ESSAYS ON RETAIL PRICES

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Content

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Introduction

The retail price of a good is the price end consumers can buy one unit of the good for in the retail market. Most people in most countries buy retail goods or services on a regular basis. Owing to the retail industry, we can get the products we require in exchange for money instead of producing them ourselves. This, in turn, imply that we spend significant amounts of money on retail goods and services (Frankel, 2018). Therefore, pricing decisions by firms are important for both firms and consumers. This thesis is about retail prices and factors that one way or another are related to firms' retail pricing behavior. A central theme in this thesis is how retail pricing affects firm performance.

Retail prices are important to profit-maximizing firms as they determine the profit margin per unit of a good. The higher is the price offered to the end user, the larger is the margin per unit. However, these prices also affect consumers' demand for a product. The more sensitive consumers are to price changes, the more sales a firm would lose by increasing the price offered to end users. Therefore, there is a trade-off between price and volume firms must take into account when determining retail prices.

How sensitive consumers are to price changes hinges among others on whether consumers can purchase the product from other sellers. Therefore, the price a firm sets on its product depends on whether it faces competition or not. If consumers can buy a good from more than one seller, price sensitivity likely increases. Prices can thus potentially tell us about the competitive situation in a market and the degree of market power of firms.

In oligopoly markets, characterized by a small number of sellers, price setting is crucial as competitors will respond to a firm's price action, which can influence market shares and profit. Since consumers have different tastes for variation, non-price competition can influence the price competition among firms as well. Consumers can value the same product of the same quality from two different brands differently even if they cost the same due to preferences for brands. Consumers might we willing to pay a higher price to get the variety of the product which they prefer the most, hence firms must take horizontal differentiation of their goods into account. Even if products are homogenous with no diversity, factors like physical distance between firms might affect consumers' ranking of one seller over another, which again influence firms' pricing decision.

Apart from price level, which price strategy to adopt is another consideration for firms to take. Most of us think of uniform pricing, that is, one fixed price on each product, as the "standard". However, firms can also price discriminate by selling two units of the same physical product at two different prices, either to the same consumer or to different consumers, after taking the cost of serving consumers into account (Tirole, 1988, p. 133). For instance, in the airline industry, youths are often offered "youth tickets" which are cheaper than ordinary tickets (see e.g. Airfrance, 2018; SAS, 2018). This is called third-degree price discrimination. Today, with all the available data on consumer information, firms are more capable of charging individual prices to each and every customer for the same good, a price strategy known as first-degree price discrimination or personalized pricing.

Even if firms set one fixed price on each good, this fixed price can vary over time. In certain markets, for instance retail gasoline markets, firms are observed to set a uniform price that varies over time in a saw-tooth pattern, with large price jumps followed by several small price cuts. These price patterns can be relatively predictable, which leave consumers the opportunity to plan their purchases by adapting to the pattern. Further, in some markets, a retail price change of one firm is observed to be followed by other firms shortly after, with a price change of approximately the same amount. Price leadership can bring on a market-wide price coordination, suggesting that retail prices in themselves can serve as a communication tool among firms.

This thesis focuses on some of the aspects of retail pricing mentioned above, and examines them in more detail.

The first chapter is co-written with Øystein Foros and Hans Jarle Kind. Motivated by the fact that consumers leave increasingly more digital footprints which improve firms' ability to practice personalized pricing (first-degree price discrimination), we ask whether there exist strategic effects that reduce firms' incentives to do so. To answer this question, we first note that it is optimal for a firm that price discriminates to set the purchasing price equal to marginal costs from consumers who buy from a rival. This is true independently of whether the rival has made any non-price commitments (e.g. strategic product differentiation). In contrast, if a firm uses uniform pricing, the rival has incentives to make strategic commitments that soften competition. Consequently, we find that firms might find it optimal to commit to uniform pricing to avoid being trapped in a highly competitive equilibrium. The key insight is that a firm's incentives to undertake strategic price-softening behavior depend on the rival's choice between uniform and personalized pricing, and not the firm's own choice.

The second chapter examines how price coordination, and importantly, coordination on price restorations, is carried out in retail gasoline markets. In the studied market, one firm breaches a fourteen-year lasting regular price cycle overnight by publicly announcing a change to its retail price policy. Prior to the announcement, the regular cycle occurred across brands and all over the country. I show that the recommended price of this particular company, which is publicly available on the company's website, serves two functions for its network of retail stations. First, it determines the price restoration level. Second, it serves as a signal of *when* to implement a restoration day: Every time this company announces an adjustment to the recommended price in the early morning, price restoration is implemented the following forenoon. I further show that other companies are following the new practice as well. Hence, a new way to coordinate on prices and synchronize price restorations inter-brand and across local markets has emerged, using prior announcements of the price leader's recommended price as a signaling device.

The third chapter is co-written with Øystein Foros and Frode Steen. First, we analyze how regular days off from competition and a time-dependent price pattern affect firm performance. Second, we examine the effects on firms' profitability from consumers' changing search- and timing behavior. We use microdata from gasoline retailing in Norway. From 2004 to 2017, firms practiced an industry-wide day off from competition, starting on Mondays at noon, by increasing prices to a common level given by the recommended prices (decided and published in advance). In turn, a foreseeable low-price window is open before every restoration. During the data period, we observe an additional weekly restoration on Thursdays at noon. The additional day off from competition increases firm performance. As expected, a conventional price search of where to buy reduces firms' profitability. In contrast, consumers who are aware of the cycle and spend effort on when to buy have a positive impact on firms' profitability. If consumers spend effort on when to buy, they attempt to tank during low price windows. By its very nature, this shrink consumers' ability to compare prices at several outlets. Consequently, more attention to when to buy may soften price competition.

The fourth chapter is co-written with Frode Steen. Applying detailed consecutive daily micro data at the gasoline station level from Sweden we estimate a structural model to uncover the degree of competition in the gasoline retail market. We find that retailers do exercise market power, but despite the high upstream concentration, the market power is very limited on the downstream level. The degree of market power varies with both the distance to the nearest station and the local density of gasoline stations. A higher level of service tends to raise a seller's market power; self-service stations have close to no market power. Contractual form and brand identity also seem to matter. We find a clear result: local station characteristics significantly affect the degree of market power. Our results indicate that local differences in station characteristics can more than offset the average market power found for the whole market.

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Chapter 1

Competition with Personalized Pricing and Strategic Product Differentiation[1]

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Abstract: Consumers leave increasingly more digital footprints which improve firms' ability to practice personalized pricing (first-degree price discrimination). We ask whether there exist strategic effects that reduce firms' incentives to do so. To answer this question, we first note that it is optimal for a firm that price discriminates to set the purchasing price equal to marginal costs from consumers who buy from a rival. This is true independently of whether the rival has made any non-price commitments (e.g. strategic product differentiation). In contrast, if a firm uses uniform pricing, the rival has incentives to make strategic commitments that soften competition. Consequently, we find that firms might find it optimal to commit to uniform pricing to avoid being trapped in a highly competitive equilibrium. The key insight is that a firm's incentives to undertake strategic price-softening behavior depend on the rival's choice between uniform and personalized pricing, and not the firm's own choice.

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1 Introduction

Personalized pricing (first-degree price discrimination) was once the prevailing pricing method in the retail sector. Indeed, prior to the mid-nineteenth century, sellers in the U.S. and Western Europe negotiated on prices with each individual customer (Phillips, 2012; Wallmeier, 2018). It was not until the 1860s that we saw a shift towards the present pricing standard, uniform pricing. The establishment of the first department stores initiated the shift. Personalized pricing requires detailed information both about purchasing prices for each single good and about individual consumers' expected willingness to pay. It thus turned out to be an inefficient pricing method for department stores that offered a wide variety of products and served a large number of customers.[2] Imposing one single fixed price on each good made the pricing task substantially less time consuming (Phillips, 2012, p.33), and by 1890 advertisements like "One Price for Every Man" and "One price to all" marked the uniform price policy as the new pricing norm (Phillips, 2012, p. 32; Resseguie, 1965, pp.302-303).[3]

Today, personalized pricing is again on the agenda. Consumers use apps that are customized to collect individual data, and leave digital footprints on the Internet. In contrast to the early nineteenth century, sellers can directly learn about consumers' willingness to pay.[4] Moreover, Big Data and machine learning algorithms allow firms to come much

[2]Clerks used to adopt a "price code" system where information about prices written on the price-tags was understandable only for the clerks and not for the customers (Phillips, 2013, p.30). Hence, when stores grew larger, not only was negotiation more time consuming, but keeping track of all the codes became more cumbersome as well.

[3]Among pioneers was Alexander T. Stewart, who established a dry-goods store in New York in 1826. Stewart is often credited as being the first to use the one-price-to-all-principle in the United States. Britannica (2018) writes the following: "Instead of haggling over prices with each individual customer, Stewart set standard prices on all his goods, which was an innovation in his time." Macy's announced its one-price policy in 1858 (Resseguie, 1965), and the same policy was applied by John Wanamaker in Philadelphia some years later. In Western Europe, some Parisian stores had one-price-to -all-ads already in the 1830s (Wallmeier, 2018; Resseguie, 1965; Phillips, 2012).

[4]The high profile Facebook-Cambridge Analytica case illustrates that such information is not restricted to information directly collected from own consumers. Cambridge Analytica achieved access to private information from the counts of more than 50 million Facebook users. The firm's tools could identify the personalities of American voters and influence their behavior, according to the New York Times (2018). Market players as well as politicians may use such information from intermediaries.

closer to applying personalized pricing than before, for instance by inducing a shift from third-degree (group based pricing) to first-degree price discrimination. Information costs are significantly reduced, and firms are often capable of practicing high-scale personalized pricing. In Varian's (2010) terminology, "Instead of a 'one size fits all' model, the Web offers a 'market of one'". This development may further give firms stronger incentives (and better abilities) to tailor their products to match individual preferences. By reducing the mismatch between basic product characteristics and what each single consumer prefers, the size of the market and the consumers' willingness to pay for the good should increase.

This development raises the question of whether personalized pricing will again become the standard in retail markets. How do firms' incentives and profitability from practicing personalized pricing compare to what we would observe if they practiced uniform pricing? Owing to textbook examples in ECO101, many relate personalized pricing to a monopolist seller who extracts all consumer surplus by charging each individual a price equal to her maximum willingness to pay for the good. Before the arrival of department stores 150 years ago, sellers were often local monopolists in their product lines (Jones, 1936, among others).[5] The advantage of using personalized pricing in such markets is well illustrated by the textbook example. However, in retail markets today, there are usually more than one seller; digitalization in itself increases the alternatives for consumers through online sales. If they use personalized pricing, firms might then end up competing intensively for each and every consumer (a "market of one").[6] As shown in the seminal paper by Thisse and Vives (1988), even though firms are better off if they all use uniform pricing, they could be trapped in a prisoner's dilemma situation where each has incentives to unilaterally adopt personalized pricing.

[5] At that time, the general retail store in a region offering some product lines was often the only source of supply of goods which people could not produce themselves in their homes. Further, special stores offering one product line were rare and usually found only in large cities (Jones, 1936, p.134).

[6] In their bestseller, written for a business audience, Shapiro and Varian (1998, pp. 40) gave a warning: "If your online travel agency knows that you are interested in deep-sea fishing, and it knows that deep-sea fishermen like yourself are often wealthy, it may well want to sell you a high-priced hotel package. On the other hand, if the travel agency knows that you like snorkeling, and snorkelers prefer budget travel, then they can offer you a budget package. In these examples, the provider can design a package that is optimized for your interests and charge you accordingly. But be careful about those premium prices for deep-sea fishermen: even wealthy deep-sea fishermen can change travel agencies."

There certainly exist examples of personalized pricing, for instance among hotel and airline agencies (see, e.g., Mohammed, 2017). However, most firms set a fixed price for each product, even when they have access to large amounts of consumer data. Hence, for the time being, a widespread shift to personalized pricing in retail markets seems to be absent. In the same vein, it is interesting to note that despite the information revolution and huge advances in for instance supply side management and computer assisted design, firms do not seem to match their products according to each consumer's preferences to such an extent as one might expect.

The continued prevalence of uniform pricing could partly be due to privacy concerns and resistance from consumers who dislike information gathering and personalized pricing (see Acquisti et al., 2016, for a comprehensive survey). Consumers might also consider personalized pricing ("haggling") as "unfair", and prefer to buy from firms that commit to "One Price for Every Man". Phillips (2012) argues that this effect can help explain the move from personalized to uniform pricing in the nineteenth century example above.

We abstract from these effects on the consumer side, and focus on strategic interactions between competing firms. In particular, we ask whether a firm by committing to uniform pricing might be able to prevent a rival from undertaking aggressive non-price decisions. More specifically, our research question is how a firm's incentives to reduce the level of mismatch cost (we consider other non-price commitments in an extension of the basic model) depends on its own and its competitor's choice of price policy (uniform pricing versus personalized pricing). We also ask whether endogenous non-price commitments change the prisoner's dilemma outcome from Thisse and Vives (1988) described above.

To approach these questions we consider competition between two firms located at each end of a Hotelling line. At stage 1, each firm can commit to using uniform pricing (price policy commitment).[7] At stage 2, the firms simultaneously choose a firm-specific level of mismatch cost. At stage 3, the firms compete in prices. If a firm has not committed to uniform pricing at stage 1, it is free to choose between uniform pricing and personalized pricing at stage 3. Stages 1 and 3 of the game resemble Thisse and Vives (1988); however, they assume that the level of mismatch cost is exogenous. In contrast, we follow Ferreira

[7] A recent example that literally fits into the spatial Hotelling framework is Staples who offered individual discounts based on the distance between the customers' location and the rival stores (Wall Street Journal, 2012).

and Thisse (1996) and let the mismatch cost be one of the firms' choice variables.

In equilibrium, a firm that uses personalized pricing will set price equal to marginal cost towards all consumers who are buying from the rival. This is a robust result, see Thisse and Vives (1988) and Lederer and Hurter (1986), and is independent of the rival's decisions on mismatch cost. In contrast, a firm that sets a uniform price will lower its price if the rival reduces its mismatch cost. This is true because the competitive pressure for the firm's marginal consumer increases in the rival's reduction of mismatch cost since the rival's product becomes more attractive. Therefore, we show that a firm's incentives to change its mismatch cost depend on the rival's choice between uniform pricing and personalized pricing. A firm finds it optimal to reduce its own mismatch cost only if the rival uses personalized pricing; the optimal choice regarding the mismatch cost is independent of the firm's own choice between price policies. Hence, a firm may choose to stick to uniform pricing in order to prevent the rival from reducing its mismatch cost and expanding its market. Personalized pricing comes at a cost because it triggers an aggressive response from the rival in tailoring its product to each consumer's preferences, which is harmful for the other firm.

More generally, a rival using personalized pricing optimally sets price equal to marginal cost in the other firm's market region, which means that the firm cannot affect the rival's behavior towards these consumers by adjusting its non-price variable (such as mismatch cost or location). Hence, price discrimination by the rival, and the rival only, removes strategic effects of non-price commitments. To our knowledge, this has not yet been highlighted in the literature. In the spirit of Fudenberg and Tirole (1984) and Tirole (1988) we show that a firm's choice of whether to commit to uniform pricing at stage 1 is a choice of whether to give the rival strategic incentives to undertake commitments in non-price variables.

The rest of the paper proceeds as follows. Section 2 reviews related literature. In Section 3 we set up the basic model with the standard assumptions in a Hotelling framework. Before solving the game we consider some general implications of personalized pricing on firms' strategic incentives in non-price variables. We extend the model in three ways in Section 4 by considering a two-sided market, location incentives and by opening up for partial multi-homing by consumers. Lastly, Section 5 concludes.

2 Literature review

Recent developments in information gathering technologies make it possible for firms to collect more accurate information about consumers' individual willingness to pay, and this increases firms' abilities to practice personalized pricing (first-degree price discrimination). Therefore, personalized pricing is on the agenda as ever before. This is reflected in recent debates both in popular media (e.g. Forbes, 2014) and in academic literature (e.g. Esteves, 2010; Valletti and Wu, 2016; Prüfer and Schottmüller, 2017).

Our study is closely related to Thisse and Vives (1988), who consider a two-stage game where each of two Hotelling firms can commit to uniform pricing before they compete in prices. For a firm that does not commit to uniform pricing in the first stage, it is optimal to use personalized pricing in the second stage. Thisse and Vives (1988) show that a prisoner's dilemma outcome emerges, where both firms in equilibrium use personalized pricing even though aggregate profit would have been higher if they both had committed to uniform pricing.[8] We build on the framework developed by Thisse and Vives, but allow each firm to choose how closely it will match its good to individual consumer preferences; the poorer the match, the greater is the hedonic consumer price (the sum of monetary price and mismatch costs). The matching choice is made prior to the price competition stage, but after firms' choice of whether to commit to uniform pricing. We show that once firms are able to make the matching choice, the prisoner's dilemma outcome described above may cease to be an equilibrium: the firms may now choose to commit to uniform pricing.

Also Ferreira and Thisse (1996)[9] open up for endogenous mismatch costs prior to the price competition stage. They consider a framework where two firms are located at each end of a Hotelling line, and show that each firm chooses to impose high own mismatch costs. This is similar to our finding under uniform pricing; going for high mismatch costs induces soft pricing behavior from the rival. Hendel and de Figueiredo (1997) assume a circular model instead of the Hotelling line, and arrive at the same qualitative result; in a setting with two firms, each of them chooses high mismatch costs in order to induce soft price competition. In contrast to us, neither Ferreira and Thisse (1996) nor Hendel and de

[8] A similar outcome is reached a two-period framework in Fudenberg and Tirole (2000) and Esteves (2010).

[9] Based on the firm-specific transportation cost framework from Launhardt (1885).

Figueiredo (1997) let firms choose between uniform and personalized pricing.[10]

It is well established in the literature on personalized pricing that firms in equilibrium set price equal to marginal cost to its marginal consumer and to consumers served by the rival (Hurter and Lederer, 1985; Lederer and Hurter, 1986; Thisse and Vives, 1988; Bhaskar and To, 2004). We show that this has the interesting implication that, in the terminology of Fudenberg and Tirole (1984) and Tirole (1988), a firm's choice of whether to commit to uniform pricing is also a choice of whether to give the rival strategic incentives to undertake non-price commitments. More precisely, if a firm uses personalized pricing, there will be no strategic effect of a rival's choice of non-price commitment. This result hinges on the assumption that firms choose both price policy and a non-price variable prior to the competition stage. Previous studies assume either fixed price policy, such that both firms per definition use personalized pricing (Hurter and Lederer, 1985; Lederer and Hurter, 1986; Bhaskar and To, 2004) or no endogenous non-price commitments (Thisse and Vives, 1988). Therefore, our result that there is no strategic effect from a firm's non-price commitment (e.g. mismatch costs) if the rival uses price discrimination is novel.

In an extension of the basic Hotelling model where firms are located at the extremes of the Hotelling line, we consider a firm that uses personalized pricing and show that its location incentives depend crucially on the pricing policy of the rival. The firm we consider perceives a rival that charges all consumers the same price (uniform pricing) as relatively soft. This indicates that it will locate closer to a rival that uses uniform pricing than to a rival that uses personalized pricing. However, as noted above, the strategic effect – which generates minimum differentiation in the standard Hotelling model – does not exist if the rival uses personalized pricing. We show that for this reason, the firm will nonetheless locate closer to a rival that uses personalized pricing than to a rival that uses uniform pricing. As a corollary, it follows that if both firms use personalized pricing, they will both have incentives to locate relatively close to each other. This result is consistent with Hurter and Lederer (1985), Lederer and Hurter (1986) and Bhaskar and To (2004), who show that if two firms compete with personalized pricing, they will choose interior locations on the Hotelling line (actually, they will choose the socially optimal locations). However, neither

[10] In von Ungern-Sternberg (1988) firms choose mismatch costs in a circular model. However, he assumes that mismatch costs and price are determined simultaneously. This implies that there is no strategic interdependence between these two choice variables.

of these studies consider the case where only one of the firms use personalized pricing. As such, their result on location is a special case of our general result. An important lesson from our analysis, is that it is not personalized pricing in itself that removes strategic effects of non-price commitments, it is personalized pricing by the rival that drives the result. As far as we know, this insight has not previously been acknowledged in the literature.

Our study also relates to the literature on product customization. Big data does not only put personalized pricing on the agenda, it also makes product customization a current topic as more information about consumer preferences is available. The mismatch cost in our model can be interpreted as product customization, where a firm can match its product better to consumers' most preferred taste by decreasing the level of transportation cost. Dewan et al. (2000; 2003) and Bernhardt et al. (2007) consider costly customization. By contrast, we bypass any costs of customization in order to isolate the strategic effects on price. Syam et al. (2005) take a similar approach, though in a different context than ours. However, none of the above papers studies the choice of price policy in relation to product customization as we do.

3 The model set-up

We consider competition between two firms, $i = 0, 1,$ located at the extremes of a Hotelling line with length 1. The location of firm i is given by x_i, where $x_i = 0$ for firm 0 and $x_i = 1$ for firm 1. Consumer tastes are uniformly distributed along the line. Throughout, we assume that both firms are active (market sharing), and we consider both personalized and uniform pricing. Under personalized pricing (first-degree price discrimination) each consumer is given an individual price $p_i(x)$, where x is the consumer's location on the Hotelling line. Under uniform pricing all consumers pay the same price $p_i(x) = p_i$, independently of location.

The consumer utility of buying from firm i for a consumer located at x can be written as

$$u_i(x) = v - m_i |x - x_i| - p_i(x). \tag{1}$$

We assume that the parameter $v > 0$ is sufficiently large to ensure market coverage. The second term in (1) captures the idea that consumers will in general not find any of the goods to be a perfect fit; the perceived mismatch costs associated with good i for a consumer located at x is $m_i |x - x_i|$, where $m_i > 0$. The smaller is m_i, the greater is the number of consumers who is willing to buy good i, other things equal. Put differently, decreasing m_i enlarges the size of the market for firm i. This modelling of the mismatch costs is equivalent to the firm-specific transportation cost used by Ferreira and Thisse (1996).[11]

The location of the consumer who is indifferent between the offers from firm 0 and 1, denoted by $\tilde{x}$, is found by setting $u_0(\tilde{x}) = u_1(\tilde{x})$:

$$D_i = \frac{m_j + p_j(\tilde{x}) - p_i(\tilde{x})}{m_i + m_j}. \tag{2}$$

Evidently, demand for good i is decreasing in own mismatch costs, $\partial D_i/\partial m_i = -D_i/(m_i + m_j) < 0$, and increasing in the rival's mismatch costs, $\partial D_i/\partial m_j = (1 - D_i)/(m_i + m_j) > 0$.

We analyze a three-stage game. At stage 1, each firm might commit to using uniform pricing towards the consumers (price policy commitment). Then, at stage 2, the firms simultaneously decide on mismatch levels. We assume that m_i is bounded by $m_i \in [\underline{m}, \overline{m}]$. At stage 3, the firms compete in consumer prices. If firm i has not made any commitment at stage 1, it is free to choose between using uniform pricing and personalized pricing at stage 3.

Each firm thus commits to uniform pricing if this is individually profitable. Such a commitment is consistent with the "one price to all" concept that was introduced by department stores 150 years ago when they through advertisement and money-back guarantees bound themselves to apply uniform pricing (Phillips, 2012). Without such a commitment, firms could be tempted to price according to what they expected each consumer to be willing to pay (personalized pricing).

Below, we first assume that one of the two firms, which we label firm k, has committed to uniform pricing, and analyze what effect this commitment might have on pricing and choice of mismatch costs. We consider both the case where the rival uses uniform pricing and where it uses personalized pricing. Then we perform the same analysis if firm k has made no price policy commitment. Since the firms are intrinsically symmetric, we will, without loss of generality, let $k = 0$.

[11] The modelling in Ferreira and Thisse (1996) builds on Launhardt (1885).

3.1 Preliminary insights: Implications of personalized pricing

Before we solve the game presented above, we show some general results on how personalized pricing affects firms' incentives to undertake strategic commitments in non-price variables. A non-price variable can for instance be mismatch costs, as in our main model, or location on the Hotelling line (see section 4.2). Denote the level of the non-price variables by n_0 and n_1 (corresponding to m_0 and m_1 in the main model). We assume that firm 0 has commited to uniform pricing at stage 1. We maintain the assumption that the levels of the non-price variables are determined non-cooperatively at stage 2, and that these variables are observable when the firms compete in prices at stage 3.

First, consider the case where both firms have committed to uniform pricing. In general we cannot say whether prices are strategic complements or strategic substitutes, but for the sake of the argument (and without affecting the qualitative results below) we assume they are strategic complements. In either case the reduced form profit of firm 0 at stage 2 can be written as

$$\pi_0(n_0, n_1, p_0(n_0, n_1), p_1(n_0, n_1)). \tag{3}$$

The total derivative of (3) with respect to the non-price variable n_0 is

$$\frac{d\pi_0}{dn_0} = \frac{\partial \pi_0}{\partial n_0} + \underbrace{\frac{\partial \pi_0}{\partial p_1}}_{+} \frac{dp_1}{dn_0}, \tag{4}$$

where

$$\frac{dp_1}{dn_0} = \left(\frac{dp_1}{dp_0}\right)\left(\frac{dp_0}{dn_0}\right).$$

The first term on the right-hand side of (4) measures the change in firm 0's profit when it increases n_0, holding the rival's price p_1 fixed. This is the direct effect of changing n_0, and in equilibrium firm 0 would solve $\partial\pi_0/\partial n_0 = 0$ if n_0 was unobservable. Let $\hat{n}_0$ denote the solution to $\partial\pi_0/\partial n_0 = 0$.

Since we have assumed that n_0 is observable prior to the price decision in stage 3, p_1 is a function of n_0. Firm 0 thus has incentives to strategically affect the price charged by the rival through the level of the non-price variable n_0 (in normal cases $\partial\pi_0/\partial p_1 > 0$). This effect is captured by the second term on the right-hand side of (4). Suppose that

$dp_0/dn_0 > 0$. Given the assumption that prices are strategic complements ($dp_1/dp_0 > 0$), it follows that firm 0 will then commit to $n_0 > \hat{n}_0$ because this induces the rival to increase its price too. In the terminology of Fudenberg and Tirole (1984), firm 0 chooses a "fat cat strategy"; it "overinvests" in the non-price variable to appear soft (it charges a higher price). In contrast, if the "investment" makes firm 0 tough (i.e., $dp_0/dn_0 < 0$), it commits to a lower value of the non-price variable ($n_0 < \hat{n}_0$) in order to make the rival set a relatively high price. This corresponds to a "puppy dog strategy" in the terminology of Fudenberg and Tirole.

Now, consider instead the case where firm 1 has not made a commitment to uniform pricing at stage 1. For now, we assume that firm 0 knows firm 1 has incentives to use personalized pricing at stage 3 in this case (we will later verify that this holds). As shown in the seminal contributions by Thisse and Vives (1988) and Lederer and Hurter (1986), a firm using personalized pricing will charge an individual price equal to the marginal cost to the "last" consumer it serves as well as all consumers served by the rival. Hence, in stage 3 firm 1 offers $p_1(\widehat{x}) = c$ towards all consumers served by firm 0. This price decision is independent of the non-price commitments made in stage 2 (n_0 and n_1). Firm 0's profit is then given by

$$\pi_0(n_0, n_1, p_0(n_0, n_1), p_1(\widehat{x})). \tag{5}$$

The total derivative of (5) is

$$\frac{d\pi_0}{dn_0} = \frac{\partial \pi_0}{\partial n_0} + \underbrace{\frac{\partial \pi_0}{\partial p_1(\widehat{x})}}_{+} \frac{dp_1(\widehat{x})}{dn_0},$$

where

$$\frac{dp_1(\widehat{x})}{dn_0} = 0.$$

Hence, the strategic effect is eliminated: When firm 1 uses personalized pricing, firm 0 cannot strategically affect firm 1's pricing behaviour, $p_1(\widehat{x}) = c$. Neither can firm 0 affect $p_1(\widehat{x}) = c$ through its choice of whether to commit to uniform pricing at stage 1.

Therefore, we have the following general result: If a firm faces a rival which uses personalized pricing, non-price commitments have no strategic effect. We can state:

Proposition 1: *Suppose that firm* 1 *uses personalized pricing. Then, there is no strategic effect neither from firm* 0*'s possible commitment to uniform pricing nor from its commitment to the non-price variable* n_0.

Proposition 1 implies that the choice of whether to commit to uniform pricing or not at stage 1 can be seen as a choice of whether to eliminate the rival's strategic incentives to undertake non-price commitments at stage 2. Put differently, a firm may commit to uniform pricing if it is profitable that the rival undertakes a strategic commitment at stage 2. In contrast, if it is profitable that the rival does not undertake a strategic commitment at stage 2, the firm may choose not to commit to uniform pricing.

It follows from Thisse and Vives (1988) and Lederer and Hurter (1986) that a firm using personalized pricing offers an individual price equal to marginal cost to all consumers served by the rival. However, Thisse and Vives (1988) do not consider endogenous non-price commitments (they do not have stage 2 in our model), while Lederer and Hurter (1986) assume that both firms use personalized pricing (they do not consider stage 1 in our model). Hence, none of them consider this general implication.

3.2 Firm 0 has committed to uniform pricing

3.2.1 Pricing (stage 3)

We now return to the specific model set-up in order to solve the corresponding game. Using backward induction, we start with the firms' pricing decisions (stage 3). At this stage the firms' product characteristics (mismatch costs) and price policies (whether they have committed to uniform pricing) are predetermined.

If firm 0 at stage 1 has committed to uniform pricing, it will solve the following maximization problem:

$$\max_{p_0} \pi_0^{UP-R} = (p_0 - c)D_0^{UP-R}, \text{ where } R\epsilon\{UP, PP\}. \tag{6}$$

Throughout, the first part of the superscript indicates the firm's own price strategy (uniform pricing, abbreviated to UP, in this case), and the second part indicates the rival's price strategy (where R is UP or PP, where the latter stands for personalized pricing).

Suppose first that also firm 1 has committed to uniform pricing. Setting $p_i(x) = p_i$ and $p_j(x) = p_j$ into equation (2) it follows that perceived demand for firm $i = 0, 1$ equals:

$$D_i^{UP-UP} = \frac{m_j - (p_i - p_j)}{m_i + m_j} \tag{7}$$

By solving (6) we now find that prices are strategic complements, and that the reaction functions are given by

$$p_i(p_j) = \frac{c + p_j}{2} + \frac{m_j}{2}. \tag{8}$$

A higher value of m_j means that the competitive pressure for firm i's marginal consumers falls. This explains why $\partial p_i(p_j)/\partial m_j > 0$. In contrast, we see that $\partial p_i(p_j)/\partial m_i = 0$; firm i's optimal price does not depend directly on its own choice of mismatch costs. The reason for this is that a higher value of m_i reduces the number of consumers who prefers good i , but does not affect the optimal price towards its remaining consumers, all else equal. However, since an increase in m_i increases the rival's price, we nonetheless find that each firm's (potential) equilibrium price is increasing both in its own and the rival's mismatch costs, albeit most in the latter. More precisely, solving (8) for the two firms' prices simultaneously, we have

$$p_i^{UP-UP} = c + \frac{m_i + 2m_j}{3}, \tag{9}$$

proving that $\partial p_i^{UP-UP}/\partial m_j > \partial p_i^{UP-UP}/\partial m_i > 0$.

Inserting for (7) and (9) into (6) yields

$$\pi_i^{UP-UP} = \frac{(m_i + 2m_j)^2}{9(m_i + m_j)}, \tag{10}$$

from which it follows that $\partial \pi_i^{UP-UP}/\partial m_j > \partial \pi_i^{UP-UP}/\partial m_i > 0$. Since higher mismatch cost softens competition when both firms use uniform pricing, it leads to higher profits.

Suppose next that only firm 0 has committed to uniform pricing. Firm 1 is then free to choose between uniform pricing and personalized pricing at the stage 3, but it will clearly select the latter. The reason for this is that with personalized pricing, it can charge a price from each consumer which is infinitesimally lower than that of firm 0 and become these consumers' preferred supplier (and this will be the optimal pricing strategy towards all consumers who thereby generates a non-negative profit). No other price schedule can possibly yield a higher profit for firm 1. Following Thisse and Vives (1988), we thus assume that when only firm 0 has made a price policy commitment, it will act as a Stackelberg leader at stage 3.[12] Inserting $p_1^{PP}(\tilde{x}) = c$ into (2), it follows that firm 0's demand becomes

$$\tilde{x} = D_0^{UP-PP} = \frac{m_1 - (p_0 - c)}{m_0 + m_1}.$$

By solving the maximization problem in (6) we then find

$$p_0^{UP-PP} = c + \frac{m_1}{2}. \tag{11}$$

Equation (11) is firm 0's equilibrium price as well as its reaction function. The latter follows because the rival always charges a price equal to marginal costs for its last consumer and for all consumers served by firm 0 (so that $p_1(x) = c$ for $x \in [0, \tilde{x}]$).

Profit of firm 0 can now be written as

$$\pi_0^{UP-PP} = \frac{m_1^2}{4\,(m_0 + m_1)}. \tag{12}$$

Firm 1 sells to all consumers in the interval $[\tilde{x}, 1]$, and these consumers are charged prices which ensure that $u_1(x) \geq u_0(x)$. In equilibrium this constraint is binding, and from equation (1) we find that $p_1(x) = c + \frac{m_1}{2} + m_0 x - m_1(1 - x)$ for $x \in [\tilde{x}, 1]$. Profit for firm 1 thus equals

$$\pi_1^{PP-UP} = \int_{\tilde{x}}^{1} (p_1(x) - c)\, dx = \frac{(2m_0 + m_1)^2}{8\,(m_0 + m_1)}. \tag{13}$$

3.2.2 Choice of mismatch costs (stage 2)

Let us now turn to firm 0's choice of mismatch costs (stage 2). With no effect on our qualitative results, we assume that the firm can costlessly choose any mismatch level it wants within the boundaries $[\underline{m}, \overline{m}]$.

By assumption, firm 0 has committed to uniform pricing. If the rival has made the same commitment (recall that it will not use uniform pricing at stage 3 unless it has committed to do so), we know from equations (9) and (10) that equilibrium prices and profits are increasing in each firm's level of mismatch costs. It thus follows that firm 0 will set $m_0 = \overline{m}$ (and firm 1 will likewise set $m_1 = \overline{m}$).

[12] If firms set prices simultaneously when one of them has committed to uniform pricing and the other uses personalized pricing, then we must solve for mixed strategies. See Thisse and Vives (1988, 1992).

In the terminology of Fudenberg and Tirole (1984) and Tirole (1988), cf. section 3.1, firm 0 uses a puppy dog strategy if the rival uses uniform pricing: it "underprovides" reductions in the mismatch level on its own good in order to induce a more soft response from the rival. This is similar to the findings in Ferreira and Thisse (1996), and is related to findings in the literature on strategic obfuscation (obfuscation complicates or prevents consumers from gathering price information). Ellison & Wolitzky (2012) show that firms may unilaterally choose to raise consumers' search costs. This may be considered as analogue to raising their own mismatch costs.

In contrast, if the rival uses personalized pricing, we know from Proposition 1 that a change in firm 0's mismatch costs does not affect firm 1's pricing behavior towards its marginal consumer or any of the consumers served by firm 0; it always sets $p_1^{PP}(x)\big|_{x\leq\tilde{x}} = c$. Consequently, as the strategic effect is eliminated firm 0 needs not worry about any aggressive response from the rival if it reduces the perceived mismatch costs associated with the good it offers. Since a reduction in own mismatch costs raises its market share $(\partial D_0^{UP-PP}/\partial m_0 < 0)$, firm 0 thus maximizes profit by setting $m_0 = \underline{m}$. Formally, this follows because equation (12) implies:

$$\frac{\partial \pi_0^{UP-PP}}{\partial m_0} = -\frac{m_1^2}{4\left(m_0 + m_1\right)^2} < 0$$

To summarize the results so far:

Lemma 1: *Suppose that firm 0 has committed to uniform pricing, and that the rival*

(a) uses uniform pricing. Then firm 0 chooses to maximize mismatch costs associated with its own good (sets $m_0^{UP-UP} = \overline{m}$).

(b) uses personalized pricing. Then firm 0 chooses to minimize mismatch costs associated with its own good (sets $m_0^{UP-PP} = \underline{m}$).

3.3 Firm 0 has not committed to uniform pricing

3.3.1 Pricing (stage 3)

Suppose that firm 1 has committed to uniform pricing, while firm 0 has made no commitment. Then we know from the analysis above that firm 0 will use personalized pricing. Due to the intrinsic symmetry of the firms, we can switch subscripts in equation (13) and deduce that the profit level of firm 0 now equals

$$\pi_0^{PP-UP} = \int_0^{\tilde{x}} (p_0(x) - c)\, dx = \frac{(m_0 + 2m_1)^2}{8\,(m_0 + m_1)}. \tag{14}$$

From equations (11) and (12) it likewise follows that

$$p_1^{UP-PP} = c + \frac{m_0}{2} \text{ and} \tag{15}$$

$$\pi_1^{UP-PP} = \frac{m_0^2}{4\,(m_0 + m_1)}. \tag{16}$$

Suppose instead that neither of the firms have committed to uniform pricing. In this case both firms will use personalized pricing.[13] Each of them will consequently set price equal to marginal cost for its last consumer ($x = \tilde{x}$) and for all consumers served by the rival (Thisse and Vives, 1988). Hence, inserting $p_0^{PP}(\tilde{x}) = p_1^{PP}(\tilde{x}) = c$ into (2) yields

$$\tilde{x} = D_0^{PP-PP} = \frac{m_1}{m_0 + m_1}. \tag{17}$$

Equivalently, $D_1^{PP-PP} = 1 - \tilde{x} = \frac{m_0}{m_0+m_1}$.[14]

Profit to firm i is then[15]

$$\pi_i^{PP-PP} = \frac{m_j^2}{2\,(m_i + m_j)}. \tag{18}$$

3.3.2 Choice of mismatch costs (stage 2)

Now, consider firm 0's incentives to reduce mismatch costs when it uses personalized pricing. Assume first that firm 1 uses uniform pricing. The discussion above then indicates that firm 0 will choose high mismatch costs, because this makes firm 1 soft. This is confirmed by differentiating equation (14) with respect to m_0 :

[13] In equation (18) below we find that $\pi_i^{PP-PP} = \frac{m_j^2}{2(m_i+m_j)}$. Since $\pi_i^{PP-PP} - \pi_i^{UP-PP} = \frac{m_j^2}{2(m_i+m_j)} - \frac{m_j^2}{4(m_i+m_j)} = \frac{m_j^2}{4(m_i+m_j)} > 0$ and $\pi_i^{PP-UP} - \pi_i^{UP-UP} = \frac{(2m_j+m_i)^2}{8(m_0+m_1)} - \frac{(2m_j+m_i)^2}{9(m_0+m_1)} = \frac{1}{72}\frac{(2m_j+m_i)^2}{m_0+m_1} > 0$ it follows that firm i will use personalized pricing whatever the price policy of the rival. Thus, it is a dominant strategy at stage 3 to choose personalized pricing for a firm that has not made any other commitment.

[14] It is straightforward to show that if firm 0 uses personalized pricing it will sell less if the rival uses personalized pricing than if the rival uses uniform pricing ($D_0^{PP-PP} < D_0^{PP-UP}$). The reason for this is that the rival sets a lower price towards its marginal consumer in the former case ($p_1^{PP}(\tilde{x}) = c < p_1^{UP-PP} = c + m_0/2$).

[15] We have $\pi_0^{PP-PP} = \int_0^{\tilde{x}} [p_0(x) - c]\, dx = \frac{m_1^2}{2(m_0+m_1)}$ and $\pi_1^{PP-PP} = \int_{\tilde{x}}^1 [p_1(x) - c]\, dx = \frac{m_0^2}{2(m_0+m_1)}$.

$$\frac{\partial \pi_0^{PP-UP}}{\partial m_0} = \frac{(m_0 + 2m_1)\, m_0}{8\,(m_0 + m_1)^2} > 0.$$

If firm 1 instead uses personalized pricing, it sets $p_1^{PP}(x) = c$ towards its marginal consumer. We again know from Proposition 1 that firm 0 then is unable to make its rival softer through choosing high mismatch costs. It is therefore unambiguously beneficial for firm 0 to reduce mismatch costs, because this will increase the size of its market. Formally, from equation (18), we have

$$\frac{\partial \pi_0^{PP-PP}}{\partial m_0} = -\frac{m_1^2}{2\,(m_0 + m_1)^2} < 0.$$

We can state:

Lemma 2: *Suppose that firm 0 uses personalized pricing, and that the rival*

(a) uses uniform pricing. Then firm 0 chooses to maximize mismatch costs associated with its own good (sets $m_0^{PP-UP} = \overline{m}$).

(b) uses personalized pricing. Then firm 0 chooses to minimize mismatch costs associated with its own good (sets $m_0^{PP-PP} = \underline{m}$).

Lemma 2 resembles Lemma 1. Each firm takes into account the fact that if the rival uses uniform pricing, then a reduction of its own mismatch costs triggers an aggressive price response from the rival. If the rival uses personalized pricing, on the other hand, a firm which decreases its mismatch costs will observe higher sales without having to reduce its price. We thus have the following striking result, which is a main lesson from the current model:

Proposition 2: *Firm i's incentives to reduce the mismatch costs of its product is independent of whether it uses uniform prices or not. It chooses to reduce mismatch costs if and only if the rival uses personalized pricing.*

Proposition 2 highlights the fact that choosing personalized pricing comes at a cost; it gives your rival incentives to tailor its good to each consumer's preferences (reduce mismatch costs). In the next section we will consider whether this effect may induce firms not to choose personalized pricing.

Note that even though a reduction in mismatch costs is individually profitable, the firms would be better off if they could make a (joint) commitment to abstain from it. To see this, assume $m_1 = m_2 = m$. Equation (18) is then simplified to $\pi_i^{PP-PP}\big|_{m_i=m_j=m} = m/4$, which is strictly increasing in m.

3.4 The choice of personalized pricing

Using the results that firm i sets $m_i = \underline{m}$ (minimum mismatch costs) if the rival uses personalized pricing and $m_i = \overline{m}$ if the rival uses uniform pricing, we can apply equations (10) and (18) to express profit if both firms use either uniform pricing or personalized pricing as respectively

$$\pi_i^{UP-UP} = \frac{\overline{m}}{2} \text{ and } \pi_i^{PP-PP} = \frac{\underline{m}}{4}. \tag{19}$$

If one and only one of the firms has committed to uniform pricing, we likewise find from equations (12) and (13) that

$$\pi_i^{PP-UP} = \frac{(\overline{m} + 2\underline{m})^2}{8(\underline{m} + \overline{m})} \text{ and } \pi_i^{UP-PP} = \frac{\overline{m}^2}{4(\underline{m} + \overline{m})}. \tag{20}$$

Let $\alpha \equiv \overline{m}/\underline{m} \geq 1$ define the ratio between maximum and minimum mismatch costs, and suppose that firm j has committed to uniform pricing. Should firm i do the same? If it does, firm j will choose high mismatch costs (soft behavior). Equations (19) and (20) yield

$$\pi_i^{UP-UP} - \pi_i^{PP-UP} = \frac{3\alpha^2 - 4}{8(1+\alpha)}\underline{m} < 0 \text{ if } \alpha < \alpha_{crit} = \sqrt{4/3} \approx 1.1547. \tag{21}$$

Thus, it is not a Nash equilibrium for both firms to choose uniform pricing if the ratio between maximum and minimum mismatch costs is below a critical value, $\alpha < \alpha_{crit}$. The reason for this is that the gain from committing to uniform pricing and making the rival soft is then low compared to the gain from charging each consumer according to her willingness to pay for the good (personalized pricing). On the other hand, if $\alpha > \alpha_{crit}$, we see that $\pi_i^{UP-UP} - \pi_i^{PP-UP} > 0$. Then, neither firm will regret committing to uniform pricing, because each of them has much to gain from having a soft rival.

What should firm i do if the rival has not committed to uniform pricing (which implies that it will use personalized pricing)? Using equations (19) and (20) we find

$$\pi_i^{UP-PP} - \pi_i^{PP-PP} = \frac{\alpha(\alpha-1) - 1}{4(\alpha+1)}\underline{m} > 0 \text{ if } \alpha > \alpha^{crit} = \frac{1}{2}\sqrt{5} + \frac{1}{2} \approx 1.618. \tag{22}$$

Hence, it is profitable for firm i to commit to uniform pricing even if the rival uses personalized pricing if $\alpha > \alpha^{crit}$. Again, the intuition is that the larger is the ratio between maximum and minimum mismatch costs, the more valuable it is to commit to uniform pricing in order to make the rival soft. The reason why $\alpha^{crit} > \alpha_{crit}$ is that the loss in market share from using uniform pricing is greater when the rival chooses personalized pricing than when it uses uniform pricing.

Inspection of (21) and (22) reveals that there does not exist any equilibrium where one firm commits to uniform pricing and the other does not[16], so we can state

Proposition 3: *Equilibrium constellations:*

(i) If $\alpha < \alpha_{crit}$, there is a unique equilibrium where both firms choose personalized pricing.

(ii) If $\alpha > \alpha^{crit}$, there is a unique equilibrium where both firms choose uniform pricing.

