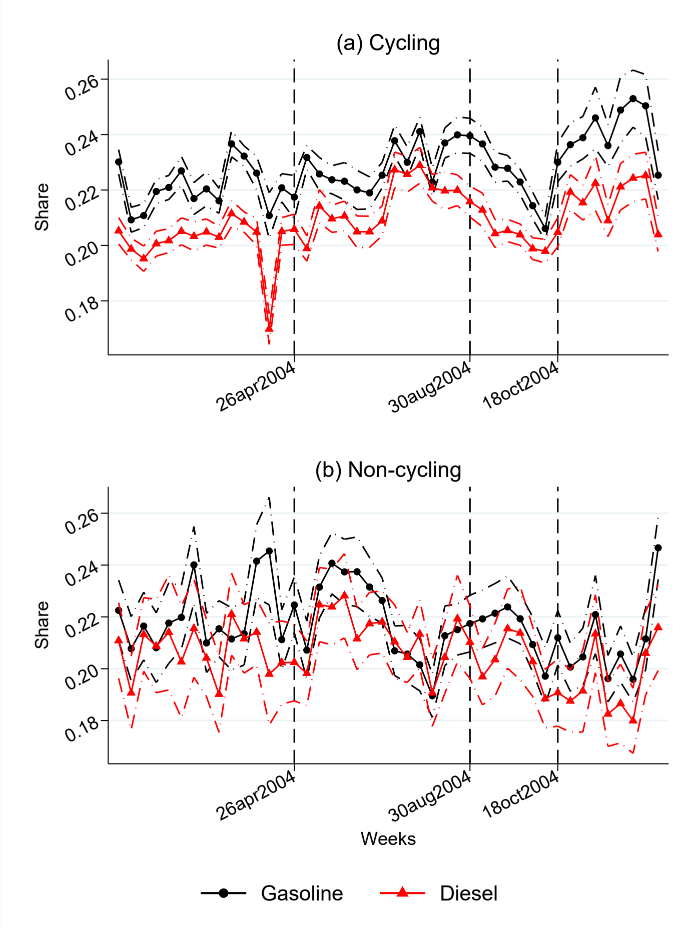
Note: The blue lines show results from Eq. 1 on a sample of stations with below the median distance to the nearest station (average distance to nearest station=3km), and the red lines the same for stations above the median distance to the nearest station (average distance to nearest station=25km). Panel (a) plots γ_τ from -20 to 27 with the difference between the Sunday average price and the weekly average price as dependant variable. Panel (b) plots the same for diesel. Panel (c) plots γ_τ from -20 to 27 with the share of total weekly gasoline volume that sold on Sunday and Monday as dependant variable. Panel (d) plots the same for diesel. 95% confidence intervals are also included.

Figure A.8: Average prices around events



Note: The figure shows results from the regression $Y_{iw} = \sum_{\tau=-20}^{27} \gamma_\tau + \theta_i + \varepsilon_{iw}$ on a sample including only treated stations, where Y_{iw} is the average weekly price of the fuel type of interest for station i in week w. θ_i represent station fixed-effects. $\sum_{\tau=-20}^{27} \gamma_\tau$ represent indicator variables for the last 20 quarters before and first 27 quarters after each event. $\tau = 0$ is the first quarter with treatment and $\tau = -1$ is the reference week. ε_{iw} an error term. Standard errors are clustered at the municipality level. Panel (a) plots γ_τ from -20 to 27 for the gasoline sample and panel (b) the same for diesel. 95% confidence intervals are also included.