(iii) If $\alpha_{crit} \leq \alpha < \alpha^{crit}$, there are multiple equilibria, where both firms choose personalized pricing or both firms choose uniform pricing.

In sharp contrast to Thisse and Vives (1988), we thus find that it is not necessarily true that firms unambiguously will choose personalized pricing (which would be a prisoner's dilemma). On the contrary, once we open up for endogenous mismatch costs, personalized pricing might not even constitute a Nash equilibrium. This is true if the span between the lowest and the highest level of mismatch costs is sufficiently large. The threat that the rival will tailor its product as closely as possible to each consumer's preferences may discipline firms and induce them to stick to uniform pricing.

4 Extensions

4.1 The mixed blessing of accessing a two-sided market

In this section, we modify the model to consider a two-sided market. One example of firms or platforms in this context is newspapers, which attract readers as well as advertisers. Another example is search engines, serving users and advertisers. Suppose firms have two sources of revenue; they charge users for their consumption, as in the main model. In addition, they charge advertisers for providing them with the users' attention. To keep

[16]This might change if the firms are ex ante asymmetric, e.g. with respect to initial data accumulation.

the framework simple, we assume that consumers are indifferent to ad levels. Hence, their utility is unaffected by the advertisement side of the market.

If firm i uses uniform pricing in the user market, it charges each user a subscription fee p_i. Further, as in Anderson et al. (2017a), we assume that the firm earns b per user in the advertising market. Its profit is therefore $\pi_i^{UP-R} = (p_i + b - c)D_i$.

First, suppose both firms use uniform pricing in the user market. Solving $\partial \pi_i^{UP-UP} / \partial p_i = 0$, $i = 1, 2$, we find

$$p_i = c - b + \frac{m_i + 2m_j}{3}.$$

Compared to the main model, the user price is in this case b units lower. This is because the possibility of selling the users' attention to advertisers intensifies firm rivalry to such an extent that they compete away advertising revenue. This so-called see-saw effect is well-known from the media economics literature (see e.g. Armstrong, 2006). Total profit for firm i is thus equal to

$$\pi_i^{UP-UP} = \frac{(m_i + 2m_j)^2}{9\,(m_i + m_j)},$$

which is the same expression as in the main model, cf. equation (10).

Assume instead that firm i uses personalized pricing in the user market. Since this requires relatively disaggregated market data, it is reasonable to assume that the firm has acquired (weakly) more information about each individual user than it would under uniform pricing. Such individualized information could be valuable for the firm when it approaches the advertising market. To capture this, assume that firm i which uses personalized pricing can charge an ad premium $\delta \geq 0$ for each user. The profit level of firm i is then $\pi_i^{PP-R} = (p_i(x) + b + \delta - c)D_i$.

In order to see the implications of the ad price premium, suppose that firm 1 uses personalized pricing, while firm 0 has committed to uniform pricing. A user located in x is now worth $p_1(x) + b + \delta - c$ to firm 1, which is δ units more than if it instead used uniform pricing. This hurts firm 0 in two ways. First, demand for good 0 falls, since the rival finds it profitable to capture more users with personalized pricing than with uniform pricing. More precisely, the location of firm 1's marginal consumer is now implicitly given by $p_1^{PP}(\tilde{x}) = c - b - \delta$, where $\tilde{x}$ evidently is decreasing in δ. Second, since firm 1 is now willing to offer its good at a price equal to $c - b - \delta$ to all consumers served by the rival, the perceived willingness to pay for good 0 falls (firm 0's demand curve shifts δ units downward). Firm 0's profit maximizing price is therefore strictly decreasing in δ. Formally, inserting for $p_1^{PP}(\tilde{x})$ into (2) and maximizing $\pi_0 = (p_0 + b - c)\, D_0^{UP-PP}$ with respect to p_0 yields

$$\tilde{x} = D_0^{UP-PP} = \frac{m_1 - \delta}{2\,(m_0 + m_1)} \text{ and } p_0^{UP-PP} = c - b + \frac{m_1 - \delta}{2}. \tag{23}$$

Note that firm 0 will have positive sales only if $m_1 > \delta$. To ensure that this is always the case, we assume that $\underline{m} > \delta$. From (23) we then find that the profit level of firm 0 equals

$$\pi_0^{UP-PP} = \frac{(m_1 - \delta)^2}{4\,(m_0 + m_1)}, \quad \frac{\partial \pi_0^{UP-PP}}{\partial \delta} = -\frac{1}{2}\frac{m_1 - \delta}{m_0 + m_1} < 0.$$

We derive firm 1's optimal price from equation (1) by setting $u_0 = u_1$. This yields $p_1(x) = c - b + \frac{m_1 - \delta}{2} + m_0 x - m_1 (1 - x)$. The fact that firm 0's optimal price falls when firm 1 uses personalized pricing forces firm 1 to reduce its price even towards consumers in its own turf. However, since firm 1 sells more and makes a higher profit per user the greater is δ, its profit level is nonetheless unambiguously increasing in δ :

$$\pi_1^{PP-UP} = \int_{\tilde{x}}^{1} \left((p_1(x) + b + \delta - c)\right) dx = \frac{(2m_0 + m_1 + \delta)^2}{8\,(m_0 + m_1)}. \tag{24}$$

Finally, it is straightforward to show that if both firms use personalized pricing, the see-saw effect once again implies that they compete away advertising revenue. Their profit level is thus the same as they would have been in the one-sided market, cf. equation (18):

$$\pi_i^{PP-PP} = \frac{m_j^2}{2\,(m_i + m_j)}.$$

As in the main model, each firm chooses to maximize mismatch costs ($\overline{m}$) if the rival uses uniform pricing and minimize mismatch costs ($\underline{m}$) if the rival uses personalized pricing. Profits can then be expressed as

$$\begin{aligned} \pi_i^{UP-UP} &= \frac{\overline{m}}{2}, \; \pi_i^{PP-PP} = \frac{\underline{m}}{4} \\ \pi_i^{UP-PP} &= \frac{(\overline{m} - \delta)^2}{4\,(\underline{m} + \overline{m})}, \; \pi_i^{PP-UP} = \frac{(2\underline{m} + \overline{m} + \delta)^2}{8\,(\underline{m} + \overline{m})}. \end{aligned} \tag{25}$$

From (25) it follows that $d\left(\pi_i^{UP-UP} - \pi_i^{PP-UP}\right)/d\delta < 0$ and $d\left(\pi_i^{UP-PP} - \pi_i^{PP-PP}\right)/d\delta < 0$. This implies that firm i is more incentivized to use personalized pricing the greater δ is. We can thus state:

Proposition 4: *Suppose that each firm has more individual reader data if it uses personalized pricing than if it uses uniform pricing in the user market. Suppose further that this generates a premium in the advertising market. The greater is the premium, the greater are each firm's individual incentives to use personalized pricing, which can lead them to end up in the low-profit equilibrium with personalized pricing.*

Profits are the same under a two-sided market and a one-sided market when firms use the same price policy due to the see-saw effect. However, the premium makes firms more incentivized to unilaterally adopt personalized pricing in a two-sided market compared to a one-sided market. Therefore, firms might prefer a one-sided market if a two-sided market induces switching to personalized pricing.

4.2 Location incentives

In this section, we extend the model to consider location incentives.[17] In relation to section 3.1, location is a non-price variable. As such, it is interesting to examine the insights from Proposition 1 on firms' location.

We assume that firm 0 uses personalized pricing and ask how its location incentives depend on firm 1's choice between uniform pricing and personalized pricing. A full-fledged location analysis will not be carried out.[18] Instead, we take firm 1's location as given and examine firm 0's location choice. We further set $m_0 = m_1 = m$ in order to hightlight the effects on location.

First, we find the profit expression for firm 0. Let firm 1 be located at $x_1 \in \left(\frac{1}{2}, 1\right]$ and firm 0 at some point x_0 to the left of firm 1, as shown in Figure 1.

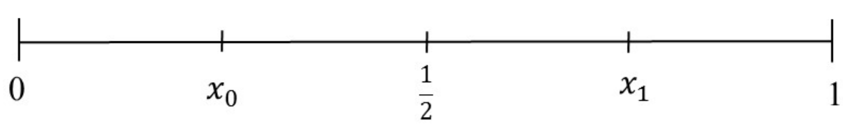

Figure 1: *Location incentives.*

[17] We now go back to the one-sided market context.

[18] Technically, the way we have modelled mismatch costs corresponds to linear transportation costs. It is well known that this is unsuited for analyzing endogenous location when firms use uniform pricing (see e.g. d'Aspremont et al., 1979).

The net utility of buying good 0 for a consumer located (weakly) to the right of x_0 is $u_0^{x\geq x_0}(x) = v - m(x - x_0) - p_0(x)$, while the net utility of buying good 1 for a consumer to the left of x_1 equals $u_1^{x\leq x_1}(x) = v - m(x_1 - x) - p_1(x)$. Using the fact that firm 0 charges $p_0^{PP}(x) = c$ from the consumer who is indifferent between good 0 and good 1, we find from $u_0^{x\geq x_0}(\tilde{x}) = u_1^{x\leq x_1}(\tilde{x})$ the demand facing firm 0

$$D_0 = \tilde{x} = \frac{x_0 + x_1}{2} + \frac{p_1(x) - c}{2m}.$$

Firm 0 maximizes profit by choosing $p_0(x)$ such that $u_0^{x\geq x_0} = u_1^{x\leq x_1}$ for all consumers between x_0 and $\tilde{x}$. This means that

$$p_0^{x\in[x_0,\tilde{x}]}(x) = p_1(x) + m(x_0 - x) - m(x - x_1) \text{ for } x \in [x_0, \tilde{x}]. \tag{26}$$

For consumers located between 0 and x_0 the net utility of buying good 0 is $u_0^{x<x_0} = v - m(x_0 - x) - p_0(x)$. In this area firm 0 optimally sets $p_0(x)$ such that $u_0^{x<x_0} = u_1^{x\leq x_1}$, yielding prices

$$p_0^{x\in[0,x_0]}(x) = p_1(x) - m(x_0 - x) - m(x - x_1) \text{ for } x \in [0, x_0].$$

Profit for firm 0 is thus

$$\pi_0^{PP-R} = \int_0^{x_0} \left(p_0^{x\in[0,x_0]}(x) - c\right) dx + \int_{x_0}^{\tilde{x}} \left(p_0^{x\in[x_0,\tilde{x}]}(x) - c\right) dx,$$

which can be rewritten as

$$\pi_0^{PP-R} = x_0(-c + p_1(x) + m(x_1 - x_0)) + \frac{(-c + p_1(x) + m(x_1 - x_0))^2}{4m}. \tag{27}$$

Suppose that firms compete in prices at stage 2, and that firm 0 chooses location at stage 1 (recall that we take firm $1'$s location as given). We solve the game through backward induction. After solving the the second stage problem, the first-order condition for stage 1 is given by (cf. section 3.1)

$$\frac{d\pi_0}{dx_0} = \frac{\partial\pi_0}{\partial x_0} + \frac{\partial\pi_0}{\partial p_1}\frac{dp_1}{dx_0} = 0. \tag{28}$$

From equation (27) we obtain

$$\frac{\partial\pi_0^{PP-R}}{\partial p_1} = \frac{-c + p_1(x) + m(x_0 + x_1)}{2m} > 0, \tag{29}$$

which is unambiguously positive since $p_1(x) \geq c$. We can now examine how the first-order condition of firm 0's location problem depends on firm 1's choice between uniform and personalized pricing.

If firm 1 uses personalized pricing, it will offer its good at a price equal to marginal cost for consumers located in $x \in [x_0, \tilde{x}]$. Inserting $p_1^{PP}(x) = c$ in equation (27) we then find

$$\pi_0^{PP-PP} = x_0 m (x_1 - x_0) + \frac{m (x_1 - x_0)^2}{4}. \tag{30}$$

Since $p_1^{PP}(x) = c$ in $x \in [0, \tilde{x}]$, firm 0 cannot affect the price that firm 1 charges consumers in this area, that is, $\frac{dp_1}{dx_0} = 0$. Therefore, the total derivative in equation (28) reduces to $\frac{d\pi_0}{dx_0} = \frac{\partial \pi_0}{\partial x_0}$. This resembles Proposition 1; only the market expansion (direct) effect of firm 0's choice of location on profit remains when firm 1 uses personalized pricing. From (30) we find

$$\frac{d\pi_0^{PP-PP}}{dx_0} = \frac{\partial \pi_0^{PP-PP}}{\partial x_0} = m (x_1 - 2x_0) - \frac{1}{2} m (x_1 - x_0) = \frac{m (x_1 - 3x_0)}{2}.$$

Consequently, solving (28) for firm 0's location yields $x_0^{PP-PP} = \frac{1}{3} x_1$.[19]

If instead firm 1 uses uniform pricing, it solves $p_1 = \arg\max \pi_1^{UP-PP}$, where $\pi_1^{UP-PP} = (p_1 - c)(1 - D_0)$. This gives the price

$$p_1 = \frac{2(c + m) - m (x_0 + x_1)}{2}. \tag{31}$$

Firm 0 faces relatively soft (potential) competition when firm 1 uses uniform pricing. Other things equal, the firm will therefore expand demand more if it locates closer to a rival using uniform pricing compared to a rival using personalized pricing. Therefore, we should expect firm 0 to locate closer to its rival when the rival uses uniform pricing. To confirm this, note that

$$\frac{\partial \pi_0^{PP-UP}}{\partial x_0} = \frac{-c + p_1 - 3mx_0 + mx_1}{2} = \frac{m (2 - 7x_0 + x_1)}{4}.$$

Since

$$\frac{\partial \pi_0^{PP-UP}}{\partial x_0} - \frac{\partial \pi_0^{PP-PP}}{\partial x_0} = \frac{m (2 - x_0 - x_1)}{4} > 0,$$

taking only the demand expansion effect into account thus indicates that $x_0^{PP-UP} > x_0^{PP-PP} = \frac{1}{3} x_1$.

[19] Due to symmetry ($x_0 = 1 - x_1$) the equilibrium location in this case would be $x_0 = \frac{1}{4}$ and $x_1 = \frac{3}{4}$. See also Bhaskar and To (2004).

However, from equation (31), $\frac{dp_1}{dx_0} = -\frac{1}{2}m$, hence one drawback of moving closer to firm 1 is that firm 1 will respond by setting a lower uniform price. Inserting for (31) into (29) we find that the strategic effect is equal to $\left(\frac{\partial \pi_0}{\partial p_1}\frac{dp_1}{dx_0}\right)^{PP-UP} = -\frac{(2+x_0+x_1)m}{8} < 0$, which encourages firm 0 to locate further away from the rival. Adding the demand expansion effect and the strategic effect yields

$$\frac{d\pi_0^{PP-UP}}{dx_0} = \frac{m\left(2 - 15x_0 + x_1\right)}{8}.$$

The first-order condition then implies that $x_0^{PP-UP} = \frac{1}{15}x_1 + \frac{2}{15}$. Since $x_0^{PP-UP} - x_0^{PP-PP} = -\frac{2(2x_1-1)}{15} < 0$, firm 0 will locate further away from firm 1 if firm 1 uses uniform pricing than if firm 1 uses personalized pricing. As an example, suppose that $x_1 = 0.75$. Then we would have $x_0 = 0.25$ if firm 1 use personalized pricing, while we would have $x_0 \approx 0.18$ if firm 1 uses uniform pricing.

One implication of personalized pricing by the rival on a firm's location incentives is therefore that the firm does not need to consider any strategic response from the rival following the firm's choice of location; only the market expansion effect on profit remains. In contrast, if the rival uses uniform pricing, the strategic effect induces the firm to differentiate more away from the rival in order to soften price competition. Hence, even though the firm considers a rival which uses uniform pricing as relatively soft compared to a rival which uses personalized pricing, it will nonetheless locate closer to a rival using personalized pricing since the rival will not respond by lowering prices. Since firm 0 by assumption uses personalized pricing, the result is purely driven by firm 1's choice of price policy. Consequently, if both firms use personalized pricing, they will locate relatively close to each other. This resembles Hurter and Lederer (1985), Lederer and hurter (1986) and Bhaskar and To (2004), who find that firms locate so as to minimize social costs. However, since they assume both firms use personalized pricing, they do not identify that the effect stems from the *rival* using personalized pricing, not *firms* using personalized pricing.

From Proposition 1, we then reach the following:

Corollary 1: *Suppose firms are symmetric ($m_0 = m_1 = m$). Then,*

(a) a firm will locate closer to a rival which uses personalized pricing compared to a rival which uses uniform pricing.

(b) if both firms use personalized pricing, they have incentives to locate relatively close to each other.

4.3 Multihoming consumers

Traditionally, consumers are restricted to buy at most one of the two goods that are offered in standard Hotelling models (which means that $D_0 + D_1 \leq 1$). We now relax this assumption by allowing consumers to buy one unit from each firm (multi-purchasing). We follow the concept of incremental pricing by Anderson et al. (2017b). The net utility of buying only good i is still given by equation (1), $u_i(x) = v - m_i |x - x_i| - p_i(x)$, while the value of buying good i in addition to good j (its incremental value) equals

$$u_{ji} = \theta \left[v - m_i |x - x_i|\right] - p_i(x), \tag{32}$$

where the parameter $\theta \in [0, 1]$. If $\theta < 1$, the incremental value of each good is smaller than its stand-alone value, for instance due to overlap in the goods' area of use.[20]

Let x_{10} denote the consumer who is indifferent between buying only good 1 and buying both goods. The location of this consumer is found by solving $u_1 = u_1 + u_{10}$. This yields

$$x_{10} = \frac{\theta v - p_0(x)}{\theta m_0}. \tag{33}$$

Note that x_{10} depends only on firm 0's price and mismatch cost, not on the rival's price and mismatch cost: The attractiveness of buying good 0 in addition to good 1 only hinges on the net utility offered by good 0.

The location of the consumer who is indifferent between buying only good 0 and buying both goods is likewise given by

$$x_{01} = 1 - \frac{\theta v - p_1(x)}{\theta m_1}. \tag{34}$$

We will analyze a market structure with partial multihoming. This means that some consumers buy both goods ($D_0 + D_1 > 1$), but none of the goods are sold to all consumers ($D_i < 1$). This market outcome is illustrated in Figure 2.[21] Demand for firm i's good and

[20] Foros, Kind and Wyndham (2018) provide an alternative utility formulation that illustrates that the outcome does not depend on consumers having a first and a second choice. However, their analysis does not consider personalized pricing and endogenous mismatch costs.

[21] Since the line has length 1, consumers located at $x < 1/2$ are closer to firm 1 and therefore have good 1 as their most preferable good. Likewise, consumers located at $x > 1/2$ are closer to firm 2 and have good 2 as their most preferable good. Hence, it follows that $\hat{x} = 1/2$. This implies that multihoming consumers to the left of $\hat{x}$ buy good 2 for its incremental value over good 1, while multihoming consumers to the right of $\hat{x}$ buy good 1 for its incremental value over good 2.

the distribution og singlehoming (SHC) and multihoming (MHC) consumers are (where x_i is firm i's location)

$$D_i = \underbrace{|x_{ij} - x_i|}_{\text{SHC}} + \underbrace{|x_{ji} - x_{ij}|}_{\text{MHC}} = |x_{ji} - x_i| \,. \tag{35}$$

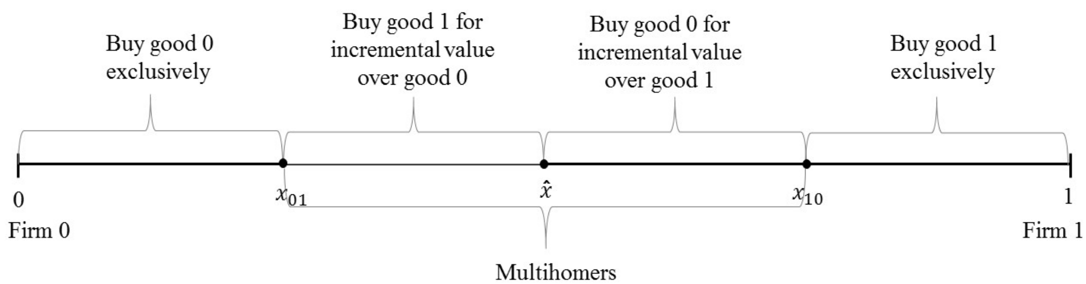

Figure 2: *Market outcome with partial multihoming.*

Hence, total demand for good 0 is $D_0 = x_{10}$, total demand for good 1 is $D_1 = 1 - x_{01}$, and the number of multihomers is given by $(x_{10} - x_{01})$.

Let us first consider the outcome when firm 0 uses uniform pricing.[22] Its profit level is then given by $\pi_0 = (p_0 - c)D_0$. Since $D_0 = x_{10}$ is independent of p_1 and m_1, the profit maximizing price and profitability of good 0 are independent of whether firm 1 uses uniform or personalized pricing:

$$p_0^{UP-R} = \frac{c + v\theta}{2} \tag{36}$$

$$\pi_0^{UP-R} = \frac{(v\theta - c)^2}{4\theta m_0}. \tag{37}$$

Inserting (36) into (33) we find that demand equals

$$D_0^{UP-R} = \frac{v\theta - c}{2\theta m_0}. \tag{38}$$

From (37) we note that firm 0 chooses to minimize own mismatch costs whatever the price policy of the rival.

[22] It is beyond the scope of the present paper to provide a complete analysis of possible singlehoming and multihoming equilibria and their stability; we limit our attention to consider candidate equilibria with partial multihoming. See the appendix in Anderson et al. (2017b) for a comprehensive analysis of deviation incentives.

Let us now assume that firm 0 uses personalized pricing. For reasons that become clear below, we assume that personalized pricing involves an extra marginal cost equal to $\phi > 0$. In equilibrium firm 0 then charges $p_0^{PP-R}(x) = v - m_0 x$ towards its exclusive (singlehoming) consumers, $p_0^{PP-R}(x) = \theta (v - m_0 x)$ towards multihoming consumers, and $p_0^{PP-R}(x) = c + \phi$ towards its marginal consumer (and those served by the rival). Thus, the smaller the mismatch costs are, the higher price can firm 0 charge each of its consumers.

Inserting that $p_0^{PP-R}(\tilde{x}) = c + \phi$ into equation (33) yields

$$D_0^{PP-R} = \frac{\theta v - (c + \phi)}{\theta m_0},$$

which shows that firm 0's total sales are decreasing in m_0. By reducing mismatch costs, the firm will therefore both be able to charge a higher price and sell more since the number of exclusive consumers for firm 0 is independent of m_0, cf. equation (34). Hence, also in this case, the firm minimizes its own mismatch costs independently of which price policy the rival uses. If firm 1 also uses personalized pricing, firm 0's equilibrium profit is

$$\begin{aligned} \pi_0^{PP-PP} &= \int_0^{x_{01}} (v - \underline{m}x - c - \phi)\, dx + \int_{x_{01}}^{x_{10}} (\theta (v - \underline{m}x) - c - \phi)\, dx \\ &= \frac{2(v - c - \phi) - \underline{m}x_{01}}{2} x_{01} + \frac{(2(v\theta - c - \phi) - \theta \underline{m}(x_{01} + x_{10}))}{2} (x_{10} - x_{01}), \end{aligned}$$

where $x_{10} = \frac{\theta v - (c+\phi)}{\theta \underline{m}}$ and $x_{01} = 1 - \frac{\theta v - (c+\phi)}{\theta \underline{m}}$.

From the above discussion, if consumers multihome, firms cannot affect the rival's price policy through its choice of mismatch costs. We can state:

Proposition 5: *Each firm will minimize mismatch costs, independently of which price policy the rival uses, if some consumers multihome.*

As noted above, x_{10} only depends on firm 0's price and mismatch cost, thus firm 0's total demand is independent of the rival's actions. On the other hand, since x_{01} only depends on firm 1's price and mismatch cost, firm 1 can by its actions affect firm 0's demand composition. Specifically, a reduction in m_1 expands firm 1's demand by turning some of firm 0's exclusive consumers into multihomers. If firm 0 uses uniform pricing, the demand composition does not matter for its profit since singlehomers and multihomers are charged the same price. However, if firm 0 uses personalized pricing, a reduction in m_1 hurts firm 0 because a multihomer is only worth θ of a singlehomer. Further, from Proposition 5, we know that firms are incentivized to minimize their mismatch costs independently of what the rival does. We then reach the following:

Corollary 2: *Assume some, but not all, consumers are multihoming. If firm i uses uniform pricing, it is not affected by the rival's choice of uniform pricing or personalized pricing. In contrast, if firm i uses personalized pricing, it is better off if the rival uses uniform pricing.*

Note that the ratio of total demand under uniform pricing and personalized pricing is

$$\frac{D^{PP-PP}}{D^{UP-UP}} = 2(1 - \frac{\phi}{v\theta - c}).$$

If $\phi = 0$, the demand is twice a large under personalized pricing than under uniform pricing, which means that the market is not covered under uniform pricing.[23] Therefore, we assume an extra marginal cost $\phi > 0$ under personalized pricing to avoid this issue.

5 Concluding remarks

In a duopoly model, we examine how a firm's incentives to reduce its mismatch cost depends on its own and on its rival's choice between uniform pricing and personalized pricing. While a rival which uses personalized pricing will not strategically respond to a firm's decisions on its mismatch cost, a rival using uniform pricing will respond aggressively by reducing its price if the firm lowers its mismatch cost. Therefore, firms' incentives to change their mismatch cost depend only on the rival's choice between uniform and personalized pricing. Firms might commit to uniform pricing in order to avoid an aggressive response from the rival in lowering its mismatch cost, which is detrimental for the firm's profit since it loses market shares.

We let firms endogenously decide whether to commit to uniform pricing as well as the level of the non-price variable prior to the price competition stage. These assumptions allow us to examine the relationship between price policy commitments by either firm and strategic commitments in the non-price variable. As non-price variables we consider the mismatch cost in our main model and location incentives in an extension.

[23] Partial multihoming implies that the total demand is strictly less than 2.

Therefore, we also contribute to the literature on personalized pricing by examining how non-price commitments in general depend on the commitment to a uniform price policy. It has been pointed out in previous works that a firm which uses personalized pricing optimally sets price equal to marginal cost in the rival's market region (Lederer and Hurter, 1986; Thisse and Vives, 1988). Given that the choice of the non-price variable is observable prior to the price competition stage, this means that the strategic effect of a firm's choice of non-price commitment in stage 2 ceases to exist if it faces a rival which uses personalized pricing. We show that it is not price discrimination in itself that removes strategic effects of non-price commitments, it is price discrimination by the rival, and the rival only, that drives the result. The choice of whether to commit to uniform pricing in stage 1 can therefore be seen as a choice of whether to give the rival strategic incentives to undertake non-price commitments in stage 2. To our knowledge, this has not yet been highlighted in the previous literature.

Our analysis highlights one potential force which may incentivize firms to continue using uniform pricing as the pricing standard even when they are capable of practicing personalized pricing. Due to rapid developments in machine learning and data collection technologies, which improve firms' capability of practicing personalized pricing as well as offering tailored products, both personalized pricing and product tailoring have been devoted great attention recently from the media (e.g. Forbes, 2014) as well as from the academic literature (e.g. Esteves, 2010; Valletti and Wu, 2016; Prüfer and Schottmüller, 2017). Our results can help explain why firms are slower to adapt personalized pricing than one would expect, despite that they have the technology and information to do so.

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Chapter 2

Price Coordination with Prior Announcements in Retail Gasoline Markets*

Mai Nguyen-Ones†

Abstract

This paper examines how price coordination, and importantly, coordination on price restorations, is carried out in retail gasoline markets. In the studied market, one firm breaches a fourteen-year lasting regular price cycle overnight by publicly announcing a change to its retail price policy. Prior to the announcement, the regular cycle occurred across brands and all over the country. I show that the recommended price of this particular company, which is publicly available on the company's website, serves two functions for its network of retail stations. First, it determines the price restoration level. Second, it serves as a signal of *when* to implement a restoration day: Every time this company announces an adjustment to the recommended price in the early morning, price restoration is implemented the following forenoon. I further show that other companies are following the new practice as well. Hence, a new way to coordinate on prices and synchronize price restorations inter-brand and across local markets has emerged, using prior announcements of the price leader's recommended price as a signaling device.

Keywords: Price coordination, price leadership, prior announcements, retail gasoline markets

JEL Codes: D22, D43, L11, L13

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1 Introduction

Overnight, the largest firm of an oligopoly of four breaches a fourteen year-long regular nationwide price cycle by publicly announcing a change to its retail price policy. Prior to the announcement, this market experienced inter-brand retail price restorations with one single large jump on fixed days of the week. Immediately after, nationwide price restorations no longer occur on specific days of the week, yet arise frequently and systematically all over the country. Figure 1 plots the occurrence of restoration days by day of the week over a one-year period for one sample station. The change in restoration behavior shows well: To the left of the dashed vertical line, which marks the date of the policy announcement, restoration occurs systematically on Mondays and Thursdays. Following the policy announcement, price no longer rises on specific days of the week.

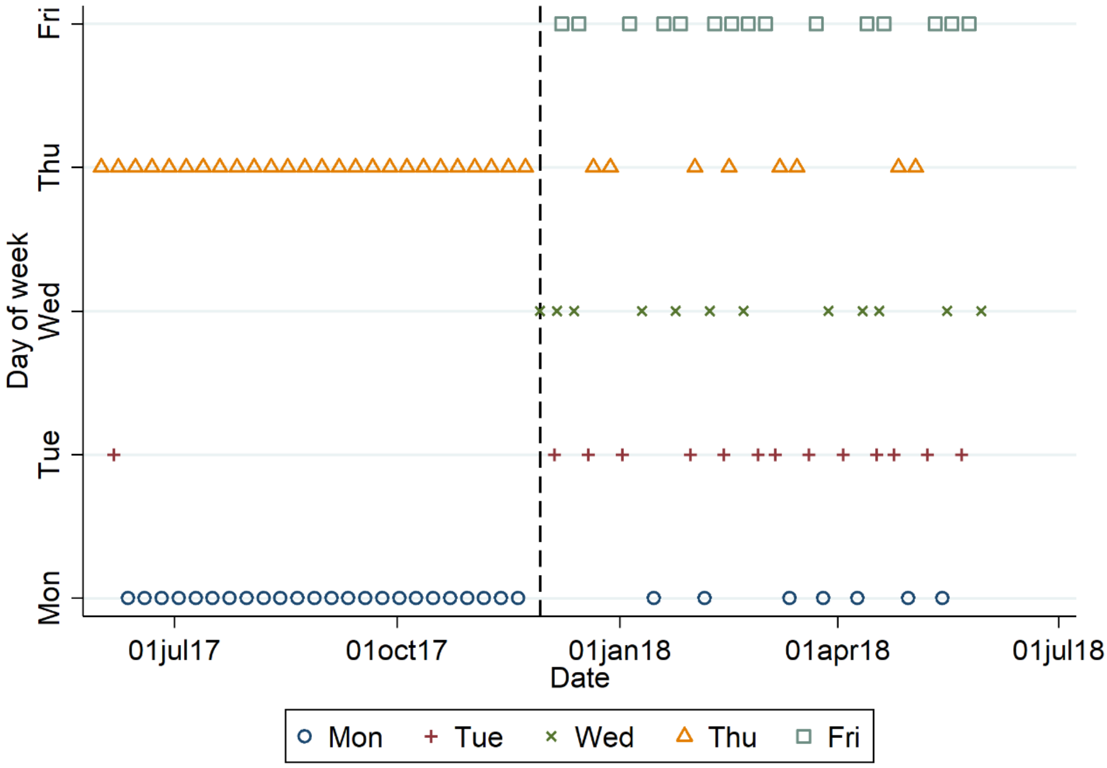


Figure 1: Occurrence of restoration days by day of the week over time for one sample station. Days of the week are measured on the y-axis and have different point markers. Sample period is 1 June 2017 to 31 May 2018. Dashed vertical line marks the date of the policy announcement (29 November 2017).

Following the price policy change, how is a new shared view on price coordination facilitated? How is when to restore prices, and to which level to restore prices, determined? Is a nationwide intra-brand and inter-brand coordination, if any, achieved? These are the main questions addressed in this study.

Specifically, I analyze how price coordination, and importantly, coordination on price restorations, is carried out in retail gasoline markets. One firm acts as a price leader by giving sign of when to restore prices and at which level to restore prices to, with use of one single signaling device. This adds to the understanding of how a new shared view to coordinate on prices can emerge in a market. The research context has one clear advantage: The policy change occurred very recently, which has enabled direct observations and discovery of changes that have occurred in the market from the very beginning.

The subject of study is the Norwegian retail gasoline industry. On 29 November 2017, the largest company in the market announces a price policy change on its websites, with the aim to have less fluctuating prices throughout the week. The company reasons the change with a survey it had carried out revealing that customers prefer to have more stable prices during the week in order to purchase gasoline whenever it suits them. One specific action the company carried out to achieve its goal of less fluctuating prices is to cut its recommended price[1] with approximately twelve cents and as such decrease the maximum retail price with the same amount. Other than this, no more information are provided as to why, how or specific aspects of the new policy. Further, nothing else of particular interest for the industry has occurred during the same time period which could explain a policy change.[2]

I address the questions by examining three datasets, each with different attributes well-suited to increase the understanding how a mutual view on how to coordinate on price can be facilitated. As the policy change occurred very recently, I was able to directly discover changes that have arrived in the market from the very beginning. In turn, this led to a data collection directly aimed to answer the questions addressed in the study. I use the first source of data to scrutinize the signaling device. The second source is used to uncover the systematic intra-brand coordination of the largest company. This data is in hourly frequency, which opens up for examination of the exact timing of price restorations as well as the exact level for which prices jump to. As prices can be quickly undercut after restoration due to local competition, hourly data does not overlook any of these changes. Hence, it contains the finest restoration and cycle details and enables thorough investigation of the coordination process after the policy change. Finally, the third source is utilized to uncover the inter-brand coordination and the nationwide implementation of the new policy. All three sources cover the calendar date of the price policy change, allowing for close examination of the pre-period leading up to this date as well as the post-period following the price policy announcement.

I find that the recommended price of the largest company, which is publicly available on the company's website, serves two functions. First, it determines the level of the price restoration, which also is the case prior to the price policy change. Second, and unique for the post-policy period, it serves as a signal of *when* to implement a restoration day: Every time the largest company announces an adjustment to the recommended price in the early morning, prices of its stations restore between 9 a.m. and noon the same day. In the pre-policy period, restorations occurred regularly on specific days of the week. Now, the practice has changed such that price restoration is implemented every time the largest company adjusts its recommended price. Hence, prior announcements of the recommended price is used as a signaling device to coordinate on retail prices. I find that price restoration is initiated highly systematically intra-brand across different local markets. Further, I show that other companies have adapted to the new practice. Hence, a new way to coordinate on prices and synchronize price restorations inter-brand and across local markets has emerged. The largest company, by

[1]Most companies post the recommended price online. According to companies' information, the recommended price is a "correct" price when costs and taxes are taken into account.

[2] I did a search in newspapers to look for events occurring around the same time, however, did not find any happenings that could be in relation to the policy change.

being a price leader with use of its recommended price as a signaling device, seems to have succeeded in introducing a new nationwide price restoration rule to the market.

Systematic use of retail prices to facilitate coordination is examined empirically in among others Noel (2007), Atkinson (2009), Wang (2009), Lewis (2012) and Byrne and de Roos (2017), who uncover regular behavior of retail prices also identified in this study. However, to the best of my knowledge, this is the first study to show that prior announcements of the recommended price of a company is used systematically as a signaling device to establish the time of a price restoration in addition to the level of a price restoration. Moreover, this paper departs from previous literature in one important way: Being aware of the change of practice from the very beginning, I made personal observations and discoveries in real-time that led me to collect data specifically targeting to answer the problem at hand. I believe this advantage enabled me to recognize small details introduced to the market that turned out to be crucial in understanding the evolvement of creating a new common view on price coordination.

The rest of the paper proceeds as follows. Section 2 describes the market and the motivation for this study. Section 3 reviews related literature. In Section 4, the data is presented. Section 5 presents the empirical analysis. Finally, Section 6 concludes.

2 Market characteristics and price behavior

There are four major nationwide gasoline companies operating at the retail level in Norway. These are Circle K Norway (market share of gasoline 32.3% in 2015), St1 Holding Oy (24.3%), Esso Norway (20.8%), and Uno-X Norway (17.8%) (Drivkraft Norge, 2017a).[3] All of them run both serviced and self-serviced stations. Circle K operates the brands Circle K and 1-2-3 (self-serviced brand), St1 runs Shell and St1 (self-serviced), Esso runs the brand Esso (both serviced and self-serviced), while Uno-X operates the brands YX and Uno-X (self-serviced). The remaining market is covered by smaller chains, among others Best, Bunker Oil and Tanken. The nationwide companies operate fully integrated as well as vertically separated stations.[4] Vertically separated stations have long-term contracts with the upstream company regarding delivery of gasoline. In principle, these outlets determine the retail price independently from the upstream company. However, the vertical restraints that are imposed on the profit sharing arrangement between the stations and the upstream company can in reality shift the price decision to the upstream firm instead (Foros and Steen, 2013).

Circle K, St1 and Uno-X publish recommended prices (excluding transport costs) on their websites.[5] These prices serve, according to the companies, to reflect the correct retail price when the wholesale price, taxes and other factors considered as relevant are taken into account. When a price restoration is implemented, retail prices restore by a large amount to the level on the recommended price (Foros et al., 2018).

For fourteen years, starting in 2004, there has been a regular price cycle in the Norwegian market with nationwide inter-brand price restorations every Monday around noon (Competition Authority, 2014). From 2008, another restoration day on Thursdays is introduced. Between

[3] St1 Holding Oy performed an acquisition of Shell Norway's retail stations in 2015.

[4] In 2016, the major companies had in total 1697 stations. Of them, 1023 were vertically company-owned stations while the remaining were dealer-owned (Drivkraft Norge, 2017b).

[5] St1 publishes recommended prices only for the corporate market.

restorations, prices are gradually undercut over subsequent periods.[6] The weekly cycle is hence characterized by a saw-toothed pattern with an abrupt price jump every Monday and Thursday. Foros and Steen (2013) show that this predictable pattern is caused by a profit sharing scheme between the upstream companies and the downstream stations involving a maximum resale price maintenance (RPM) and price support. The price support of varying size enables stations to compete by undercutting prices, but whenever it is withdrawn, stations must increase their prices to the maximum RPM, which is set to the level of the recommended price, to not sell with a loss. Thus, inter-brand coordination of retail prices is obtained when all companies withdraw the price support simultaneously.

On 29 November 2017, Circle K (2017) announces on its website that it will from this date cut its recommended price with 1 NOK, with the aim to have less fluctuating prices throughout the week. The (claimed) background for this is a survey the company had carried out, showing that their customers prefer to purchase gasoline when it suits them the most, rather than on Sunday and Monday morning when prices are at their lowest under the predictable cycle. By decreasing the recommended price with 1 NOK, Circle K essentially cuts the maximum retail price with the same amount.

From this day, with Circle K's announcement of a price policy change, the fourteen-year lasting predictable weekly cycle with price restoration every Monday and Thursday ended overnight.

2.1 Motivation based on direct observations

When I became aware of Circle K's announcement of a price policy change, I started to follow prices on two stations in Bergen in the morning and in the afternoon, one Circle K station and one Shell station, respectively.[7] I was familiar with these stations' previous price setting behavior as I also had collected prices from them on an earlier occasion. In addition, I collected the recommended prices for the private market available for two of the companies, Circle K and Uno-X. Soon after, I noticed that the two stations still had restored prices in the afternoon on the same day to approximately the same level. The Circle K station I followed set its restoration price to the recommended price plus a fixed transportation cost. The Shell station restored its price to approximately the same level. Except that prices no longer jumped every Monday and Thursday, things seemed familiar: prices restore to the level of the recommended price, and there are signs of inter-brand coordination.

However, after observing prices for a few weeks, I noticed that price restoration occurred earlier during the day than before the policy change: Already around 10 a.m., prices at the Circle K station had jumped to the restoration level. By 12 p.m., it had restored at the Shell-station as well. From past experience, I expected the recommended price to be adjusted approximately once per week with around 0.10 NOK in either direction. Now, I observed that changes were made more frequently. Moreover, adjustments were much smaller in magnitude. Also, there was more information regarding the recommended price on Circle K's website than I recalled

[6] Prices of stations are announced on large signs outside stations. Each station monitors the neighbor stations and report prices to the headquarter (Competition Authority, 2014).

[7] I followed the Circle K station every day, while the Shell station I checked a couple of times during the week.

to have seen earlier. In particular, it now informed that the recommended price is in force from 10 a.m. on the stated date.

So I started to check when during the day the recommended price was adjusted by updating the websites of Circle K and Uno-X several times in the morning. On days when it was updated, Circle K was always first out with changing the recommended price between 7:45 a.m. and 8 a.m. Whenever Circle K adjusted it, Uno-X did accordingly around one to two hours later, always before 10 a.m. Uno-X did not adjust its recommended price if Circle K did not do it. It seemed as if Uno-X followed Circle K on the recommended price, not only regarding which days to adjust it, but also regarding the level: Uno-X’s prices were always set 0.02 NOK above Circle K’s prices, both for gasoline and diesel.

I also came to notice that *every* time Circle K’s recommended price was adjusted, prices of the two stations I followed restored to the new recommended price within the same day. Of curiosity, I once looked at the price sign of the Circle K station right before 10 a.m. and noticed the retail price changed at 10 a.m. sharp. The next time the recommended price was adjusted in the morning, I did the same. Again, the retail price changed exactly at 10 a.m. So a colleague checked another Circle K station at the same time as I was checking the station I already followed. Price restored exactly at 10 a.m. for both of the stations.[8] According to the Norwegian company registry, one of the Circle K stations is company-owned, the other one is dealer-owned or franchise-owned. Still, these two stations systematically restored prices simultaneously at exactly 10 a.m. As dealer-owned stations determine their own retail prices in principle (Shepard, 1993), this seemed too much of a coincidence. We started to do the same for an Esso-station nearby one day Circle K’s recommended price was adjusted in the morning. Also this one restored its price exactly at 10 a.m., indicating strong inter-brand coordination after the policy change as well.

Questioning whether this is a local market phenomenon or whether this is a nationwide practice, I therefore accessed a gasoline application in Norway where users can report prices from all over the country in real-time.[9] Following this application, I saw the same behavior of stations from all over the country.

These observations are the motivation behind the data collection I have made, which is well suited to formally investigate the factors I spotted by direct observation. The following analysis’ aim is to provide a better understanding of the role of the recommended price as a signaling the device, the intra-brand coordination within the network of Circle K’s stations, the inter-brand coordination among the companies, as well as the new price policy as a nationwide practice.

3 Literature review

Public announcements of price policy changes have taken place prior to this one. Andreoli-Versbach and Franck (2015) describe a similar event to the new policy change in Norway

[8] At some occasions, the two Circle K stations restored prices at 10:10 a.m. simultaneously. The point here is not that prices restore at 10 a.m. sharp as such, but rather the systematic coordination of this restoration. That said, it is quite peculiar to see prices jump exactly at 10 a.m. based on an indication from the website that the recommended price of the posted date applies from this time.

[9] This application is called “BensinPris” (“GasolinePrice”).

happening in the Italian market, however, the new price policy differs from the Norwegian case. On 6 October 2004, the market leader publicly announced its commitment to a sticky-pricing policy, with larger single price adjustments when price is adjusted. The authors show that the average time lag between price adjustments increased from six to twenty days and the absolute average price change increased from 1% to 5.4% for the market leader with the new price policy. The market leader which initiated the policy change also coordinated price changes in the market, as the other companies followed this new price policy. This is somewhat similar to the Norwegian case, except I only identify the initiator of the new price policy as the leader or coordinator of price restorations.

The way Circle K uses the recommended price as well as retail prices at its stations to signal and potentially coordinate with rivals relates to findings in Byrne and de Roos' (2017a). They show that one firm in the Australian market uses retail prices to communicate and facilitate a mutual understanding among rivals to transit to a new price equilibrium. Further, the authors argue that since prices are highly transparent and easy to adjust and experiment with, prices have great communicative power. Thus, explicit communication is not necessary to establish a collusive strategy. As other companies seem to have abandoned the regular time-dependent price cycle in favor of Circle K's price policy, Circle K has succeeded in using recommended prices and retail prices to signal a new price behavior to its competitors. However, one difference from Byrne and de Roos' (2017a) case is that prior announcements of the recommended price is used as a signaling device to coordinate on retail prices, together with a simultaneous intra-brand price jump by Circle K as an additional signal, rather than only using the retail price itself.