Figure A.9: Sale-period volume share, 2004

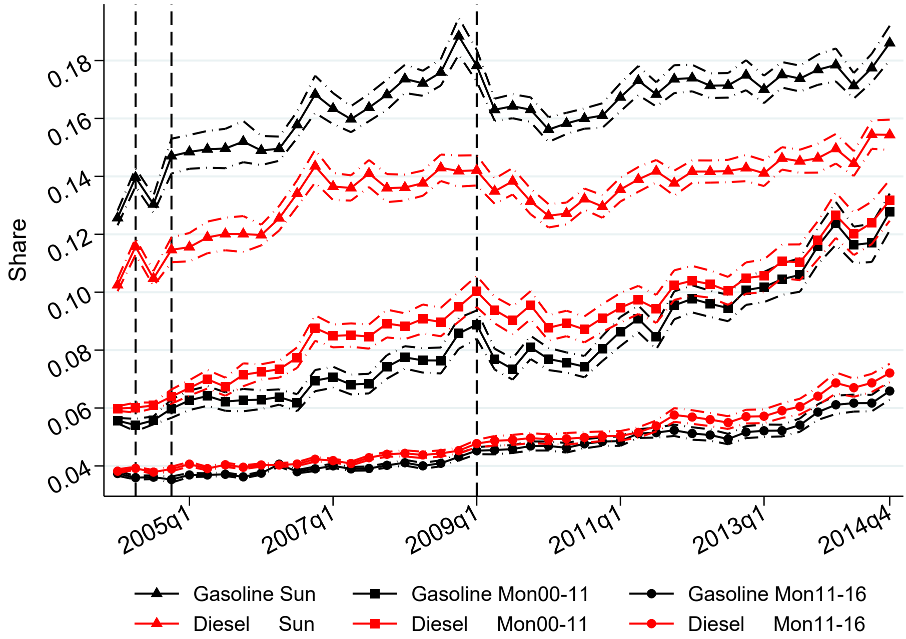


Note: The figure shows cycling stations' week-to-week development in the share of gasoline and diesel volume sold in the sale-period. The first vertical line marks the first week with Mon restorations, and the second and third vertical lines mark the last week before and first week after the 6-week reversion period. Take note of the following:

1. Non-cycling stations' diesel and gasoline sale-period volume shares are stationary through 2004.
2. Cycling stations' gasoline (diesel) sale-period volume share increases slightly from an average of 22% (20%) in the period before the transition to Monday restorations to 23% (22%) in the first 4 months after the transition.
3. In the 6-week reversion period, the sale shares fall to about the same level as before the transition to Monday restorations. After the reversion period, the sale share increases again to 24% (22%).
4. There are some indications that the sale share is increasing over time in the periods with Monday restorations. The gasoline sale share is close to 22% (21%) in the first weeks with Monday restorations and 24-25% (22-23%) in the end of 2004.

*Point estimates are based on the coefficients from a model similar to Eq. 2, but with θ representing weeks. Each point is the sum of β_n, θ_τ and $\gamma_{\tau n}$. 95% confidence intervals based on standard errors calculated with the delta method are shown.

Figure A.10: Sale-period split, cycling stations

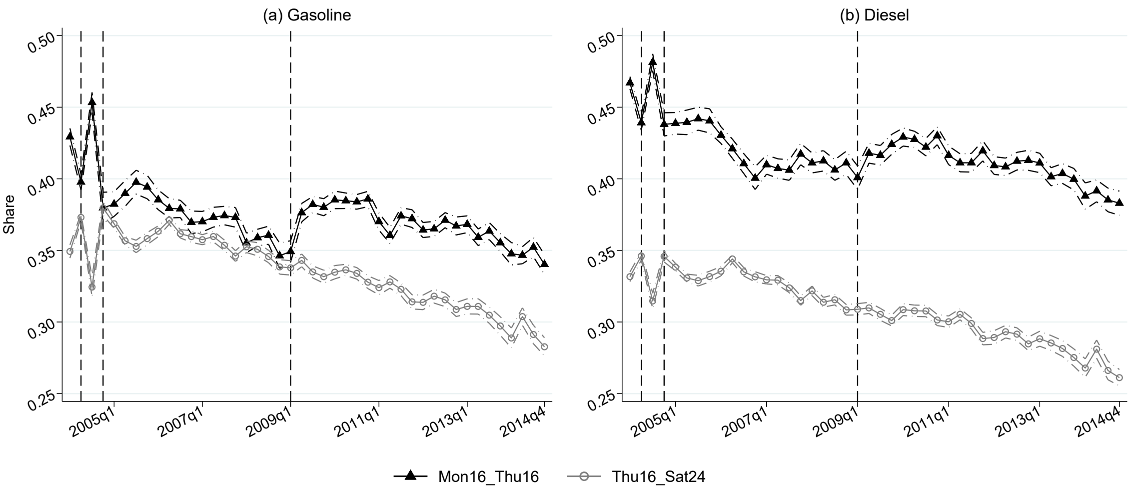


Note: Note: The figure shows cycling stations' quarterly development in the share of gasoline and diesel volume sold in different parts of the sale period. The first and second vertical lines mark the 2 periods in 2004 with Monday restorations, 2004q2 and 2004q4. The third vertical line marks 2009q1. Take note of the following:

1. The gasoline (diesel) Sunday volume shares increase from 15% (11%) in 2004q4 to 18% (14%) in 2009q1 . They then fall to 16% (13%) from 2009q2-2010q4, and then increase to around 18% (14-15%) in 2011 and mostly stay at this level.
2. The gasoline (diesel) Monday morning volume shares increase from 6% (6%) in 2004q4 to 9% (10%) in 2009q1. They then fall to 8% (9%) from 2009q2-2010q4 and gradually increase to about 13% in 2014.
3. The Monday midday volume shares increase from 3.5% (3.9%) in 2004q4 to 4.5% (4.8%) in 2009q1. They continue to gradually increase to 6.6% (7.4) in 2014.

*Point estimates are based on the coefficients from a model similar to Eq. 2, but with the sale period split in Sunday, Monday until 11:00, and Monday 11:00-16:00. Each point is the sum of β_n, θ_τ and $\gamma_{\tau n}$. The 95% confidence intervals based on standard errors calculated with the delta method.

Figure A.11: Volume shares in non-sale periods

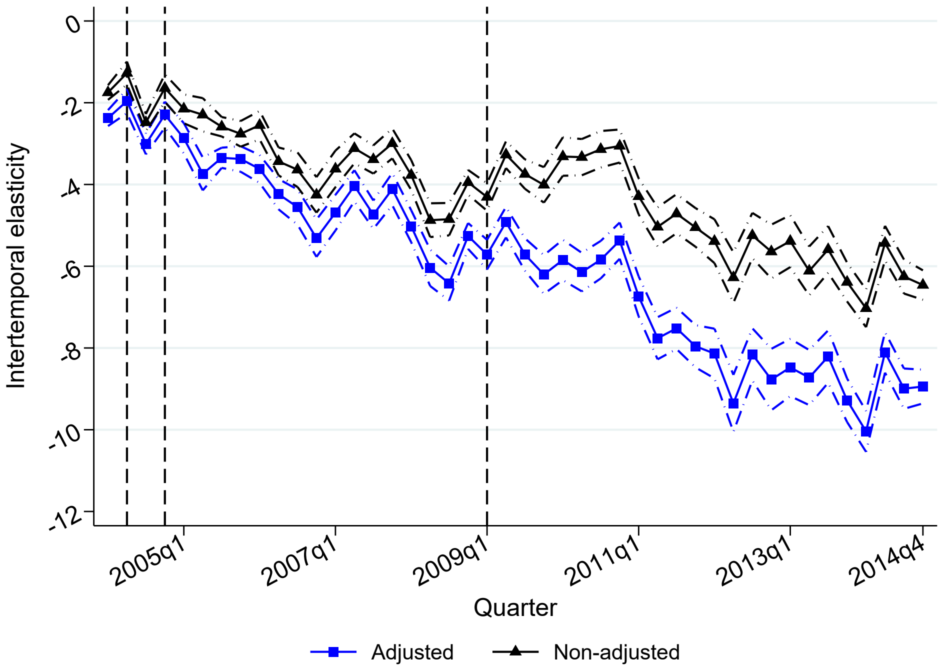


Note: The figure shows cycling stations' quarterly development in the share of gasoline and diesel volume sold in respectively Monday 16:00–Thursday 16:00 and Thursday 16:00–Saturday 24:00. The first and second vertical lines mark the two periods in 2004 with Monday restorations, 2004q2 and 2004q4. The third vertical line marks 2009q1. Take note of the following:

1. The Monday 16:00–Thursday 16:00 volume shares decrease steadily after 2004q4.
2. The Thursday 16:00–Saturday 24:00 shares mostly decrease until a sudden increase in 2009q2. They start to decrease again in 2011 and continue to fall through the rest of the sample period.

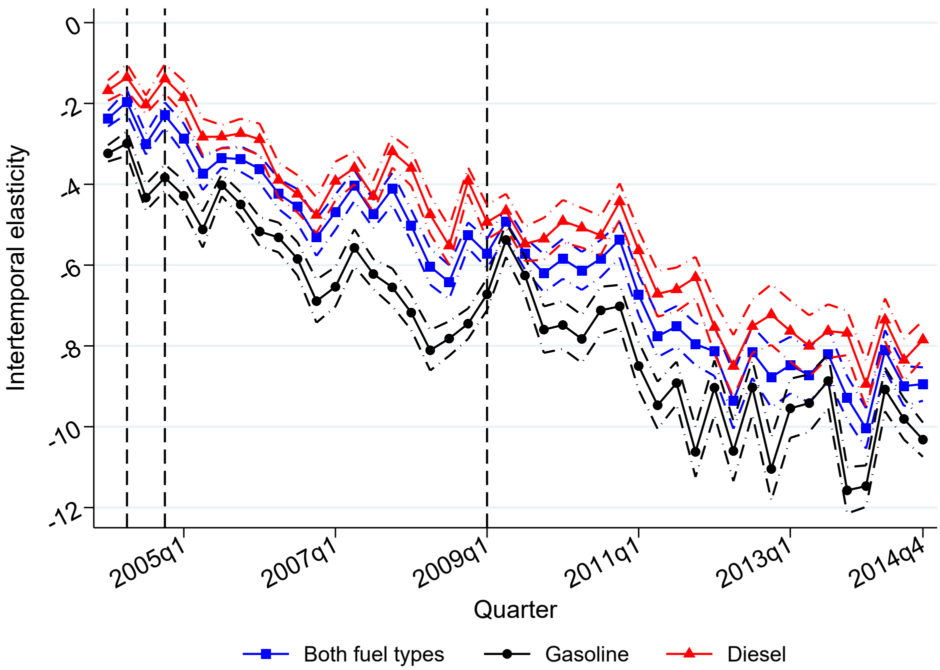
*Point estimates are based on the coefficient Eq. 2. Each point is the sum of β_n, θ_τ and $\gamma_{\tau n}$. 95% confidence intervals based on standard errors calculated with the delta method are shown.