The theoretical literature distinguishes between three types of price leadership: dominant, barometric and collusive. Dominant leadership occurs when a large firm decides prices and smaller fringe firms follow by adjusting their prices accordingly (e.g. Deneckere and Kovenock, 1992). On the other hand, under barometric leadership, one firm has more information than others, thus other firms change prices whenever the better informed firm does so (e.g. Cooper, 1997). The more informed firm has no power to impact prices of other firms, rather, its price serves a pure informative role. The last category involves price leadership as a way of facilitating tacit collusion (e.g. Markham, 1951; Rotemberg and Saloner, 1990; Mouraviev and Rey, 2011; Harrington, 2017). Testing and categorizing which category the Norwegian case best fits into is difficult without high-frequency price observations of all companies in the market. Nonetheless, some general points can be made. Circle K's public announcement of a new price policy was an announcement not only to the public, but also, and arguably primarily, to its competitors in an attempt to establish a new industry-wide practice of price setting and underline its own commitment to it. Everything points to Circle K's attempt being highly successful, as evidence from data as well as direct observations suggest the other companies are following Circle K's price restorations closely. Circle K signals a price restoration day by changing its recommended price, hence it is a price leader in the sense of determining when prices are restored, and other companies are followers in the sense that they accept these days to be restoration days by initiating restorations of prices at their stations as well. Although it is the largest company in the industry, it is not sufficiently large to fit into the category of dominant leadership, hence the other three companies are unlikely to take Circle K's price as given. On the other hand, whether intentionally or not, the new practice probably serves as a common understanding on how to coordinate on prices.

Several papers empirically address price coordination and whether there is one or more firms taking the role as a price leader. Lewis (2012) documents for markets in the Midwestern U.S. that one particular retail chain behaves like a price leader in each city, signaling price restoration to rivals by simultaneously increasing prices at all its stations to the same level. Further, the same firm often initiates restoration in several different local markets simultaneously to further strengthen the signal. This is quite similar to what I find is Circle K's role in the Norwegian market. Each morning of a new restoration day, the company signals a start of a restoration to competitors by adjusting the recommended price online. Few hours later, retail prices at its stations jump up to the same level, which is the recommended price, throughout the country, no matter which level prices are at right before the price jump. Wang (2009), looking at the market of Perth, Australia, also documents that one large firm initiates price restoration in the Australian market before the introduction of a law which allows firms only to change price once a day and simultaneously. After the law is set in force, three firms are identified as price leaders. Atkinson (2009), studying the market in Guelph, Canada, finds that five stations, all of them major brand stations, often increase their prices first during restorations. On the other hand, Noel (2007) does not find one single firm which frequently initiates price restorations in the Toronto market, however, large integrated firms are more likely to initiate restorations for its stations than independent stations. The finest data granularity used in these studies are 12-hourly observations (Noel, 2007) or bi-hourly observations (Atkinson, 2009; Lewis, 2012). One of the datasets in use in this study contains hourly observations from four different cities. Especially in fine cycles where prices often are undercut quickly after restoration due to local competition, data of such a high frequency open up for thorough examination of price behavior, especially related to the timing and level of restoration, which may be ignored with infrequent data.

This study also relates to the literature on price cycles. Cyclical prices are observed in several retail gasoline markets in Canada (e.g. Eckert, 2003; Eckert and West, 2006; Atkinson, 2009; Noel, 2007), the U.S. (e.g. Doyle et al., 2010; Lewis, 2012), Australia (e.g. Wang, 2009) and European markets (e.g. Germany: Haucap et al., 2015; Austria: Dewenter and Heimeshoff, 2017). The saw-tooth pattern in retail prices is often associated with Edgeworth cycles by Maskin and Tirole (1988). In this price cycle, two homogenous firms undercut each other's prices by small amounts in an alternating move game.[10] Prices eventually get close to costs such that one firm must increase prices in a single large jump. The other firm then follows, and the cycle repeats itself. Support for the existence of Edgeworth cycles is found in among others the U.S. (Lewis, 2012), Canada (Noel, 2007) and Australia (Wang, 2009). Some predictions of Edgeworth cycles fit well to the Norwegian case. First, prices make one single jump by a large amount during restoration, while they decrease by smaller amounts several times during the undercutting phase. Second, retail prices fluctuate even if the wholesale price does not. These observations are in line with theory. On the other hand, the underlying factors which trigger restoration is not as clearly in line with this phenomenon. Before the policy change, specific

[10] Eckert (2003) extends the model to allow for asymmetric firm size, while Noel (2008) opens up for different kinds of asymmetric equilibria.

days of the week triggered price restoration. As such, price behavior in the pre-period is inconsistent to the theory, which predicts that restoration occurs when price is competed down to marginal costs. After the policy change, price restoration is initiated whenever Circle K adjusts its recommended price. At this point, what triggers Circle K to signal price restoration remains unknown. The war of attrition-phase predicted by theory causes companies to take turn in carrying forward the burden of restoring prices first. However, the same company initiates price jumps every time in this market, which is one argument against the existence of Edgeworth cycles.[11]

Finally, this paper relates to other studies on the Norwegian market. Prior to this study, two papers have examined the Norwegian market in addition to market reports by the Competition Authority. Foros and Steen (2013), using station-specific prices from 2003 to 2006, establish a nationwide weekly cycle in prices with price restorations every Monday followed by smaller price decreases throughout the rest of the week. Moreover, based on interviews with 35 retail outlet managers, they describe how the gasoline companies control retail prices on independent stations with use of a vertical restraint involving price support and an RPM, similar to findings from the Australian market (Wang, 2009). Stations receive price support which enable them to compete by undercutting prices, but whenever it is withdrawn, they must increase their prices to the maximum RPM, which is essentially the recommended price, to not sell with a loss. As such, the upstream companies control retail prices of their stations independently of contract form. Thus, a price restoration is implemented when all companies withdraw the price support simultaneously. While the authors mark the start of the weekly cycle after the Easter of 2004, what caused this shift remains unknown. On the other hand, I show in detail how the new pattern is announced and implemented in late 2017. Foros et al. (2018), with use of station-specific prices from 2004 to 2015, find that an additional weekly restoration on Thursdays is introduced to the cycle. Moreover, they show that the additional restoration day increases firms' profitability significantly.

4 Data

This paper makes use of three datasets, each with different attributes in order to better understand the problem at hand. The first is a daily time series of the wholesale price of conventional gasoline and the recommended price by the largest company in the market, spanning from 1 January 2013 to 31 May 2018 (referred to as time series data).[12] I use this data to examine the relationship between the underlying cost and the posted recommended price. Further, I use it to study how the recommended price has evolved over time in terms of level and frequency, and how it serves as a signaling device to facilitate a common view of coordination on retail prices.

[11] I do not identify any price in the station panel which would give a negative gross margin, which goes against the possible reason of price restoration due to prices which have been competed down to the cost level. Note that this panel includes one station from a local market known for having the most aggressive price competition in the country. Even for this station, gross margins are always positive after the policy change.

[12] The wholesale price is the gasoline regular unleaded 10 ppm Amsterdam-Rotterdam-Antwerp (ARA) series listed in US dollar/metric ton, converted into NOK/liter.

The second source contains station-specific retail gasoline prices, spanning from 1 January 2017 to 28 February 2018. Prices are reported by users of a cellphone application called "BensinPris" ("GasolinePrice") and cover stations throughout the country, including all major cities (referred to as user-reported data).[13] Every price report contains information about time and date of the observed price, station name, station brand and address. The sample consists of 106 361 observations from 630 different stations, covering the four largest brands as well as minor brands. I use this information to establish that the change in the market is nationwide and applied inter-brand, and to show that there are signs of price leadership.

The last dataset consists of station-specific prices from four Circle K stations located in four different cities (first to fourth largest) (referred to as station panel). All of these stations operate under the brand of the largest company in Norway. The data period is 1 June 2017 to 31 May 2018, covering six months with the old price regime and six months with the new one. Prices are reported each hour, and the reported price is the lowest one which is set within the current transaction hour. This data source is useful for studying the implementation of the new price setting regime in detail, and specifically, whether there is any systematic regularity in how price restoration is determined intra-brand, and whether price setting is different than previous to the new price setting regime announced. It also allows for detailed examination of the distribution of prices before and after the implementation of the new price regime, as well as fine details of how prices evolve during a typical cycle.[14]

The commodity of interest is unleaded 95-octane gasoline.[15] Prices addressed in the analysis are in NOK per liter, unless otherwise is stated.[16]

5 Empirical analysis

5.1 The recommended price: A coordination device

In the following, I examine how Circle K can use the recommended price as a signaling device to coordinate the price restoration *level* as well as the *timing* of price restoration. Figure 2 plots the recommended price and the wholesale price of conventional gasoline over a five and a half year period. As expected, the recommended price of Circle K follows the wholesale price closely in the long run, suggesting that the recommended price eventually is set according to costs.

To study the frequency of adjustments in the recommended price, I count the number of times Circle K changes its recommended price during the sample period. The number of changes per year is reported in Table 1. On average, the recommended price changes 50 times

[13] User-reported data are also applied by e.g. Eckert and West (2003), Lewis and Marvel (2011) and Byrne and de Roos (2017b). Atkinson (2008) studies potential sample selection bias in these kind of data by comparing user-reported price data with price data collected by direct observations. He concludes that user-reported data is reliable for addressing questions regarding daily prices of major brand station prices. In addition, I feel confident in using the user-reported data as the predictable cycle in the pre-policy period is well established in this data, which gives credibility to the dataset also in the post-policy period.

[14] Time series data are partly accessed through Datastream and partly provided by Circle K. User-reported data are provided by Bit Factory, the developers of the application "BensinPris". Station panel data are provided by Circle K.

[15] Similar patterns are observed for diesel.

[16] 1 USD≈8 NOK in 2018-figures.

each year from 2013 to 2016, which counts for approximately once per week. Taking a closer look at 2017, the year in which the new price policy is implemented, the recommended price changed nineteen times from the beginning of the year to 28 November. In comparison, from 29 November and to the end of the year, the recommended price changed nine times. Hence, during the one month period right after Circle K's announcement of a price policy change, the recommended price was adjusted half as many times as it did in total the eleven months before the price policy change. Even more interesting, during the first six months of 2018, the company changed its recommended price approximately as many times as during a whole year for the previous years (on average 1.69 times a week).

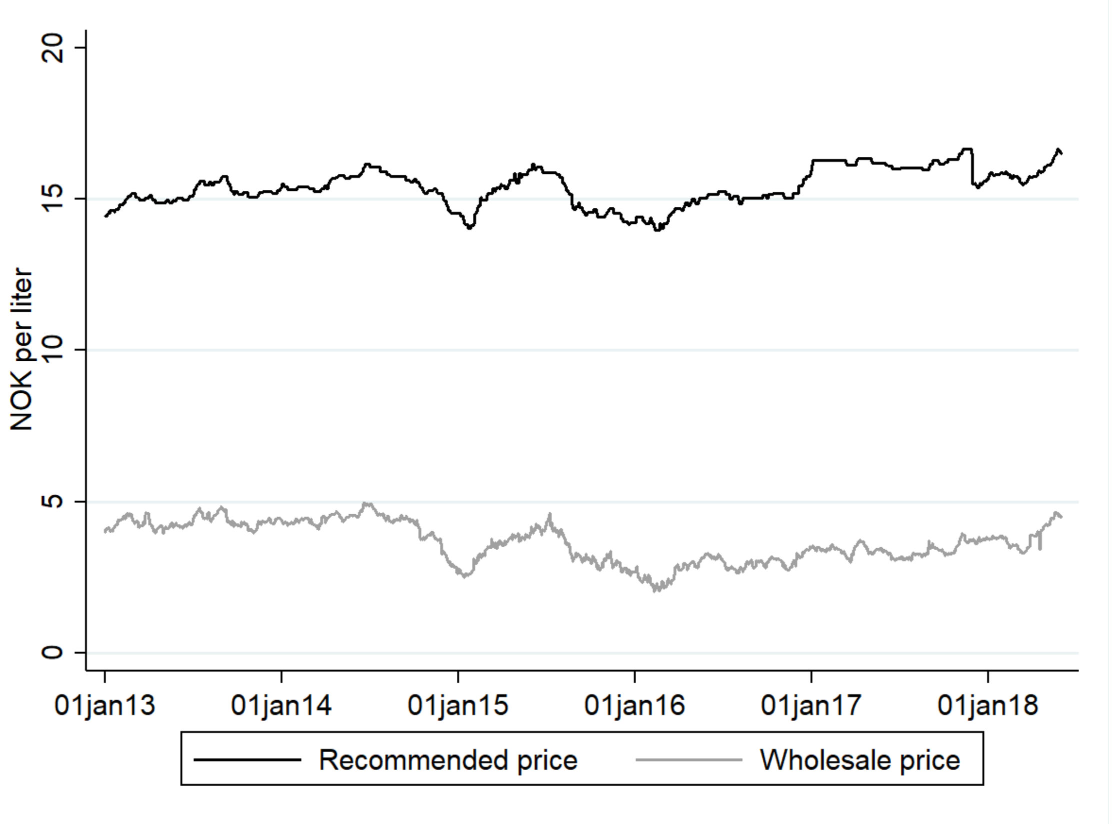


Figure 2: Recommended price of Circle K and wholesale price over time. Sample period is 1 January 2013 to 31 May 2018.

To further evaluate the recommended price, I look at the level of changes. I take the first difference in the recommended price , $\Delta rp_t = rp_t - rp_{t-1}$, where t indexes day. If $\Delta rp_t = 0$, then there are two consecutive days with no adjustment in the recommended price. Since interest lies in days where the price actually changes, I drop all observations for which $\Delta rp_t = 0$. I also examine the absolute value of Δrp_t in order to avoid positive and negative changes cancelling out each other. Table 2 reports summary statistics for Δrp_t and $|\Delta rp_t|$. Of particular interest here is the mode, which is 0.1 NOK or -0.1 NOK for all years except for 2018, where the mode is -0.02 NOK. In absolute terms, the mode this year is one fifth of the mode of all other years. This suggests that the recommended price is adjusted by much less in magnitude in 2018 compared to the other years.[17]

Table 1: Number of times recommended price of Circle K has changed by year and day of week. Sample period is 1 January 2013 to 31 May 2018.

	2013	2014	2015	2016	2017	2018
Mon	15	15	15	8	8	7
Tue	6	5	10	5	2	10
Wed	12	8	14	9	7	9
Thu	6	9	15	10	4	5
Fri	15	6	8	8	7	13
Sat	1	0	0	0	0	0
Sun	1	0	0	0	0	0
Sum	56	43	62	40	28	44

Table 2: Summary statistics of Δrp_t and $|\Delta rp_t|$. Sample period is 1 January 2013 to 31 May 2018.

	Mean	Median	Mode	Std.dev.	Min	Max
2013						
Δrp_t	0.016	0.050	0.100	0.091	-0.150	0.150
$\|\Delta rp_t\|$	0.088	0.100	0.100	0.029	0.050	0.150
2014						
Δrp_t	-0.020	-0.080	-0.100	0.097	-0.150	0.150
$\|\Delta rp_t\|$	0.094	0.100	0.100	0.024	0.050	0.150
2015						
Δrp_t	-0.005	-0.050	-0.100	0.140	-0.300	0.300
$\|\Delta rp_t\|$	0.128	0.100	0.100	0.055	0.050	0.300
2016						
Δrp_t	0.043	0.100	0.100	0.137	-0.250	0.250
$\|\Delta rp_t\|$	0.134	0.120	0.100	0.049	0.050	0.250
2017						
Δrp_t	-0.011	0.050	0.100	0.227	-1.000	0.340
$\|\Delta rp_t\|$	0.136	0.100	0.100	0.180	0.050	1.000
2018						
Δrp_t	0.020	0.020	-0.020	0.074	-0.120	0.200
$\|\Delta rp_t\|$	0.060	0.045	0.020	0.047	0.010	0.200

Hence, two changes seem to have been introduced to the recommended price along with the introduction of the new pricing policy. First, the recommended price is adjusted almost twice as frequently compared to the pre-policy periods. Second, the size of each change is on average much smaller. Both changes enable the recommended price to fit better as a signaling device because it now can be adjusted frequently as a communication tool and still keep it correlated

[17] Note the minimum value of 2017 of 1 NOK. This is the announced decrease of the recommended price made by Circle K in relation to the new pricing policy.

with the underlying costs. My conjecture is that the recommended price is used as a signaling device for coordinating the price restoration *level* as well as the *timing* of price restoration. The former conjecture is already established in previous literature (Foros and Steen, 2013; Foros et al., 2018). I will argue for the latter conjecture in the analysis of the two other datasets. The discussion so far is well summarized in Figure 3, which plots the first difference in the recommended price over time (first differences equal to zero are omitted). The change in behavior of the recommended price in terms of frequency and level shows well from the Figure: Prior to 29 November 2017 (vertical dashed line), adjustments in the recommended price are spread out over time and lie mainly around 0.10 NOK in absolute terms. From 29 November 2017, Δrp_t clusters around the zero line and occurs much more frequently.

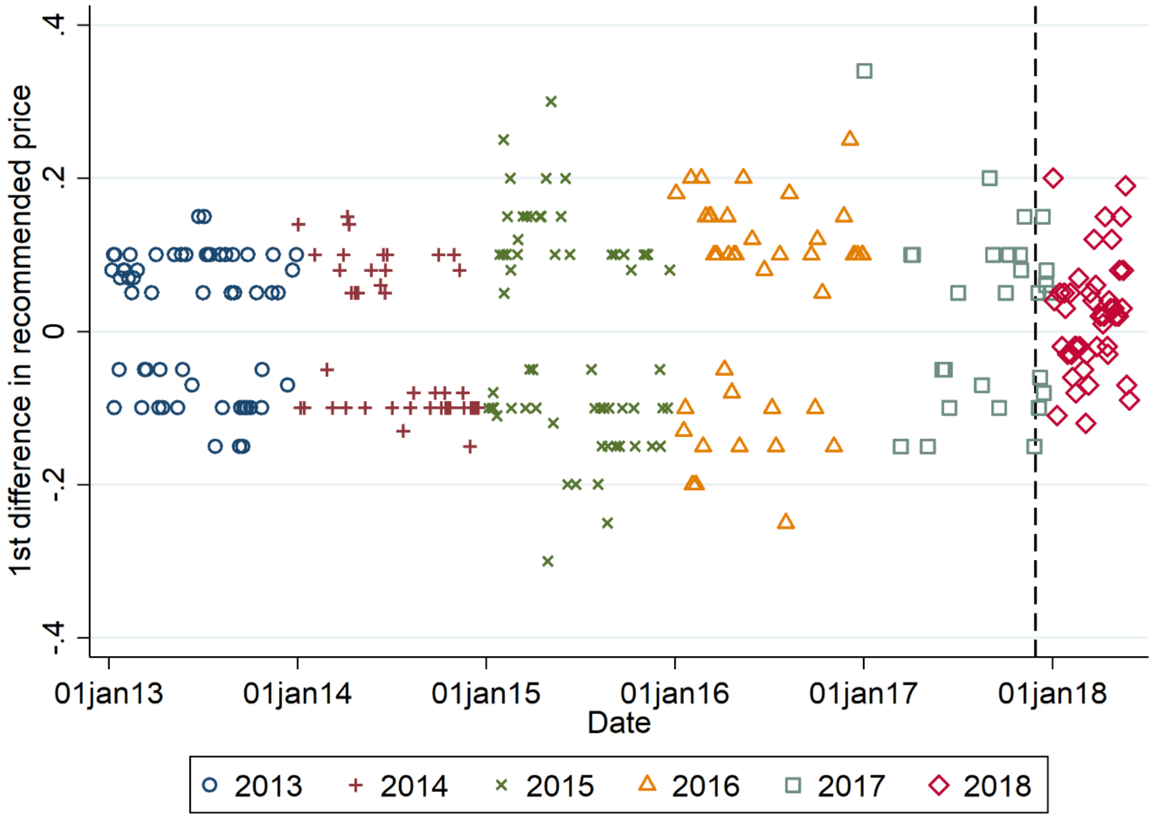


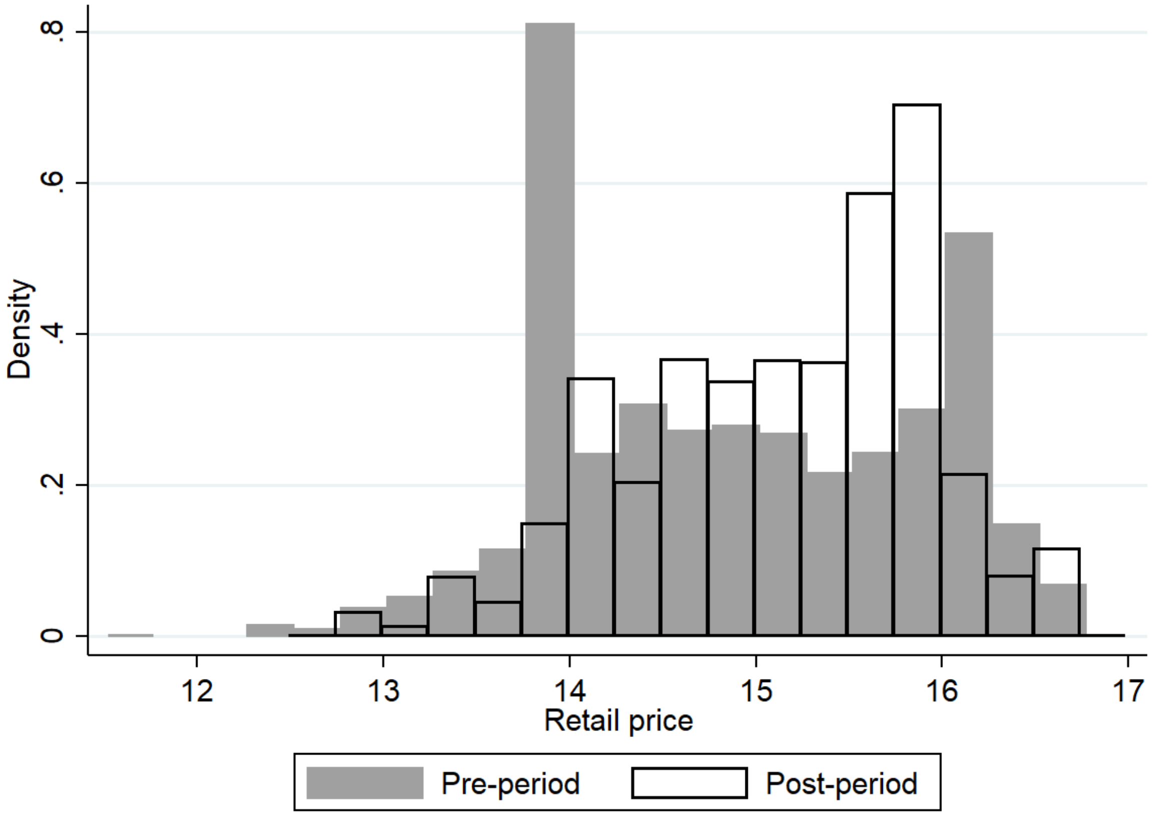
Figure 3: Δrp_t of Circle K over time. Sample period is 1 January 2013 to 31 May 2018. Δrp_t=0 is omitted. Dashed vertical line marks 29 November 2017.

5.2 Retail prices and restoration

Having established a change in the behavior of the recommended price, I move on to examine retail prices, first with use of the station panel consisting of accurate hourly data. Data contain one station from each of the first to fourth largest city in Norway. These cities are geographically dispersed from each other and are considered as four separate local markets.[18] Therefore, due to different local market conditions, one would expect these stations to act differently in terms of pricing according to the local market for which each of them is situated. Summary statistics of retail prices are given in Table 3 while a histogram as well as the kernel density distribution of prices for the whole sample is shown in Figure 4. Looking at the distributions, prices seem more centered after the price policy change, while more dispersed in both directions before the policy change. I formally examine the equality of price distributions before and after the policy change using the Kolmogorov-Smirnov test. The test clearly rejects the null hypothesis of equal distributions.[19] Hence, price behavior significantly changes from 29 November 2017.

Table 3: Summary statistics of hourly retail prices. Sample period is 1 June 2017 to 31 May 2018.

	No. of obs.	Mean	Std.dev.	Min	Max
Pre-period	17365	14.894	0.950	11.52	16.76
Post-period	17664	15.135	0.806	12.49	16.78
Total	35029	15.015	0.888	11.52	16.78



[18] The largest to fourth largest city are Oslo, Bergen, Trondheim and Stavanger. The drive time between the cities, using Google Maps, are: Trondheim-Oslo six hours, Trondheim-Bergen ten hours, Trondheim-Stavanger thirteen hours, Oslo-Stavanger seven hours, Oslo-Bergen seven hours, and Bergen-Stavanger five hours.

[19] The test yields a p-value of approximately 0.00.

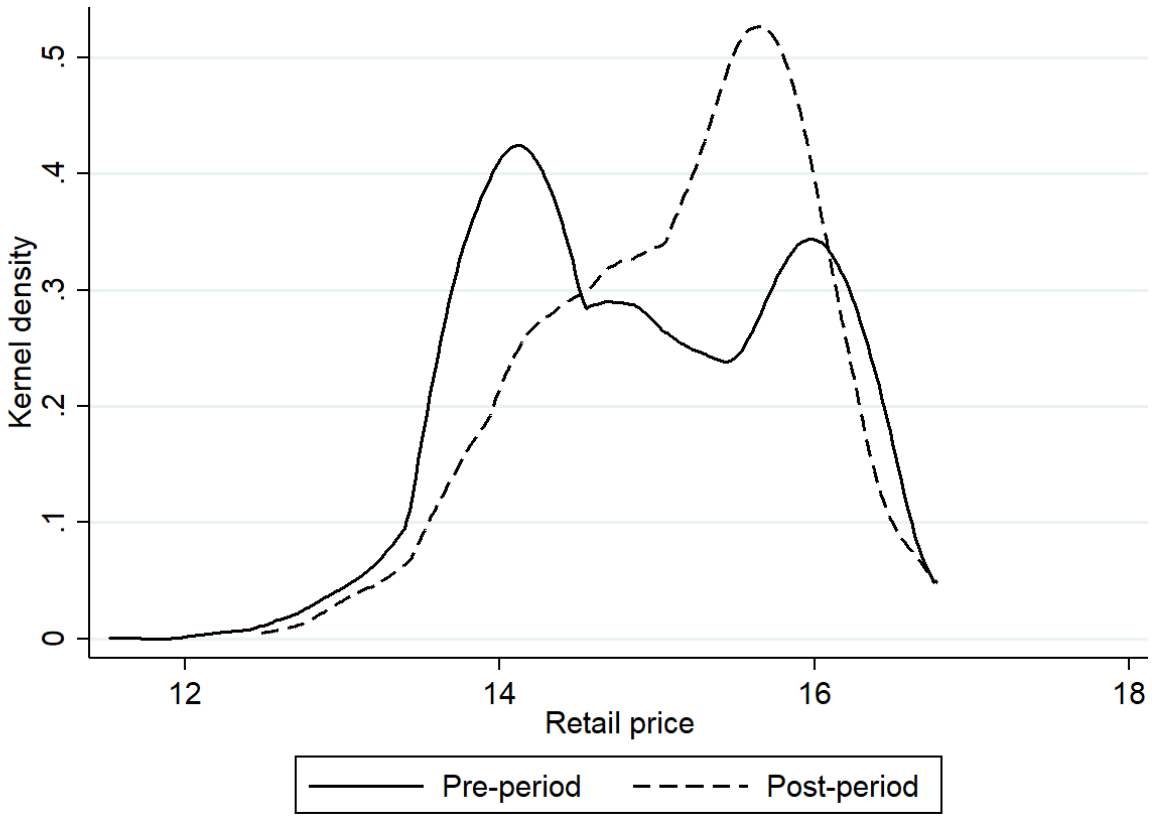


Figure 4: Histogram (top panel) and kernel density distribution (bottom panel) of retail prices for the pre- and post-period. Sample period is 1 June 2017 to 31 May 2018.

To examine whether the old cycle with weekly peaks every Monday and Thursday after noon is present in the data, I take the mean retail price at 3 p.m. for each day of the week across stations before and after 29 November 2017. Under the old cycle, prices are documented to be restored by 3 p.m. every Monday and Thursday (Foros and Steen, 2013; Foros et al., 2018). Indeed, Figure 5, which is a plot of the mean retail prices, demonstrates the old pattern (solid line) quite well: Prices are low on Sundays and Wednesdays followed by restoration on Mondays and Thursdays (upper panel). However, from 29 November 2017 (dashed line), the pattern is no longer present. Furthermore, there does not seem to be clear specific days of the week for which price restores after the policy change, as there are no clear-cut peaks and bottoms in the mean prices. The same pattern before and after 29 November 2017 is found when plotting mean prices for each station separately (lower panel). In addition, we see that station 4 faces stronger competition, as prices decrease faster and to a lower level than the other three stations.[20]

[20] This station is located in the fourth largest city in Norway. In this local market, competition is well known for being intense compared to the rest of the country.

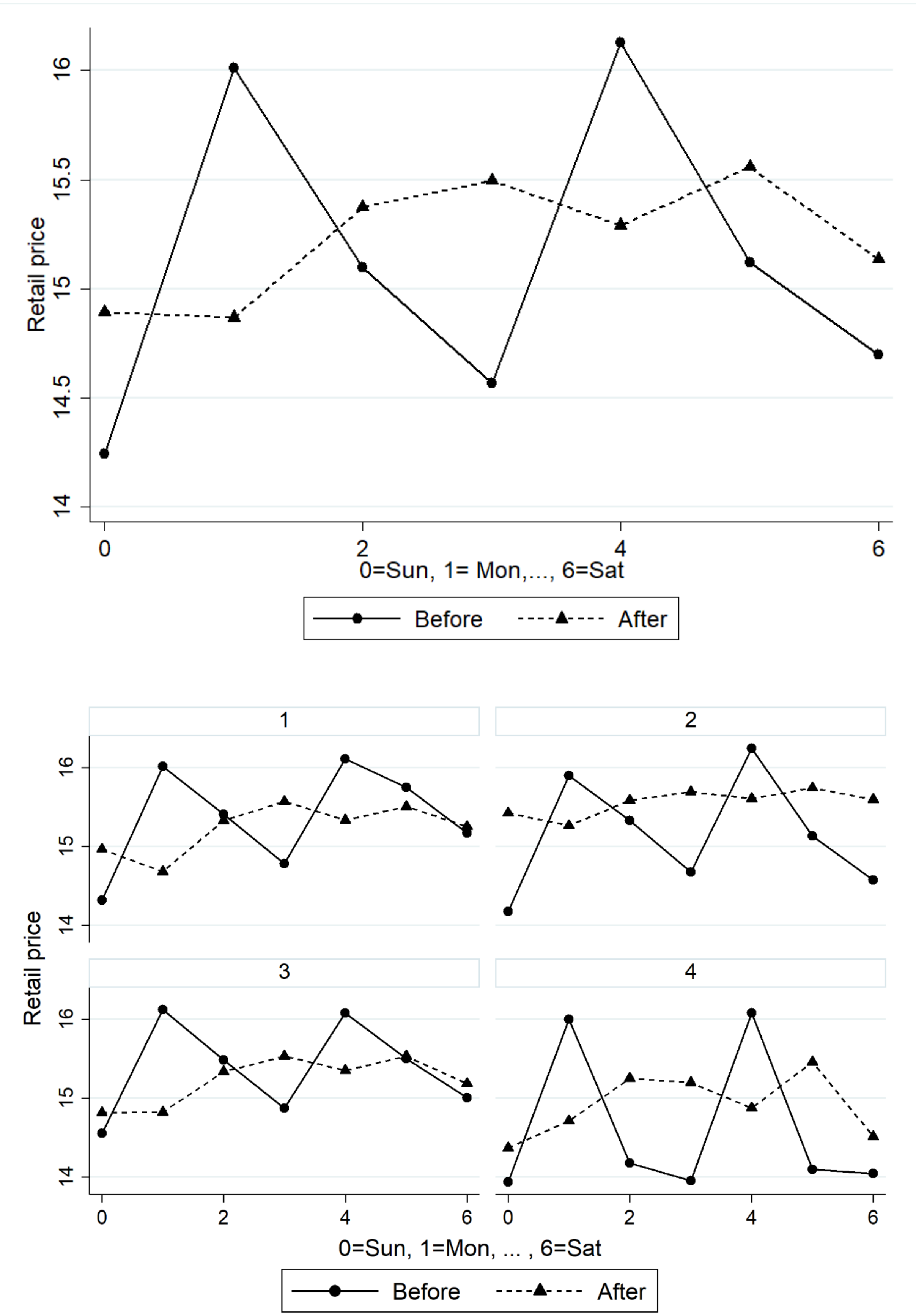


Figure 5: Mean retail prices at 3 p.m. per day of week before and after policy change across stations (top panel) and per station (bottom panel). Sample period is 1 June 2017 to 31 May 2018.

However, even though prices do not jump at specific days of the week, Figure 6 shows that they still evolve in cycles with periods of undercutting followed by large peaks. More specifically, there is great asymmetry in price increases compared to price decreases also in the post-period, as reported in Table 4. Price decreases occur on average over four times as often as price increases, however, each price increase is on average over 4.5 times larger than each price decrease. Further, price is undercut on average one to two times each day, while price increases occur on average once every third day. This reveals that whereas price undercutting happens in several stages, price restoration takes place with one single jump.

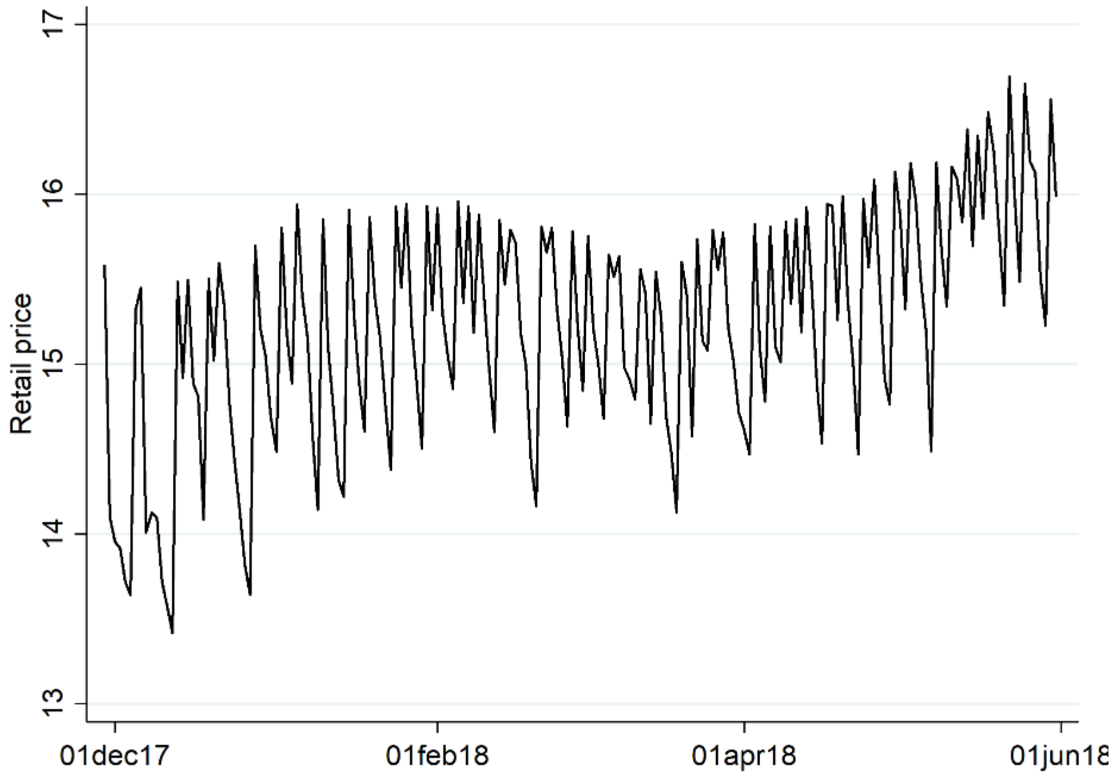


Figure 6: Mean retail price at 3 p.m. across the four stations over time after policy change. Sample period is 29 November 2017 to 31 May 2018.

Table 4: Retail price changes across stations. Sample period is 1 June 2017 to 31 May 2018.

Period	Price increase				Price decrease			
	Mean Number	Mean	Std.dev.	Mean daily number	Mean number	Mean	Std.dev.	Mean daily number
Pre-period	66 (262)	1.862	1.020	0.362	348 (1390)	-0.351	0.505	1.920
Post-period	61 (245)	1.196	0.699	0.333	272 (1086)	-0.263	0.355	1.476

Note: Mean number is the number of observations of price increases and decreases, respectively, divided by the number of stations. Number of observations are reported in parentheses. The pre-period (1 June 2017 to 28 November 2017) consists of 181 days, while the post-period (29 November 2017 to 31 May 2018) consists of 184 days. The mean daily number is calculated by dividing the mean by the number of days in each period.

The question is then: Following the policy change, how is price restoration determined? It turns out that restoration days coincide close to *perfectly* with days for which Circle K changes its recommended price, that is, when $\Delta rp_t \neq 0$. Figure 7 is the same plot as Figure 6, however, with additional vertical lines placed on each date where $\Delta rp_t \neq 0$ in order to mark days with adjustments in the recommended price. From 29 November 2017, the recommended price changes 55 times in total. For the four stations, this gives 220 possible daily observations of restoration. Of these, there are only four observations where the price does not restore following a change in the recommended price. This translates into 1.8% deviation. This strongly suggests that a change in the recommended price by Circle K is used as a signaling device: If the recommended price on a specific day is changed, stations of Circle K know that a nationwide restoration is coordinated the same day. Further, since stations are from four different geographically dispersed cities, observations suggest that Circle K succeeds in implementing nationwide within-brand price restorations. Later, I provide findings which strongly indicate that not only does Circle K manage to initiate intra-brand coordination; it also succeeds in initiating inter-brand coordination.

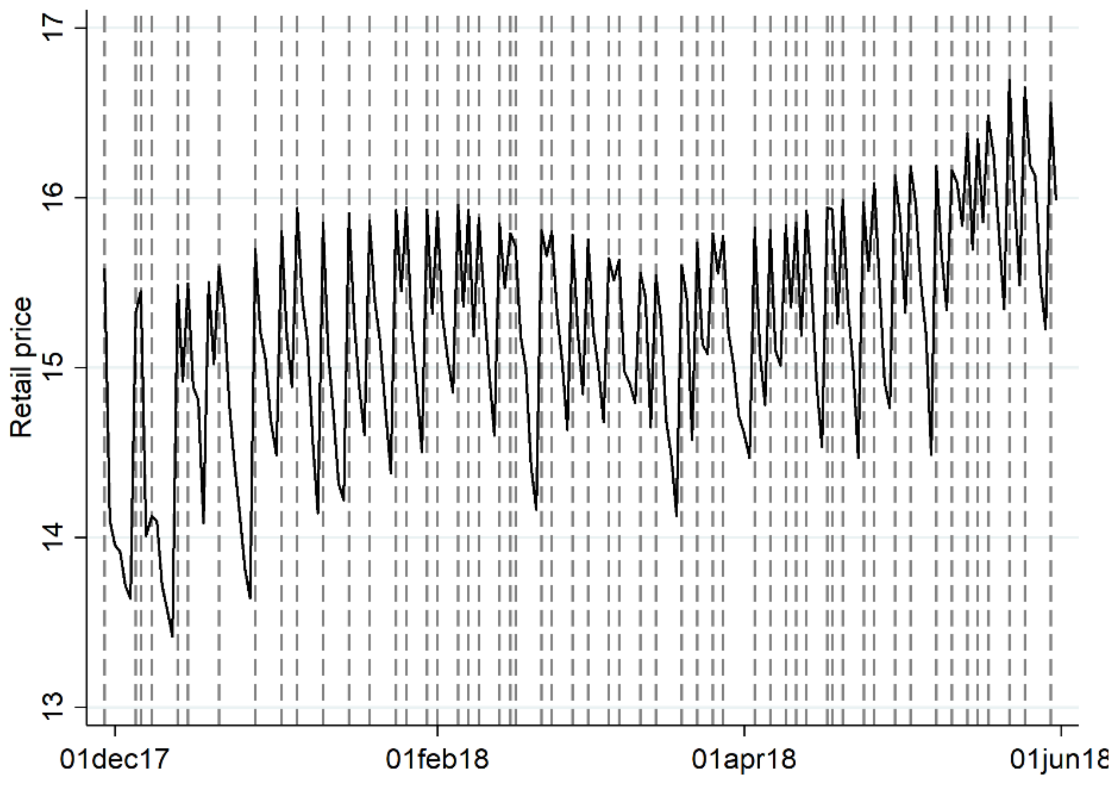


Figure 7: Mean retail price at 3 p.m. across the four stations over time after policy change. Vertical dashed lines mark dates with a change in the recommended price. Sample period is 29 November 2017 to 31 May 2018.

Note from Table 1 and the text that the recommended price for gasoline changed 53 times from 29 November 2017 to 31 May 2018 (9 + 44). Most of the time, the recommended price for gasoline and diesel are adjusted on the same dates. However, on two occasions in the sample, 1 February 2018 and 27 February 2018, only the recommended price for diesel was adjusted while the recommended price for gasoline remained unchanged. Nonetheless, the price on gasoline still restored. Direct observations made by myself in the post-sample period shows the same behavior. Due to this, I count these two days as restoration days and refer to restoration days as days where either the recommended price on gasoline, the recommended price on diesel, or both are adjusted. The fact that a change in the recommended price on diesel triggers price restoration on gasoline (and vice versa) further suggests that adjustments made to recommended prices serve as a signal for implementing a restoration in retail prices.

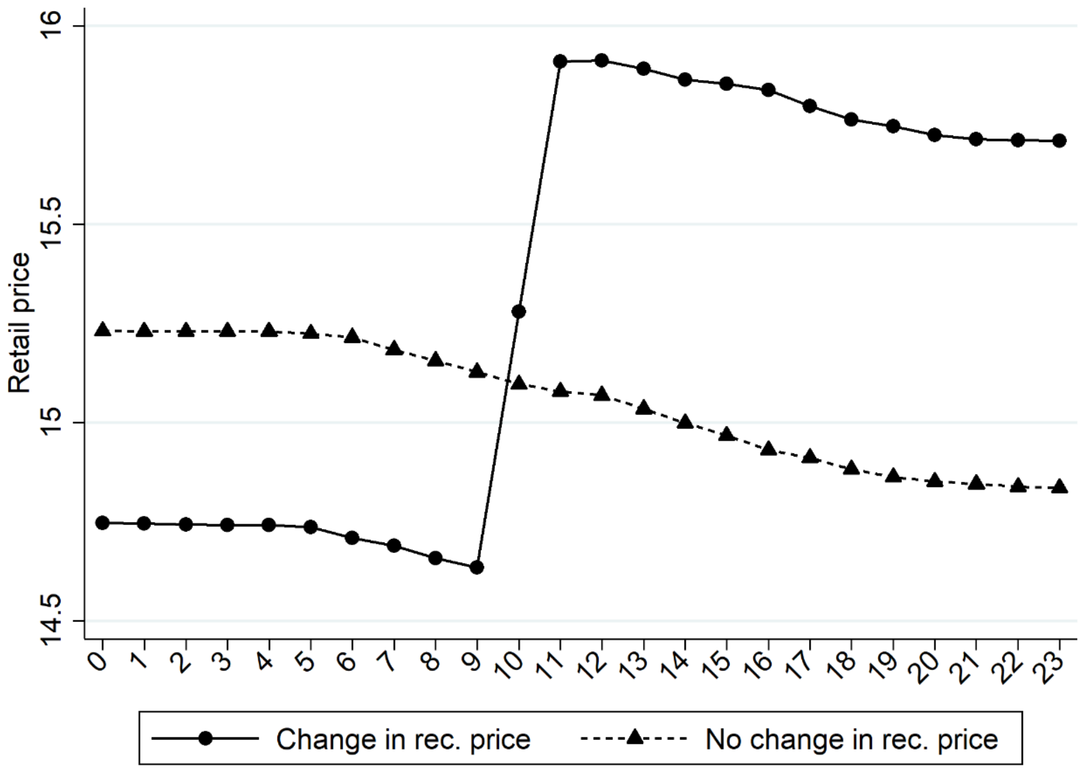


Figure 8: Mean retail price per hour across stations separately for days with change in the recommended price and for days with no change in recommended price. Sample period is 29 November 2017 to 31 May 2018.

I look further into whether prices restore at a particular time during a signaled restoration day. Of the 216 observations for which price restores, price increases at 10 a.m. 118 times (54.6% of the time), at 11 a.m. 96 times (44.4%), and at 12 p.m. two times (0.9%). In this data, the reported price is the lowest price that has been valid during the current hour. This means that if price restores during a particular hour and not exactly at a particular hour, the restoration price will be the reported price of the following hour. Hence, in this sample, price restores 54.6% of the time between 9 a.m. and 10 a.m. or at 10 a.m. sharp, 44.4% between 10 a.m. and 11 a.m. or at 11 a.m. sharp, and finally, 0.9% of the time between 11 a.m. and 12 p.m. or at 12 p.m. sharp.[21] Price restoration seems to be strikingly systematic: Every time Circle K signals that the current day is a restoration day, stations restore their retail price between 9 a.m. and 11 a.m. In Figure 8, I plot the average price each hour across stations separately for non-restoration

[21] All four stations have restored prices at both 10 a.m. and 11 a.m., however, not necessarily during the same hour on the same restoration dates.

days ($\Delta rp_t = 0$) and restoration days ($\Delta rp_t \neq 0$).[22] The pattern is clear and sums up the discussion above well: price restoration now occurs between 9 a.m. and 11 a.m. on days where Circle K adjusts its recommended price. Hence, prior announcements of the recommended price initiates coordination of intra-brand retail prices.