Figure A.12: Non-adjusted and adjusted intertemporal elasticity



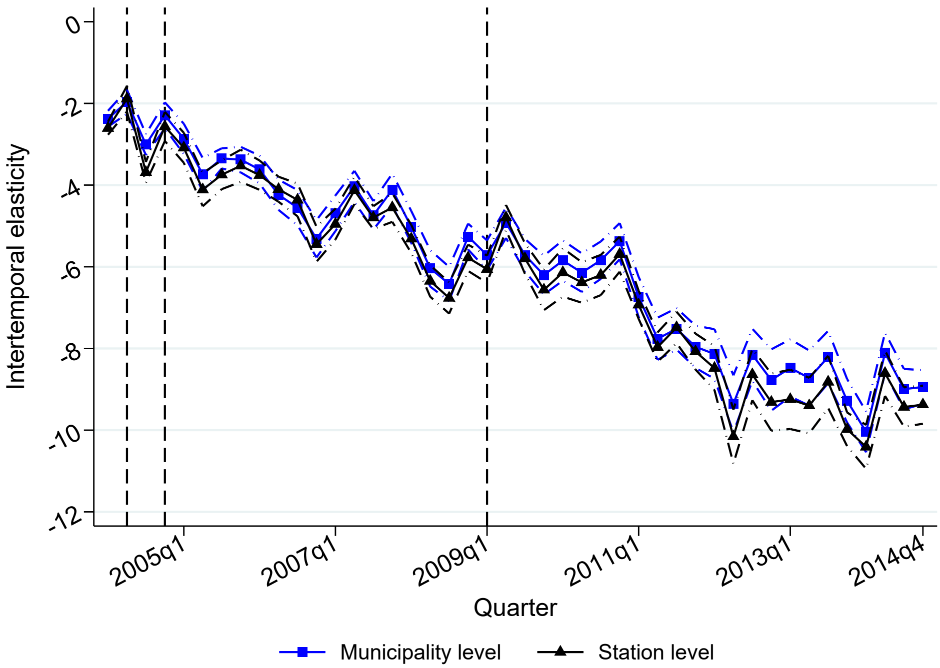
Note: The figure depicts the development in the adjusted and unadjusted intertemporal elasticities for cycling stations in the overall retail fuel market. The first and second vertical lines mark the two periods in 2004 with Monday restorations, 2004q2 and 2004q4. The third vertical line marks 2009q1. *The lines plots the β_τ from Eq. 3 with respectively unadjusted and adjusted volumes as dependant variable. 95 % confidence intervals are also shown.

Figure A.13: Intertemporal elasticity, gasoline, diesel and overall



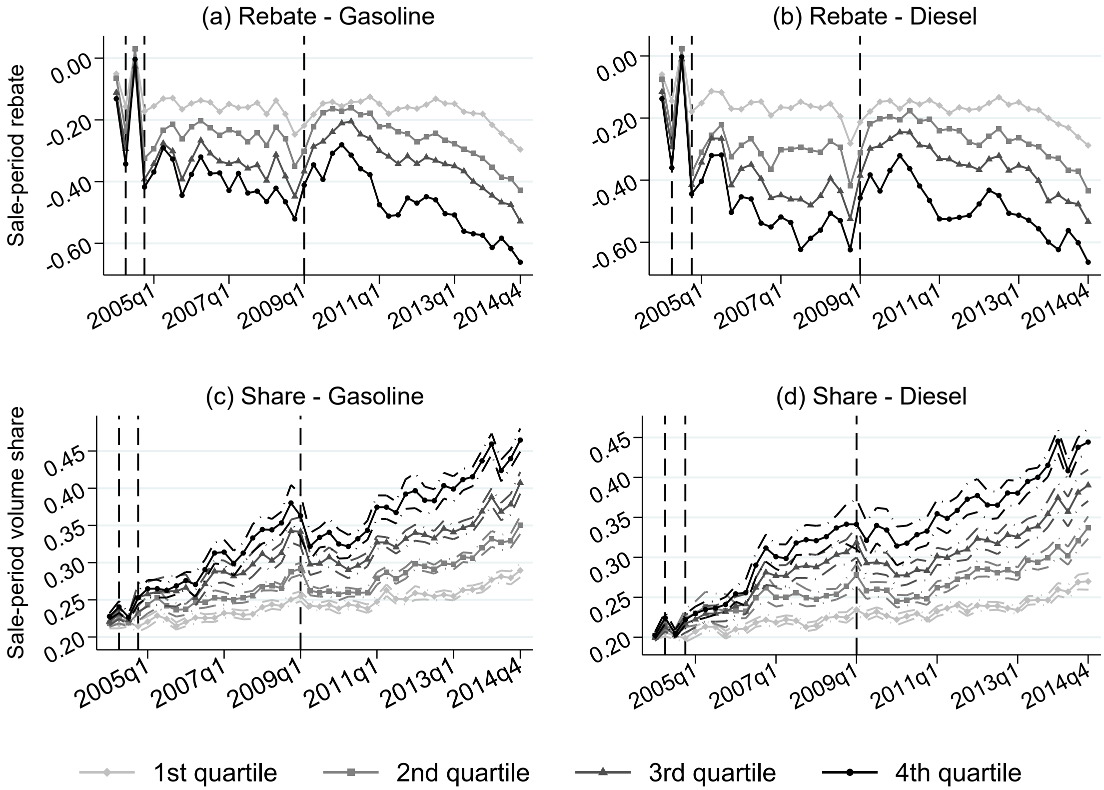
Note: The figure depicts the development in the adjusted intertemporal elasticities for cycling stations in the overall retail fuel market, for gasoline retailing and diesel retailing. The first and second vertical lines mark the two periods in 2004 with Monday restorations, 2004q2 and 2004q4. The third vertical line marks 2009q1.
*The line plots the β_τ from Eq. 3 on a sample consisting of respectively both gasoline and diesel, only gasoline, and only diesel. 95 % confidence intervals are also shown.

Figure A.14: Intertemporal elasticity, municipality and station level



Note: The figure depicts the development in the adjusted intertemporal elasticities for cycling stations estimated on respectively a dataset aggregated to the municipality level and a station-level dataset. The first and second vertical lines mark the two periods in 2004 with Monday restorations, 2004q2 and 2004q4. The third vertical line marks 2009q1.
*The line plots the estimated β_τ from Eq. 3. When estimating is run on the station level dataset, the municipality fixed-effects are replaced with station fixed-effects and standard errors are clustered at the municipality level. 95 % confidence intervals are also shown.

Figure A.15: Sale-period rebates and volume, groups with different cycle amplitude



Note: The stations are split in four quartiles, where the first quartile is the 25% stations with the lowest average difference between the top of the cycle (prices on Monday between 16:00 and 24:00) and the bottom of the cycle (prices on Monday between 00:00 and 11:00) across all operative weeks between 2004q4 and 2014q4. The fourth quartile is the 25% of stations with highest average difference between top and bottom.
Panel (a) and (b) show the development in the sale-period rebates (average prices across Sundays and Monday before 11:00 relative to the weekly average price) for the different quartiles. Panel (c) and (d) show the development in the share of volume that is sold in the sale-period for the different quartiles. The first and second vertical lines mark the two periods in 2004 with Monday restorations, 2004q2 and 2004q4. The third vertical line marks 2009q1.
*Point estimates in panel (c) and (d) are based on the coefficients from Eq. 2 run on the four different quartile samples. Each point is the sum of β_n, θ_τ and $\gamma_{\tau n}$. Standard errors for the combined coefficients are calculated with the delta method.