Next, I study whether there is coordination in the price restoration level. Foros and Steen (2013) show that under the regular pattern with restoration every Monday and Thursday, prices jumped to the recommended price plus a fixed transportation cost.[23] I find the same behavior after the policy change is implemented, as shown in Figure 9. In order to capture the price right before restoration as well as the price right after restoration, I plot the retail price at 9 a.m. and the retail price at 11 a.m. for all days for which the recommended price changes. Whereas the retail price usually is below the recommended price at 9 a.m., with few exceptions as mentioned above, prices have restored to the recommended price at 11 a.m. The systematic restoration of prices is strikingly clear-cut, both when it comes to timing of the restorations as well as the level of restorations.

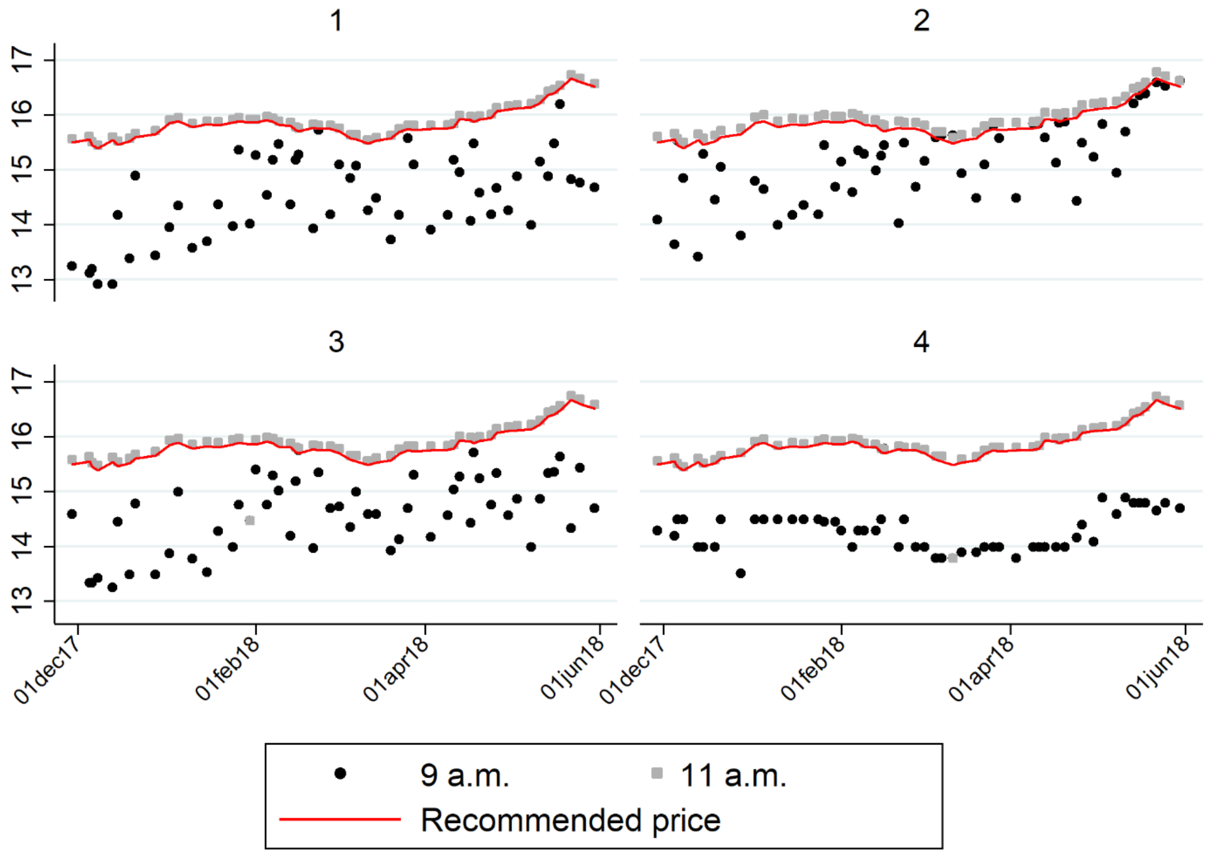


Figure 9: Retail price at 9 a.m. and 11 a.m. per station on days the recommend price changes. Sample period is 29 November 2017 to 30 May 2018.

[22] A similar pattern is found for each separate station.

[23] The transportation cost lies between 0.06 and 0.11 NOK for the sample stations.

5.3 The likelihood of the occurrence of price restorations

To more formally investigate the relationship between the occurrence of price restoration and time, I run regressions on the probability of a restoration in the retail price on different predictors for time during a week and other indicators to allow for separation between the pre- and post-policy change period. I create an indicator variable, $priceup_{it}$, which is equal to one if the retail price of hour t (on day j) for station i increases to the restoration price from the previous hour. As explanatory variables I include a set of indicator variables for the clock hours 10 a.m. to 4 p.m., denoted $H_l, l = 10,..,16$, using all other hours as baseline. I do not include a full set of hour indicators because no restoration is identified in the sample for the remaining hours. I also include a set of indicator variables for Monday to Friday, denoted $D_k, k = 1,..,5$, using Saturday and Sunday as baseline, an indicator variable, $post$, which is equal to one if the hour t is in the post-policy change period, and an indicator variable, $changerp$, equal to one if hour t is on a restoration day. I two-way interact all hours with all days, all hours with $post$ and $changerp$, respectively, all days with $post$ and $changerp$, respectively, in addition to an interaction term between $post$ and $changerp$. Three-way interaction terms between hour, $post$ and $changerp$, and day, $post$ and $changerp$ are also included. The wholesale price, $wholesale_j$, is controlled for. Finally, I include station fixed effects, which is equivalent to city fixed effects since each station is located in different cities, to control for time-invariable differences across stations.[24]

Regressing $priceup_{it}$ on these predictors allows the probability of $priceup_{it}$ to change with the included time dimensions. In addition, I open up for these time dimensions to depend on each other, and I allow for behavior to be different in the two different price policy periods. The specification also opens up for further investigation of the role of a change in the recommended price. I run a logit regression and a probit regression using maximum likelihood. Clustered standard errors on the day level to allow for relation between prices within the same day are calculated. Coefficients of the models are provided in the Appendix.[25]

5.3.1 Regression results

Of particular interest for the new price policy is the variable $changerp$. From the estimated coefficients, I therefore calculate the marginal effects on $priceup$ from a change in $changerp$. Since $changerp$ is categorical, the marginal effect is calculated as the change in the probability of $priceup = 1$ when $changerp$ goes from zero to one for different combinations of days of the week and hours. The other categorical variables for days of the week and hours are set to zero. I fix the remaining independent variables at their sample mean values. Further, I investigate the marginal effects of $changerp$ separately for the pre- and post-period. Marginal

[24] Hence, the specification takes the following form:

$\Pr(priceup_{it} = 1|\boldsymbol{X}) = f[\alpha_0 + \sum_{l=10}^{16}\beta_l H_l + \sum_{k=1}^{5}\gamma_k D_k + \alpha_1 post + \alpha_2 changerp_j + wholesale_j + \sum_{l=10}^{16}\sum_{k=1}^{5}\delta_{lk}H_l D_k + \sum_{l=10}^{16}(\zeta_l H_l \times post) + \sum_{l=10}^{16}(\eta_l H_l \times changerp_j) + \sum_{k=1}^{5}(\theta_k D_k \times post) + \sum_{k=1}^{5}(\eta_k D_k \times changerp_j) + \lambda post \times changerp_j + \sum_{l=10}^{16}(\mu_l H_l \times post \times changerp_j) + \sum_{k=1}^{5}(\rho_k D_k \times post \times changerp_j) + \tau_i + \epsilon_{it}]$.

[25] Note that some coefficients are omitted for the logit and probit specifications. The reason is two-fold. First, if a right-hand side variable perfectly predicts success or failure in $priceup$, no coefficient can be fit to the variable as it adds no variation to the estimation process and hence get omitted. Second, due to many indicator variables, some variables are omitted due to collinearity.

effects with respect to $changerp$ with corresponding standard errors over different days of the week and hours are presented in Table 5. Standard errors are calculated using the delta method.

Table 5: Marginal effects of $changerec$ on $Pr(priceup = 1)$.

		Logit		Probit	
Day	Hour	dy/dx	S.E.	dy/dx	S.E.
Pre-period					
Mon	10				
Tue	10				
Wed	10				
Thu	10				
Fri	10				
Mon	11	-0.029	0.048	-0.028	0.044
Tue	11				
Wed	11	-0.003	0.003	-0.002	0.003
Thu	11	-0.004	0.005	-0.003	0.007
Fri	11				
Post-period					
Mon	10	0.352***	0.107	0.402***	0.105
Tue	10	0.533***	0.053	0.524***	0.050
Wed	10	0.550***	0.056	0.547***	0.055
Thu	10	0.585***	0.063	0.573***	0.060
Fri	10	0.560***	0.091	0.561***	0.076
Mon	11	0.668***	0.075	0.682***	0.066
Tue	11	0.440***	0.054	0.433***	0.051
Wed	11	0.414***	0.060	0.409***	0.055
Thu	11	0.430***	0.065	0.433***	0.060
Fri	11	0.377***	0.077	0.384***	0.070
No. of obs.		31 553		31 553	

Note: Marginal effects are computed separately for the pre-and post- period. Delta standard errors are reported. Independent variables are fixed at the sample mean. *** p<0.01, ** p<0.05, * p<0.1. Sample period is 1 June 2017 to 31 May 2018.

From Table 5, the effect of $changerec$ on the probability of $priceup = 1$ in the post-period is positive and significant for hour 10 and 11 across all days. Magnitudes are in general quite similar across the two models. The expected probability of restoration is around 0.5 higher during hour 10 (10 a.m.) on days where the recommended price changes compared to days where it does not change. For hour 11, the expected probability of restoration is between 0.4 and 0.7 higher compared to days with no change in the recommended price. On the other hand, there are no corresponding significant effects in the pre-period. Due to the omission of coefficients and empty cells, some marginal effects are not possible to calculate for the pre-period. When the interaction between $changerec$, days of the week and hours is such that there are few or no observations for which $priceup = 1$, there are few or no responses to calculate the marginal effects over, or in this case, a discrete change from one state to the other, which probably is why the effects are inestimable. Finally, for both the pre- and post-period, I find either insignificant or inestimable marginal effects for all hours except 10 a.m. and 11 a.m. In sum, these results confirm that a significant change in the way Circle K initiates price restoration has taken place.

Table 6: Marginal effects of Monday and Thursday on $Pr(priceup = 1)$.

		Logit		Probit	
Day	Hour	dy/dx	S.E.	dy/dx	S.E.
Pre-period					
Mon	10	0.012***	0.010	0.006	0.009
Mon	11	0.063**	0.029	0.060**	0.026
Mon	12	0.097***	0.026	0.088***	0.027
Mon	13	0.230***	0.046	0.216***	0.046
Mon	14				
Mon	15				
Mon	16				
Thu	10	0.010	0.007	0.012	0.008
Thu	11	-0.001	0.009	-0.004	0.008
Thu	12				
Thu	13				
Thu	14				
Thu	15				
Thu	16				
Post-period					
Mon	10	-0.001	0.002	-0.002	0.002
Mon	11	-0.002	0.003	-0.001	0.005
Mon	12	0.002	0.014	0.005	0.016
Mon	13	0.009	0.006	0.016	0.010
Mon	14				
Mon	15				
Mon	16				
Thu	10	0.010	0.010	0.009	0.009
Thu	11	0.001	0.005	-0.001	0.004
Thu	12				
Thu	13				
Thu	14				
Thu	15				
Thu	16				
No. of obs.		31 553		31 553	

Note: Marginal effects are computed separately for the pre-and post- period. Delta standard errors are reported. $changerec$ is set to zero. The remaining independent variables are fixed at the sample mean. *** p<0.01, ** p<0.05, * p<0.1. Sample period is 1 June 2017 to 31 May 2018.

To examine the old pattern, I calculate the marginal effects of Monday and Thursday, respectively. This is because price restoration is triggered by specific days of the week before the policy change. I keep the remaining independent variables at sample means except for $changerec$, which I set equal to zero because the recommended price is seldomly adjusted in the pre-period. These effects are reported in Table 6. Again, the lack of observations where $priceup = 1$ for other hours and days is probably the reason why the estimation of marginal effects is problematic for most hours in both periods. The empty cells give no basis to calculate the discrete change in the probability of moving from the baseline to the value of interest, which here is Monday and Thursday of specific hours. This underlines how systematic price restoration occurs in the pre-period. For the estimable combinations of days and hours, I find that the probability of restoration increases with around 0.09 on Mondays at 12 p.m. and around 0.21 at 13 p.m., which is consistent with results in Foros and Steen (2013) and Foros et al. (2018).[26]

5.4 Evolvement of prices between restorations

One implication of having a regular cycle dependent on day of the week is that the duration between restorations is fixed: There are two days between the Monday and Thursday restoration, and three days between the Thursday and Monday restoration. I define the duration of a cycle as the number of days *between* two restoration days. This is essentially the undercutting phase. With the new price policy, the duration between two restorations in the sample varies between zero (two restoration days in a row) and six, with a duration of one day and three days occurring most frequently.[27] Table 7 provides an overview of the number of days between restoration before and after the policy change. Note that data cover six months with the old price regime and six months with the new one.

Table 7: Number of days between two restorations before and after the price policy change. Sample period is 1 June 2017 to 31 May 2018.

Days between	0	1	2	3	4	5	6
Before			25	26	1		
After	3	17	9	12	9	3	1

One interesting question is then how prices evolve between restorations, and whether they evolve differently depending on the duration of the undercutting phase between two restorations. To investigate this, I follow Lewis (2012) and first subtract the restoration price off the retail price for each station in order to obtain a normalized price relative to the restoration level. As documented, the restoration price of Circle K's stations is simply the recommended price plus a fixed station-specific transportation cost.[28] I then separate undercutting periods of

[26] If I ignore the issue with lack of data I find an increase in probability of 0.455 for hour 14 on Monday and 0.738 for hour 14 on Thursday using the logit specification. Other combinations of days, hours and pre- and post-period give no significant effect on the probability or restoration. Results are similar for the probit specification. This is in line with direct observations from the data as well as with findings in Foros and Steen (2013) and Foros et al. (2018).

[27] Six days between restorations occurred once during the Christmas holiday 2017. I will leave this case out from the rest of the analysis as holidays are special occasions. Under the old price regime, restoration occurred once on a Tuesday instead of a Monday due to a public holiday, resulting in four days between restorations.

[28] I do not subtract the transportation cost because it will not affect the analysis as it is fixed for each station.

different lengths, varying from one to five days, and look at the price distribution for the stations of different durations separately. I limit the analysis to daily prices by looking at the 11 a.m. price each day. At 11 a.m., prices are all restored if there is a restoration day. As such, it gives a good picture of how prices evolve on a daily basis.

The top panel in Figure 10 presents sets of box plots of normalized prices at 11 a.m. for the stations, where each set is categorized by the duration to the next restoration day.[29] Cycle durations of different lengths are given separate colors on the boxes. For instance, the green set of box plots represents the price distribution of two-day duration cycles. The x-axis shows the day number within a cycle, where day zero is the restoration day, day one is the first day following the restoration day, and so on. For example, the green box plot at point one on the x-axis shows the distribution of prices of the first undercutting day (the first day following the restoration day) for cycles with two-day duration. Figure 10 leaves no doubt of how systematic the coordination of price restorations for Circle K stations is; strictly speaking, regardless of duration length, at the restoration time all prices perfectly match the recommended price.[30] This can be seen by looking at day zero (the restoration day) along the x-axis. Here, all the boxes of different colors, representing price distributions for varying durations of a cycle, show virtually no variation in price regardless of duration length. There is variation in prices over the course of a cycle. In general, prices seem to decrease for each day within the cycle, as the median is lower for each day number during a cycle. Notably, the lower duration of the undercutting phase, the less prices fall. This suggests that prices often jump back to the restoration price even if they still are not yet competed down to a sufficiently low level. Comparing the one-day duration prices with the five-day duration prices, a cycle of one day barely gives time to undercut prices, which further implies that aggressive undercutting is unlikely to be the only reason to initiate price restoration.

To compare with the period prior to the policy change, I do the same exercise for the pre-period sample, except that instead of using the 11 a.m. price as the daily observation, I now instead use the 3 p.m. price. The reason for this choice is that under the old pattern, prices have jumped within 3 p.m. during a restoration day. The average distribution of normalized prices in the pre-period is reported in the bottom panel of Figure 10.[31] First, compare the case of a two-day duration of the undercutting phase between the pre-and the post-policy period. Before the policy change, the median normalized price drops from 0.06 NOK to -0.79 NOK on the first day after restoration. After the policy change, the corresponding drop is from 0.07 NOK to -0.215 NOK. On the second day after restoration, the median normalized price drops from -0.79 NOK to -1.555 NOK for the old pattern, while the corresponding drop is from -0.215 NOK to -0.635 NOK for the new pattern. Clearly, prices fell on average more between Monday and Thursday before the policy change compared to the average cycle of the same duration after a policy change. Comparing the case of duration of three days between restorations shows the same trend: Before the policy change, the median normalized price drops on average from 0.06 NOK to -0.815 NOK the first day, to -1.41 NOK the second day and to -2.015 NOK the third

[29] A boxplot is read the following way: The floor of the box displays the 25th percentile, the roof of the box displays the 75th percentile, while the horizontal line inside the box displays the 50th percentile. The line on the lower whisker displays the 5th percentile and line on the upper whisker displays the 95th percentile.

[30] Prices are a little above zero, which accounts for the transportation cost.

[31] Complete summary statistics are provided in the Appendix.

day. After the policy change, the corresponding average drop is from 0.08 NOK to -0.09 NOK the first day, to -0.65 NOK the second day and to -1.105 NOK the third day.

In addition to considering price distributions for different durations separately I also report the average distribution of normalized prices of all durations together in Figure 11. Results tell in general the same story; for each day following a restoration, price gets lowered by more under the old price regime. Circle K announced with the new policy change that it will cut the recommended price, which essentially is the restoration price, with 1 NOK from thereon to avoid large fluctuations in prices.[32] One way of interpreting this cut is that while the maximum retail price is lowered by 1 NOK, the competitive level in local markets is, all else equal, unaffected by the policy change. Hence, the price roof is lowered while the price floor stays unchanged. Therefore, one would expect the jump in price during a restoration to be on average 1 NOK lower, and as such, smaller price drops during the undercutting phase is as anticipated. However, does this drop correspond to the 1 NOK cut in the recommended price? Going back to Table 4, which reports mean retail price changes without taking duration into account, if we compare the mean of price increases before (1.862) and after (1.196) the price policy change, the numbers tell the same story as Figure 10 and Figure 11 of a larger price jump in the pre-period. To formally test this, I perform a two-sided t-test for comparison of means where the null hypothesis is that the difference between the pre-period and post-period mean in price increases is equal to 1.[33] The test statistic is -4.33, leading to rejection of the null hypothesis at the 1% significance level. Thus, albeit smaller restorations in magnitude after the policy change, the t-test suggests that the 1 NOK drop in the restoration price has not yet been fully passed over to smaller price jumps of 1 NOK in size.

Another interesting observation is that the most frequently occurred cycle duration is one day. Hence, prices barely fall before increasing to the restoration level, meaning that prices might fluctuate less, nonetheless, at a relatively high price level.

[32] A direct quote from the policy announcement is: “In particular, Circle K will from today, Wednesday 29 November, reduce the recommended price on gasoline and diesel with 1 NOK per liter on serviced stations to reduce de big difference between the highest and the lowest price during a week” (Circle K, 2017).

[33] The Brown- Forsythe’s test of equal variances leads to rejection of the null hypothesis of equal variances between price increases in the pre-and post-period at the 1% significance level, therefore I assume unequal variances when comparing the means.

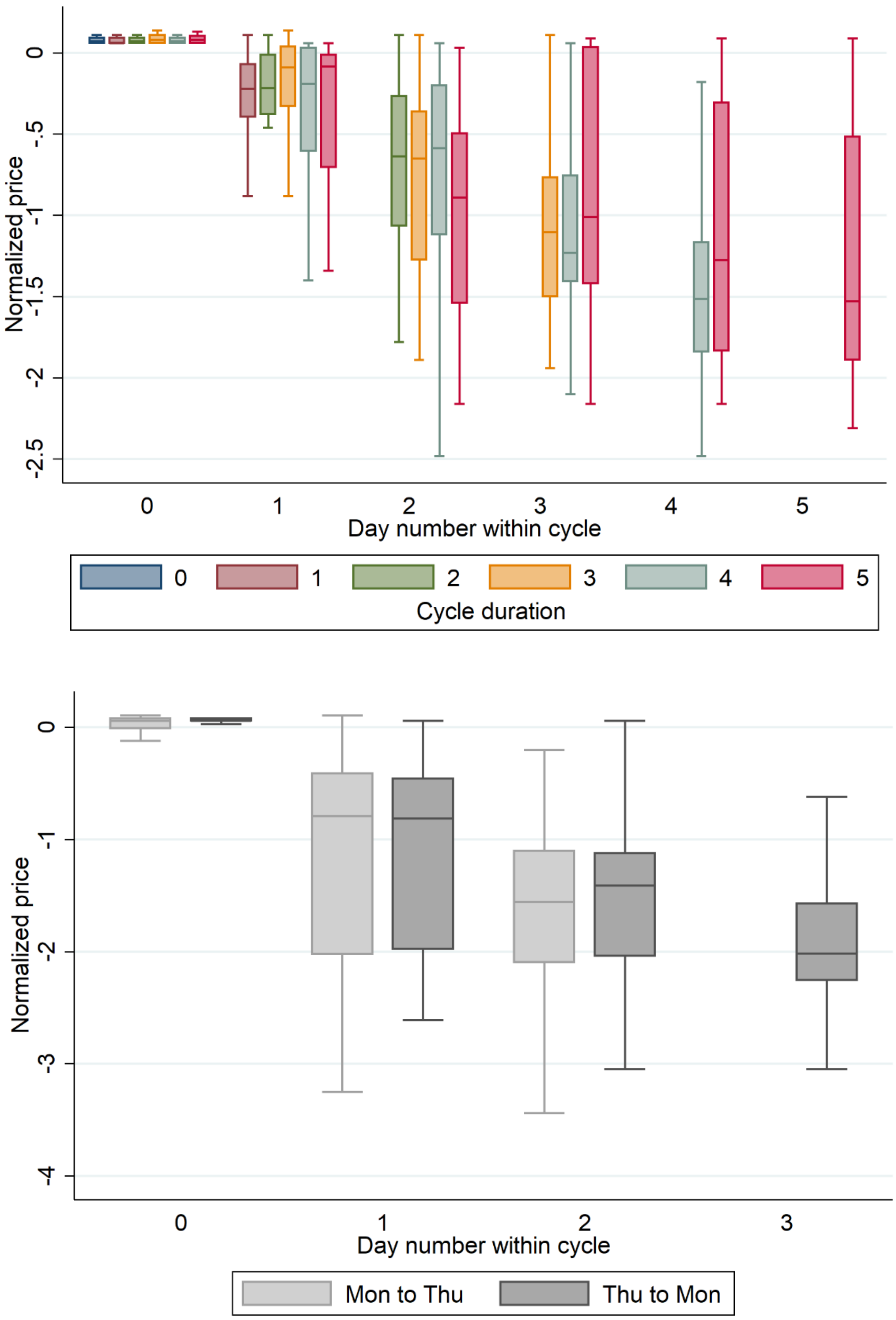


Figure 10: Set of box plots with average 5th, 25th, 50th, 75th and 95th percentile of 11 a.m. normalized prices (top panel) and 3 p.m. normalized prices (bottom panel) categorized by cycle duration. A set of boxes of different colors represent distributions for varying durations of a cycle, where 0 represents cycles consisting of only the restoration day and 5 represents cycles with five undercutting days. The x-axis reports the day of a cycle duration where 0 is the restoration day. Sample period is 1 June 2017 to 28 November 2017 (bottom panel) and 29 November 2017 to 31 May 2018 (top panel). Outliers are omitted.

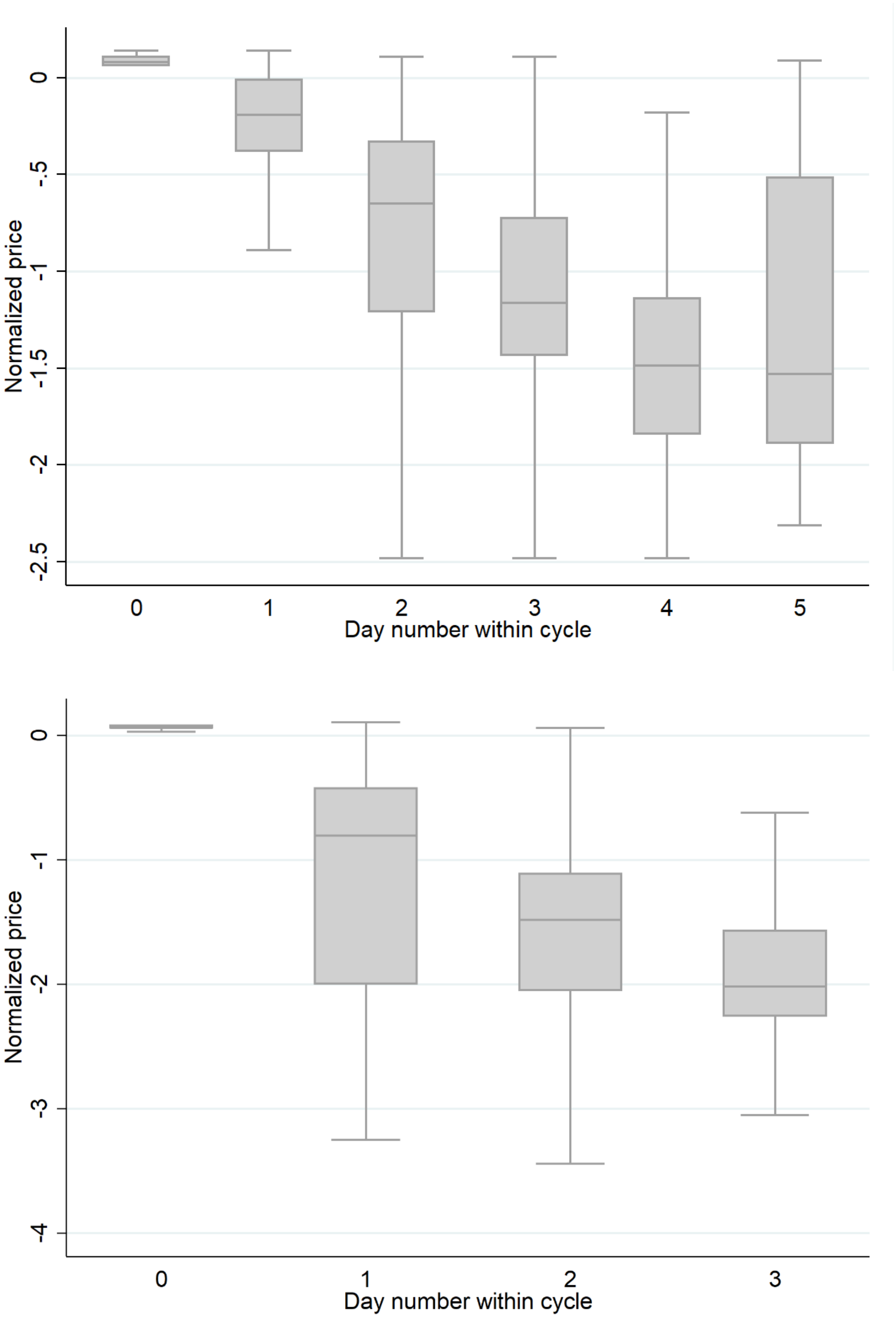


Figure 11: Set of box plots with average 5th, 25th, 50th, 75th and 95th percentile of 11 a.m. normalized prices (top panel) and 3 p.m. normalized prices (bottom panel) averaged over all cycle durations. The x-axis reports the day of a cycle duration where 0 is the restoration day. Sample period is 1 June 2017 to 28 November 2017 (top panel) and 29 November 2017 to 31 May 2018 (bottom panel). Outliers are omitted.

5.4.1 Price level and persistence

The previous analysis suggests that in general price evolves between relatively high and low levels during a cycle. I therefore look further on price levels and the persistence of price. Specifically, I examine whether there are any significant low and high price states that price evolve between, and if so, what average price level defines the different states. I run a simple dynamic two-regime Markov-switching regression on each station's series with a state-dependent intercept. Further, I add a control for the post-period which impact is allowed to vary with states.[34] Retail prices are observed to fluctuate between relatively high and low prices. Therefore, a dynamic Markov-switching model which allows the process to develop differently in the different regimes is suitable for investigating these series. The specification for two states, $s_t = \{1, 2\}$ is

$$p_t = \mu_{s_t} + \beta_{s_t} post_t + \epsilon_{s_t}$$

where p_t is retail price at time (hour) t, μ_{s_t} is the state-dependent intercept, $post_t$ is an indicator variable equal to 1 if the time period belongs to the post-policy period and ϵ_{s_t} is white noise with mean zero and state-dependent variance. Results are presented in Table 8 together with the estimated transition probabilities between states.[35]

Table 8: Markov-switching estimates and transition probabilities.

	Station 1	Station 2	Station 3	Station 4
Regime 1				
Constant	14.36***	14.39***	14.49***	13.96***
	(0.109)	(0.015)	(0.016)	(0.002)
Post	-0.152*	0.327***	-0.0551*	0.236***
	(0.082)	(0.026)	(0.028)	(0.006)
Regime 2				
Constant	15.98***	15.77***	15.95***	15.55***
	(0.078)	(0.019)	(0.011)	(0.037)
Post	-0.313***	0.0814***	-0.286***	-0.0904**
	(0.066)	(0.020)	(0.013)	(0.039)
pr11	0.977***	0.981***	0.980***	0.984***
	(0.002)	(0.002)	(0.002)	(0.002)
pr22	0.981**	0.984***	0.981***	0.972***
	(0.002)	(0.001)	(0.001)	(0.001)
$E(D_1)$	43.67	53.53	48.95	61.49
$E(D_2)$	52.44	61.90	51.32	35.70
No. of obs.	8 756	8 760	8 760	8 753

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The expected duration of state i, D_i, is $E[D_i] = 1/(1 - pr_{ii})$, which is calculated with more decimals than reported in the Table to increase precision. Sample period is 1 June 2017 to 31 May 2018.

[34] I allow the variance to differ with regimes because doing so increases the model fit.

[35] The model is estimated using maximum likelihood. The transition probability to state j in period t given state i in period $t - 1$ is $\Pr(s_t | s_{t-1}) = pr_{ij}$.

Considering all four models, the specification identifies a “low price” state (state 1) with an average price between 13.96 NOK and 14.49 NOK and a “high price” state (state 2) with an average price between 15.55 NOK and 15.98 NOK. $Post$ has a significant impact on all stations and in both regimes, and seems in general to impact the average price in both directions depending on state and station. Importantly, the two states are still distinguishable when taking $post$ into account.

The probability of staying in both states are above 0.97 for all stations, suggesting that both the low price state and high price state are highly persistent. For station 1 to station 3, the expected duration of the low price state is between 43 and 53 hours, while the corresponding number for the high price state is between 52 and 62 hours.[36] This corresponds to around two days duration on average for both states. The expected durations suggest that after the policy change, there are still large fluctuations in price, with persistent periods of relatively high prices as well as persistent periods of relatively low prices over the course of an average price cycle.

5.5 Evidence of inter-brand coordination

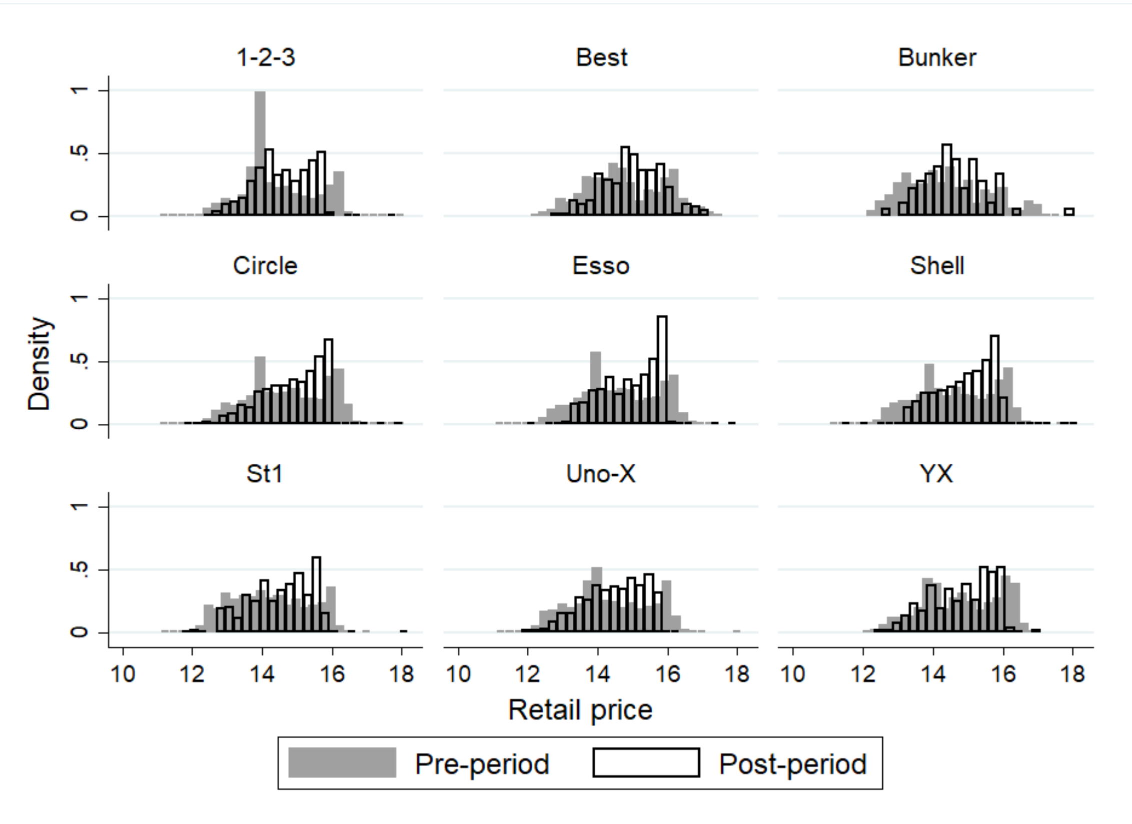
Table 9: Summary statistics of hourly retail prices by brand. Sample period is 1 January 2017 to 28 February 2018.

Brand	No. of stations	No. of obs.	Mean	Std.dev.	Min	Max
Pre-period						
1-2-3	24	3045	14.452	1.046	11.090	17.940
Best	10	711	14.808	1.109	12.090	17.480
Bunker	5	270	14.424	1.193	12.140	17.510
Circle	136	19139	14.727	1.109	11.090	17.980
Esso	113	17989	14.642	1.080	11.090	17.260
Shell	182	25562	14.667	1.108	11.050	17.920
St1	30	5704	14.242	1.107	11.110	16.970
Uno-X	93	13366	14.345	1.116	11.130	17.950
YX	32	2253	14.831	1.098	11.990	16.940
Total	625	88039	14.596	1.113	11.050	17.980
Post-period						
1-2-3	23	658	14.621	0.820	12.340	17.620
Best	10	153	15.009	0.857	12.690	17.040
Bunker	5	70	14.637	0.900	12.550	17.960
Circle	134	4039	14.888	0.871	11.790	17.850
Esso	112	3515	14.966	0.801	12.000	17.770
Shell	181	5096	14.927	0.798	11.410	17.970
St1	30	1130	14.511	0.887	11.700	17.980
Uno-X	90	3173	14.490	0.862	11.870	16.290
YX	32	488	14.856	0.892	12.350	16.950
Total	617	18322	14.811	0.857	11.410	17.980

[36] Station 4 stands out with almost twice as high expected duration of the low state compared to the high state. This is as anticipated considering the high degree of competition in the geographical area for which the station is located as previously mentioned.

Up until now, I have shown how Circle K signals intra-brand price restoration by implementing adjustments to its recommended price. One question remains: do changes in Circle K's recommended price initiate inter-brand price restoration? The user-reported data is well suited for this purpose, as it covers all major brands as well as minor brands located throughout the country, from small rural areas to larger cities. Observations are from 17 out of in total 18 counties, which covers 122 out of 426 municipalities.[37] Summary statistics are given in Table 9.

First, I examine whether price distributions differ in the pre-and the post-period across different brands. From Figure 12, in general there seems to be a change to more centered prices, as compared to the pre-period with more dispersed prices in both directions. Applying the Kolmogorov-Smirnov test of equality of distributions provides p-values between approximately 0.00 and 0.03 for all brands, implying that price behavior is significantly different for all brands before and after 29 November 2017. This is consistent with what I found from the station panel data.



[37] The one not covered is Finnmark, the northernmost county.

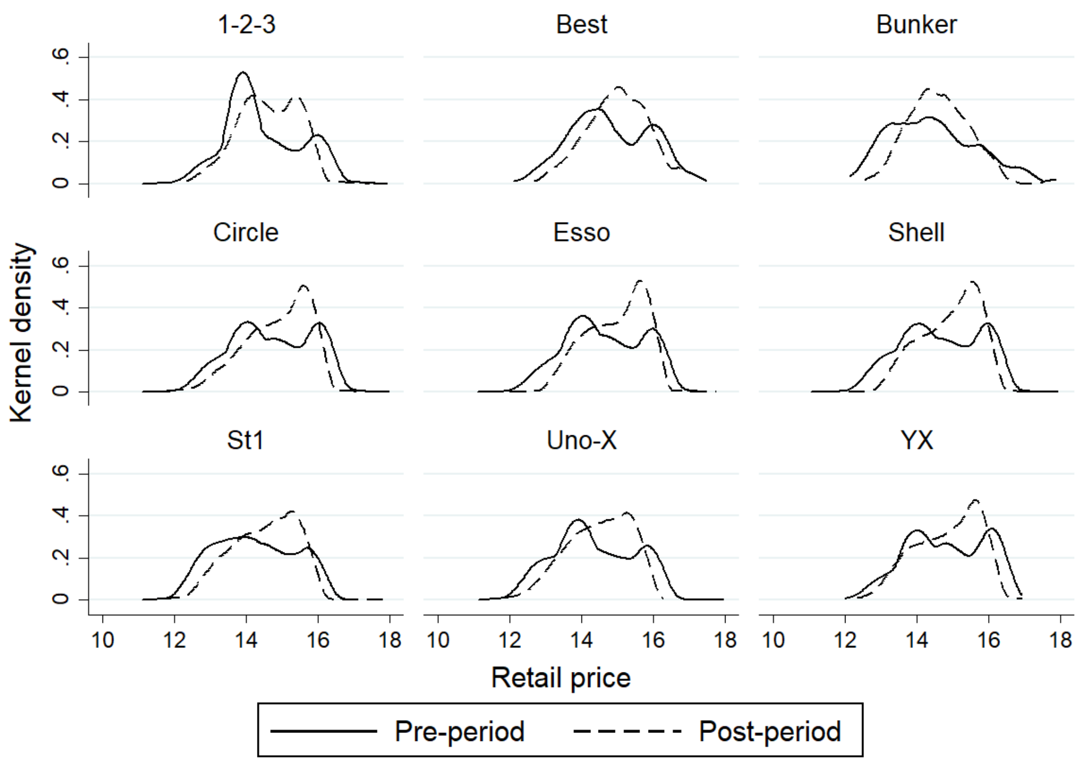


Figure 12: Histogram (top panel) and kernel density distribution (bottom panel) of retail prices for the pre- and post-period by brand. Sample period is 1 January 2017 to 28 February 2018.

Since this dataset is unbalanced, when examining whether the old predictable cycle is present in the data, only studying 3 p.m. prices will utilize less information than the data contain, in contrast to the balanced station panel where all 3 p.m. observations for the Circle K stations are available. To overcome this, I calculate the mean price for the a.m. hours (12 a.m. to 11 a.m.) and p.m. hours (12 p.m. to 11 p.m.) during a day for each brand, treating each day as consisting of two prices, one a.m. and one p.m. price. In this way, by looking at the daily p.m. prices, I am able to trace out if there has been a change in the price pattern for the different brands before and after Circle K's policy change. In Figure 13, where the mean p.m. prices for different days of the week are presented separately for the pre-period and the post-period, the old pattern with restorations on Mondays and Thursdays after noon is visible for all brands. Further, the breach in the old regime is also clear, as there seems to be no pattern after 29 November 2017.

Prices look more stable at a higher level after the price policy change, with less fluctuations upward as well as downward. This reflects the fact that restoration can occur on whichever day of the week. Hence, when averaging the p.m. prices for each day of the week, since each day can in essence both be a "low price" day as well as a restoration day, large peaks are smoothed away. All these observations point in the direction of that Circle K has managed to change how restoration days are determined not only for its own stations, but also for the other companies' stations. Seemingly, Circle K has taken the role as a price leader and been accepted as a price leader by the other companies: prior announcements of the recommended price by the price leader initiates coordination of inter-brand retail prices.

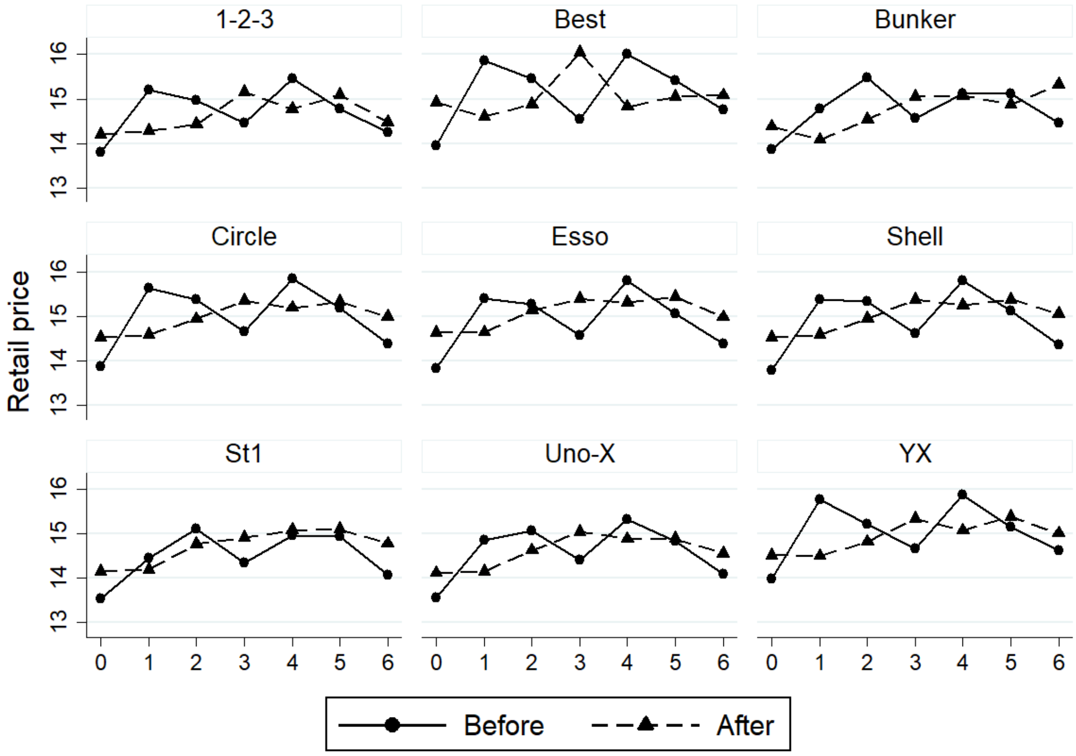


Figure 13: Mean p.m. retail prices per day-of-the-week before and after the price policy changes across brands. On the x-axis, 0= Sunday,.., 6= Saturday. Sample period is 1 January 2017 to 28 February 2018.

Having established a change in price behavior for other brands than those belonging to Circle K from 29 November 2017 as well, I investigate whether there is any relationship between Circle K's recommended price and price restoration for different companies. I carry out the same exercise as in Figure 7 by looking at retail prices together with days for which Circle K changes its recommended price, except that I instead look at the mean daily p.m. prices for each brand over time for reasons addressed above. Figure 14 shows the same behavior for brands belonging to other companies. In particular, the major brands Shell, Esso and Uno-X seem to implement price restorations on days when Circle K announces an adjustment in their recommended price.