Table A.1: Event study diff-in-diff

	(a)Gasoline rebates		(b)Diesel rebates		(c) Gasoline vol. share		(d) Diesel vol. share	
$treat \times \gamma_{-20}$	-0.01	(0.01)	-0.04	(0.02)	-0.28	(0.75)	0.17	(0.99)
$treat \times \gamma_{-19}$	-0.02	(0.02)	-0.04	(0.02)	0.28	(0.52)	-0.93	(0.65)
$treat \times \gamma_{-18}$	-0.03	(0.01)	-0.05	(0.02)	0.18	(0.50)	-0.26	(0.77)
$treat \times \gamma_{-17}$	-0.03	(0.02)	-0.04	(0.04)	-0.03	(0.48)	0.28	(0.75)
$treat \times \gamma_{-16}$	-0.03	(0.02)	-0.03	(0.02)	-0.03	(0.46)	-0.01	(0.72)
$treat \times \gamma_{-15}$	-0.04	(0.02)	-0.02	(0.01)	0.44	(0.49)	-0.56	(0.70)
$treat \times \gamma_{-14}$	-0.02	(0.02)	-0.01	(0.02)	0.59	(0.57)	-0.21	(0.60)
$treat \times \gamma_{-13}$	-0.01	(0.01)	-0.01	(0.02)	0.90	(0.73)	0.08	(0.67)
$treat \times \gamma_{-12}$	-0.01	(0.01)	-0.00	(0.01)	0.85	(0.56)	-0.45	(0.55)
$treat \times \gamma_{-11}$	-0.01	(0.01)	-0.01	(0.02)	-0.45	(0.38)	-0.37	(0.53)
$treat \times \gamma_{-10}$	0.00	(0.01)	0.02	(0.02)	0.03	(0.55)	0.08	(0.47)
$treat \times \gamma_{-9}$	-0.00	(0.01)	0.01	(0.01)	-0.20	(0.49)	0.25	(0.49)
$treat \times \gamma_{-8}$	-0.00	(0.01)	0.01	(0.01)	-0.37	(0.37)	-0.50	(0.51)
$treat \times \gamma_{-7}$	-0.02	(0.01)	0.01	(0.01)	-0.68	(0.53)	0.36	(0.50)
$treat \times \gamma_{-6}$	0.00	(0.01)	0.02	(0.01)	-0.03	(0.45)	0.15	(0.44)
$treat \times \gamma_{-5}$	-0.01	(0.01)	0.00	(0.01)	-0.53	(0.51)	0.40	(0.42)
$treat \times \gamma_{-4}$	0.00	(0.01)	0.00	(0.01)	-0.36	(0.49)	0.13	(0.34)
$treat \times \gamma_{-3}$	0.01	(0.01)	-0.00	(0.01)	-0.01	(0.37)	-0.09	(0.41)
$treat \times \gamma_{-2}$	0.01	(0.01)	0.00	(0.00)	-0.23	(0.34)	-0.07	(0.33)
$treat \times \gamma_{0}$	-0.11	(0.02)	-0.13	(0.03)	0.57	(0.37)	0.18	(0.50)
$treat \times \gamma_{1}$	-0.17	(0.02)	-0.19	(0.03)	1.07	(0.55)	1.12	(0.66)
$treat \times \gamma_{2}$	-0.18	(0.03)	-0.21	(0.03)	0.97	(0.53)	1.41	(0.52)
$treat \times \gamma_{3}$	-0.18	(0.02)	-0.20	(0.03)	1.50	(0.56)	2.18	(0.57)
$treat \times \gamma_{4}$	-0.18	(0.02)	-0.18	(0.03)	1.89	(0.62)	2.68	(0.70)
$treat \times \gamma_{5}$	-0.18	(0.02)	-0.20	(0.03)	2.23	(0.55)	2.81	(0.61)
$treat \times \gamma_{6}$	-0.19	(0.02)	-0.21	(0.02)	2.33	(0.62)	2.90	(0.71)
$treat \times \gamma_{7}$	-0.21	(0.02)	-0.23	(0.03)	2.30	(0.60)	3.71	(0.83)
$treat \times \gamma_{8}$	-0.19	(0.02)	-0.21	(0.03)	2.41	(0.56)	3.48	(0.76)
$treat \times \gamma_{9}$	-0.19	(0.02)	-0.18	(0.02)	2.27	(0.57)	3.33	(0.73)
$treat \times \gamma_{10}$	-0.17	(0.02)	-0.16	(0.03)	2.06	(0.54)	2.46	(0.65)
$treat \times \gamma_{11}$	-0.16	(0.02)	-0.18	(0.03)	2.33	(0.50)	2.95	(0.76)
$treat \times \gamma_{12}$	-0.19	(0.02)	-0.17	(0.03)	2.21	(0.53)	3.80	(0.80)
$treat \times \gamma_{13}$	-0.17	(0.02)	-0.15	(0.02)	2.46	(0.56)	3.80	(0.91)
$treat \times \gamma_{14}$	-0.21	(0.03)	-0.19	(0.03)	2.51	(0.57)	3.94	(0.69)
$treat \times \gamma_{15}$	-0.20	(0.02)	-0.20	(0.03)	3.02	(0.62)	3.79	(0.80)
$treat \times \gamma_{16}$	-0.22	(0.03)	-0.19	(0.03)	3.59	(0.74)	4.74	(0.79)
$treat \times \gamma_{17}$	-0.23	(0.03)	-0.20	(0.03)	2.90	(0.73)	4.59	(0.89)
$treat \times \gamma_{18}$	-0.21	(0.03)	-0.17	(0.03)	3.51	(0.83)	4.71	(0.85)
$treat \times \gamma_{19}$	-0.21	(0.03)	-0.17	(0.03)	4.24	(0.85)	5.19	(0.93)
$treat \times \gamma_{20}$	-0.20	(0.03)	-0.15	(0.03)	3.61	(0.80)	5.17	(0.89)
$treat \times \gamma_{21}$	-0.21	(0.03)	-0.18	(0.03)	4.44	(0.99)	5.50	(1.10)
$treat \times \gamma_{22}$	-0.19	(0.03)	-0.15	(0.03)	4.44	(0.94)	4.73	(1.14)
$treat \times \gamma_{23}$	-0.20	(0.03)	-0.17	(0.03)	4.40	(0.99)	5.89	(1.25)
$treat \times \gamma_{24}$	-0.19	(0.03)	-0.14	(0.03)	3.95	(1.03)	6.86	(1.25)
$treat \times \gamma_{25}$	-0.20	(0.04)	-0.13	(0.03)	4.49	(1.07)	6.46	(1.31)
$treat \times \gamma_{26}$	-0.20	(0.03)	-0.13	(0.03)	5.03	(1.04)	7.09	(1.06)
$treat \times \gamma_{27}$	-0.20	(0.03)	-0.08	(0.03)	5.81	(1.04)	6.65	(1.54)
Constant	-0.01	(0.00)	-0.01	(0.00)	26.53	(0.02)	25.24	(0.02)
$Event \times StationFE$	Yes		Yes		Yes		Yes	
$Event \times \tau FE$	Yes		Yes		Yes		Yes	
Observations	433234		478549		433234		478549	
R2	0.43		0.40		0.29		0.15	