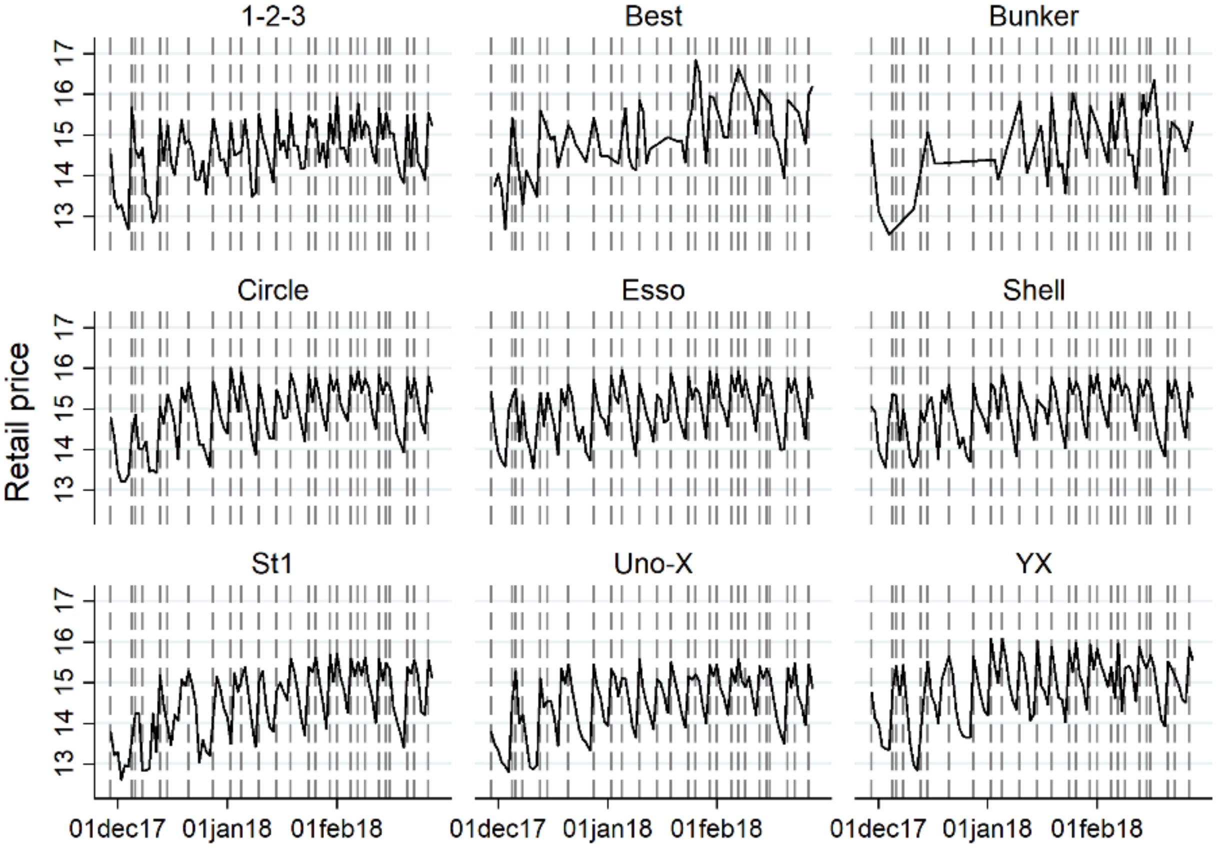


Figure 14: Mean p.m. retail prices by brand over time after the policy change. Vertical dashed lines mark dates with a change in the recommended price of Circle K. Sample period is 29 November 2017 to 28 February 2018.

Is price restoration as systematic as it is found to be for Circle K's stations in terms of when price restores during the day? Although one should be careful looking at single observations from user-reported data, they can still give an indication of how prices behave. To keep the most accurate stations, I exclude all stations with less than hundred observations in the post-period, leaving thirteen stations left. These stations cover all the four major companies from five different counties. Table 10 gives an overview of brand and ownership. Within a restoration day, I look at stations with price reports before in addition to after the 9 a.m. to 11 a.m. window within the same day. Then, I am able to tell whether the station's price has restored within the day, depending on when the price report after the 9 a.m. to 11 a.m. window is made. In many cases, I observe a price report before as well as a price report within the 9 a.m. to 11 a.m. window. As such, for those stations on those particular days, I can study the timing of a price restoration more carefully. For other cases, I only observe a price before this "restoration window" on a restoration day and another price report the day after, or a price report the day before a restoration day and another price report after the restoration window on the restoration day. Hence, while I do not observe the exact time of restoration if any, these observations still indicate whether price restoration occurred within those two times.

I find that for all the different pairs of observations as explained above, the behavior of the Esso, Shell/St1 and Uno-X stations are very similar to those of Circle K stations. I see numerous observations showing that on days where Circle K adjusts its recommended price, retail price is relatively low in the early morning, while has restored within the 9 a.m. to 11 a.m. window. In general, I do not observe that prices restore on days where Circle K does not adjust its recommended price. This again suggests that the new pattern is adapted by all the four major companies. In addition, since the time during the day when price restores seems quite systematic, it suggests that the cause of price restorations by other companies is because they follow and adapt Circle K's announcement of a nationwide restoration of prices for their stations, rather than that single stations follow Circle K stations' restorations in the local market.[38]

Table 10: Overview of brand and ownership for stations with hundred or more observations from 29 November 2017.

Brand	Owner	No. of stations
1-2-3	Circle K	1
Circle K	Circle K	4
Esso	Esso	2
Shell	St1	1
St1	St1	2
Uno-X	Uno-X	3
Total	4	13

After Circle K's price policy change, Uno-X adjusts its recommended price whenever Circle K does so.[39] In fact, based on personal observations from March to July 2018, 100% of Circle K's adjustments of recommended prices are followed up by changes in the recommended prices of Uno-X within 90 minutes later. Further, in this period, their recommended price is always set 0.02 NOK above Circle K's. Since the recommended prices are available online, observations made by myself suggest that while Circle K posts adjusted recommended prices between 7:30 a.m. and 8 a.m. on the restoration day, Uno-X adjusts their recommended prices accordingly between 8:30 and 9:30 a.m. the same day. This implies that at least Uno-X follows Circle K's decisions on when to implement restorations for its stations. In fact, Uno-X's use of the recommended price seems to work as a device to signal back to the leader that it will follow on the retail prices. Whereas Esso does not post recommended prices online while Shell/St1 does so only for the corporate market, findings from the user-reported data further suggest that Esso and St1 now behave according to the new common view.

[38] Information available online suggests that there is a mix of dealer-owned or franchise-owned and company-owned stations in this sample, which suggests that the price policy applies regardless of contract form.

[39] The recommended price is posted on YX's webpage, Uno-X's serviced brand. Unfortunately, I am not able to examine whether this is the case also before the policy change.

6 Concluding remarks

This paper examines how price coordination, and importantly, coordination on price restorations, is carried out in retail gasoline markets. I show that the recommended price of the largest company, which is publicly available on the company's website, serves two functions. First, it determines the level of the price restoration. Second, it serves as a signal of *when* to implement a restoration day: Every time the largest company announces an adjustment to the recommended price in the early morning, price restoration is implemented the following forenoon. I show that a new systematic way to coordinate on prices and synchronize price restorations inter-brand and across local markets has emerged with the use of prior announcements of the price leader's recommended price as a signaling device. This paper contributes to existing literature by adding to the understanding of how the creation of a new common view evolves in oligopoly markets, and how prior signals can successfully facilitate price coordination.

Several papers empirically addressing price coordination and leadership find systematic coordination of prices among firms similar to the Norwegian case (e.g., Noel, 2007; Wang, 2009; Atkinson, 2009; Lewis, 2012). However, this case is special in that the recommended price is used as a signaling device to coordinate on the retail prices. To my knowledge, there is no similar occasion yet detected in previous literature on gasoline retailing.[40] Byrne and de Roos (2017a) show how retail prices can be used to communicate among firms, with main focus on how a mutual understanding originates, and this study relates as such. Yet, this case differs in one important way: Being aware of the change of practice from the very beginning, I made observations in real-time that led me to specifically scrutinize how a new common view of price behavior emerges.

Concentrated markets with few firms present, homogenous products and stable demand are more likely to facilitate (tacit) collusion (Markham, 1951; Harrington, 2008). Price leadership need not aim at achieving implicit communication[41]; other possible theoretical explanations are dominant firm (Deneckere and Kovenock, 1992) or barometric (Cooper, 1997) leadership. Yet, leadership pricing is one common way to aid implicit collusion (Harrington, 2017). In the Norwegian case, undercutting of prices between restorations within the local market confirms that there are periods of hard competition. Nonetheless, companies can still find it gainful to make a commitment to regularly end the undercutting phase by simultaneously jumping prices back up to a more profitable level. Hence, Circle K's systematic use of the recommended price as a signaling device has unlikely emerged by chance.

Why would any firm take initiative to be the only price leader? In an infinitely repeated game with price leadership, Harrington (2017) shows that with partial mutual understanding of the collusive price the leader faces the risk of lower demand and profits because rivals might not follow immediately.[42] However, this cost can in practice be prevented if the price leader instead makes an announcement regarding the future price in advance. Then, the leader can expect all firms to jump retail prices simultaneously rather than risk that the others do not

[40] One example of leadership pricing in relation to prior announcement of prices is from the U.S. airline industry in the 1990s (Borenstein, 2004).

[41] Seaton and Waterson (2013) identify price leadership in British supermarkets, but find no evidence of collusion.

[42] In this context, perfect mutual understanding can be translated to explicit communication.

follow. To accomplish such announcements, a channel that ensures all competitors have received the announcement must be in place. In the Norwegian market this channel is arguably the website of Circle K where recommended prices are posted, and it is a suitable medium for three reasons. First, as the recommended price already serves the function of determining the restoration level, companies for sure follow each other's recommended prices closely. Second, recommended prices are supposed to guide consumers on which prices are "correct" when taking costs into account at all times, hence the announcement of them serves a valid (claimed) purpose towards customers. Third, even though recommended prices are available to guide consumers, few consumers actually check it on a regular basis.[43] As such, using the recommended price as a signaling device will receive little attention from others than the companies themselves. Therefore, abruptly changing the behavior of the recommended price by adjusting it more frequently by smaller amounts, followed by a simultaneous jump of all the stations in its network, is a relatively safe approach by the price leader to ensure that competitors learn that a new rule is about to be initiated.

Hence, one possible explanation to why Circle K is the price leader is that it is in possession of a well-suited prior announcement channel at the same time as it now avoids the risk of losing demand and profits if rivals do not respond rapidly. Another explanation is that the firm in the price leader role can earn higher profits if there is asymmetric information. Rotemberg and Saloner (1990) show that if firms are somewhat asymmetrically informed of demand, the less informed firm can earn more by having the rival as a price leader, while the more informed firm yields higher profits by taking the leader role. Thus, both firms agree upon which firm should be the price leader.

One question remains: Why end a stable arrangement of cycling prices after fourteen years? The arrangement clearly was profitable with increasing retail margins over time (Foros and Steen, 2013; Foros et al., 2018). Moreover, having a long-lasting cycle breached overnight with one single public announcement also underlines the fact that each company had the option to leave the practice of a regular weekly cycle every week since 2004, however, chose to stay as it was profitable to do so. In recent years, the predictable pattern has received increased attention from the Norwegian Competition Authority (2015), which on several occasions has expressed the opinion that the fixed cycle causes limited competition in the market. Further, in relation to adjustments in gasoline taxes in the beginning of 2017, the finance minister devoted great attention to the competitive level in the industry (TV2, 2017). In addition, the Norwegian Consumer Council (2017) has actively advised consumers to pay attention to the cycle and time their purchases in order to avoid the peak prices. Hence, one possible reason for the implementation of a new policy of more discrete ways to coordinate on prices and restorations is to receive less attention from the broad audience.

Another possible explanation is that Circle K wishes to smooth out demand at its stations throughout the week. Since low price periods were highly predictable under the old cycle, stations might have experienced queues and depletion of inventories in the time periods prior to price restorations. However, this can hardly be the only incentive: Apart from the announcement on its website 29 November 2017, as far as I am aware, Circle K has not

[43] In fact, conversations with the Norwegian Competition Authority reveal they do not find this price interesting either.

attempted to inform consumers about the price policy change. It is reasonable to believe that if capacity constraints is the main incentive, Circle K would more actively inform about the change through for instance advertisements.

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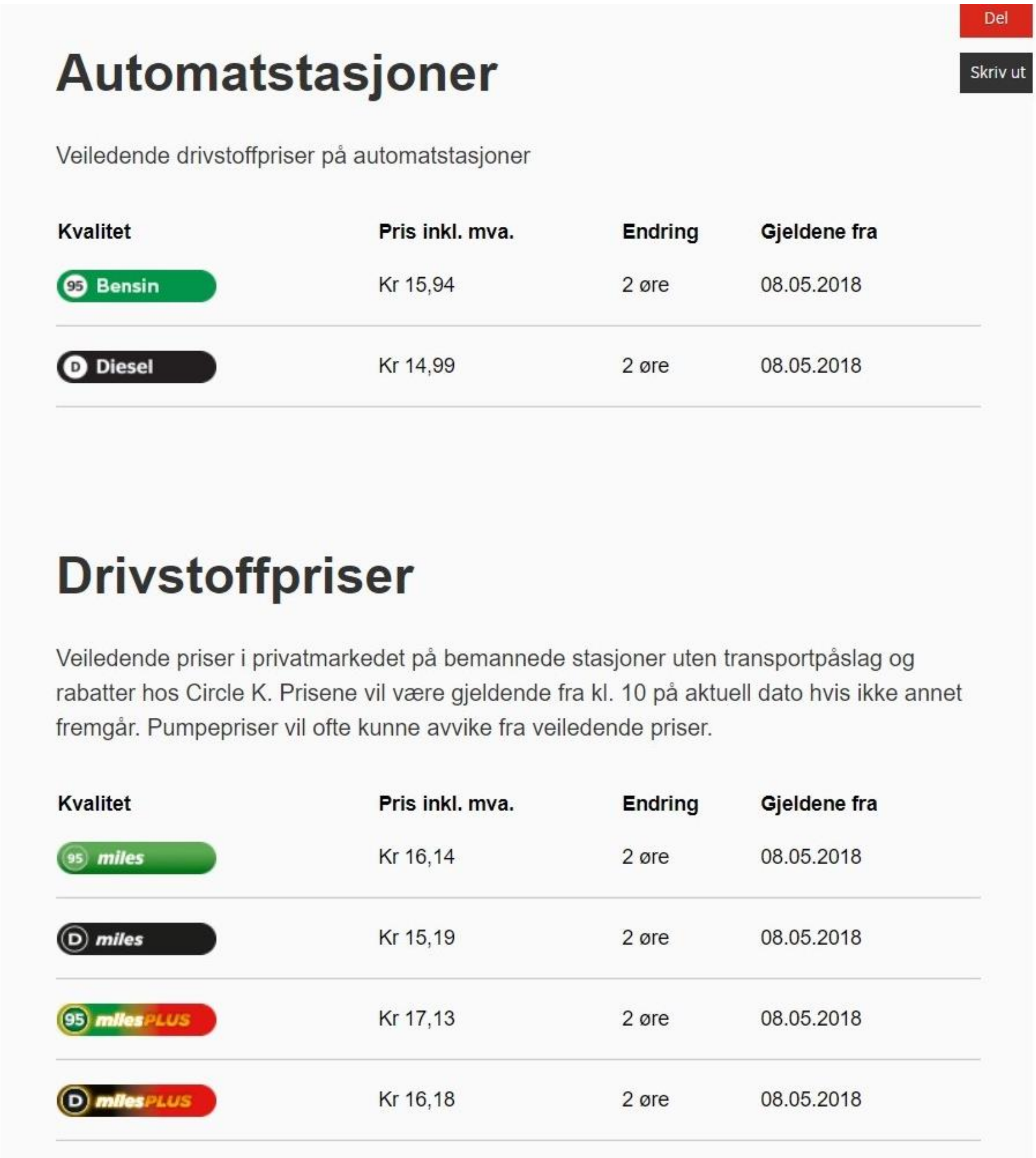
Appendix

A. Further information regarding the price policy announcements

Figure A.1: Announcement of Circle K's price policy change (the first paragraphs of it).



Del

Skriv ut

Automatstasjoner

Veiledende drivstoffpriser på automatstasjoner

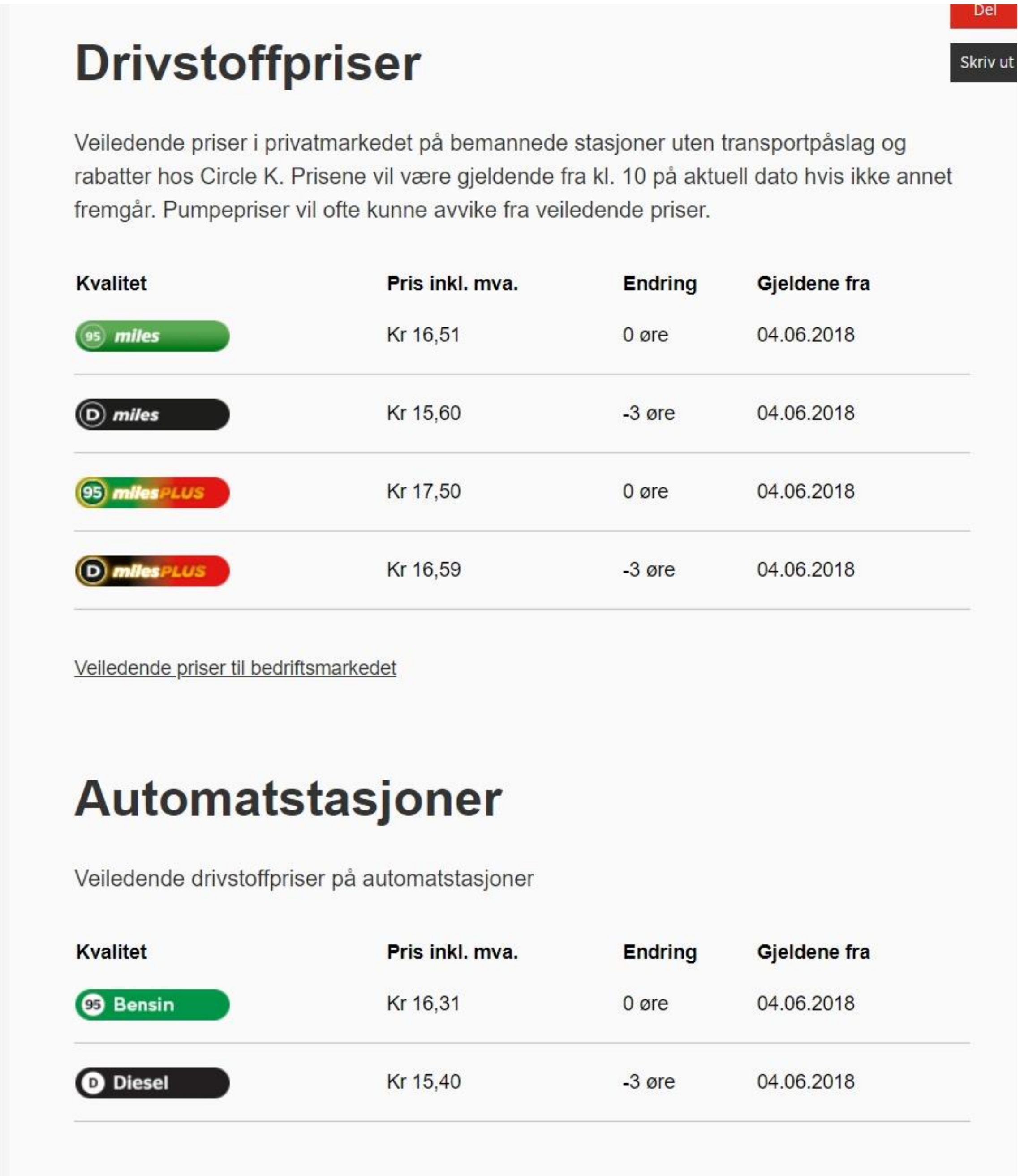
Kvalitet	Pris inkl. mva.	Endring	Gjeldene fra
95 Bensin	Kr 15,94	2 øre	08.05.2018
D Diesel	Kr 14,99	2 øre	08.05.2018

Drivstoffpriser

Veiledende priser i privatmarkedet på bemannede stasjoner uten transportpåslag og rabatter hos Circle K. Prisene vil være gjeldende fra kl. 10 på aktuell dato hvis ikke annet fremgår. Pumpepriser vil ofte kunne avvike fra veiledende priser.

Kvalitet	Pris inkl. mva.	Endring	Gjeldene fra
95 miles	Kr 16,14	2 øre	08.05.2018
D miles	Kr 15,19	2 øre	08.05.2018
95 milesPLUS	Kr 17,13	2 øre	08.05.2018
D milesPLUS	Kr 16,18	2 øre	08.05.2018

Figure A.2: Website of Circle K with posted recommended prices. Screenshot from 8 May 2018.



Del

Skriv ut

Drivstoffpriser

Veiledende priser i privatmarkedet på bemannede stasjoner uten transportpåslag og rabatter hos Circle K. Prisene vil være gjeldende fra kl. 10 på aktuell dato hvis ikke annet fremgår. Pumpepriser vil ofte kunne avvike fra veiledende priser.

Kvalitet	Pris inkl. mva.	Endring	Gjeldene fra
95 miles	Kr 16,51	0 øre	04.06.2018
D miles	Kr 15,60	-3 øre	04.06.2018
95 milesPLUS	Kr 17,50	0 øre	04.06.2018
D milesPLUS	Kr 16,59	-3 øre	04.06.2018

Veiledende priser til bedriftsmarkedet

Automatstasjoner

Veiledende drivstoffpriser på automatstasjoner

Kvalitet	Pris inkl. mva.	Endring	Gjeldene fra
95 Bensin	Kr 16,31	0 øre	04.06.2018
D Diesel	Kr 15,40	-3 øre	04.06.2018

Figure A.3: Website of Circle K with posted recommended prices. Example of an announcement of only a change in the recommended price of diesel. Screenshot form 4 June 2018.

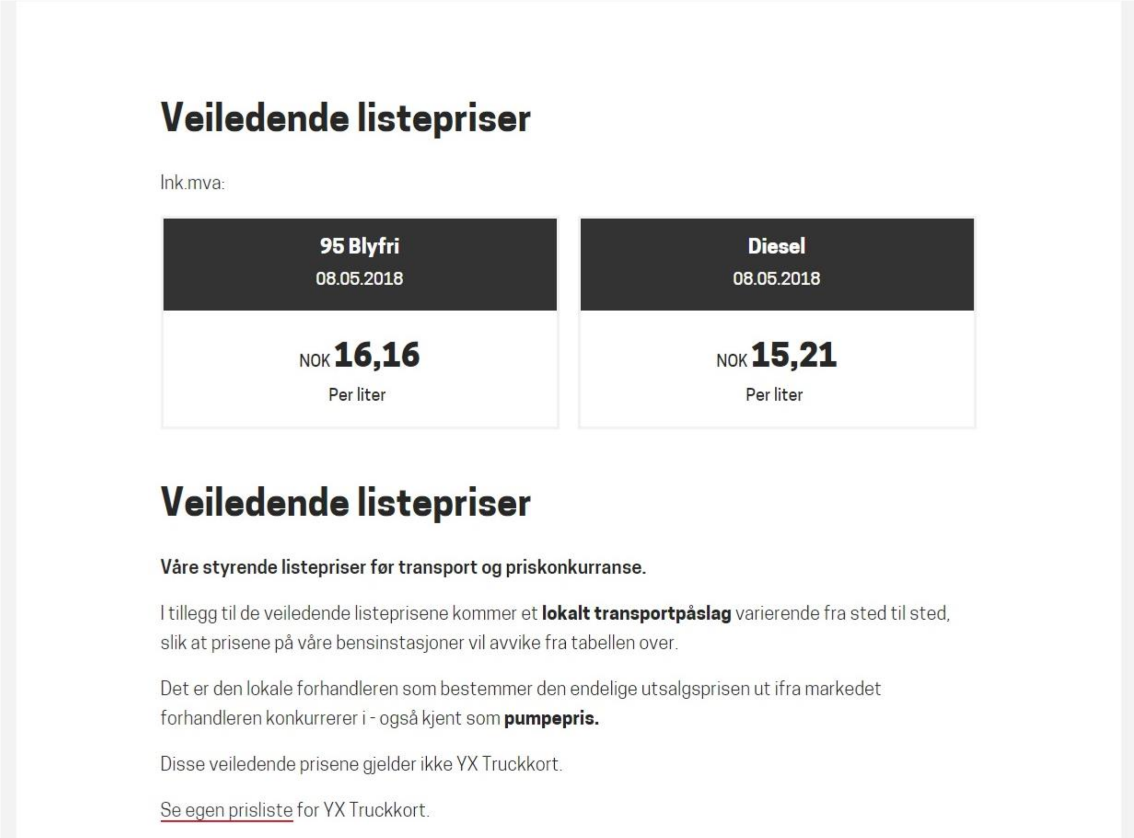
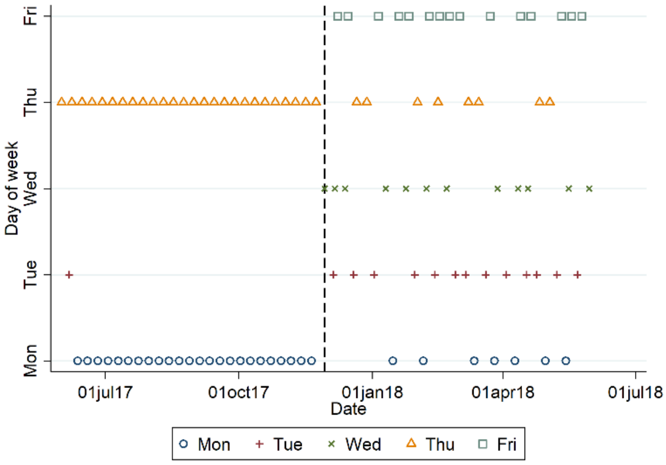
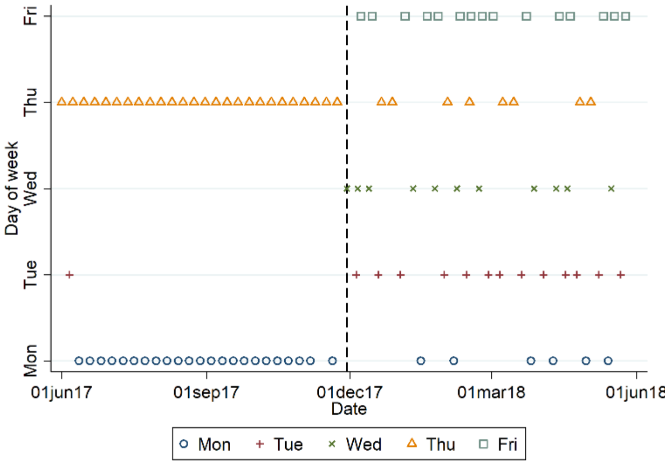
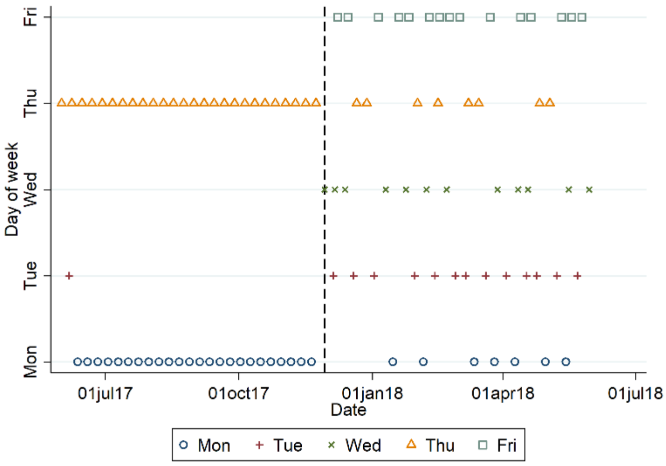


Figure A.4: Website of YX with posted recommended prices. Screenshot from 8 May 2018.

B. Hourly panel







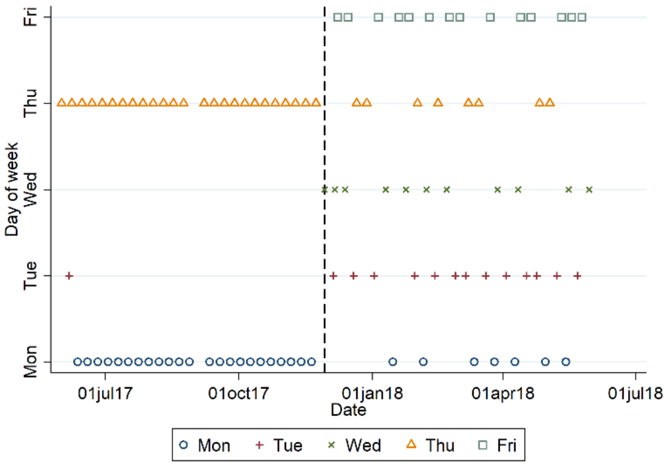


Figure B.1: Occurrence of restoration days by day of the week over time for station 1 (Oslo, top left), station 2 (Bergen, top right), station 3 (Trondheim, bottom left) and station 4 (Stavanger, bottom right). Sample period is 1 June 2017 to 31 May 2018. Days of the week are measured on the y-axis and have different point markers. Dashed vertical line marks the date of the policy announcement (29 November 2017).

Table B.1: Summary statistics of hourly retail price. Data period is 1 June 2017 to 31 May 2018. Pre-period is 1 June 2017 to 28 November 2017. Post-period is 29 November 2017 to 31 May 2018.

	Mean	Std.dev.	Min	Max
Pre-period				
Mon	14.306	0.653	12.470	16.490
Tue	14.796	1.172	12.470	16.760
Wed	15.288	0.902	13.090	16.710
Thu	14.696	0.720	12.540	16.280
Fri	15.028	1.033	11.520	16.760
Sat	15.368	0.858	12.470	16.710
Sun	14.766	0.749	12.470	16.710
Total	14.894	0.950	11.520	16.760
Post-period				
Mon	14.939	0.758	12.910	16.630
Tue	14.780	0.810	12.910	16.630
Wed	15.063	0.899	12.910	16.780
Thu	15.290	0.778	12.910	16.640
Fri	15.265	0.708	12.910	16.630
Sat	15.350	0.734	12.490	16.710
Sun	15.244	0.776	12.910	16.630
Total	15.135	0.806	12.490	16.780

Table B.2: Retail price changes by station. Sample period is 1 June 2017 to 31 May 2018.

	Price increase			Price decrease		
Station	Number	Mean	Mean daily number	Number	Mean	Mean daily number
Pre-period						
1	70	1.918	0.387	272	-0.497	1.503
2	73	1.709	0.403	583	-0.214	3.221
3	62	1.785	0.343	419	-0.264	2.315
4	57	2.070	0.315	116	-1.013	0.641
Post-period						
1	65	1.271	0.353	248	-0.320	1.348
2	61	0.738	0.332	250	-0.170	1.359
3	62	1.216	0.337	461	-0.161	2.505
4	57	1.579	0.310	127	-0.706	0.690

Table B.3: Summary statistics of normalized price at 3 p.m. for the pre-period and 11 a.m. for the post-period. Data period is 1 June 2017 to 31 May 2018. Pre-period is 1 June 2017 to 28 November 2017. Post-period is 29 November 2017 to 31 May 2018.

Day of cycle		Obs.	Mean	Std.dev.	5 pctl	25 pctl	50 pctl	75 pctl	95 pctl
Pre-period									
2-day duration									
	0	104	-0.191	0.721	-2.240	-0.010	0.060	0.080	0.110
	1	104	-1.103	0.864	-2.530	-2.025	-0.790	-0.410	0.060
	2	100	-1.621	0.671	-2.685	-2.095	-1.555	-1.100	-0.530
3-day duration									
	0	104	-0.060	0.649	-0.260	0.060	0.060	0.080	0.110
	1	104	-1.075	0.801	-2.280	-1.980	-0.815	-0.455	0.040
	2	104	-1.497	0.695	-2.460	-2.040	-1.410	-1.120	-0.190
	3	104	-1.949	0.604	-2.980	-2.255	-2.015	-1.570	-0.820
Average all durations									
	0	208	-0.126	0.687	-2.050	0.060	0.060	0.080	0.110
	1	208	-1.089	0.831	-2.460	-1.995	-0.805	-0.425	0.060
	2	204	-1.558	0.685	-2.560	-2.050	-1.480	-1.110	-0.410
	3	104	-1.949	0.604	-2.980	-2.255	-2.015	-1.570	-0.820
Post-period									
1-day duration									
	0	68	0.056	0.179	0.060	0.060	0.060	0.095	0.110
	1	68	-0.407	0.547	-1.610	-0.395	-0.220	-0.070	0.060
2-day duration									
	0	36	0.029	0.295	0.060	0.060	0.070	0.095	0.110
	1	36	-0.338	0.527	-1.760	-0.380	-0.215	-0.010	0.110
	2	36	-0.719	0.579	-1.760	-1.065	-0.635	-0.265	0.110
3-day duration									
	0	48	0.080	0.022	0.060	0.060	0.080	0.110	0.110
	1	48	-0.288	0.507	-1.470	-0.330	-0.090	0.040	0.110
	2	48	-0.766	0.561	-1.760	-1.275	-0.650	-0.360	0.050
	3	48	-1.099	0.524	-1.910	-1.500	-1.105	-0.765	-0.090
4-day duration									
	0	40	0.078	0.021	0.060	0.060	0.070	0.095	0.110
	1	40	-0.419	0.646	-1.860	-0.605	-0.190	0.030	0.060
	2	36	-0.704	0.621	-2.100	-1.120	-0.585	-0.200	0.060
	3	36	-1.137	0.545	-2.100	-1.405	-1.230	-0.755	0.030
	4	36	-1.453	0.564	-2.140	-1.840	-1.515	-1.165	0.030
5-day duration									
	0	12	0.084	0.024	0.060	0.060	0.080	0.105	0.130
	1	12	-0.357	0.504	-1.340	-0.705	-0.085	-0.010	0.060
	2	12	-0.994	0.666	-2.160	-1.540	-0.890	-0.495	0.030
	3	12	-0.879	0.805	-2.160	-1.420	-1.010	0.035	0.090
	4	12	-1.102	0.811	-2.160	-1.835	-1.275	-0.305	0.090
	5	12	-1.266	0.845	-2.310	-1.890	-1.530	-0.515	0.090
Average all durations									
	0	216	0.064	0.157	0.060	0.060	0.080	0.110	0.110

1	204	-0.366	0.550	-1.610	-0.380	-0.190	-0.010	0.080
2	132	-0.757	0.591	-1.760	-1.210	-0.650	-0.330	0.060
3	96	-1.086	0.572	-1.940	-1.435	-1.160	-0.725	0.060
4	48	-1.365	0.644	-2.140	-1.840	-1.485	-1.140	0.030
5	12	-1.266	0.845	-2.310	-1.890	-1.530	-0.515	0.090

Table B.4: Coefficient estimates from the linear, logit and probit model. Dependent variable is $priceup_{it}$.

Variables	Linear	Logit	Probit
Mon	0.0191***	-0.1794	0.0141
	(0.003)	(0.628)	(0.198)
Tue	0.0017	0.2428	0.0652
	(0.002)	(0.580)	(0.194)
Wed	0.0020	0.4771	0.1497
	(0.002)	(0.447)	(0.151)
Thu	0.0216***	0.3736	0.1301
	(0.003)	(0.647)	(0.218)
Fri	0.0001	-0.3992	-0.1428
	(0.002)	(0.773)	(0.246)
H10	-0.0016	0.0611	0.0074
	(0.005)	(1.219)	(0.395)
H11	0.0121*	1.3913*	0.4499
	(0.006)	(0.765)	(0.278)
H12	0.0116**	1.0422	0.3835
	(0.006)	(0.843)	(0.288)
H13	0.0158***	0.2129	0.1349
	(0.005)	(0.892)	(0.292)
H14	0.0894***	2.5270**	0.9265**
	(0.014)	(1.054)	(0.385)
H15	0.0165***	3.3304***	1.2981***
	(0.004)	(0.883)	(0.308)
H16	-0.0002	1.6492**	0.5877**
	(0.002)	(0.794)	(0.297)
changerp	-0.0051	-0.8700	-0.3139
	(0.004)	(1.416)	(0.528)
post	0.0098***	-1.9885**	-0.5114**
	(0.002)	(0.891)	(0.249)
Mon×H10	-0.0184	1.8729	0.4102
	(0.018)	(1.457)	(0.545)
Mon×H11	0.0592***	2.1920**	0.8649**
	(0.020)	(1.068)	(0.394)
Mon×H12	0.0522***	2.9244***	1.1102***
	(0.015)	(1.065)	(0.389)
Mon×H13	0.1113***	4.7097***	1.8890***
	(0.026)	(1.111)	(0.405)
Mon×H14	0.2410***	3.4998***	1.8259***
	(0.037)	(1.206)	(0.444)
Mon×H15	0.0070	-1.9233	-0.8536*
	(0.006)	(1.459)	(0.512)
Mon×H16	0.0042	-0.4889	-0.1583
	(0.005)	(1.482)	(0.484)
Tue×H10	0.0013	0.1033	0.0695
	(0.014)	(1.277)	(0.412)
Tue×H11	-0.0084	-1.2701	-0.4319
	(0.014)	(1.055)	(0.379)
Tue×H12	0.0035	0.0496	0.0968
	(0.010)	(1.140)	(0.380)
Tue×H13	0.0074	1.3017	0.4489
	(0.011)	(1.488)	(0.516)

Tue×H14	0.0080	-0.8142	-0.2738
	(0.017)	(1.329)	(0.501)
Tue×H15	0.0100	-1.7032	-0.6761
	(0.008)	(1.215)	(0.442)
Tue×H16	0.0066	0.2182	0.1559
	(0.014)	(1.324)	(0.429)
Wed×H10	-0.0139	-1.3381	-0.4767
	(0.014)	(1.076)	(0.383)
Wed×H11	-0.0118**		
	(0.006)		
Wed×H12	-0.0004		
	(0.005)		
Wed×H13	-0.0018		
	(0.018)		
Wed×H14	0.0111	-1.8456*	-0.7369*
	(0.007)	(1.055)	(0.386)
Wed×H15	0.0075	-0.6096	-0.2391
	(0.010)	(1.327)	(0.476)
Wed×H16	0.0175	1.1343	0.4939
	(0.012)	(1.315)	(0.427)
Thu×H10	-0.0039	-0.5127	-0.1484
	(0.013)	(1.054)	(0.384)
Thu×H11	-0.0110**		
	(0.005)		
Thu×H12	-0.0015		
	(0.004)		
Thu×H13	0.3761***	4.2080***	2.4653***
	(0.045)	(1.186)	(0.441)
Thu×H14	0.1045***	0.8126	0.5131
	(0.018)	(0.999)	(0.348)
Thu×H15	0.0129*		
	(0.008)		
Thu×H16	0.0175	1.1343	0.4939
	(0.012)	(1.315)	(0.427)
Fri×H10	0.0361	1.6208	0.6920
	(0.026)	(1.350)	(0.458)
Fri ×H11	-0.0188	-0.2630	-0.1113
	(0.021)	(1.106)	(0.410)
Fri ×H12	-0.0055	-1.2681	-0.3637
	(0.008)	(1.116)	(0.382)
Fri ×H13	0.0058	0.6311	0.2514
	(0.008)	(1.642)	(0.539)
Fri ×H14	0.0058		
	(0.019)		
Fri ×H15	0.0268**		
	(0.011)		
Fri ×H16	-0.0004		
	(0.003)		
Mon×changerp	-0.0005	1.5640	0.4384
	(0.008)	(1.355)	(0.532)
Tue×changerp	0.0054	2.5989**	0.8680**
	(0.005)	(1.185)	(0.409)
Wed×changerp	0.0058*	1.1019	0.4288
	(0.004)	(1.513)	(0.561)
Thu×changerp	0.0070	1.4655	0.5432

	(0.005)	(1.223)	(0.450)
H10×changerp	-0.0099	4.2572***	2.3047***
	(0.009)	(0.851)	(0.318)
H11×changerp	-0.0098	-1.2219	-0.3778
	(0.017)	(0.919)	(0.355)
H12×changerp	0.0065	-0.7839	-0.1409
	(0.020)	(1.075)	(0.486)
H13×changerp	-0.0247	-1.7398	-0.6701
	(0.022)	(1.092)	(0.494)
H14×changerp	0.0418	-0.6519	-0.1514
	(0.066)	(0.814)	(0.379)
H15×changerp	-0.0135	-0.5993	-0.2585
	(0.016)	(0.624)	(0.250)
H16×changerp	0.0080	0.2035	0.0816
	(0.016)	(1.141)	(0.423)
Mon×post	-0.0381***	-2.5859**	-0.9736**
	(0.003)	(1.202)	(0.495)
Tue×post	-0.0023	0.0560	-0.0249
	(0.002)	(1.008)	(0.295)
Wed×post	-0.0015	0.6066	0.1482
	(0.002)	(1.121)	(0.328)
Thu×post	-0.0414***	0.2802	-0.0408
	(0.002)	(0.985)	(0.296)
Fri×post	0.0024	2.0901**	0.6325*
	(0.005)	(0.999)	(0.330)
H10×post	0.0050	1.6214*	0.4433
	(0.008)	(0.894)	(0.324)
H11×post	-0.0129*	0.8931	0.2280
	(0.007)	(1.007)	(0.340)
H12×post	-0.0071	2.4601**	0.6737*
	(0.007)	(1.136)	(0.386)
H13×post	-0.0298***	1.1732	0.1505
	(0.009)	(1.285)	(0.479)
H14×post	-0.1820***		
	(0.020)		
H15×post	-0.0362***	-1.7685	-0.9088**
	(0.007)	(1.135)	(0.390)
H16×post	-0.0026	0.6368	0.1702
	(0.004)	(1.447)	(0.460)
changerp×post	0.0014	-0.0011	-0.0275
	(0.006)	(1.148)	(0.405)
H10×changerp ×post	0.5295***		
	(0.038)		
H11×changerp ×post	0.4531***	5.8699***	2.7252***
	(0.039)	(1.420)	(0.519)
H12×changerp ×post	-0.0053	-0.6932	-0.3664
	(0.021)	(1.710)	(0.679)
H13×changerp ×post	0.0200		
	(0.023)		
H14×changerp ×post	-0.0393		
	(0.069)		
H15×changerp ×post	0.0079	0.7520	0.3953
	(0.017)	(1.673)	(0.584)
H16×changerp ×post	-0.0082	-0.9171	-0.2503
	(0.017)	(2.357)	(0.741)

Mon×changerp ×post	0.0065	1.5826	0.7776
	(0.010)	(1.556)	(0.627)
Wed×changerp ×post	-0.0015	0.6857	0.1691
	(0.006)	(1.306)	(0.467)
Thu×changerp ×post	-0.0008		
	(0.007)		
Wholesale	-0.0015*	-0.1793*	-0.1172*
	(0.001)	(0.107)	(0.063)
Constant	0.0030	-5.1823***	-2.3235***
	(0.003)	(0.489)	(0.237)
No. of obs.	35 029	31 553	31 553
R-squared	0.329		

Note: Standard errors clustered on the day level in parentheses. All models include *wholesale* and station fixed effects. *** p<0.01, ** p<0.05, * p<0.1. Data period is 1 June 2017 to 31 May 2018.

C. User-reported data

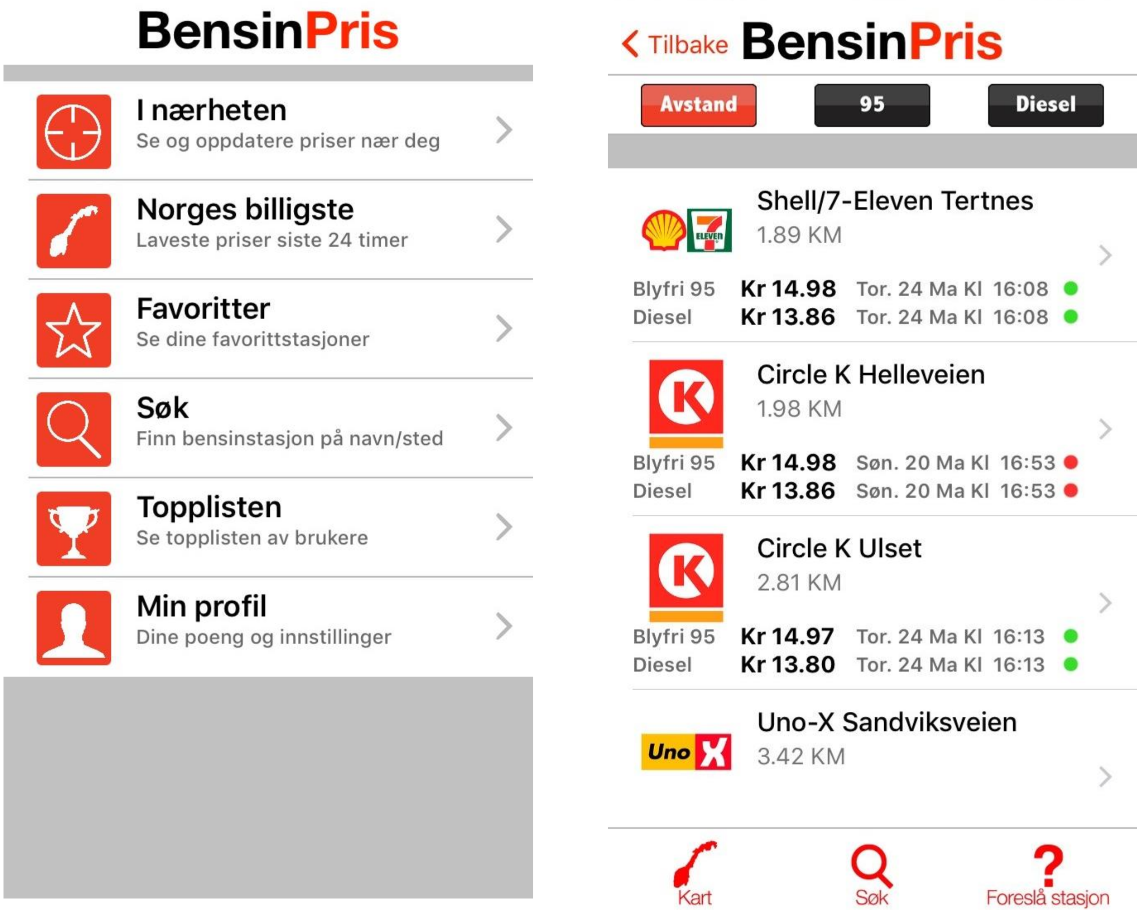


Figure C.1: BensinPris application. Screenshot from 24 May 2018.