Note: The table shows results from Eq. 1. Rows (a)-(d) correspond to panels (a)-(d) in Figure 4.

Table A.2: Gasoline and diesel, sale-period volume shares

Quarter	Gasoline	Diesel
2004q1	0.221 (0.001)	0.201 (0.001)
2004q2	0.229 (0.002)	0.215 (0.002)
2004q3	0.222 (0.002)	0.204 (0.001)
2004q4	0.241 (0.004)	0.216 (0.003)
2005q1	0.249 (0.004)	0.223 (0.003)
2005q2	0.253 (0.005)	0.230 (0.004)
2005q3	0.250 (0.005)	0.229 (0.004)
2005q4	0.247 (0.005)	0.228 (0.005)
2006q1	0.251 (0.004)	0.234 (0.003)
2006q2	0.249 (0.003)	0.235 (0.003)
2006q3	0.259 (0.003)	0.254 (0.004)
2006q4	0.271 (0.005)	0.268 (0.005)
2007q1	0.272 (0.004)	0.261 (0.004)
2007q2	0.267 (0.004)	0.264 (0.004)
2007q3	0.272 (0.004)	0.270 (0.004)
2007q4	0.281 (0.005)	0.268 (0.005)
2008q1	0.292 (0.005)	0.267 (0.005)
2008q2	0.290 (0.004)	0.274 (0.005)
2008q3	0.294 (0.005)	0.278 (0.005)
2008q4	0.315 (0.006)	0.280 (0.005)
2009q1	0.313 (0.005)	0.290 (0.006)
2009q2	0.281 (0.004)	0.272 (0.005)
2009q3	0.283 (0.004)	0.278 (0.005)
2009q4	0.288 (0.004)	0.275 (0.005)
2010q1	0.280 (0.004)	0.262 (0.005)
2010q2	0.279 (0.004)	0.265 (0.004)
2010q3	0.282 (0.004)	0.270 (0.005)
2010q4	0.286 (0.004)	0.268 (0.005)
2011q1	0.306 (0.005)	0.283 (0.005)
2011q2	0.311 (0.005)	0.283 (0.005)
2011q3	0.303 (0.005)	0.290 (0.005)
2011q4	0.314 (0.005)	0.292 (0.005)
2012q1	0.322 (0.005)	0.301 (0.005)
2012q2	0.317 (0.005)	0.298 (0.005)
2012q3	0.313 (0.005)	0.296 (0.005)
2012q4	0.324 (0.005)	0.302 (0.006)
2013q1	0.321 (0.005)	0.301 (0.006)
2013q2	0.330 (0.005)	0.313 (0.006)
2013q3	0.332 (0.006)	0.315 (0.006)
2013q4	0.347 (0.006)	0.325 (0.007)
2014q1	0.363 (0.007)	0.344 (0.008)
2014q2	0.350 (0.006)	0.327 (0.007)
2014q3	0.356 (0.006)	0.349 (0.007)
2014q4	0.377 (0.006)	0.356 (0.007)

Note: The table shows the development in the sale-period volume share based on Eq. 2 for cycling stations. The results are also reported in panel (a) in Figure 5.