Table C.1: Overview of counties covered. Sample period is 1 January 2017 to 28 February 2018.

County	No. of obs.
Østfold	7977
Akershus	25 819
Oslo	21 773
Hedmark	1796
Oppland	1077
Buskerud	6841
Vestfold	4274
Telemark	754
Aust-Agder	595
Vest-Agder	1078
Rogaland	19 464
Hordaland	6086
Sogn og Fjordane	381
Møre og Romsdal	725
Nordland	863
Troms	1408
Trøndelag	5450
Total	106 361

Chapter 3

The Effects of a Day Off from Retail Price Competition: Evidence on Consumer Behavior and Firm Performance in Gasoline Retailing*

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Abstract

First, we analyze how regular days off from competition and a time-dependent price pattern affect firm performance. Second, we examine the effects on firms' profitability from consumers' changing search- and timing behavior. We use microdata from gasoline retailing in Norway. From 2004 to 2017, firms practiced an industry-wide day off from competition, starting on Mondays at noon, by increasing prices to a common level given by the recommended prices (decided and published in advance). In turn, a foreseeable low-price window is open before every restoration. During the data period, we observe an additional weekly restoration on Thursdays at noon. The additional day off from competition increases firm performance. As expected, a conventional price search of where to buy reduces firms' profitability. In contrast, consumers who are aware of the cycle and spend effort on when to buy have a positive impact on firms' profitability. If consumers spend effort on when to buy, they attempt to tank during low price windows. By its very nature, this shrink consumers' ability to compare prices at several outlets. Consequently, more attention to when to buy may soften price competition.

Keywords: Pricing cycles, Firm performance, Gasoline markets

JEL Codes: D22, L25, L42, L81

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1 Introduction

Time-dependent price patterns with a saw-tooth shape are observed in various markets. In gasoline retailing, several empirical studies (see Noel, 2016, and Eckert, 2013, for comprehensive surveys) find support for such intertemporal price dispersion as the outcome of a sequential competitive pricing game, known as Edgeworth cycles, as formalized by Maskin and Tirole (1988).[1] Saw-tooth shaped price patterns can also be the outcome of intertemporal price discrimination (e.g. Conlisk et al., 1984). Furthermore, firms may find it profitable to add complexity to their price structure in order to soften price competition (Carlin, 2009, and Ellison and Wolitzky, 2012, among others).

If firms charge uniform prices independently of *when* consumers make their purchases, consumers are harmed if firms manage to reduce or eliminate inter-brand price competition.[2] However, what is the effect of a short but regular period like a weekday off (or a *holiday*) from price competition? Consumers are worse off if they buy on days on which competition is absent, but they now have the option to move their purchases away from these periods. Furthermore, since the pattern is predictable, price competition can be intensified before the weekdays off from competition.

Regular time-dependent price patterns make consumers face an intertemporal menu of prices. If consumers are endowed with a given capacity of effort for search activity, shrinking the time window in which competition is present reduces consumers' ability to search for the where to buy. Complexity also increases since one has to consider both *when* to buy and *where* to buy.[3] Having decided to move one's purchases to a low-price window (e.g. a given day of the week or a happy hour), it becomes more costly to find the seller with the best offer within this time limited low-price window. If the consumer learns that *when* rather than *where* to buy is more effective in terms of savings, she may even reduce her search for the cheapest provider at any given time and instead spend her effort on adapting to the time cycle. Hence, from the consumer's point of view a possible trade-off arises as spending effort on timing purchases to periods with low prices might increase the marginal cost of finding the cheapest provider.

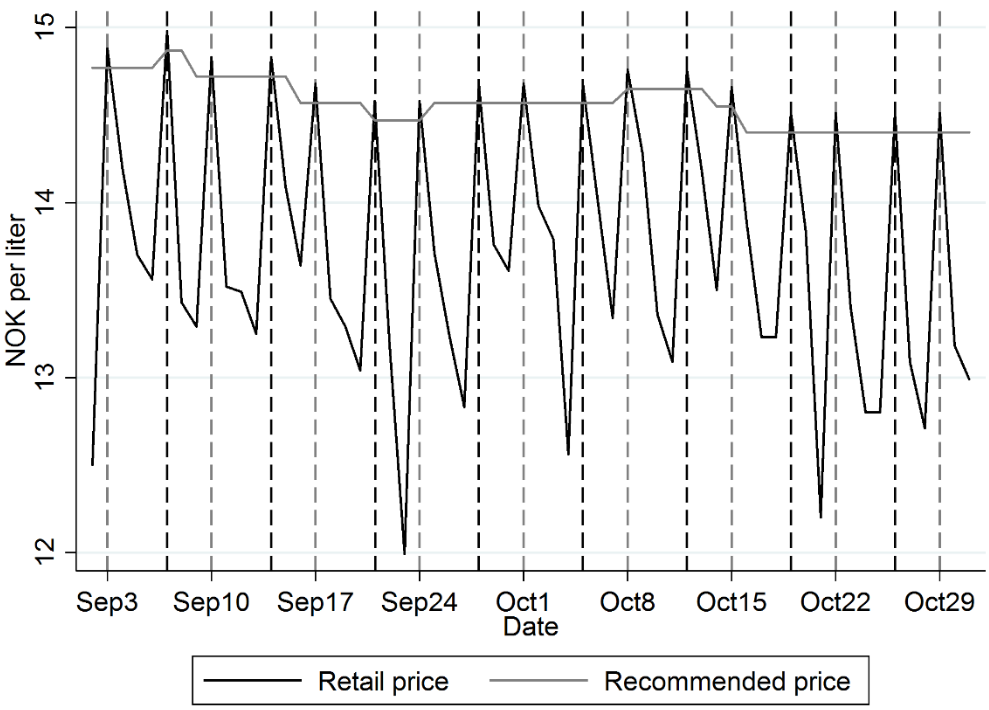
There may be countervailing forces at both sides of the market. If firms expect price wars to end at a given time, they do not need to be concerned about further undercutting in the

[1] Similar findings are made for search-engine advertising (Zhang and Feng, 2005).
[2] At least if we consider product quality and variety as exogenously given.
[3] General search models (Diamond, 1971, and Stahl, 1989, are seminal papers) predict that prices increase in search costs, and firms may find it optimal to make their own prices more complex for consumers (Ellison and Wolitzky, 2012).

next period. Consider a time-constrained low-price window such as Black Friday. Firms know that they can lower prices without fear of competitors undercutting on the succeeding days. For consumers, it is more efficient to consider *when* rather than *where* to buy in a Black Friday-regime. They move purchases of e.g. electronic products to Black Friday. However, short low-price windows make comparison of prices between several providers challenging.

We focus on the retail gasoline market. If we take into account the entire commuting path for a driver during a week, she may substitute stations located far from each other if she focuses on *where* it is cheapest during the week. However, if she focuses on *when* to buy (Monday morning), only stations closely located to her position at that time are alternatives.[4]

Figure 1: Retail prices and recommended prices for one gasoline station. Data period is 2 September to 31 October 2015. Black dashed lines mark Mondays while grey dashed lines mark Thursdays. The figure is constructed by using the last current retail price each day, except from Monday and Thursday in which the highest price is used for illustrative purposes. 1 EUR ≈ 9.50 NOK.



The Norwegian retail gasoline market is a picture perfect application. From 2004 to 2017, the four major retail chains have managed to take a day off from competition on Mondays. Every Monday around noon, all retail outlets throughout the country symmetrically raise their

[4] Houde (2012) considers retail gasoline competition in a Hotelling framework where consumers' locations are defined as their entire commuting paths.

pump prices in accordance with the recommended price set by the retail chains' headquarters. Price dispersion is then eliminated throughout the market, and all outlets raise their prices to the same level within approximately an hour. Recommended prices are published on the retail chains' websites, hence they easily detect if a rival deviates from the established practice both with respect to *when* the prices should increase (Monday) and to *which level* the prices should be increased (the recommended price). Prices then gradually decline over the subsequent days of the week when competition is in force. Since 2008 firms have implemented an additional day off from competition on Thursdays.[5] Similar to Mondays, we now observe a countrywide increase of retail prices to the recommended price also on Thursdays around noon. The resulting price cycle is illustrated in Figure 1 for one of the stations included in our sample over a nine-week period in 2015.[6] The Norwegian Competition Authority (2014, 2015), and Foros and Steen (2013) document that this has been a country-wide practice (on Mondays from 2004, on Thursdays from 2008). Foros and Steen (2013) show that the regular pattern is controlled by the major retail chains and is *de facto* caused by the supply side. The upstream companies maintain the price pattern with use of a profit sharing scheme involving periods with and without price support arrangements.[7] Topography leads to geographically isolated local monopolies in some parts of the country. In these locations, we observe that retail prices equal the recommended price throughout the week (Foros and Steen, 2013).[8] As such, we define the recommended price as the monopoly price (Bresnahan and Reiss, 1991). Accordingly, when the price level in geographically competitive locations equals the recommended price, we interpret the situation as a day off from competition.

In Figure 2 we illustrate gross margins on the restoration day. The illustration is eye-catching. The figure plots real gross margins at 8 a.m. and 2 p.m. for 43 stations on Monday 21 April 2008 and 44 stations on Monday 24 August 2015 from the same local market (Oslo, the capital and the most populous city in Norway).[9] First, there is a huge difference between

[5] Norwegian Competition Authority (2014).

[6] The four major nationwide gasoline companies are Circle K (market share 33%), Shell (25%), Esso (21%) and Uno-X (17%). See www.drivkraftnorge.no, the webpage of the Norwegian association for fuel and energy companies, for further details. Towards non-integrated retailers, headquarters make use of a maximum resale price maintenance system, recommended prices and a price support arrangement for which the upstream firm decides when to be operative. Symmetric cycles are hence a result of the upstream firms simultaneously deciding to disengage the price support on Mondays, and after 2008 also on Thursdays each week. A more thorough description is given in Appendix D.

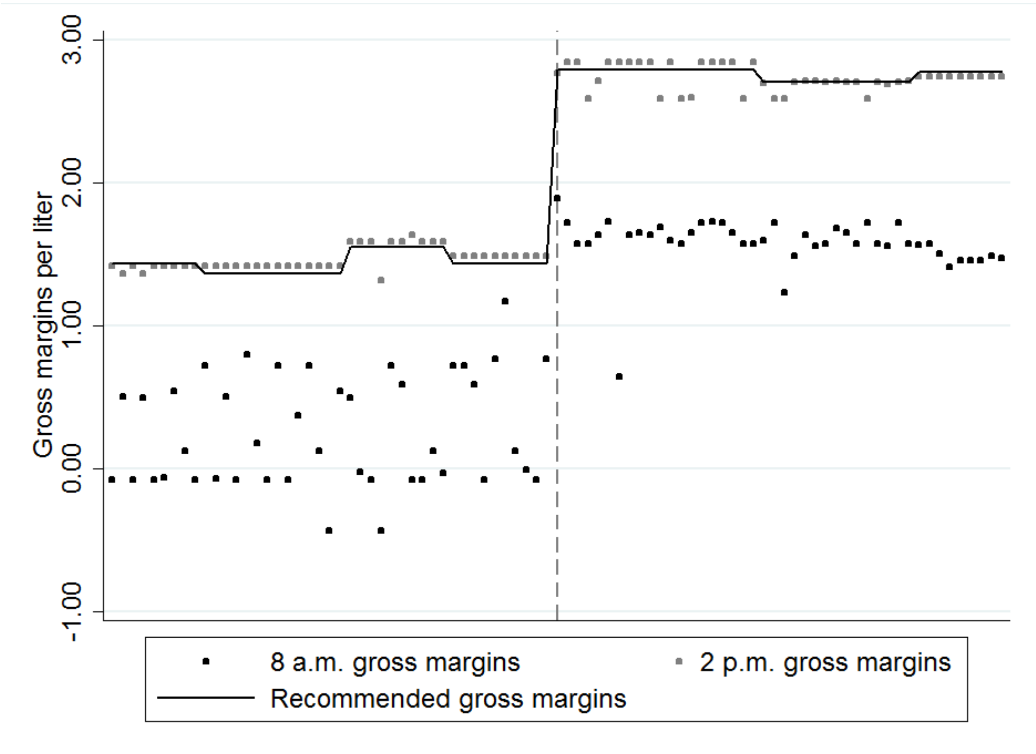
[7] The underlying mechanism is described in Appendix D.

[8] This is well illustrated in a statement to a local newspaper made by the manager of an outlet with no nearby stations: "*We had no competition, and used consistently the recommended price on gasoline*" (Bergens Tidende, 2018).

[9] The gross margin is the retail price deducted the wholesale price for gasoline, taxes and VAT. In 2015 the gross margin amounted to 13.6% of the retail price on average.

morning and afternoon gross margins across all retailers and different companies. Secondly, during an eight-year period (2008-2015), gross margins have increased when prices are at their highest after restoration but, most importantly, also when prices are lowest right before restoration. From the consumer's perspective, Figure 2 shows that spending effort on *when* rather than *where* to buy is more efficient.

Figure 2: Gross margins in NOK for gasoline stations in Oslo on Monday 21 April 2008 and Monday 24 August 2015. Margins are in real terms (2015-NOK=1). Each black mark and corresponding grey mark vertically above it are observations for one station. The 2008 observations are to the left of the vertical dashed line, while 2015 observations are to right of the same line. 1 EUR ≈ 9.50 NOK.



This leads us to the findings made by the Norwegian Competition Authority (2014, 2015). Using data on price and quantity from 2004 to 2011 for the entire population of stations in Norway, they show that consumers have only marginally adjusted to the price pattern by moving their purchases to the low price window on Sundays, despite that the Monday peak has existed throughout the country since the beginning of the sample period. Therefore, the introduction of another day off from competition is unlikely caused by changes on the demand side. Neither do they find any evolvement in costs which can account for the pattern. This supports Foros and Steen's (2013) pure firm-driven explanation to the driving force behind the cycle. Next, even with some increased adaption by consumers, gross margin per liter has been raised significantly in recent years, agreeing with Figure 2's observations.

We exploit the established predictable restoration pattern dating back to 2004 together with the new restoration day appearing after 2008. The additional day off from competition provides us with a scenario that allows us to analyze how regular days off from competition influence consumer behavior and firms' profitability.

We proceed in two steps. First, we study the impact of the time-dependent price pattern on firms' profitability. In particular, we pay attention to the effect of establishing an additional weekly restoration on Thursdays. To the best of our knowledge, our approach is novel.[10]

With the use of a panel dataset of daily gasoline prices covering different periods between 2004 and 2015, we are able to investigate the effect of the development of a second restoration day on profitability over time. We show that the introduction of another day off from competition has increased firms' gross margins throughout the week. This may explain why firms use a significant amount of effort on continuing to ensure that the system is in use every week.

In the second step, we investigate how consumer behavior influences firms' profitability by matching demand side variables from a survey dataset with the price panel. The survey is constructed to achieve knowledge about consumer awareness and purchasing behavior. It is carried out in four different years between 2005 and 2015 overlapping with the panel in addition to being conducted at retail stations included in the panel. The survey data allow us to scrutinize the interaction between the demand and supply side in a market with next to perfectly predictable prices.

Results show that the Monday restoration increases firms' profitability by 35.6%, while profitability in relation to the Thursday restoration increases by 22.2%. When allowing the Thursday effect to differ before and after the introduction of a second price peak in 2008, estimates suggest that being on a Thursday has an additional positive effect of 9.56% in the post-period, giving a total impact of 27.2%. Now, the Thursday effect is closer to the magnitude of the Monday effect.

Turning to the demand side, we find that increasing the share of consumers searching for the cheapest outlet by 1% decreases firms' profits by 0.5%, indicating that intensified search for where to buy in a market is healthy for competition, as expected. On the other hand, increasing the share of consumers who adapt to the cycle by following a timing rule by 1%, raises firms' profitability by 0.27%. The effect is significant at the 1% level, suggesting that

[10] Noel (2015) analyzes the effects on prices from a natural experiment (a refinery fire) where price cycles were temporarily eliminated.

pure adaptation to the cycle independent of station search may be beneficial to sellers. The introduction of an additional day off from competition on Thursdays reduces the competitive time window and likely increases the price complexity for consumers. When separating the effect before and after the establishment of the new Thursday peak, we find that with the new pattern in place, profitability increases by another 0.56%. We also show that the results are robust to various model specifications, in particular also to long run changes in the cost structure and the Norwegian business cycle.

In sum, results suggest that when more consumers spend effort on *when* to buy rather than *where* to buy, competition softens. This shift in consumer behavior de-incentivizes firms to compete since competition will only marginally affect consumers' choice of station during the two brief time windows with lower prices. The introduction of a second restoration day reduces the time window with normal price competition and increases profitability.

The rest of the paper proceeds as follows: Section 2 reviews related literature. Section 3 presents the data, while Section 4 provides preliminary results. Section 5 puts forth the methodology. In Section 6, results are presented and discussed. Robustness analyses are found in Section 7. Finally, Section 8 concludes.

2 Literature Review

Our point of departure is the interplay between consumer behavior and supply side profitability in the presence of a time-based pricing pattern. A crucial feature is the time dependency, leading the price pattern to be predictable for both suppliers and consumers. This is in contrast to random sales as analyzed in Stigler (1961), Salop and Stiglitz (1977) and Varian (1980), among others.[11] While our study provides support for that consumers engaging in search for where to buy are unfavorable to firms' profitability, our conjecture is that the cycle may drive consumers' attention away from spending effort on traditional search towards rather considering when to buy.

[11] Stigler (1961) was the first to develop a framework for which price dispersion is an equilibrium outcome due to costly search. Following Stigler (1961), Salop and Stiglitz (1977) show that price dispersion may arise in equilibrium with oligopolistic firms due to consumers who differ in the costs related to information acquisition. Whereas the price dispersion in this framework is persistent in that some sellers always have a higher price than others, Varian (1980) allows the same seller to set different prices over time (temporal price dispersion). In equilibrium, firms randomize prices in order to price discriminate between uninformed and informed consumers. See Tellis (1986) for a survey that makes the distinction between periodic and random sales (discounts). A thorough overview of the literature on search and price dispersion is given in Baye et al. (2006).

In the literature on information acquisition, some studies emphasize obfuscation as an explanation for firms' pricing behavior and consumers' response to it. Obfuscation complicates or prevents consumers from gathering price information. Ellison and Wolitzky (2012) show that firms may unilaterally choose to raise consumers' search costs (see also Wilson, 2010). Other papers analyze obfuscation as arising from bounded rationality on the consumer side where consumers for instance follow a rule of thumb. Chioveanu and Zhou (2013) show how firms may use price frames that confuse consumers and thereby affect consumers' ability to compare prices offered. The result is lower price sensitivity and, in turn, lower degree of price competition (see also Piccione and Spiegler, 2012). Carlin (2009) demonstrates that firms might want to add complexity to the price structure, and that the number of consumers who are able to choose the firm with the lowest price decreases in complexity.

De Roos and Smirnov (2015) develop a theory of optimal collusive intertemporal price dispersion. The motivation is the gasoline market, where they show how collusion can generate asymmetric price cycles which resemble Edgeworth cycles. Price dispersion clouds consumers' awareness of prices, which helps firms to coordinate on dispersed prices by decreasing their gains from deviations through price reductions.[12]

If we take into account the entire commuting path for a driver during a week, a consumer may substitute a number of stations located far from each other if she focuses on *where* it is cheapest during the week. This is in line with Houde (2012), where a consumer's entire commuting path is treated as the consumer's location ala a Hotelling framework. However, if she focuses on *when* to buy (Monday morning), only stations closely located to her position at that time are alternatives, similar to Houde's (2012) single-address approach. In the current application, our conjecture is that firms can make it more costly for consumers in terms of effort to buy from the cheapest provider. The reason is simply that rational consumers know that they need to buy during a brief low price window (Monday morning). It then becomes more costly in terms of effort to tank at the outlet with the lowest price. Furthermore, consumers might adapt to a simple rule of thumb saying that they should ensure to tank on Monday morning (Sunday as the second choice). When acting according to a rule of thumb, the attention is devoted to *when* to buy rather than *where* to buy. More attention to *when* to buy may reduce price competition.

[12] Complex price setting is found not only in commodity markets, but also in retail financial markets (Carlin, 2009, and Woodward and Hall, 2012), electricity markets (Waddam and Wilson, 2010) and online markets (Ellison and Ellison, 2009).

Price patterns with a saw-tooth shape, often labeled Edgeworth cycles (Edgeworth, 1925), are widely observed in retail gasoline markets.[13] As formally shown by Maskin and Tirole (1988), this pricing behavior can be the outcome of a sequential competitive pricing game. Firms successively undercut each other in a price-undercutting phase. The process continues until further undercutting becomes too costly. They then run into a war of attrition phase until one of them takes on the burden and raises its prices. The other firms will follow and increase their prices, but not to the same level as the firm that initiated the price increase.[14] Price cycles open up for intensive price undercutting between peaks. The war of attrition phase varies in length. Hence, equilibrium price cycles vary in duration and amplitude. Firms have a common incentive to end the war of attrition game as soon as possible (Wang, 2009). The empirical literature displays that several practices have emerged in order to end the war of attrition phase (see e.g. Wang, 2009, and Foros and Steen, 2013). In the current application, as shown by Foros and Steen (2013), retail chains symmetrically increase prices to the recommended prices on Mondays, and as shown in the present paper, now also on Thursdays. The undercutting phase might be consistent with the predictions from the Edgeworth cycle theory, while the price increases depend on time (day(s) of the week) rather than on a war-of-attrition game when further undercutting becomes too costly.[15]

The vast majority of papers analyzing cycles in retail gasoline markets focus on firms' pricing behavior. As pointed out in the literature surveys of Eckert (2013) and Noel (2016), the empirical literature on retail gasoline pricing is sparse on consumer behavior. Exceptions are Noel (2012) and Byrne and De Roos (2017), who examine how consumers respond to retail gasoline price cycles.[16]

An alternative explanation for price patterns with a saw-tooth shape is intertemporal price discrimination (Conlisk et al., 1984 and Sobel, 1984, among others[17]). In contrast to

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[13] Studies on pricing in gasoline retailing are carried out for markets in numerous European countries, e.g. Haucap et al. (2015) for Germany and Dewenter and Heimeshoff (2012) for Austria. See Eckert (2013) and Noel (2016) for surveys of both theoretical and empirical literature on pricing in retail gasoline markets.

[14] Eckert (2003) and Noel (2007; 2008), provide theoretical extensions of Maskin and Tirole (1988). These extensions show that Edgeworth cycles are not restricted to a symmetric duopoly with homogenous goods.

[15] Sequential undercutting as in Maskin and Tirole (1988) and coordination to end the war-of-attrition phase may be complementary. One example is that one firm takes the role as the price leader (Wang, 2009 and Lewis, 2012). In Norway, Foros and Steen (2013) describe how all firms increase prices at Mondays around noon, giving rise to a regular weekly price cycle.

[16] In contrast to the Norwegian market, cycles are less regular in the Canadian market considered by Noel (2012) and Byrne and De Roos (2017). The latter study finds that consumer responsiveness increases around price restoration periods; forward looking stockpiling behavior is anticipated as a crucial force in generating the cycles. Noel (2012) analyzes four purchase timing strategies consumers can follow to move their consumption. He finds that surprisingly few consumers use such strategies.

[17] In Conlisk et al. (1984) a monopoly firm offers durable goods. The firm uses periodic price reductions to discriminate between low- and high-value consumers. In each period new consumers enter the market.

Maskin and Tirole (1988), firms' incentives to reduce prices under intertemporal price discrimination arise from the presence of heterogeneous consumers (they differ in their willingness or ability to wait). Some observations are, however, inconsistent with price discrimination as the main driving force behind cycles. Eckert and West (2004) and Foros and Steen (2013), in the Canadian and Norwegian market, respectively, find that in some regions with high concentration, cycles are absent. Prices are then always equal to the recommended prices. Under intertemporal price discrimination, as in e.g. Conlisk et al. (1984), a monopolist will use price discrimination as well. Foros and Steen (2013) also shows that other explanations for weekly cycles, like costs or demand (volume) cycles are not present in the Norwegian market.

A further finding from our survey data is that consumer awareness in terms of learning and adjustment to the simple weekly cycle evolves rather slowly. This implies that intertemporal price discrimination is hardly the driving force behind firms' practice of the price support system and the recommended prices to ensure industry-wide identical retail prices on Mondays (and Thursdays).[18] However, as emphasized by Noel (2012; 2016), even if intertemporal price discrimination is unlikely as the main driving force behind firms' pricing behavior, the fact that competition creates these types of price cycles allows consumers to adapt to the pattern. In particular, this will be the case under regular calendar-based strategies as in Norway.

3 Data

We make use of three different datasets to address our research question.

3.1 Panel data

We use a panel covering different time periods between 3 May 2004 and 31 October 2015.[19] Data constitute daily price observations for unleaded 95-octane gasoline in NOK per

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Consumers who do not buy stay in the market, and the residual demand increases until price cuts become profitable. Sobel (1984) extends the former paper to a competitive setting. Dutta et al. (1984) combine repeated game and durable goods models. They demonstrate that the existence of an equilibrium with temporary price reduction requires that firms are more patient than consumers.

[18] Results are in line with the findings of the Norwegian Competition Authority (2914; 2015), which confirms that the increase in the volume purchased in low-price periods only amounts to a small fraction of the total weekly volume.

[19] The Monday peak was first observed after 27 April 2004 (Foros and Steen, 2013). Hence, we limit the data period to after this date.

liter from 11 local gasoline stations in Bergen (second largest city in Norway). Observations from 2004 and partly from 2005 are from a national website-based (NWB) data set in which consumers reported prices via text messages or e-mails throughout the day.[20] The rest of the dataset is collected in the afternoon (after 12 o'clock in the daytime) either by ourselves or provided to us by Circle K Norway.[21,22] In total, we have 2,165 observations. We acknowledge that our panel is highly unbalanced and unequally spaced. However, we have no reason to suspect that unbalancedness is caused by systematic reasons. We measure profitability as real gross margin per liter.[23] We calculate daily gross margins by subtracting the value-added tax (VAT), the gasoline tax, the CO_2 tax and the daily Rotterdam spot price in NOK from the retail price. Taxes are set by the Norwegian Tax Administration.[24]

Finally, all variables are measured in real terms with 2015 as the base year using the yearly Consumer Price Index available at the Statistics Norway's websites.[25]

3.2 Survey data

A survey questionnaire constructed to obtain knowledge about cycle awareness and purchasing behavior among consumers was repeatedly carried out in 2005, 2006, 2008 and 2015 at two different gasoline stations in Bergen, giving 867 respondents in total. These data provide us with unique information about how consumer awareness has evolved over an 11-year period. The surveys were conducted on the restoration days. To prevent selection bias among the customers we asked both before and after price restoration. The questionnaire was conducted with in-person interviews, in which costumers were approached and questioned

[20] This gives us several observations per station for many dates. Therefore, we take the average of reported prices for each station within each day from noon in order to obtain a unique daily observation per station.

[21] Prices accessed via Circle K Norway are quoted for each hour in which the price changes. We take the arithmetic average of prices from noon to obtain one price each day. For days without any changes from noon, we use the last applicable price. This concerns mostly Sundays.

[22] Since we are dealing with afternoon prices, Monday and Thursday are regarded as the high price days while Sunday and Wednesday are considered as the low price days.

[23] A complete overview of local stations and period for which we have data can be found in Table A.1 in the Appendix. All stations except Uno-X Kokstaddalen are full-service stations, but we include the station in order to increase sample size and hence preciseness in estimates. We have checked that our main results are robust to excluding this station.

[24] The VAT rate is set to 25% of the sum of the retail price, while the gasoline tax and the CO_2 tax are quantity taxes in NOK per liter and adjusted from year to year. Tax figures are available at the Norwegian Petroleum Industry Association's (NP) websites. The Rotterdam wholesale prices are accessed through Thomson Reuters and provided to us by NP. These are initially quoted in $/ton, but NP gives to us already converted data measured in NOK/liter. Wholesale prices are not quoted for the weekends. We therefore assume Friday prices for Saturdays and Sundays.

[25] See http://www.ssb.no/.

while they were filling their tanks.[26] From this dataset, we measure different demand side factors, which are used in our study.[27]

3.3 Cross-sectional data

In addition, as a supplement to the datasets for Bergen, we use data for retail prices at 8 a.m. and 2 p.m. from 43 stations on Monday 21 April 2008 and 44 stations on Monday 24 August 2015 in Oslo, Norway's capital city.[28] Stations for all the big four companies are included. From the prices, we calculate real gross margins and compare them to recommended gross margins. This dataset let us analyze the development of profitability over time both at the bottom as well as at the top of the price cycles. Hence, it allows us to better understand the price determination scheme in time-dependent markets.

For the sake of examining the establishment of the Thursday restoration, we also consider data from the same sample for two consecutive Thursdays in 2015, namely 27 August with observations from 43 stations and 3 September with observations from 42 stations.

3.4 Combining panel data and survey data

We examine the interaction between demand side factors and firms' profitability by matching the measures constructed from the survey data with the price panel. Specifically, we match survey variables with price variables based on matching year.[29] Since the survey data leave us with a yearly frequency in the variable measures, all observations within a year are matched with the same value, independent of station. Nonetheless, we bear in mind that we allow for stations to react differently to variation in the demand side measures. The stations in our panel are from the same geographical region as where the survey is carried out. Further, as the saw-tooth pattern in prices has been a country-wide practice, our sample is representative for the population despite its size.

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[26] Interviewers filled out the questionnaire while interviewing costumers. The survey consists of ten closed-ended questions and one open-ended question in addition to requests for personal information.

[27] An overview of station, date and number of respondents each year is given in Table B.2.1 in the Appendix. The survey questionnaire is presented in Appendix B.1.

[28] This represents all stations in the two cities.

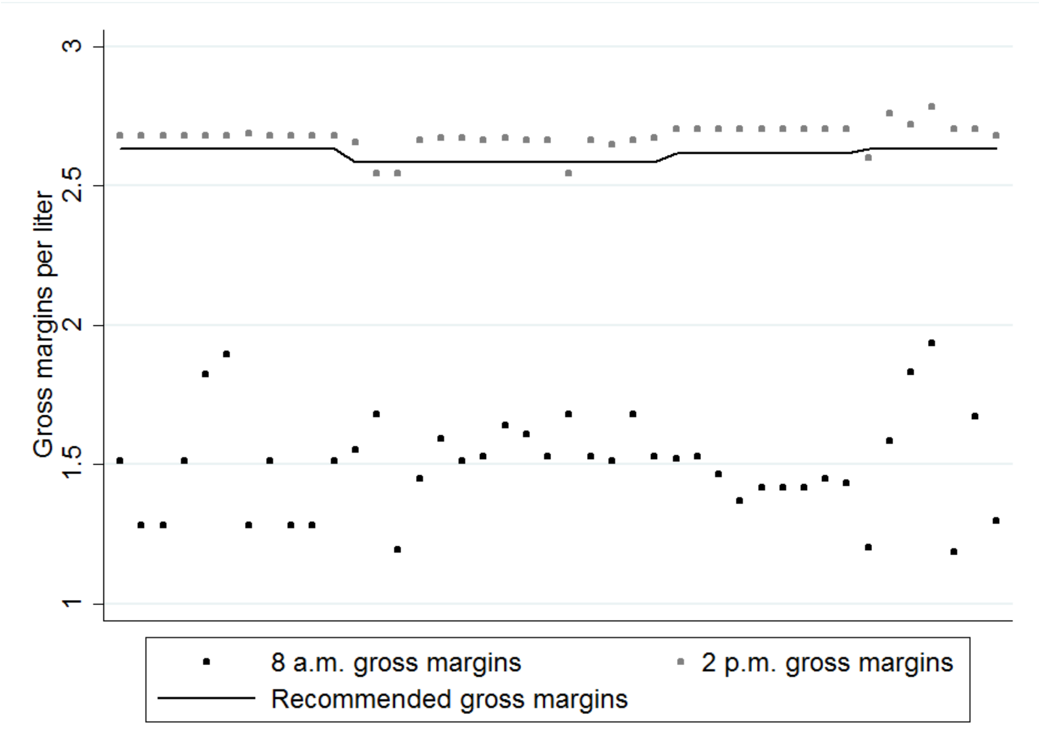
[29] Since our panel covers 2004, 2005, 2006, 2008 and 2015 while we lack survey data for 2004, we use values for 2005 for 2004.

4 Preliminary descriptive results

4.1 Firms' profitability

We start with the cross-sectional data. For the Monday data, we calculate real gross margins at 8 a.m. and 2 p.m. as well as recommended gross margins for each station in 2008 and 2015 (base year 2015). A plot of these data is presented in Figure 2 in the Introduction. We find some striking results. First, the average recommended margins have increased since 2008 by 91.9%. Second, the difference in average real gross margins between these two random Mondays is 86.6% at 2 p.m. and as much as 510.9% at 8 a.m. Third, the Levene's test reveals significantly less dispersed gross margins at 8 a.m. in 2015 compared to 2008. The two-sample t-test shows that the increase in average gross margins at both 8 a.m. and 2 p.m. is significant.[30]

Figure 2: Retail gross margins in NOK for gasoline stations in Oslo on Thursday 3 September 2015. Each black mark and corresponding gray mark vertically above it are observations for one station.

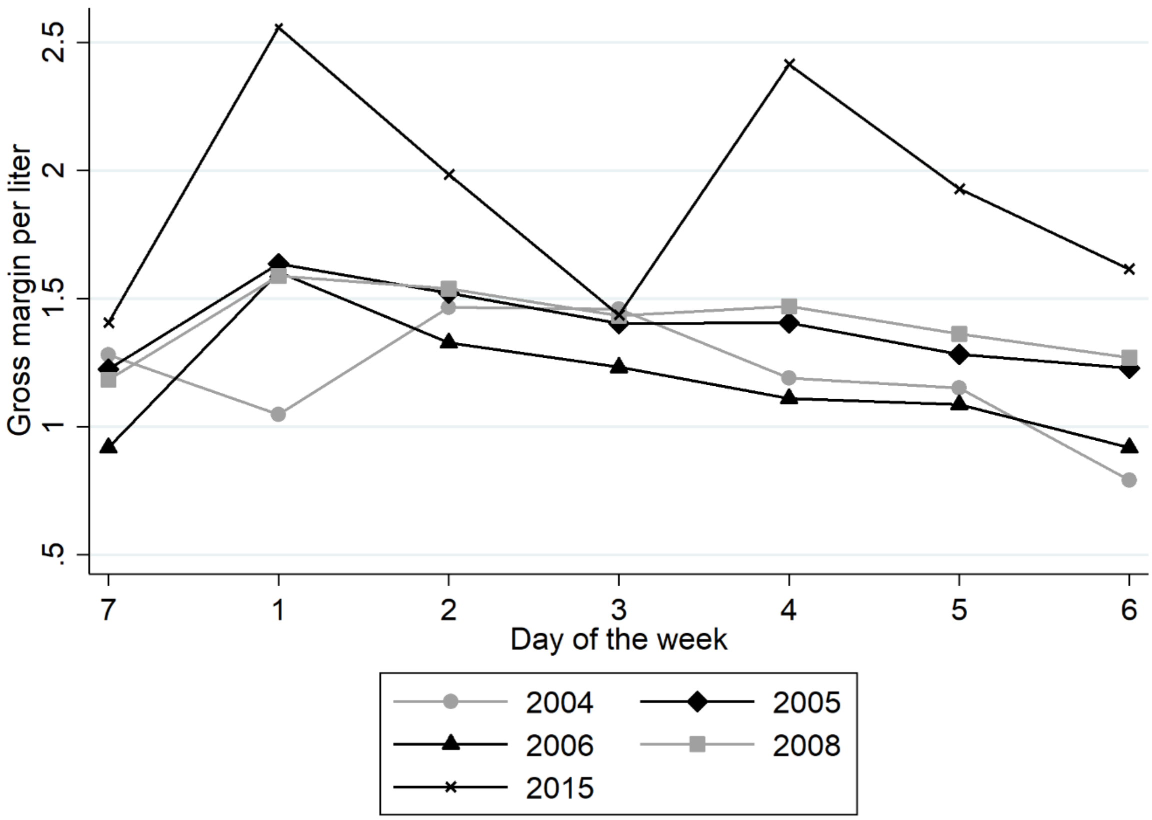


In 2008, the lowest gross margin at 8 a.m. is even negative. From Figure 2, we detect that this is the case for several stations. In contrast, only positive gross margins are observed at 8 a.m. in 2015. Considering the magnitude of the gross margin increase together with the Levene's test, we observe that synchronization of prices has been established even in the low

[30] Summary statistics and tests for the cross-sectional data are reported in Table C.1 to C.4 in the Appendix.

price window. Moreover, there has been an increasing trend in average gross margins as well as in recommended margins in Oslo during the seven-year period.

Figure 4: Mean gross margin by day of the week and year. Day 1 corresponds to Monday, while day 7 corresponds to Sunday.



Moving to the Thursday data, observations depicted in Figure 3 demonstrate the exact same pattern as detected for Mondays in prices and hence in gross margins on Thursdays too.[31] Further, behavior is similar for two consecutive Thursdays, assuring that predictability in prices is not caused by sampling reasons. On 27 August, gross margins increase on average by 59.4% from 8 a.m. to 2 p.m., while the corresponding increase is 78.1% on 3 September. The mean for the 2 p.m. gross margins is around 1 NOK higher than for the 8 a.m. gross margins. Next, compared to 8 a.m. observations, standard deviations for 2 p.m. observations are three times smaller for 27 August and almost four times smaller for 3 September. From this, we observe that the systematic behavior in prices in 2015 is completely present on Thursdays as well. Around noon, prices increase to the recommended prices for practically all stations. During the

[31] We have checked that an analogous pattern exists for Thursday 27 August.

morning, there is a higher degree of dispersion. Furthermore, none of the stations has negative gross margins for any of the Thursdays.

We now continue with the panel data. Summary statistics of the price data are reported in Table A.2 to A.4 in Appendix. Figure 4 depicts the mean gross margin by day of the week and year. We notice that the magnitude of profitability in 2015 clearly stands out compared to previous years. Even the Wednesday margin, just before the new day off from competition (Thursday), has not been reduced. Another insight is that whereas there are signs of a small increase in the Thursday margin in 2005 and 2008, the jump in 2015 is as clear-cut as the Monday peak. Nevertheless, in the following analysis, we rely on the Competition Authority's (2014) observation of 2008 as the start of the establishment of the Thursday restoration.

In sum, we observe that firms' profitability has increased in line with the implementation of a second day off from competition, which is consistent with our conjecture.

4.2 Consumer behavior

From the questionnaire, we create variables based on each respondent's reply to the different questions. Variables are presented as response share of the total number of respondents by year. Table 1 to Table 4 provide descriptive statistics for the most important questions.[32] Overall, respondents seem to become more aware of the price pattern over time. From Table 1, we see that whereas 35% have the impression that the retail price increases on specific days of the week in 2005, 44% and 53% believe so in 2006 and 2008, respectively, and as many as 81% in 2015. Still, the measure does not tell whether the perceptions are in line with the actual cycle or not. Turning to Table 2, in 2005, 11% of the respondents have the correct impression that Monday is the only restoration day, while 28% give the same answer in 2015. The emergence of a second restoration day has confused consumers further, since only 14% believe correctly that only Monday and Thursday are the only restoration days in 2015.

Question 6, presented in Table 3, concerns whether consumers who are aware of the cycle move their purchases to low-price windows. Of those who are aware of the retail price increasing on specific days of the week, 31% take this information into account very often when making their purchases in 2005, while 39% do so in 2015.[33] At first glance, this observation can be misinterpreted as increasing price sensitivity between 2008 and 2015. However, it might just indicate that more consumers move their attention towards *when* to tank rather than where

[32] Tables B.2.2 to B.2.3 in the Appendix present the remainder. Summary statistics are reported in Table B.2.5.

[33] Note that the shares are decreasing from 2005 to 2006 and 2008. We do not have an explanation for this.

to tank simply because they follow a rule of thumb, as discussed in the Introduction. If *when* to purchase rather than *whe*re to purchase becomes the main factor to act by, it is reasonable to expect that these consumers more often refill at the same station (e.g. the most convenient station to drop by on Monday morning). Provided that consumers have a given capacity of effort, brief low price windows leave little scope for searching between stations.

We are interested in establishing a measure of consumers who are concerned with when to purchase during a week. To follow a rule of purchasing based on timing requires the consumer to know when restorations occur and thereby when low price windows occur. Therefore, we classify a consumer as following a purchasing rule based on when to buy, denoted *timing* , if she is aware that the price increases on specific days during a week (as identified by Question 6 alternative "Very often" or "Fairly often" in Table 3), in addition to making all purchases at the same station (as identified by Question 8 in Table B.2.4). This measure is presented in Table 5. We note that the share of consumers classified as timing consumers increases over time, from 12% in 2005 to 27% in 2015. Intuitively, following for instance a rule of thumb based on when to tank, seems like a rational action as more consumers become aware of the existence of a predictable pattern in prices. As emphasized, our conjecture is that consumers focusing on *when* to buy can soften inter-brand price competition since focus is moved away from where to tank.

In addition, we want a measure of searching consumers as an indication of the consumers concerned with where to find the lowest prices. We assume that a consumer who compares retail prices announced on large signs outside stations during a week drops by the station with the lowest price when she is in need of gasoline. It is reasonable to think that consumers who compare prices on signs are more focused on searching than those who do not check the sign. Intuitively, drivers pass many stations during the week, and while driving can pay attention to the price signs outside stations, which are easily visible from the road.[34] Hence, we define a searching consumer as one who checks the signs outside stations and makes her purchases at more than three different stations. Table B.2.4 shows that 36% of the respondents purchase at more than three different stations compared to 26% in 2005. Moreover, from Table 4 we see that the share of consumers that check the price on signs has almost doubled since 2005. When combining these two requirements, we note from Table 5 that the measure of searching consumers, *search*, has increased from 8% in 2005 to 17% in 2015. This suggests

[34] Our measure of search is motivated by the standard literature in search theory in which consumers' information gathering in prices is costly. One of the classic frameworks is provided by Stigler (1996).

that consumers have become more price conscious with time by attempting to exploit inter-station dispersion.

One should anticipate that both the search and the timing consumers are more present in the low-price window. As a simple consistency check, we therefore construct the variables separately for 2015-observations before and after restoration. For *timing* the shares are 31% and 20% before and after restoration, respectively. For *search* the shares are 21% and 11% before and after peak, respectively. Hence, the numbers are in accordance with our anticipations.

Table 1: Shows the answers from question 4: "Do you think the retail price increases on specific days of the week?". Numbers in parentheses are total number of respondents by year. Shares not summing to 100% are due to non-response.

	Yes	No	Do not know
2005 (289)	35 %	63 %	1 %
2006 (151)	44 %	56 %	0 %
2008 (225)	53 %	28 %	19 %
2015 (202)	81 %	9 %	10 %

Table 2: If yes on Question 4, which day of the week does the retail price increase? Numbers in parentheses are total number of respondents by year. Shares not summing to 100% are due to non-response.

	Only Monday	Only Thursday	Only Monday and Thursday
2005 (289)	11 %	0 %	0 %
2006 (151)	23 %	1 %	1 %
2008 (225)	29 %	1 %	1 %
2015 (202)	28 %	0 %	14 %

Table 3: If yes on Question 4, how often do you take this into account when making your purchases? Numbers in parentheses are total number of respondents by year. Shares not summing to 100% are due to non-response. Shares summing to over 100% are due to rounding numbers.

	Very often	Fairly often	Neither	Fairly seldom	Very seldom
2005 (289)	31 %	9 %	7 %	8 %	39 %
2006 (151)	21 %	17 %	12 %	8 %	33 %
2008 (225)	13 %	15 %	18 %	7 %	45 %
2015 (202)	39 %	13 %	12 %	4 %	33 %

Table 4: Where do you check the retail price? Numbers in parentheses are total number of respondents by year. Shares not summing to 100% are due to non-response.

	Do not check the price	Check on the pump	Check on the sign outside of station	Other
2005 (289)	46 %	7 %	31 %	0 %
2006 (151)	35 %	15 %	50 %	0 %
2008 (225)	48 %	13 %	38 %	0 %
2015 (202)	38 %	2 %	60 %	0 %

Table 5: Measure of timing and search by year. Numbers in parentheses are total number of respondents by year.

	Timing	*Search*
2005 (289)	12 %	8 %
2006 (151)	11 %	11 %
2008 (225)	20 %	8 %
2015 (202)	27 %	17 %

5 Methodology

5.1 Measuring the impact of predictable time-dependent price cycles on profitability

We use a fixed effects model for our specification, and our main model is

$$M_{it} = \beta_0 + \sum_{j=1}^{6} \delta_j D_j + \gamma t + \beta_1 D_4 \times post07 + \beta_2 pwhole_t + \mu_i + \epsilon_{it}$$

The dependent variable is the log of gross margin in real NOK per liter for station i on day t. Due to time-dependent cycling prices, the main explanatory variables of interest are a full set of day-of-week dummies D_j, using Sunday as baseline. Note that we have defined our days as noon to noon, implying that the Sunday dummy will pick up the lowest prices in the week: Sunday afternoon and Monday morning. In order to investigate the development of the Thursday peak over time, we also include an interaction term between the Thursday dummy variable and a dummy variable $post07 = 1$ if the year is 2008 or later. The division in time is chosen based on the Norwegian Competition Authority's (2014) detection of the Thursday restoration for the first time in 2008. As control variables we include the log of wholesale price in real NOK $pwhole_t$ and a daily linear trend t. Finally, μ_i are station-specific fixed effects and ϵ_{it} are idiosyncratic error terms. We use White's robust standard errors.[35]

[35] Note that we do not have a sufficient number of stations to use cluster standard errors.

For the sake of investigating whether the development in trend differs by day of the week, we also estimate a model where a full set of interaction terms between the day-of-week dummy variables and the linear trend is included instead of the interaction term $D_4 \times post07$. This specification is given by

$$M_{it} = \beta_0 + \sum_{j=1}^{6} \delta_j D_j + \gamma t + \sum_{j=1}^{6} (\lambda_j D_j \times t) + \beta_1 pwhole_t + \mu_i + \epsilon_{it}$$

5.2 Measuring the impact of consumer behavior on profitability

We analyze the effect of two different demand side variables. We underline that changes in the price pattern are highly unlikely caused by the demand side. The Competition Authority (2014, 2015), using data from 2004 to 2011 for the entire population of stations in Norway, documents that consumers have only marginally adjusted to the price pattern by moving their purchases to the low price window on Sundays, despite that the Monday peak has existed throughout the country since the beginning of the sample period. Therefore, it cannot be the case that the introduction of Thursday as a day off from competition is caused by changes in the demand side. This observation is also supported by Foros and Steen’s (2013) pure firm-driven explanation to the driving force behind the cycle. Hence, reversed causality in the sense that market demand changes have driven the answers we observe in stated consumer surveys is not supported from what we know about the market and the demand conditions.

The first model in the investigation of consumer behavior examines the impact of search behavior on gross margin development, according to the specification

$$M_{it} = \alpha_0 + \alpha_1 search_t + \alpha_2 search_t \times post07 + \sum_{j=1}^{6} \delta_j D_j + \gamma t + \alpha_3 D_4 \times post07 + \alpha_4 pwhole_t + \mu_i + \epsilon_{it}$$

The explanatory variable of interest is the log of searching consumers $search_t$. This measure is constructed as the share by year of consumers that check the price on signs outside stations and make purchases at more than three different stations. Identification of α_1 hence stems from changes in the share of searching consumers over time. The inclusion of an interaction term between $search_t$ and the dummy variable $post07 = 1$ if the year is 2008 or later, further allows us to analyze the effect of search behavior on profitability after the establishment of a new weekly peak. In addition, the log of the wholesale price, a full set of day-of-week dummies and a daily trend are included as controls.

We are also interested in the effect of consumers who adapt their purchases to the predictable cycle. The second model therefore includes a measure of the share of consumers who act by timing the cycle, $timing$, as the main explanatory variable:

$$M_{it} = \alpha_0 + \alpha_1 timing_t + \alpha_2 timing_t \times post07 + \sum_{j=1}^{6} \delta_j D_j + \gamma t + \alpha_3 D_4 \times post07 + \alpha_4 pwhole_t + \mu_i + \epsilon_{it}$$

The variable measures the share of consumers who predict when low price windows occur during a week, for instance by following a rule of thumb, and move their purchases to these points in time. These consumers hence do not spend effort on price search because they regard timing purchases as more gainful than exploiting price dispersion across stations.[36]

Finally, since we estimate a margin model over a long period, also other factors might influence margin development, e.g., changes in costs beyond the wholesale price. In the robustness section we estimate models allowing for different additional control variables to see whether our results are robust also when controlling for these.

6 Results

6.1 The impact of predictable time-dependent price cycles on profitability

Table 6 presents our main results on price cycles. From the simplified specification in column (A) in which $D_4 \times post07$ is omitted, all day-of-week dummy coefficients are positive and significant except from the Saturday dummy. Being on Monday increases firms' profitability by 35.6%. The effect then declines when moving to Tuesday and Wednesday, until reaching a new increase on Thursday to 22.2%. Throughout the rest of the week, the effect descends compared to Sunday, which appears to be the day with the lowest profitability during a week (the low price window: noon Sunday to noon Monday). Results hence demonstrate the presence of a weekly cycle, with large price increases on Monday and Thursday, which in turn increase firms' profitability.

The linear trend coefficient is positive and significant, indicating that gross margins indeed have increased over time. If we calculate the effect of the trend from 3 May 2004 to 31 October 2015, the average margin in real terms has increased by NOK 0.428 - which is a significant amount compared to an average margin in 2004 of NOK 1.22. The real average margin increased by more than 35% over the data period.

[36] In the following, unless it is necessary for avoiding confusion, we will suppress station and time notation.

Model (A) shows the average cycle over the period 2004 to 2015. In model (B), we include the interaction term $D_4 \times post07$ to allow for the new restoration day introduced on Thursdays. The coefficient is positive and significant at the 1% level, suggesting that from 2008, the extra effect of Thursday as the current day of the week is 9.56%. The total effect of being on a Thursday from 2008 is hence 27.2%, which is stronger than the average effect measured in model (A). Of the day-of-week dummies, inclusion of $D_4 \times post07$ only changes the coefficient of the Thursday dummy, which now decreases to 0.176. This suggests that the Thursday peak has not been present during the whole sample period, as coefficients now slowly decline from Monday and throughout the week. The positive average trend effect now suggests an increase in the real margin of NOK 0.441. Thus, model (B) presents very similar results, but also that Thursday emerges as a new restoration day.

In order to analyze the development in trend based on days of the week, model (C) replaces $D_4 \times post07$ in favor of a full set of interaction terms between the trend variable and the day-of-week dummies. We find significant trend effects for four days. These are highest on the new restoration day Thursday, and second highest on Monday and Friday. Monday remains as the day on which firms earn the highest gross margins. To illustrate the development in the margins over time as predicted by model (C), we calculate the trend effect over the whole data period by adding the trend effect from each day-estimates to the benchmark estimate, e.g., for Thursday; 0.063 + 4198 days × 0.000102 = 0.063 + 0.428 = 0.491. This is illustrated for model (A) to (C) in Figure 5.

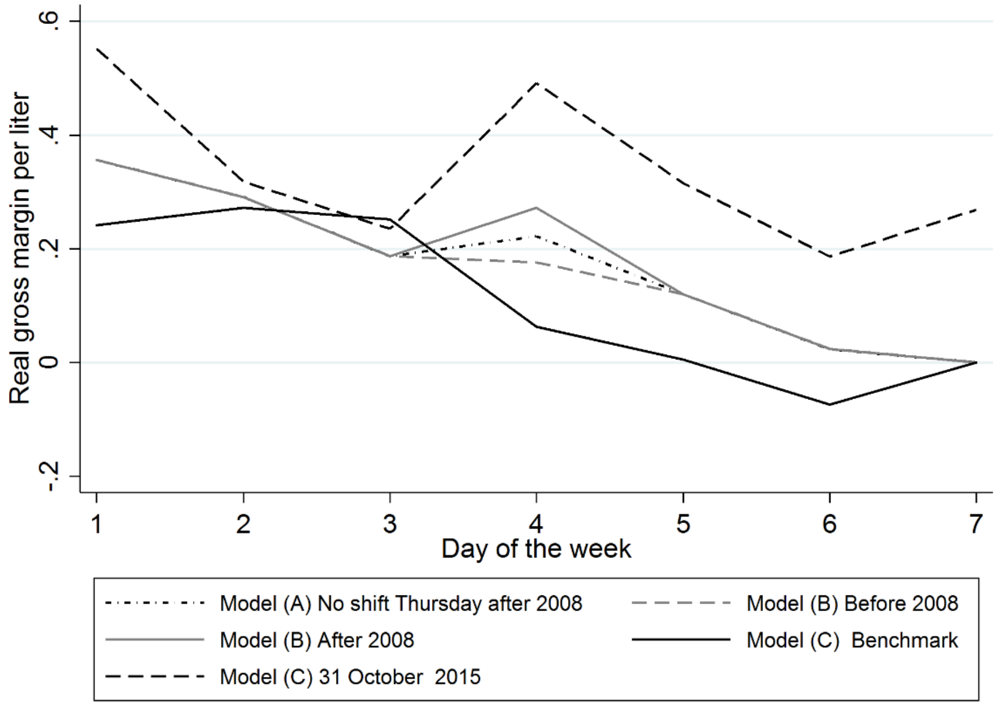
Several features become clear from Figure 5. Models (A) and (B) display the same pattern except for Thursday, where model (A) predicts the average effect of the before/after 2008 effects of the introduction of a second restoration day. First, the most flexible model (C) suggests that the Thursday effect has become stronger and very similar to the Monday effect, but that Monday still has the highest margin (0.55 vs 0.49). Second, we observe a marginally small trend-based reduction in the Wednesday margin over the data period (small negative trend coefficient). This is reasonable, since Wednesday (recall that this refers to noon Wednesday to noon Thursday) is now the low price window just before the second restoration on Thursday afternoon, and in the new cycle Wednesday has the same role as Sunday.

Table 6: Regression results. Dependent variable is log of gross margin in NOK per liter.

	(A)	(B)	(C)
Mon	0.356***	0.356***	0.241***
	(0.026)	(0.026)	(0.051)
Tue	0.291***	0.291***	0.272***
	(0.026)	(0.026)	(0.052)
Wed	0.187***	0.187***	0.252***
	(0.027)	(0.027)	(0.052)
Thu	0.222***	0.176***	0.063
	(0.028)	(0.038)	(0.053)
Fri	0.120***	0.120***	0.005
	(0.030)	(0.030)	(0.057)
Sat	0.023	0.024	-0.074
	(0.031)	(0.031)	(0.059)
Trend	0.000105***	0.000102***	0.000064***
	(0.000008)	(0.000008)	(0.000017)
Trend×Mon			0.000074***
			(0.000021)
Trend×Tue			0.000011
			(0.000026)
Trend×Wed			-0.000040
			(0.000025)
Trend×Thu			0.000102***
			(0.000023)
Trend×Fri			0.000074***
			(0.000024)
Trend×Sat			0.000062**
			(0.000024)
Wholesale price	-0.133***	-0.151***	-0.131***
	(0.033)	(0.034)	(0.032)
Thu×post07		0.096***	
		(0.037)	
Constant	0.116**	0.144***	0.178***
	(0.045)	(0.047)	(0.056)
Observations	2,165	2,165	2,165
R-squared	0.229	0.231	0.246
Station FE	YES	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data period is 3 May 2004 to 31 October 2015.

Figure 5: Predicted daily gross margins per liter.



Finally, if we compare the estimates to what we saw in Figure 1, model (C) suggests an increase in the Monday afternoon gross margin of 128% (2004-2015). These numbers correspond well with Table C.1 in the Appendix, where the increase from 2008 to 2015 was more than 90%. The new restoration day increases the Thursday margin by nearly 700%.

In sum, results from models (B) and (C) propose that the introduction of a new weekly day off from competition on Thursdays partly explains the observed increase in profitability. Hence, cycling markets appear to be beneficial for firms. As firms are able to increase markups for most days over time, they will gain in terms of volume-weighted gross margins regardless of when consumers purchase. Thus, another restoration day in the middle of the week shrinks the initial weekly low price window. This is in line with our preliminary findings in Section 5.

Lastly, we briefly pay attention to the effect of the wholesale price. The estimated coefficient on $pwhole$ lies between -0.131 and -0.151. Hence, increasing the wholesale price by 1% decreases gross margins by approximately 0.13%. This suggests that the change in the wholesale price is not perfectly passed through into retail prices. This may indicate that profitability in time-dependent markets is to a certain extent influenced by variable costs. As fluctuations in prices depend on the current day of the week, whereas the development in wholesale prices does not behave in a similar way, prices already more than account for the increase in costs. Hence, firms may trade off passing through the whole cost increase against maintaining the weekly cycle because the weekly price schedule is, overall, more gainful. We will anticipate that wholesale prices do not affect the margin in the long run, which is also in line with the results we get in the robustness section (7.1) introducing more long run trend control variables. The wholesale price effect is less pronounced in the robustness section.

6.2 The impact of consumer behavior on profitability

We now consider the impact of demand side variables by including these factors in our specification. First, we examine the measure of search behavior on where to buy. Results of the main model are presented in column (A) in Table 7, whereas the model in column (B) is presented for the sake of comparison.

As expected, the effect of $search$ is negative and significant at the 1% level, suggesting that increasing the share of searching consumers by 1% decreases firms' profitability by 0.5%. Search (where-) activity is hence unfavorable to sellers. An increased amount of search initiated by consumers increases consumers' knowledge about of prices.

Next, we elaborate on the effect of search in relation to the introduction of the Thursday restoration by including the interaction term $search \times post07$. This specification is presented in column (C). The coefficient of the $search$ variable is now almost doubled, indicating that a 1% increase in searching consumers decreases profitability by 0.92%. The effect is significant at the 1% level. However, the coefficient for $search \times post07$ is 0.114, which is positive and significant at the 1% level. This suggests that searching consumers were more unfavorable to retailers before the establishment of another restoration day. In fact, estimates indicate two potential features: In a situation with only Monday as a restoration day, increased consumer search activity is even worse for retailers. However, after the introduction of a second restoration day, which seems to suggest that consumers are exposed to more noise, search activity has less negative influence on retailers because they manage to confuse consumers with their price setting schedule. Hence, the Thursday restoration acts as obfuscation which makes consumers less informed. Further, from model (D), which replaces $D_4 \times post07$ with a full set of interaction terms between the trend variable and the day-of-week dummies, we can confirm that gross margins have increased for most days of the week over time. The coefficients on $search$ and $search \times post07$ are similar to the former specification.

Table 7: Effect of $search$. Dependent variable is log of gross margin in NOK per liter.

	(A)	(B)	(C)	(D)
Search	-0.499***	-0.510***	-0.922***	-0.922***
	(0.094)	(0.093)	(0.126)	(0.127)
Search×post07			0.114***	0.110***
			(0.015)	(0.015)
Mon	0.354***	0.238***	0.356***	0.240***
	(0.026)	(0.051)	(0.026)	(0.051)
Tue	0.288***	0.268***	0.289***	0.269***
	(0.026)	(0.052)	(0.025)	(0.051)
Wed	0.186***	0.249***	0.186***	0.249***
	(0.026)	(0.052)	(0.026)	(0.051)
Thu	0.191***	0.059	0.178***	0.059
	(0.037)	(0.052)	(0.037)	(0.051)
Fri	0.119***	0.002	0.117***	0.000
	(0.029)	(0.056)	(0.029)	(0.056)
Sat	0.022	-0.076	0.021	-0.079
	(0.031)	(0.058)	(0.030)	(0.057)
Trend	0.000201***	0.000163***	0.000325***	0.000285***
	(0.000022)	(0.000027)	(0.000032)	(0.000036)
Thu×post07	0.060		0.086**	
	(0.037)		(0.037)	
Trend × Mon		0.000075***		0.000074***
		(0.000022)		(0.000021)
Trend × Tue		0.000013		0.000013
		(0.000026)		(0.000026)
Trend × Wed		-0.000039		-0.000039
		(0.000026)		(0.000025)
Trend × Thu		0.000103***		0.000103***
		(0.000023)		(0.000022)
Trend × Fri		0.000075***		0.000075***
		(0.000024)		(0.000024)
Trend × Sat		0.000063***		0.000063***
		(0.000024)		(0.000024)
Wholesale price	-0.369***	-0.361***	-0.125**	-0.123**
	(0.054)	(0.053)	(0.057)	(0.057)
Constant	-0.942***	-0.920***	-2.345***	-2.289***
	(0.216)	(0.217)	(0.339)	(0.342)
Observations	2,165	2,165	2,165	2,165
R-squared	0.252	0.268	0.265	0.280
Station FE	YES	YES	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data period is 3 May 2004 to 31 October 2015.

Table 8: Effect of *timing*. Dependent variable is log of gross margin in NOK per liter.

	(A)	(B)	(C)	(D)
Timing	0.269***	0.289***	2.094***	2.117***
	(0.086)	(0.085)	(0.320)	(0.320)
Timing×post07			0.564***	0.563***
			(0.081)	(0.081)
Mon	0.355***	0.239***	0.356***	0.242***
	(0.026)	(0.052)	(0.026)	(0.051)
Tue	0.290***	0.271***	0.293***	0.278***
	(0.026)	(0.052)	(0.026)	(0.051)
Wed	0.187***	0.251***	0.189***	0.258***
	(0.027)	(0.053)	(0.026)	(0.051)
Thu	0.186***	0.062	0.178***	0.061
	(0.038)	(0.053)	(0.037)	(0.052)
Fri	0.120***	0.004	0.119***	0.004
	(0.030)	(0.057)	(0.029)	(0.056)
Sat	0.024	-0.073	0.023	-0.073
	(0.031)	(0.059)	(0.030)	(0.058)
Trend	0.000045**	0.000003	-0.000180***	-0.000222***
	(0.000019)	(0.000023)	(0.000044)	(0.000046)
Thu×post07	0.072*		0.088**	
	(0.038)		(0.037)	
Trend × Mon		0.000074***		0.000073***
		(0.000021)		(0.000021)
Trend × Tue		0.000012		0.000009
		(0.000026)		(0.000026)
Trend × Wed		-0.000040		-0.000043*
		(0.000025)		(0.000025)
Trend × Thu		0.000102***		0.000102***
		(0.000023)		(0.000023)
Trend × Fri		0.000074***		0.000074***
		(0.000024)		(0.000024)
Trend × Sat		0.000062**		0.000062**
		(0.000024)		(0.000024)
Wholesale price	-0.291***	-0.286***	0.058	0.063
	(0.058)	(0.058)	(0.058)	(0.057)
Constant	0.914***	1.012***	4.649***	4.750***
	(0.249)	(0.246)	(0.703)	(0.702)
Observations	2,165	2,165	2,165	2,165
R-squared	0.236	0.252	0.257	0.273
Station FE	YES	YES	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data period is 3 May 2004 to 31 October 2015.

We now move on to examine the effect of consumers who follow a rule of thumb and make purchases close to the restoration, $timing$. The measure serves as a proxy for consumers who have learned the behavior of the present cycle and move their purchases to points in time with the lowest prices, regardless of station. Hence, when a consumer drops by a station it is due to convenience and not due to the particular station itself. Results are presented in Table 8 column (A). Column (B) includes interaction terms between the trend variable and day-of-week dummies instead of $D_4 \times post07$ for comparability.

The coefficient of $timing$ is 0.269 and significant at the 1% level, meaning that increasing the share of consumers who purchase close to the restoration by 1% increases profitability by 0.27%. One interpretation is that a sole adaptation to the cycle without participating in search is beneficial for sellers. Intuitively, consumer adjustment to predictable low price windows (more when-behavior) also makes consumers' purchasing behavior easily foreseeable for firms. Thus, sellers have less incentives to undercut each other as harsh price competition will not have a large impact on consumers' choice of station in the brief low price window since consumers' marginal cost of searching across stations has increased. In turn, competition is weakened and makes firms better off. Hence, this may explain the positive coefficient on $timing$. The effect is quite similar when including a full set of interaction terms between the trend variable and day-of-week dummies in column (B).

We now include the interaction term $timing \times post07$ for the sake of investigating the impact of the introduction of the Thursday peak. The coefficient of $timing$ is increased to a significant 2.094, and the coefficient for $timing \times post07$ is 0.564 and significant at the 1% level, meaning that the effect of consumers who adapt to the cycle is larger in magnitude after the introduction of another weekly peak. One interpretation is that the new pattern allows consumers to purchase cheaply in two periods rather than one during a week. Hence, there is now an additional window in which firms see no point in competing with each other. The total effect of timing may therefore increase due to impaired price dispersion twice a week.[37]

7 Robustness analysis and supplementary examination

This section presents additional results in the interest of investigating the robustness of our main findings.

[37] In models (C) and (D), the effect of trend becomes negative and significant, while the effect of the wholesale price becomes positive and insignificant. We do not have a proper explanation for this.

7.1 Inclusion of additional control variables

First, we introduce two cost shifters, the log of the wage index in the merchandising sector (*wage*), the log of the number of self-serviced stations (*self-service*), and a variable controlling for the business cycle and overall activity level in the Norwegian economy, the log

Table 9: Inclusion of additional variables into main models of effect of *search*. Dependent variable is log of gross margin in NOK per liter.

	(A)	(B)	(C)	(D)
Search	-0.698***	-0.702***	-0.578***	-0.568***
	(0.122)	(0.122)	(0.157)	(0.156)
Search×post07			-0.112	-0.126
			(0.0822)	(0.0811)
GDP	2.839***	2.715***	3.256***	3.182***
	(0.492)	(0.478)	(0.533)	(0.518)
Wage	0.158	0.357	-3.373	-3.595
	(1.210)	(1.204)	(2.433)	(2.391)
Self-service	4.751***	4.832***	5.780***	5.988***
	(1.112)	(1.103)	(1.624)	(1.606)
Trend	-0.000181	-0.000234	-0.0000292	-0.0000633
	(0.000186)	(0.000185)	(0.000174)	(0.000173)
Wholesale price	0.00211	0.0107	0.0347	0.0474
	(0.0692)	(0.0678)	(0.0810)	(0.0795)
Thu×post07	0.0866**		0.0860**	
	(0.0366)		(0.0365)	
Observations	2,165	2,165	2,165	2,165
R-squared	0.277	0.292	0.278	0.293
Trend × day of week	NO	YES	NO	YES

Robust standard errors in parentheses. Day of the week and station dummies, and a constant term (not reported) included. *** p<0.01, ** p<0.05, * p<0.1. Data period is 3 May 2004 to 31 October 2015.

of the domestic gross product (*GDP*) (2015 as base year).[38] As our data span over ten years we can test whether these variables account for some of the increase in profitability over this period.

Table 9 and Table 10 show that *GDP* increases profitability with 3 to 4%, suggesting that gross margins follow movements in the general economy. With coefficients between 0.04 and 0.06, *self-service* leads to increases around 4 to 6% in gross margins. Self-serviced stations are cheaper to run, leaving firms with higher profitability. Whereas *wage* is insignificant in Table 9 its impact is negative and around 6% in Table 10. Hence, wage increases lead to between zero and negative effect on gross margins. These impacts are in line with expectations, regarding that we already have taken the growth in CPI into account.

[38] *GDP* and *self-service* are yearly data while *wage* is quarterly data.

Table 10: Inclusion of additional variables into main models of effect of *timing*. Dependent variable is log of gross margin in NOK per liter.

	(A)	(B)	(C)	(D)
Timing	1.424***	1.439***	1.664***	1.609***
	(0.237)	(0.236)	(0.535)	(0.532)
Timing×post07			0.126	0.0897
			(0.234)	(0.231)
GDP	4.016***	3.902***	3.885***	3.809***
	(0.494)	(0.479)	(0.495)	(0.481)
Wage	-6.727***	-6.627***	-5.685**	-5.889**
	(1.910)	(1.900)	(2.344)	(2.305)
Self-service	4.691***	4.766***	3.906*	4.208**
	(1.053)	(1.043)	(2.139)	(2.118)
Trend	-0.0000749	-0.000122	-0.000122	-0.000155
	(0.000178)	(0.000177)	(0.000169)	(0.000168)
Wholesale price	0.130*	0.140**	0.126*	0.137*
	(0.0687)	(0.0674)	(0.0718)	(0.0705)
Thu×post07	0.0856**		0.0856**	
	(0.0366)		(0.0366)	
Observations	2,165	2,165	2,165	2,165
R-squared	0.275	0.291	0.276	0.291
Trend × day of week	NO	YES	NO	YES

Robust standard errors in parentheses. Day of the week and station dummies, and a constant term (not reported) included. *** p<0.01, ** p<0.05, * p<0.1. Data period is 3 May 2004 to 31 October 2015.

When looking at the main variables, in general, coefficients of *search* are quite similar in magnitude to the main results. The coefficients of *timing* are larger for model (A) and (B) while smaller for model (C) and (D). The post 2007 effects of *search* and *timing* are no longer significant. This suggests that, when controlling for more cost factors, the effect of the Thursday peak on the demand side variables is absent. In all models, *trend* becomes insignificant, meaning that variations in *GDP*, *wage* and *self-service* are accounted for by the general long run trend when not explicitly included in the model. Furthermore, these variables account for the main part of the *trend* variable. Accounting for more long run controls, the *wholesale price* effects are reduced in significance. Coefficients of the wholesale price changes sign as compared to our models above, but are very small and insignificant in Table 9, somewhat larger in Table 10, but only significant on a 10% level for 3 out of 4 cases. Suggesting that controlling for more long run trends, the wholesale price do not affect margins.

7.2 Newey-West standard errors

Table 11: Newey-West standard errors. Dependent variable is log of gross margin in NOK per liter.

	(A)	(B)	(C)	(D)	(E)	(F)
Search			-0.922***	-0.922***		
			(0.241)	(0.241)		
Search×post07			0.114***	0.110***		
			(0.027)	(0.027)		
Timing					2.094***	2.117***
					(0.604)	(0.606)
Timing×post07					0.564***	0.563***
					(0.151)	(0.152)
Mon	0.356***	0.241***	0.356***	0.240***	0.356***	0.242***
	(0.025)	(0.050)	(0.025)	(0.050)	(0.025)	(0.050)
Tue	0.291***	0.272***	0.289***	0.269***	0.293***	0.278***
	(0.024)	(0.049)	(0.024)	(0.048)	(0.024)	(0.049)
Wed	0.187***	0.252***	0.186***	0.249***	0.189***	0.258***
	(0.023)	(0.044)	(0.022)	(0.044)	(0.023)	(0.044)
Thu	0.176***	0.063	0.178***	0.059	0.178***	0.061
	(0.027)	(0.039)	(0.027)	(0.039)	(0.027)	(0.039)
Fri	0.120***	0.005	0.117***	0.000	0.119***	0.004
	(0.020)	(0.039)	(0.019)	(0.039)	(0.019)	(0.039)
Sat	0.024	-0.074**	0.021	-0.079**	0.023	-0.073**
	(0.015)	(0.032)	(0.015)	(0.031)	(0.015)	(0.031)
Trend	0.000102***	0.000064***	0.000325***	0.000285***	-0.000180**	-0.000222***
	(0.000012)	(0.000018)	(0.000060)	(0.000063)	(0.000083)	(0.000083)
Wholesale price	-0.151***	-0.131**	-0.125	-0.123	0.058	0.063
	(0.057)	(0.057)	(0.097)	(0.097)	(0.098)	(0.098)
Thu×post07	0.096***		0.086***		0.088***	
	(0.030)		(0.028)		(0.028)	
Constant	0.144*	0.178**	-2.345***	-2.289***	4.649***	4.750***
	(0.077)	(0.085)	(0.640)	(0.644)	(1.332)	(1.333)
Observations	2,165	2,165	2,165	2,165	2,165	2,165
R-squared	0.231	0.246	0.265	0.280	0.257	0.273
Station FE	YES	YES	YES	YES	YES	YES
Trend × day of week	NO	YES	NO	YES	NO	YES

Newey-West standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data period is 3 May 2004 to 31 October 2015.

One concern when working with long panels is that residuals are likely to be autocorrelated. Therefore, we here report Newey-West standard errors, allowing for seven lags due to the weekly pattern in prices.[39]

From Table 11, results show that the significance of coefficients is similar to the main results. Generally, standard errors of demand side coefficients are almost doubled. However, conclusions regarding significance remain unchanged. Standard errors of the day-of-week dummies are mostly slightly smaller. Major conclusions are unchanged.

[39] The number of lags coincides with a rule-of-thumb given by the integer of $\sqrt[4]{n}$, for which n is the total number of observations (Baum, 2006, p.140).

7.3 Inclusion of $pwhole_{t-7}$ as explanatory variable

Table 12: Inclusion of $pwhole_{t-7}$. Dependent variable is log of gross margin in NOK per liter.

	(A)	(B)	(C)	(D)	(E)	(F)
Search			-0.904***	-0.907***		
			(0.125)	(0.125)		
Search×post07			0.102***	0.097***		
			(0.014)	(0.014)		
Timing					2.203***	2.224***
					(0.301)	(0.301)
Timing×post07					0.580***	0.577***
					(0.075)	(0.074)
Mon	0.390***	0.333***	0.389***	0.331***	0.389***	0.333***
	(0.025)	(0.049)	(0.025)	(0.049)	(0.025)	(0.049)
Tue	0.311***	0.333***	0.311***	0.331***	0.312***	0.334***
	(0.027)	(0.056)	(0.026)	(0.054)	(0.026)	(0.054)
Wed	0.205***	0.301***	0.204***	0.300***	0.205***	0.302***
	(0.028)	(0.057)	(0.027)	(0.055)	(0.027)	(0.056)
Thu	0.165***	0.078	0.170***	0.073	0.171***	0.073
	(0.040)	(0.058)	(0.039)	(0.056)	(0.039)	(0.057)
Fri	0.138***	0.042	0.135***	0.037	0.136***	0.037
	(0.031)	(0.061)	(0.030)	(0.059)	(0.030)	(0.060)
Sat	0.051	-0.011	0.048	-0.016	0.049	-0.015
	(0.032)	(0.063)	(0.031)	(0.061)	(0.031)	(0.061)
Trend	0.000094***	0.000076***	0.000309***	0.000288***	-0.000208***	-0.000232***
	(0.000009)	(0.000019)	(0.000033)	(0.000038)	(0.000042)	(0.000043)
Thu×post07	0.128***		0.113***		0.113***	
	(0.038)		(0.038)		(0.038)	
Wholesale price t	-1.289***	-1.261***	-1.270***	-1.258***	-1.211***	-1.197***
	(0.163)	(0.162)	(0.157)	(0.156)	(0.160)	(0.158)
Wholesale price t-7	1.145***	1.144***	1.113***	1.105***	1.254***	1.248***
	(0.168)	(0.167)	(0.169)	(0.168)	(0.164)	(0.162)
Constant	0.146***	0.139**	-2.247***	-2.233***	4.929***	4.995***
	(0.048)	(0.059)	(0.330)	(0.334)	(0.669)	(0.667)
Long run effect of Wholesale price	-0.144***	-0.117***	-0.158***	-0.153**	0.043	0.050
	(0.035)	(0.034)	(0.061)	(0.061)	(0.059)	(0.058)
Observations	1,951	1,951	1,951	1,951	1,951	1,951
R-squared	0.267	0.281	0.307	0.322	0.301	0.316
Station FE	YES	YES	YES	YES	YES	YES
Trend × day of week	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data period is 3 May 2004 to 31 October 2015.

Whereas the wholesale price typically changes on a daily basis, the recommended price changes around once a week.[40] Recommended prices serve to represent the correct retail price when taking costs into account. As such, the wholesale price affects recommended prices and, in turn, retail prices with a fall-back over several periods. In this regard, we add dynamics to

[40] For one of the brands, during a nine week period in 2015, the recommended price changed ten times.

our specification by including the seventh lag of the wholesale price, $pwhole_{t-7}$, in favor of allowing the retail price and hence gross margins to adjust slowly to changes in costs.

Results are reported in Table 12. We will pay attention to the model in column (A), keeping in mind that estimates are quite similar for all models. The coefficient on $pwhole_t$ is -1.289, while the coefficient on $pwhole_{t-7}$ is 1.145. The instant effect of the wholesale price on firms' profitability is negative, as 1% increase lowers gross margins by 1.27%. However, taking slow adjustment into account, the long-run effect is reduced to -0.14%. By comparing the estimates with the coefficient of -0.15 in Table 6 column (B), the long-run effect corresponds well to our main findings.[41]From columns (C) and (D), we note that adding $pwhole_{t-7}$ to the specification lowers the magnitude of $search$ and $search \times post07$ slightly. On the other hand, the coefficients of $timing$ and $timing \times post07$ in columns (E) and (F) increase slightly. In sum, results do not differ much from the main models. The size of the coefficient on $D_4 \times post07$ is 0.128 in column (B) compared to 0.096 in the leading results. Overall, estimates are much the same as in the main models.[42]

8 Concluding remarks

We empirically examine the impact of time-dependent price patterns on consumer behavior and firms' profitability. The Norwegian retail gasoline market is a picture perfect application. From 2004 to 2017, a regular country-wide weekly price pattern with a saw-tooth shape was present. On Mondays around noon all the four major retail chains increase their retail prices to the recommended price. The retail chains decide their recommended prices in advance, and publish recommended prices on their websites. Consequently, each retail chain knows when to raise the price, and to what level. Moreover, they are immediately able to observe should a rival deviate from the established practice.

In local markets with high concentration (long distance between competing outlets), retail prices are equal to the recommended prices throughout the week. Therefore, we consider the level of recommended prices as a measure of the monopoly price. In less concentrated areas, firms undercut each other during the rest of the week, such that the price level is regularly at its

[41] An F-test rejects the null hypothesis of the long run effect being equal to 0.

[42] To account for potential inertia of profitability we also estimated models where we allowed for an AR(1) process, including yesterday's gross margin. The AR(1) term is significant, and the weekly pattern is still present with highest margins on Monday and Thursday in our preferred model. The trend is still positive and significant. The wholesale price is negative and in the same range as before in the models without demand controls.

lowest on Monday morning. From 2008, retail chains managed to introduce another day off from competition on Thursdays. Like on Mondays, there was an industry-wide synchronization of retail prices to the level of the recommended prices on Thursdays.

We combine panel data on supply side measures and survey data containing information on consumer behavior with a time span between 2004 and 2015. This allows us to scrutinize the interplay between firms' and consumers behavior. Consumers face a menu of prices depending on when they buy. With a given capacity of effort, there are typically larger savings to gain by using effort on timing of when to buy rather than on where to buy. As expected, we find that conventional price search on where to buy reduces firms' profitability. In contrast, consumers who are aware of the cycle and act by when to make their purchases have a positive impact on firms' profitability. For consumers in a market with a predictable cycle, it might be rational to adopt to a simple rule of thumb: tank on Sunday or on Monday morning. However, competition among sellers are highly driven by price search. Consequently, if consumers (rationally) spend their effort on when to buy rather than on where to buy, price competition might be softened (even in the in low-price windows). We show that the effects are robust also when accounting for long run changes in cost structure and the Norwegian business cycle.

For policy makers and consumer associations this creates a difficult trade-off when advising consumers. On the one hand, there are huge savings for consumers if they adapt to the pattern and tank gasoline in the weekly low-price windows. On the other hand, if more consumers, by for instance adapting to a rule of thumb, pay less attention to where to buy, retailers lose incentives to compete aggressively. In this respect, the weekly price pattern has been given a great deal of media coverage since it was initiated in 2004.

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Appendices

A Panel data

Table A.1: Overview of gasoline stations and data periods.

Station	Brand	Data periods
1	Esso	03.05.2004-30.11.2004*
		12.02.2005-23.03.2005*
2	Hydro Texaco	23.01.2005-01.05.2005
		13.05.2005-17.05.2005
3	Hydro Texaco	03.05.2004-30.11.2004*
		10.02.2005-23.03.2005*
4	Hydro Texaco	31.01.2005-03.07.2005
		28.01.2008-21.07.2008
5	Statoil	23.01.2005-01.05.2005
		13.05.2005-26.06.2005
		28.01.2008-21.07.2008
6	Statoil	23.01.2005-03.07.2005
		17.10.2005-15.03.2006
		28.01.2008-21.07.2008
		22.06.2015-16.08.2015
		02.09.2015-31.10.2015
7	Statoil	20.06.2004-30.11.2004*
		15.02.2005-17.02.2005*
		17.10.2005-15.03.2006
		28.01.2008-21.07.2008
		02.09.2015-31.10.2015
8	Statoil	16.05.2004-30.11.2004*
		22.03.2005
9	Shell	08.05.2004-20.10.2004*
		09.03.2005-23.03.2005*
10	Shell	17.10.2005-15.03.2006
		28.01.2008-21.07.2008
11	Hydro Texaco	02.07.2004-16.11.2004*

Periods with the asterisk * are non-consecutive.

Table A.2: Summary statistics. Data period is 3 May 2004 to 31 October 2015.

	Mean	Std. dev.	Min	Max
2004				
Price	12.079	0.541	10.689	12.718
Wholesale price	2.639	0.173	2.289	2.930
Tax	5.806	0.000	5.806	5.806
VAT	2.416	0.108	2.138	2.544
Gross margin	1.218	0.423	0.171	1.952
2005				
Price	12.543	0.650	10.830	14.000
Wholesale price	2.812	0.306	2.254	3.450
Tax	5.837	0.023	5.820	5.869
VAT	2.509	0.130	2.166	2.800
Gross margin	1.386	0.388	0.380	2.051
2006				
Price	12.839	0.506	11.603	13.745
Wholesale price	3.276	0.152	2.917	3.555
Tax	5.819	0.000	5.819	5.819
VAT	2.568	0.101	2.321	2.749
Gross margin	1.176	0.442	0.078	1.982
2008				
Price	14.487	0.696	12.517	15.869
Wholesale price	4.362	0.516	3.533	5.293
Tax	5.821	0.018	5.814	5.871
VAT	2.897	0.139	2.503	3.174
Gross margin	1.407	0.291	0.539	2.109
2015				
Price	14.006	0.915	11.990	15.980
Wholesale price	3.484	0.476	2.818	4.612
Tax	5.820	0.000	5.820	5.820
VAT	2.801	0.183	2.398	3.196
Gross margin	1.901	0.578	0.486	2.945
Total				
Price	13.455	1.157	10.689	15.980
Wholesale price	3.530	0.821	2.254	5.293
Tax	5.826	0.020	5.806	5.871
VAT	2.691	0.231	2.138	3.196
Gross margin	1.407	0.414	0.078	2.945

All values are in real NOK per liter.

Table A.3: Mean retail price by day of the week and year. Data period is 3 May 2004 to 31 October 2015.

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
2004							
Mean	11.780	12.265	12.501	12.167	11.983	11.608	12.260
Std.dev.	0.715	0.237	0.141	0.505	0.593	0.647	0.273
Min	10.812	11.931	12.288	11.058	10.689	10.812	11.956
Max	12.558	12.718	12.718	12.583	12.558	12.288	12.718
2005							
Mean	12.846	12.701	12.549	12.572	12.434	12.366	12.335
Std.dev.	0.492	0.568	0.680	0.645	0.636	0.671	0.689
Min	11.084	11.072	11.120	11.120	11.120	10.830	10.830
Max	14.000	13.564	13.782	13.782	13.600	13.661	13.661
2006							
Mean	13.393	13.028	12.883	12.718	12.744	12.534	12.525
Std.dev.	0.290	0.378	0.347	0.474	0.506	0.484	0.454
Min	12.293	12.174	12.174	11.722	11.662	11.603	11.603
Max	13.745	13.518	13.316	13.602	13.685	13.447	13.447
2008							
Mean	14.713	14.623	14.527	14.561	14.441	14.325	14.216
Std.dev.	0.643	0.608	0.608	0.653	0.714	0.762	0.750
Min	13.395	13.532	13.418	12.950	12.517	12.517	12.517
Max	15.846	15.812	15.869	15.869	15.869	15.846	15.846
2015							
Mean	14.846	14.130	13.431	14.632	14.028	13.635	13.394
Std.dev.	0.602	0.990	0.859	0.681	0.719	0.694	0.720
Min	14.010	12.115	11.990	13.290	12.020	11.990	11.990
Max	15.830	15.880	14.680	15.980	15.780	15.220	14.780

All values are in real NOK per liter.

Table A.4: Mean gross margin by day of the week and year. Data period is 3 May 2004 to 31 October 2015.

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
2004							
Mean	1.048	1.465	1.459	1.263	1.151	0.790	1.280
Std.dev.	0.545	0.170	0.274	0.370	0.540	0.417	0.098
Min	0.299	1.139	1.197	0.442	0.171	0.274	1.113
Max	1.588	1.717	1.952	1.607	1.896	1.294	1.439
2005							
Mean	1.636	1.521	1.403	1.406	1.283	1.228	1.223
Std.dev.	0.285	0.349	0.361	0.382	0.377	0.384	0.386
Min	0.486	0.380	0.606	0.525	0.525	0.501	0.501
Max	2.051	1.997	1.968	2.029	1.956	1.956	1.939
2006							
Mean	1.604	1.327	1.232	1.110	1.085	0.918	0.917
Std.dev.	0.289	0.351	0.289	0.423	0.468	0.434	0.410
Min	0.594	0.449	0.717	0.315	0.126	0.078	0.078
Max	1.961	1.822	1.613	1.982	1.924	1.734	1.734
2008							
Mean	1.590	1.539	1.433	1.471	1.363	1.269	1.182
Std.dev.	0.220	0.214	0.245	0.261	0.277	0.289	0.293
Min	0.673	0.624	0.708	0.605	0.635	0.635	0.539
Max	2.048	1.999	1.999	1.950	2.109	1.991	1.991
2015							
Mean	2.560	1.985	1.436	2.416	1.929	1.615	1.405
Std.dev.	0.255	0.531	0.434	0.424	0.417	0.333	0.365
Min	1.874	0.486	0.582	0.869	0.900	0.876	0.876
Max	2.893	2.714	2.169	2.945	2.481	2.194	2.554

All values are in real NOK per liter.

B Survey data

B.1 Survey Questionnaire

1. Type of fuel

1. Unleaded gasoline 95: ___________
2. Unleaded gasoline 98: ___________
3. Diesel: ___________
4. Other: ___________

2. How often do you purchase gasoline?

1. 4 times or more per month: ___________
2. 2-4 times per month: ___________
3. Once per month or less: ___________

3. How often do you think that the retail price changes?

1. Several times per day: ___________
2. Once per day: ___________
3. Every 2^{nd} or 3^{rd} day: ___________
4. Every 7^{th} day or less: ___________
5. Do not know: ___________

4. Do you think the retail price increases on specific days of the week?

1. Yes: ___________
2. No: ___________ (Go to Question 7)
3. Do not know: ___________

5. If yes on Question 4, which days?

Sunday : ___________

Monday: ___________

Tuesday: ___________

Wednesday: ___________

Thursday: ___________

Friday : ___________

Saturday: ___________

Sunday: ___________

6. If yes on Question 4, how often do you take this into account when making purchases?

(Very often) 1 2 3 4 5 (Very seldom)

7. How often do you fill full tank?

(Very often) 1 2 3 4 5 (Very seldom)

8. Where do you purchase gasoline?

1. At the same station every time: ___________
2. At 2 or 3 different stations: ___________
3. At more than 3 different stations: ___________

9. How far do you drive per year?_______ km

10. Where do you check the retail price?

1. Do not check the price: ___________
2. Check on the pump: ___________
3. Check on the sign outside station: ___________
4. Other: ___________

11. Do you observe a weekly price pattern – if so, which? ___________

Gender:

Male: ___________

Female: ___________

Age:

18-24: ___________

25-34: ___________

35-45: ___________

45-66: ___________

Over 66: ___________

B.2 Questionnaire Overview

Table B.1: Overview of station, date of survey and number of respondents.

Name	Brand	Date of survey	Day of week	Number of respondents
Hydro Texaco Tertnes	Hydro Texaco	29.04.2005	Friday	39
		06.06.2005	Monday	29
		10.06.2005	Friday	49
		30.03.2006	Thursday	30
		03.04.2006	Monday	33
		04.02.2008	Monday	50
		07.02.2008	Thursday	39
Statoil Helleveien	Statoil	25.04.2005	Monday	47
		29.04.2005	Friday	44
		06.06.2005	Monday	42
		10.06.2005	Friday	39
		30.03.2006	Thursday	50
		03.04.2006	Monday	38
		04.02.2008	Monday	78
		07.02.2008	Thursday	58
		21.09.2015	Monday	58
		24.09.2015	Thursday	49
		28.09.2015	Monday	48
		01.10.2015	Thursday	47
Sum				867

Table B.2: How often do you think the retail price changes?

	Several times during a day	Once a day	Every 2nd or 3rd day	Every 7th day or Less	Do not know
2005 (289)	18 %	31 %	31 %	10 %	0 %
2006 (151)	24 %	22 %	30 %	18 %	0 %
2008 (225)	13 %	27 %	20 %	16 %	24 %
2015 (202)	23 %	19 %	32 %	8 %	18 %

Numbers in parentheses are total number of respondents by year. Shares not summing to 100% are due to non-response.

Table B.3: How often do you fill full tank?