Table A.3: Quarterly intertemporal elasticity

	Overall		Gasoline		Diesel	
2004q1 × ln(price)	-2.38	(0.099)	-3.24	(0.10)	-1.68	(0.13)
2004q2 × ln(price)	-1.96	(0.15)	-2.99	(0.15)	-1.36	(0.17)
2004q3 × ln(price)	-3.01	(0.13)	-4.33	(0.17)	-2.03	(0.12)
2004q4 × ln(price)	-2.29	(0.16)	-3.83	(0.17)	-1.39	(0.19)
2005q1 × ln(price)	-2.87	(0.19)	-4.29	(0.19)	-1.85	(0.21)
2005q2 × ln(price)	-3.74	(0.21)	-5.12	(0.23)	-2.83	(0.23)
2005q3 × ln(price)	-3.35	(0.13)	-4.02	(0.14)	-2.82	(0.15)
2005q4 × ln(price)	-3.38	(0.16)	-4.50	(0.15)	-2.74	(0.18)
2006q1 × ln(price)	-3.62	(0.17)	-5.17	(0.18)	-2.89	(0.20)
2006q2 × ln(price)	-4.24	(0.19)	-5.32	(0.19)	-3.89	(0.22)
2006q3 × ln(price)	-4.55	(0.22)	-5.85	(0.21)	-4.24	(0.24)
2006q4 × ln(price)	-5.31	(0.23)	-6.89	(0.27)	-4.76	(0.23)
2007q1 × ln(price)	-4.69	(0.22)	-6.54	(0.25)	-3.92	(0.24)
2007q2 × ln(price)	-4.03	(0.19)	-5.57	(0.23)	-3.60	(0.21)
2007q3 × ln(price)	-4.74	(0.18)	-6.22	(0.19)	-4.29	(0.20)
2007q4 × ln(price)	-4.11	(0.20)	-6.55	(0.24)	-3.19	(0.20)
2008q1 × ln(price)	-5.02	(0.20)	-7.18	(0.22)	-3.60	(0.22)
2008q2 × ln(price)	-6.04	(0.23)	-8.11	(0.25)	-4.75	(0.24)
2008q3 × ln(price)	-6.42	(0.21)	-7.82	(0.22)	-5.52	(0.24)
2008q4 × ln(price)	-5.26	(0.16)	-7.45	(0.19)	-3.91	(0.17)
2009q1 × ln(price)	-5.72	(0.18)	-6.72	(0.20)	-4.94	(0.22)
2009q2 × ln(price)	-4.92	(0.19)	-5.38	(0.22)	-4.66	(0.21)
2009q3 × ln(price)	-5.71	(0.20)	-6.26	(0.24)	-5.47	(0.22)
2009q4 × ln(price)	-6.20	(0.24)	-7.60	(0.29)	-5.35	(0.27)
2010q1 × ln(price)	-5.85	(0.25)	-7.48	(0.30)	-4.91	(0.27)
2010q2 × ln(price)	-6.14	(0.24)	-7.83	(0.30)	-5.08	(0.25)
2010q3 × ln(price)	-5.84	(0.23)	-7.12	(0.30)	-5.27	(0.24)
2010q4 × ln(price)	-5.37	(0.23)	-7.02	(0.27)	-4.43	(0.23)
2011q1 × ln(price)	-6.74	(0.25)	-8.50	(0.30)	-5.64	(0.25)
2011q2 × ln(price)	-7.76	(0.26)	-9.47	(0.30)	-6.71	(0.29)
2011q3 × ln(price)	-7.52	(0.26)	-8.92	(0.27)	-6.60	(0.28)
2011q4 × ln(price)	-7.96	(0.26)	-10.6	(0.32)	-6.31	(0.26)
2012q1 × ln(price)	-8.14	(0.31)	-9.03	(0.35)	-7.54	(0.33)
2012q2 × ln(price)	-9.35	(0.36)	-10.6	(0.38)	-8.50	(0.39)
2012q3 × ln(price)	-8.16	(0.33)	-9.03	(0.34)	-7.51	(0.34)
2012q4 × ln(price)	-8.77	(0.38)	-11.0	(0.40)	-7.23	(0.38)
2013q1 × ln(price)	-8.48	(0.36)	-9.54	(0.37)	-7.63	(0.38)
2013q2 × ln(price)	-8.72	(0.34)	-9.42	(0.36)	-8.00	(0.39)
2013q3 × ln(price)	-8.21	(0.33)	-8.87	(0.34)	-7.63	(0.34)
2013q4 × ln(price)	-9.28	(0.27)	-11.6	(0.29)	-7.68	(0.28)
2014q1 × ln(price)	-10.0	(0.25)	-11.5	(0.26)	-8.95	(0.29)
2014q2 × ln(price)	-8.11	(0.25)	-9.08	(0.28)	-7.35	(0.27)
2014q3 × ln(price)	-9.00	(0.25)	-9.81	(0.26)	-8.35	(0.27)
2014q4 × ln(price)	-8.94	(0.21)	-10.3	(0.22)	-7.85	(0.24)
Constant	22.6	(0.38)	26.3	(0.41)	20.4	(0.40)
$\lambda_i \theta_w \gamma_f$	Yes		Yes		Yes	
Observations	5369767		2677705		2692170	
R2	0.86		0.85		0.87	

Note: The table shows the development in the intertemporal elasticity based on Eq. 3 for cycling stations. The results are also reported in Figures 6 and A.13.

Graphic design: Communication Division, UIB / Print: Skipnes Kommunikasjon AS

uib.no

ISBN: 9788230866979 (print)
9788230841662 (PDF)