	Very often	Fairly often	Neither	Fairly seldom	Very seldom
2005 (289)	44 %	13 %	11 %	8 %	11 %
2006 (151)	56 %	9 %	14 %	9 %	11 %
2008 (225)	59 %	8 %	8 %	8 %	16 %
2015 (202)	65 %	9 %	13 %	2 %	11 %

Numbers in parentheses are total number of respondents by year. Shares not summing to 100% are due to non-response.

Table B.4: Where do you purchase gasoline?

	Same station every time	2 or 3 different stations	More than 3 different stations
2005 (289)	37 %	31 %	26 %
2006 (151)	30 %	42 %	27 %
2008 (225)	44 %	34 %	22 %
2015 (202)	29 %	36 %	36 %

Numbers in parentheses are total number of respondents by year. Shares not summing to 100% are due to non-response.

Table B.5: Summary statistics.

	Mean	Std.dev	Min	Max
Timing	0.163	0.050	0.110	0.270
Search	0.090	0.025	0.080	0.170
Purchase at the same station	0.385	0.053	0.290	0.440
Purchase at more than 3 stations	0.253	0.038	0.220	0.360
Check price on the sign outside station	0.381	0.086	0.310	0.600
Retail price increases on specific days of the week	0.469	0.130	0.350	0.810
Fill full tank very often	0.530	0.078	0.440	0.650

C Cross-sectional data

Table C.1: Monday summary statistics in NOK per liter.

	Mean	Std.dev.	Min	Max
21.04.2008				
Gross margins 8 a.m.	0.258	0.391	-0.435	1.170
Gross margins 2 p.m.	1.465	0.078	1.316	1.635
Recommended gross margins	1.438	0.071	1.361	1.553
24.08.2015				
Gross margins 8 a.m.	1.576	0.182	0.642	1.890
Gross margins 2 p.m.	2.734	0.089	2.586	2.842
Recommended gross margins	2.760	0.040	2.706	2.794

n=43 for 21.04.2008 and n=44 for 24.08.2015.

Table C.2: Thursday summary statistics in NOK per liter.

	Mean	Std.dev.	Min	Max
27.08.2015				
Gross margins 8 a.m.	1.665	0.227	1.222	2.190
Gross margins 2 p.m.	2.655	0.075	2.330	2.734
Recommended gross margins	2.550	0.076	2.454	2.646
03.09.2015				
Gross margins 8 a.m.	1.503	0.182	1.185	1.937
Gross margins 2 p.m.	2.676	0.047	2.545	2.785
Recommended gross margins	2.612	0.022	2.585	2.633

n= 43 for 27.08.2015 and *n*=42 for 03.09.2015.

Table C.3: Levene's test and Brown-Forsythe test for the equality of variances for real gross margins in 2008 and 2015.

	Levene	Brown-Forsythe
8 a.m.	55.353***	31.303***
2 p.m.	0.226	0.557

H_0: Population variances are equal. H_1: Populations variances are different. Values are test statistics. Degrees of freedom are (1, 85). *** p<0.01, ** p<0.05, * p<0.1.

Table C.4: Two-sample t-test with for real gross margins in 2008 and 2015.

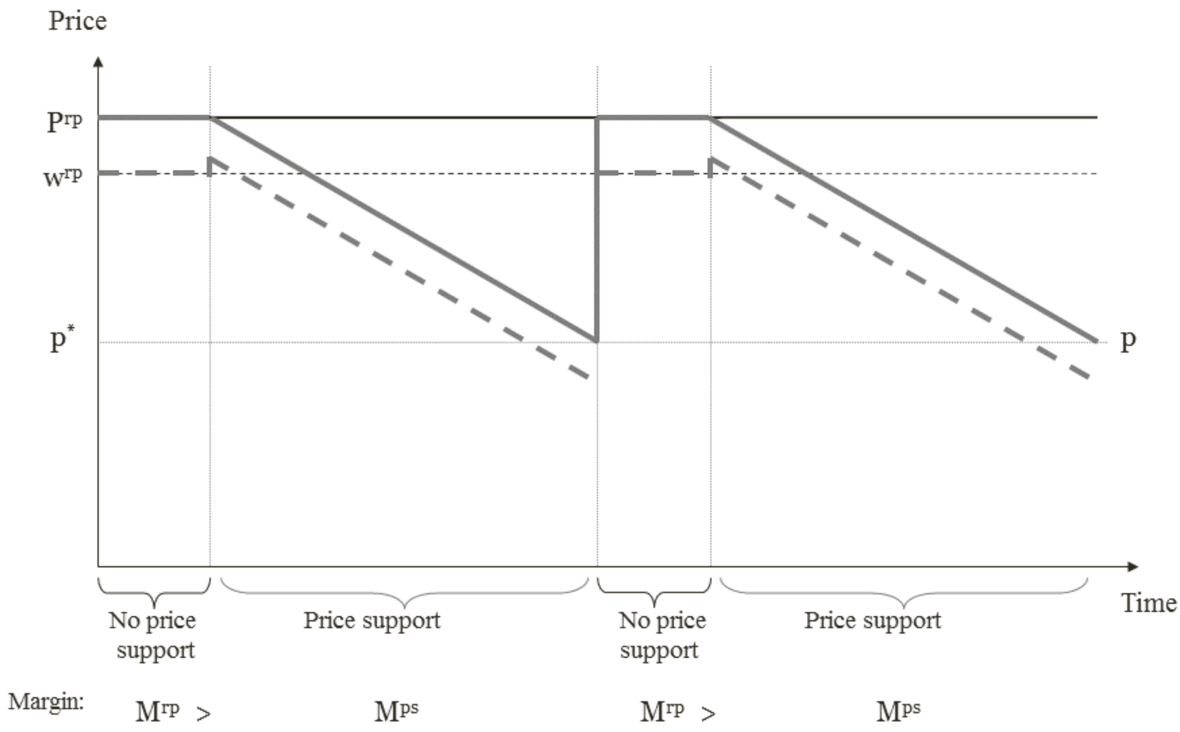
	Variance assumption	Test statistics	Degrees of freedom
8 a.m.	Unequal	-20.090***	59.086 1
2 p.m.	Equal	-71.160***	85

H_0: Population means are equal. H_1: Populations means are different. Values are test statistics. [1]Degrees of freedom are of Satterthwaite's type. *** p<0.01, ** p<0.05, * p<0.1.

D Retail price determination

Our research question heavily relies on the calendar based price cycle recognized in the Norwegian market. A theoretical framework illustrating the observed price behavior is given in Foros & Steen (2013), which suggests an explanation to how headquarters of gasoline companies manage to simultaneously increase retail prices to the recommended prices published online even for vertically separated outlets. This arrangement is depicted in Figure D.1.

Figure D.1 Price support arrangements in the retail gasoline market.



The upstream firm establishes a profit-sharing scheme consisting of two parts, dividing the margin $p - c$ per liter of gasoline between itself and the downstream firm, where p is the retail price and c is the upstream firm's input price, respectively.

A maximum retail price maintenance (RPM hereafter) equal to the recommended price p^{rp} is introduced in the first part of the agreement. If the retailer sets his price equal to the maximum RPM, the upstream firm charges him a wholesale price w^{rp} where $w^{rp} < p^{rp}$, leaving the retailer with a margin $M^{rp} = p^{rp} - w^{rp}$ per liter sold. The wholesale price exceeds the cost per liter of gasoline c, such that the upstream firm also receives a strictly positive profit. This part of the agreement is at disposal during the entire week.

The second part is called price support, in which the retailer receives a margin $M^{ps} < M^{rp}$ if he sets the retail price below the maximum RPM. In contrast to the first part of the scheme, the upstream firm decides when the price support is in force.

Therefore, if the upstream firm chooses w^{rp} so as to induce the retailer to set $p = p^{rp}$ when the price support is inoperative, the profit sharing scheme essentially induces falling prices due to competition during the price support interrupted by immediate restorations when the support is withdrawn. Hence, theory suggests that symmetric cycles may be a result of the four upstream firms simultaneously deciding to disengage the price support on Mondays and Thursdays each week. Retailers are then effectively forced to set price equal to the recommended price in order to avoid negative margins. Price competition among sellers are thus only possible when the price support is in force, unless they want to operate with losses. Since the recommended prices across companies are close to identical, a deviation of a firm from the pricing rule will immediately be discovered by its rivals. Consequently, the arrangement entails an effective commitment to having identical prices as the rivals twice a week.

Chapter 4

Measuring Market Power in Gasoline Retailing: A Market- or Station Phenomenon?*

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Abstract

Applying detailed consecutive daily micro data at the gasoline station level from Sweden we estimate a structural model to uncover the degree of competition in the gasoline retail market. We find that retailers do exercise market power, but despite the high upstream concentration, the market power is very limited on the downstream level. The degree of market power varies with both the distance to the nearest station and the local density of gasoline stations. A higher level of service tends to raise a seller's market power; self-service stations have close to no market power. Contractual form and brand identity also seem to matter. We find a clear result: local station characteristics significantly affect the degree of market power. Our results indicate that local differences in station characteristics can more than offset the average market power found for the whole market.

Keywords: Gasoline markets, market power, markup estimation, local market competition

JEL Codes: D22, L13, L25, L81

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"*...the stations' gross margins naturally vary over time and depend on the local competition pressure*."

Swedish Competition Authority (2013, p.128)

1. Introduction

The same pattern is present in most countries: Gasoline markets are highly concentrated upstream, consisting of tight oligopolies, but often with a dispersed downstream retail market where the individual gasoline stations are operated through various vertical contract arrangements. One important question raised is whether upstream market concentration restricts the level of competition downstream. The market structure has motivated much attention from both regulators and researchers, where pricing strategies and competition are studied.[1] Local competition, brand identity and contractual arrangements are all factors that the literature has pointed to in the understanding of the competitive pressure in this market.

We study the competitive situation in the gasoline retail sector, scrutinizing in particular the impact of local market conditions and station characteristics on stations' competitive grounds. Specifically, in this paper we do the following. First, having access to detailed daily micro data at the station level, both on price and quantity, we estimate a structural model to uncover the degree of competition. Hence, we overcome one substantial limitation of previous studies, which, while endowed with rich price measures, often have to settle for aggregated quantity measures (see e.g. Noel, 2016 for a survey). In contrast, our volume and price data share the same frequency. Second, utilizing detailed knowledge on each station's (i) brand identity and contractual arrangements, (ii) station amenities and (iii) local competition factors, we extend the model to analyze how these factors impact the competition level. We are thus able to address a relatively large but yet non-conclusive empirical literature on how competition in gasoline retailing relates to local station characteristics. Whereas most of the previous literature typically focuses on either one or two of these factors, we look at all three issues in this paper.[2]

[1] For examples of government initiated studies, see for instance ACCC (2007) for the Australian market, the Irish CA (2003) for the Irish market and the Norwegian CA (2014) for the Norwegian market.

[2] Examples on *local competition* studies include Alderighi and Baudino (2015), Firgo et al. (2015), Hosken et al. (2008), Barron et al. (2004), Barron et al. (2007), Cooper and Jones (2007) and Clemenz and Gugler (2006). Examples on *station amenities* studies include Haucap et al. (2017), Hosken (2008) and Eckert and West (2005). Examples on *brand identity and contractual forms* studies include Verlinda (2008), Cooper and Jones (2007), Hastings (2004), and Slade (1987).

We analyze the Swedish market, which shares features with most concentrated national gasoline markets. At the upstream level, the market consists of four major companies having 99% of the market during the sample period. As in many other countries, antitrust concerns have been raised on several occasions. In 2005, the Swedish Market Court found the major oil companies guilty of illegal cooperation. They were sentenced for, among other things, coordinated rebate reductions, internal agreements not to compete for customers among themselves, and agreements on increasing the retail price (Swedish Market Court, 2005). As a result, the companies paid 112 million SEK in fines. Between 2007 and 2010, the market went through four major mergers, thereby increasing concentration further. Later, in 2012, due to worries on the potential lack of competition, the Swedish government required the Swedish Competition Authority (SCA) to initiate studies of the market structure in the industry.[3]

We estimate a structural model of demand and supply at the retail level using the method suggested by Bresnahan (1982) and Lau (1982). Endowed with a panel of daily quantity and price data at the station level for a whole consecutive year (2012), together with detailed information on the competitive situation, including distance to competitors, number of stations, ownership and contractual status, station amenities and demography on local markets, we provide estimates of the degree of market power. The richness of the data, consisting of daily price and quantity measures for 180 sample stations, allows us to introduce structure into the model. [4] For the majority of previous literature, detailed volume data have been unavailable (as far as we are aware, exceptions are Slade, 1987 and Wang, 2009), restricting research to mainly study reduced form models using aggregate data. Others have employed proxies of quantity (e.g., Lewis, 2011), which are exposed to measurement errors. The gasoline market is divided into several local markets due to geographical restrictions; applying aggregate data might lead to imprecise insights into the local competition conditions. As such, we are in a favorable position to study the problem at hand. We get around both limitations in terms of measurement errors and aggregation biases, and, combined with information on local market characteristics and station amenities, we establish a yet unexplored channel of insights into a highly explored market.

[3] As a result, the SCA initiated two studies of the competitive structure of the Swedish retail market, see Foros and Steen (2013) and Ganslandt and Rönnholm (2014).

[4] Our data originate from an analysis performed by Foros and Steen (2013) initiated by the SCA. To obtain sufficient micro information at the station level 180 stations were picked for the calendar year 2012. The data were collected by the NCA, and stations were chosen to be representative for the whole of the Swedish market. For instance, the analysis covered all companies for different regional areas in Sweden in terms of urban and regional status as well as various city sizes. In our sample the highway market is also included as a separate group.

Our demand estimates suggest an inelastic gasoline demand at the market level (significant negative elasticity of 0.72), which is in line with several other studies. The Bresnahan-Lau approach requires adding interaction terms between exogenous demand side variables and the retail price in the demand specification. Changes in these variables both shift and pivot the demand curve, hence the degree of market power is identified through these terms. Therefore, a critical requirement for this identification process to work empirically is that the exogenous demand variables chosen enter the demand equation in a well-behaved fashion. We use local income, local population and supply of public transportation in the region in these price interactions. They all come in significant, and produce reasonable and significant elasticities. The income elasticity suggests a normal good (elasticity=1.12) and an increased supply of public transportation reduces demand (elasticity=-0.44), suggesting substitutability, both elasticities also being significant. The interaction term with local population size is significant, and the elasticity suggests a marginal positive demand effect of 0.01, though not significant.

Using the information from the demand estimates we identify market power through the estimated supply relations. We find that retailers do exercise some (significant) market power in the Swedish market, but despite the high upstream concentration, the market power is very limited on the downstream level. This result is in line with what others have found using much more aggregated data (Houde, 2012; Manuszak, 2009).

Despite the very modest findings of market power, the competitive level varies significantly with local retail station characteristics. First, we estimate separate models where we control for the different characteristics in turn. When it comes to *local competition*, we show that the degree of market power varies with both the distance to the nearest gasoline station and with the local density of stations. A station with no competitors within a distance of 5 km or more, as compared to a station with the nearest competitor very close by (like 20 meters) has twice as high markup as the average station. High station density within a radius of 3 km also lowers market power. Gasoline station *amenities* are a potential source to differences in market power, as a higher level of service tends to raise a seller's market power. In particular, we find that self-service stations have close to no market power. Finally, *contractual form and brand identity* seem to matter, too. However, we are not able to distinguish the effects fully in the sense that the only brand in our data which operates commissioned gasoline stations (and only such stations) also has a significantly higher markup than the other brands which predominantly have fully vertically integrated gasoline stations.

When controlling for all three characteristics (local competition, amenities and brand/contractual form) in the same models simultaneously, our results generally indicate higher market power. Further, we find similar effects for the three groups of retail station characteristics as we do when estimating them separately. Indeed, there is one clear result: local station characteristics significantly affect the degree of market power for the local gasoline station.

To illustrate our results, we construct estimates for two stations with different local competitive characteristics. We show that differences in local station characteristics, even within the scope of the variation in our sample, have a large effect on local market power. The magnitude in these local differences implies that in some local markets, the station will be able to extract market power. In other markets, local competition factors will remove this possibility.

Hence, we both establish the effects of local station characteristics on market power and show that these differences can more than offset the average market power found in the baseline model where we do not account directly for these effects on the estimated markup.

The rest of the paper proceeds as follows. In Section 2 we discuss the literature on measurement of market power and provide an overview of the most common sources of market power in gasoline retailing. Section 3 presents the structural Bresnahan-Lau model, while Section 4 decribes the data and the industry. Section 5 presents the empirical specification of the Bresnahan-Lau model. The results are discussed in Section 6. Finally, Section 7 concludes.

2. Literature review

2.1 Measuring market power in gasoline retailing

Previous literature suggests several factors that might impact local price competition in retail gasoline markets. These are mainly demographics, station amenities, contractual forms, and station location and density. The majority of empirical studies look at the retail price as a function of independent determinants and derive the potential effects on competition from these results. Data from several different countries, e.g. the US, Canada, Australia and European countries, are used. Our approach is to estimate the market power parameter directly by applying the oligopoly model by Bresnahan (1982) and Lau (1982). To the best of our knowledge, few papers estimate the degree of market power explicitly, and no study has yet used the Bresnahan-Lau method in examining gasoline retailing.[5]

[5] See Bresnahan (1989) for a discussion of this model. Several studies have applied this methodology in various disguises on several industries. For some of these see, for *consumer credit*: Toolsema (2002), for *banking*: Gruben

Further, as already emphasized, our price and quantity data are of daily frequency, at the station level and consecutive for a whole year, allowing us to obtain precise estimation of structural demand and supply models. Even though high-frequency price data are available in most retail markets, quantity data at the station level have so far been rare in the literature of gasoline retailing. As far as we are aware, the only exceptions are Slade (1987) and Wang (2009).

A few papers estimate structural models of supply and demand in order to evaluate the degree of market power. Slade (1987) estimates demand, cost and reaction functions at the station level for the sake of modeling a repeated game approach to competition between stations. Using data on daily price, volume and cost figures from stations in Vancouver, Canada, she finds that the actual outcome is less profitable than the cooperative solution while more profitable than the non-cooperative solution, suggesting that sellers in this market exercise some market power.

Houde (2012) considers stations close to the same commuter route as substitute stations as perceived by consumers. Estimating a model of spatial competition using bi-monthly station level data as well as data on road network structure for Quebec, Canada, he finds low markups and hence concludes that the degree of market power is low. With the use of monthly volume, price and station characteristics data from Hawaii, USA, Manuszak (2009) estimate a discrete choice model of demand and supply models for both the upstream- and the downstream market, and finds that the downstream market power is low.

In addition, many studies relate the degree of market power of retailers to how retail prices and margins respond to changes in input prices. For instance, Borenstein and Shepard (1996) examine price patterns that are consistent with models of tacit collusion and find that retail margins are higher when the wholesale price is anticipated to fall as predicted by these models. Further, Borenstein et al. (1997) and Deltas (2008) relate asymmetric response of retail prices to wholesale price changes to market power of retailers by estimating lag adjustment models.

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and McComb (2003), Shaffer (2002;1993) Suominen (1994), for *petroleum*: Considine (2001), for *cement*: Rosenbaum and Sukharomana (2001), for *cigarettes*: Delipalla and O'Donnel (2001), for *beef processing*: Muth and Wohlgenant (1999); for *salmon*: Steen and Salvanes (1999); for *sugar*: Genesove and Mullin (1998); for *advertising*: Jung and Seldon (1995), for *lumber*: Bernstein (1994), for *coconut oil*: Buschena and Perloff (1991) and for *electricity:* Puller (2007) and Graf and Wozabal (2013).

2.2 Sources of market power in gasoline retailing

Local competition

When it comes to local competition, studies have found ambiguous relations between station density and price. On the one hand, Barron et al. (2004), Barron and Waddel (2007) and Clemenz and Gugler (2006) show that higher station density tends to lower average prices, suggesting that a higher number of sellers raises local competition. This is in line with our findings, which propose that a seller's market power decreases in the number of neighbour stations. Similarly, Alderighi and Baudino (2015) suggest that stations' prices rely on neighbour stations' prices within around 1km. On the other hand, Hosken et al. (2008) find no relation. However, they show that price tends to increase with the distance to the closest station. Comparable results are found by Cooper and Jones (2007). We cannot directly relate our findings to these, as we do not examine the effect on price explicitly. Nonetheless, we show that a seller's market power parameter tends to increase with the distance to the closest competitor and decrease with station density. Firgo et al. (2015) suggest that sellers who have a central location in a market relative to their competitors in a market have a stronger influence on pricing decisions of competitors and on the equilibrium market price.

Station amenities

Regarding the impact of station amenities on prices and competition, previous studies provide mixed results. Eckert and West (2005) find that local market structure and station characteristics affect sellers' (uniform) price setting and suggest the presence of imperfect competition. Haucap et al. (2017) document that prices are positively related to station service levels. In contrast, Hosken et al. (2008) find no impact of station amenities.

Brand identity and contractual forms

Turning to the effect of contractual forms and brand identity, Eckert and West (2005) show that major brand stations with supplier control are more likely to set the market mode price, suggesting that the presence of vertically integrated major brand stations might increase incentives to tacitly collude. Cooper and Jones (2007) document that interbrand competition is more intensive than intrabrand competition. Hastings (2004) finds that the presence of independent retailers serves to decrease prices due to higher local price competition, while Verlinda (2008) finds that brand identity impacts how sellers respond to cost shocks, suggesting that asymmetric price responses may be explained by local market power.

3. The Bresnahan-Lau model

We make use of the Bresnahan-Lau model, after Bresnahan (1982) and Lau (1982). By simultaneous estimation of market demand and a cost relation, a parameter referring to the level of competition in the market is identifiable.

Market demand is described by the function

$$Q = D(P, Z; \alpha) + \epsilon \tag{1}$$

where Q is aggregate quantity, P is price, Z is a vector of exogenous demand side variables, α a vector of parameters which are to be estimated and ϵ the error term.

Under the assumption that sellers are profit maximizing, the structure of the supply side depends on whether sellers are price-takers or not. Under perfect competition, the first-order condition of the profit maximization problem leads to price equal to marginal cost $c(\cdot)$, which can be written as

$$P = c(Q, W; \beta) + \eta \tag{2}$$

where W is a vector of exogenous supply side variables, β a vector of supply side parameters and η the error term. However, if sellers are not price takers, perceived marginal revenue is set equal to marginal cost. The price relation is then[6]

$$P = c(Q, W; \beta) - \lambda h(Q, Z;\ \alpha) + \eta. \tag{3}$$

$h(\cdot)$ is defined as

$$h(\cdot) = \frac{\partial D^{-1}(Q, Z; \alpha)}{\partial Q} Q. \tag{4}$$

Hence, $P + h(\cdot)$ is industry marginal revenue while $P + \lambda h(\cdot)$ is the seller's perceived marginal revenue. λ can be interpreted as the industry average conjectural variation elasticity, where firm i's conjectural variation elasticity is (Dickson, 1981);

$$\lambda_i = \frac{\partial Q/Q}{\partial q_i/q_i} = \frac{\partial Q}{\partial q_i}\frac{q_i}{Q}. \tag{5}$$

That is, λ_i measures firm i's anticipated change in the output of all remaining firms following a change in its own output. Likewise, λ measures the industry's average level of competition

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[6] Profit maximization at the industry level is (simplified by omitting vectors of explanatory variables and parameters) $Max_Q\ \Pi = QD^{-1}(Q) - C(Q)$, where $D^{-1}(Q)$ is the inverse demand function and $C(Q)$ the cost function. Solving for P from the first-order condition yields $P = (\partial C(Q)/\partial Q) - (\partial D^{-1}(Q)/\partial Q)Q$. The average fraction of a firm's industry profits is λ, hence $P = (\partial C(Q)/\partial Q) - \lambda(\partial D^{-1}(Q)/\partial Q)Q$, which is equivalent to Eq. (3) where $c(\cdot) = \partial C(Q)/\partial Q$ and $h(\cdot) = (\partial D^{-1}(Q)/\partial Q)Q$.

and lies in the range [0,1] if it is to be given meaningful economic translation. $\lambda = 0$ thus implies perfect competition, $\lambda = 1$ implies a perfect cartel, while intermediate values refer to various sorts of oligopoly regimes.

Bresnahan (1982) and Lau (1982) show that by interacting exogenous demand side variables Z with P in the demand specification, changes in these variables both shift and pivot the demand curve such that λ can be econometrically identified. Formally, assuming that both the demand function and the marginal cost function are linear, the latter of which is given by $c(\cdot) = \beta_0 + \beta_1 Q + \beta_2 W$, the simultaneous equation system consisting of the demand and supply relation is[7]

$$Q = \alpha_0 + \alpha_1 P + \alpha_2 Z + \alpha_3 PZ + \epsilon \quad (6)$$

$$P = \beta_0 - \lambda \left[\frac{Q}{\alpha_1 + \alpha_3 Z}\right] + \beta_1 Q + \beta_2 W + \eta. \quad (7)$$

By first estimating Eq. (6) of the equation system, α_1 and α_3 can be treated as known parameters. In Eq. (7), there are two included endogenous variables, Q and $Q^* = Q/(\alpha_1 + \alpha_3 Z)$, and two excluded exogenous variables, Z and PZ. The term $\alpha_3 Z$ allows separation between Q and $Q^* = Q/(\alpha_1 + \alpha_3 Z)$ and hence identification of λ. If PZ is omitted in Eq. (6), $Q^* = Q/\alpha_1$. Then, we would have two structural parameters λ and β_1, but only one estimate based on the coefficient of Q. The supply relation is still identified, but we would not know whether we have to do with the case of $P = c(\cdot)$ or $MR = c(\cdot)$. Hence, inclusion of the interaction term PZ is crucial for identification of the level of competition in the market.

The Bresnahan-Lau model along with other conjectural variation (CV) models received critique in the late nineties for being atheoretical, in particular from Corts (1999). His argument is that inference regarding the extent of market power cannot be made without specifying underlying behavior. More specifically, he argues that the mapping between equilibrium variation and the equilibrium value of the elasticity-adjusted price cost margin is not valid, unless average and marginal responses of margins to demand shifters are the same. However, at the same time Genesove and Mullin (1998) assessed actual, as opposed to potential, bias in CV models as predicted by Corts, using data on observed costs and margins in the sugar refining industry. The sugar refining industry's very simple fixed coefficient technology serves as an

[7] Note that the inverse demand function is $D^{-1}(Q) = (Q - \alpha_0 - \alpha_2 Z)/(\alpha_1 + \alpha_3 Z)$. Hence, $h(\cdot) = Q(\partial D^{-1}(Q, Z; \alpha)/\partial Q) = Q(1/(\alpha_1 + \alpha_3 Z))$. Marginal revenues are $MR = (\partial(Q \times P)/\partial Q) = P + h(\cdot) = P + Q/(\alpha_1 + \alpha_3 Z)$. If there is monopoly pricing, the equilibrium condition is $c(\cdot) = MR$, and solving for P we obtain $P = \beta_0 - (Q/(\alpha_1 + \alpha_3 Z)) + \beta_1 Q + \beta_2 W$. It follows that the econometric specification for supply is $P = \beta_0 - \lambda(Q/(\alpha_1 + \alpha_3 Z)) + \beta_1 Q + \beta_2 W + \eta$ (or, alternatively, $P = \beta_0 + \lambda(-Q/(\alpha_1 + \alpha_3 Z)) + \beta_1 Q + \beta_2 W + \eta$).

objective benchmark to the estimated models. They find that estimated and actual cost margins are quite close, and the potential bias as suggested by Corts very small, if even existing, which they argue favors the atheoretical CV model. They directly address Corts' argument (p.369): "*The proper test of a methodology is not the correctness of its assumptions, however, but its success or failure in doing what it is meant to do. So while acknowledging the failure of an assumption to hold, we examine how well the methodology does in reproducing the full-information estimates of conduct and cost*". In a very recent study discussing among other things the CV models, Aquirregabiria and Slade (2017) also conclude accordingly. The Bresnahan-Lau and Genesove- Mullin conduct approach is thus still valid as an empirical way of measuring market power. It was recently applied in an empirical study of pass-through, where Weyl and Fabinger (2013) postulate a model where the elasticity-adjusted Lerner index is set equal to a conduct parameter in the fashion of Bresnahan (1989) and Genesove and Mullin (1998).

4. Overview of industry and data

4.1 Industry characteristics

During the sample period, there are four major companies in the Swedish market; Statoil Fuel & Retail AB (operating the brands Statoil and Jet), St1 Energy AB (operating the brands St1 and Shell), OK-Q8 AB and Preem AB.[8] These four companies run 2 416 of 2 716 retail stations (Ganslandt and Rönnholm, 2014). Statoil Fuel & Retail AB has a market share in volume of gasoline of 34.9%, St1 Energy AB of 22.6%, OK-Q8 of 27.9% and Preem AB of 14.2% (SPBI, 2013). In total, the four majors have a market share of over 99%, and the Herfindahl index of the industry is 2 173, suggesting that the market is concentrated.[9] The majority of retail stations are vertically integrated in the sense that the upstream company owns the stations and is responsible for running them. The rest of the stations are either commissioned agent stations, franchise stations or dealer owned stations.[10]

[8] Of these brands, Jet and St1 only operate self-serviced retail stations.

[9] Typically, the other stations are small. As opposed to the 99.6% market share in volumes, the four firms have more than ten percentage points fewer stations (89%).

[10] In gasoline retailing, the most common contract types are (i) company-owned contracts, which correspond to full vertical integration, (ii) franchising contracts which assign some control to the upstream firm, and (iii) open-dealer contracts at the other end, corresponding to full vertical separation (Shepard, 1993).

Market power is a highly relevant issue in this industry, hence assessing the degree of competition in the market is important. This is underlined both by the vast existing general literature on the topic, and, more specifically, by a high focus on the part of the regulators on competition challenges in the Swedish gasoline market. In 2005 the Swedish Market Court found the major oil companies were found of illegal cooperation during the year 1999. They were penalized for, among other things, coordinated rebate reductions in order to sort customers into different groups, internal agreements not to compete for customers among themselves, and agreements on increasing the retail price (Swedish Market Court, 2005). Common for these actions was their potential to soften competition. In total, the companies paid 112 million SEK in fines.[11] At that time, there were six major companies operating; OK-Q8 (market share 26.20%), Statoil (24.0%), Shell (16.70%), Hydro (11.9%), Preem (10.90%) and Jet (8.3%) (Foros and Steen, 2013). This corresponds to a Herfindahl index of 1 874, which is lower than the 2012 level. The growth in concentration is mainly due to four major mergers taking place between 2007 and 2010.[12] This also led to steadily increasing gross margins over the period by around 30%.[13] Later, in 2012, and partly due to this development and worries about the potential lack of competition, the SCA was required by the government to initiate studies of the market structure in this market.[14]

4.2 Data

The data period is 1 January 2012 to 31 December 2012 and the sample consists of 180 stations. Sample stations are from four different geographical regions. These are «larger cities» (Stockholm, Gothenburg and Malmo, the respective first, second, and third largest cities in Sweden), «smaller cities» (cities with population of between 33 000 and 80 000), «E6 highway»[15] and «rural areas» (population below 10 000). Regions can be subdivided into counties and municipalities.[16] An overview of station and municipality distribution for the sample is provided in Table 1.

[11] In 2005, one US dollar was worth between 6.8 and 7.6 SEK.
[12] In 2007, Statoil acquired Norsk Hydro, in 2008 Statoil acquired Jet from Conoco Phillips, in 2009 St1 acquired 158 automat stations from Statoil, and in 2010 St1 bought Shell (Ganslandt and Rönnholm, 2014).
[13] See report by the Swedish Competition Authorities (2013), in particular Figure 3.11, p 123.
[14] As a result, the Swedish CA initiated two studies of the competitive structure of the Swedish gasoline retail market, see Foros and Steen (2013) and Ganslandt and Rönnholm (2014).
[15] E6 is a part of the international E-road network. We consider it a separate geographical region as customers who frequent stations along the highway mostly are busy highway commuters. Further, it is likely that demand around highways is more variable in relation to weekends and holidays.
[16] Sweden is divided into 21 counties and 290 municipalities. Some counties are represented in several of the geographical regions because the E6 highway is located near several larger and smaller cities. Our sample consists of observations from 14 distinct counties.

Table 1: Station and municipality distribution across geographical regions.

Region	Number of stations	Number of municipalities
Larger cities	81	8
Smaller cities	32	6
E6 highway	26	9
Rural areas	41	28
Total	180	51

Information on station characteristics and facilities includes the distance to the nearest, second nearest and third nearest competitor, as well as which company a station belongs to. These data are obtained from the firms through the SCA. From the information on distance to the nearest competitors, we compute the number of stations within three km from each seller, which we use as a measure of station density. Further, a carwash indicator and a self-service indicator are obtained from the petroleum companies' websites.[17]

Table 2: Overview of data definition and sources.

Data definition	Variable name	Level	Frequency	Source
95 octane gasoline retail price per liter	*P*	Station	Daily	SCA
Volume in liters sold of 95 octane gasoline	*Q*	Station	Daily	SCA
Rotterdam wholesale price per liter (Platts)	Wholesale price	Industry	Daily	SCA
Brand	Brand	Station	Yearly	SCA
Distance to nearest competitor in kilometers	Distance to competitor	Station	Yearly	SCA
Number of stations within 3 km radius	Station density	Station	Yearly	SCA
Average disposable income in 1000 SEK	*Y*	Municipality	Yearly	Statistics Sweden
Population number in 1000	Population	Municipality	Quarterly	Regional Facts
Supply of public transportation in 1000 kilometers per capita	Public transportation	County	Yearly	STA

We assemble data on demographics from 'Regional Facts', data on average disposable income[18] from Statistics Sweden, and data on public transportation[19] from the Swedish

[17] Some facility information is accessed in 2017. Hence, we implicitly assume that these facilities are the same in 2017 as in 2012.
[18]Disposable income is measured as the sum of all tax deductible and non-tax deductible income subtracted taxes and other negative transfers.
[19] The supply of public transportation measured in kilometers is the sum of kilometers driven by buses, trains, trams and lightrails.

Transport Analysis (STA) based on the stations' location, using their addresses. These data are either at the municipality or the county level and are either quarterly or yearly data. A complete overview of data and sources as presented in Table 2.

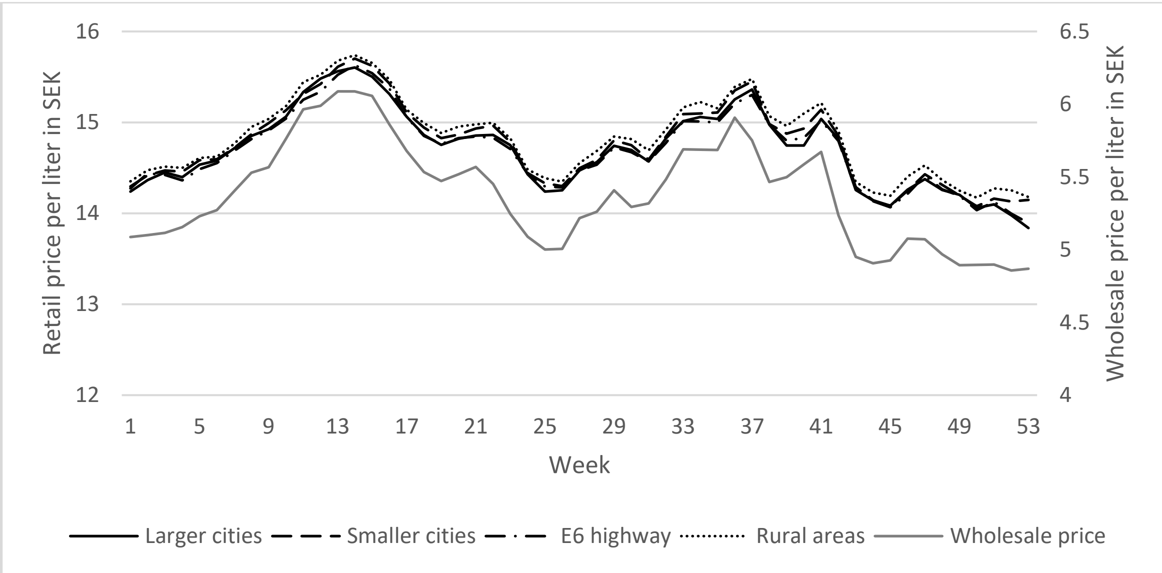

Figure 1: Average weekly retail price for each geographical region (left axis) and wholesale price (right axis). Sample period is 1 January 2012 to 31 December 2012.

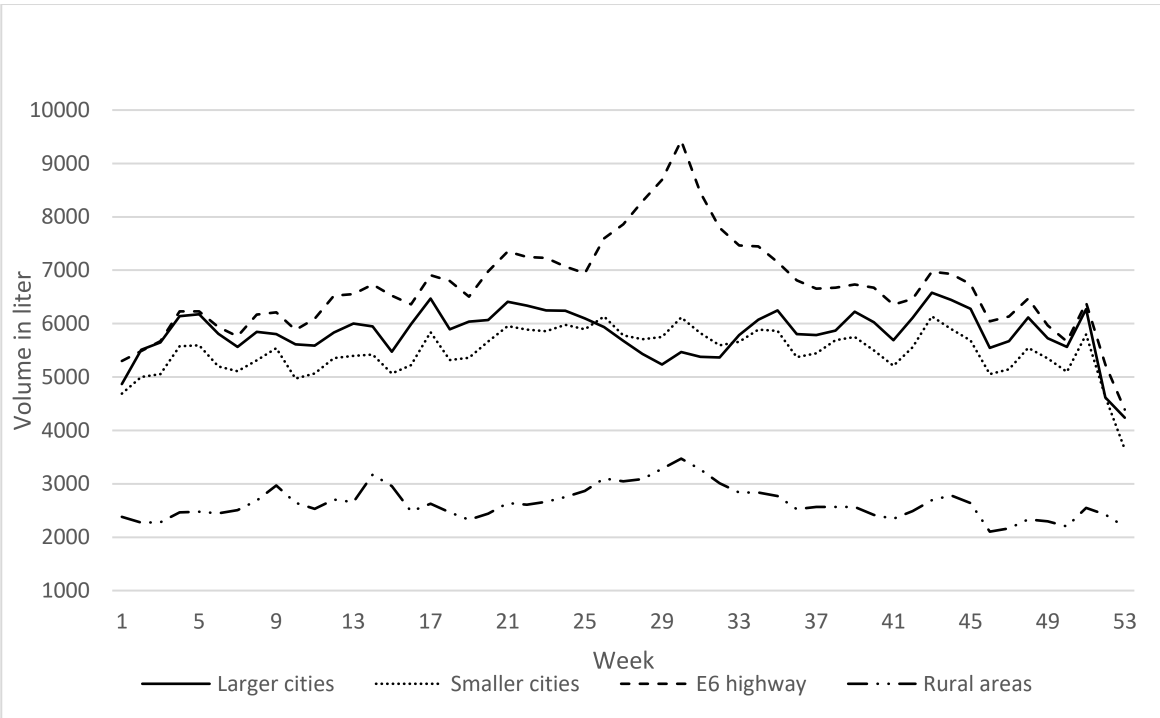

Figure 2: Average weekly quantity sold at the station level in different geographical regions. Sample period is 1 January 2012 to 31 December 2012.

Figure 1 depicts the retail price averaged over stations within each geographical region. Prices across regions are quite similar, but, rural areas have slightly higher prices than other regions in most parts of the sample period. Prices are highest during the spring and autumn months, and fluctuations seem to follow those observed in the wholesale price. On the other hand, as shown in Figure 2, the average quantity sold for stations varies more across regions as compared to prices. Average quantity sold per station is highest in the cities and the E6 highway, while lowest in rural areas. Volumes resemble the population in these areas, as more inhabitants naturally lead to higher consumption of fuel. The E6 highway is one of the main commuting highways in Sweden, which explains the high average volume sold in this region. Further, the summer holiday season stands out for the E6 highway with an upward peak in the volume sold in the summer months (July and August) due to increased traffic. Descriptive statistics of the main variables are presented in Table 3.

Table 3: Statistical properties of main variables (number of stations n=180).

Variable name	Mean	St.dev.	Min	Max
P	14.755	0.473	13.300	15.950
Q	5190.336	3775.662	11.000	29833.630
Wholesale price	5.394	0.358	4.800	6.151
Y	384.522	58.941	295.700	616.700
Public transportation	81.407	18.257	31.707	114.630
Population	244.058	277.776	3.196	881.235
Number of stations	49.951	33.322	4	122
Distance to competitor	1.819	3.731	0.020	30
Station density	2.396	1.416	0	4
Carwash	0.307	0.461	0	1
Self-service	0.364	0.481	0	1
Vertically integrated	0.761	0.426	0	1
Commissioned agent	0.205	0.403	0	1
Franchise	0.011	0.106	0	1
Independent	0.023	0.149	0	1

5. Empirical specification of the Bresnahan Lau model

The first equation in our simultaneous equation system is the demand function

$$Q_{it} = \alpha_0 + \alpha_1 P_{it} + \boldsymbol{z}'\boldsymbol{\alpha_z} + P_{it}\boldsymbol{z}'\boldsymbol{\alpha_{Pz}} + \boldsymbol{x}'\boldsymbol{\alpha_x} + \epsilon_{it}, \tag{8}$$

where i indexes station and t indexes day of the week. Q_{it} is the daily volume sold in liters and P_{it} is the price per liter at station i at time t. In the theory section, we showed that the inclusion of interactions between variables in $\boldsymbol{z}$ and P_{it} are crucial for the identification of the supply side equation, and that the choice of $\boldsymbol{z}$-variables hence identifies the markup in the Bresnahan-Lau framework. There is not a lot of guidance with respect to the criteria for which $\boldsymbol{z}$-variables to include from neither the theoretical nor the empirical literature on the Bresnahan-Lau model. Typically, one chooses variables that from theory are believed to both be exogenous to quantity demanded and very likely shift demand. There are several candidates used in the literature, but the most commonly used variable is either related to factors believed to affect demand through income or market size, or variables related to substitute products.[20] The $\boldsymbol{z}$-variables validity are empirically evaluated in these models based on two factors, whether they enter significantly in the estimated demand equation and whether the demand elasticities where these $\boldsymbol{z}$-variables enter predict reasonable values according to theory and market characteristics. In our case, we choose $\boldsymbol{z}$ as a $K \times 1$ column vector of exogenous variables consisting of average disposable income, average disposable income squared and the population in the municipality. Increased disposable income is believed to shift the demand curve for gasoline outwards, likewise will gasoline demand increase with population. Furthermore, we introduce a variable representing a substitute, by including the number of 1000 kilometers driven by public transportation per capita in $\boldsymbol{z}$. Gasoline as a fuel does not have any obvious substitutes, thus we are not able to include the price of a substitute good in $\boldsymbol{z}$. Nonetheless, the use of public transportation is a substitute for car consumption and as such serves a similar function as a substitute price. Hence, in we include four interaction terms, three that relates to income and market size, and one variable representing a substitute variable.

We also include additional exogenous variables which do not interact with P_{it} in the $K \times 1$ column vector $\boldsymbol{x}$, consisting of the number of stations in the regional county, distance to the nearest competitor and a dummy for whether station i is self-serviced or not. In addition, $\boldsymbol{x}$ includes a full set of day-of-the-week dummy variables using Monday as baseline, a full set of month dummy variables using January as baseline, and a full set of region dummy variables (Foros and Steen, 2013). We include three regional dummy variables, one for smaller cities, one for rural areas and one for E6 highway stations. The larger cities serve as reference category. A complete overview of variable definitions, data source, granularity and frequency

[20] Prices of substitute goods and income are commonly applied as $\boldsymbol{z}$-variables in studies of commodity markets (e.g., Steen and Salvanes, 1999; Buschena and Perloff, 1991; Rosenbaum and Sukharomana, 2001). Time trends and seasonal factors have also been applied (e.g., Buschena and Perloff, 1991; Considine, 2001). In the banking literature, market interest rates, which serve as substitute prices, and GDP, a measure of macroeconomic activity, are used (e.g., Toolsema, 2002; Shaffer, 1993, 1994; Suominen, 1994). Graf and Wozabal (2013) use a temperature index as an exogenous demand rotator in their study of electricity markets. Jung and Seldon (1995) include the number of new products introduced to the advertising market when studying the advertisement market.

is presented in Section 4. Finally, ϵ_{it} is the idiosyncratic error term representing unobserved factors which have an impact on the quantity demanded on each station.

The supply specification is

$$P_{it} = \beta_0 + \lambda Q_{it}^* + \beta_1 Q_{it} + \boldsymbol{w}'\boldsymbol{\beta_w} + \eta_{it}, \tag{9}$$

where $Q_{it}^* = -Q_{it}/(\alpha_1 + \boldsymbol{z}'\boldsymbol{\alpha_{Pz}})$. $\boldsymbol{w}$ is a $K \times 1$ column vector of exogenous supply side variables consisting of the daily wholesale price, a dummy for whether station i offers carwash or not, a dummy for whether station i is self-serviced or not, a full set of month dummy variables, a full set of region dummy variables, contractual form dummies and a full set of brand dummy variables.[21] η_{it} is the idiosyncratic error term which represents unobserved differences in sellers' marginal costs while Q_{it} is the actual quantity sold at station i on day t.[22]

A fundamental endogeneity problem arises as quantity demanded affects the price sellers set, while price setting also affects the quantity demanded by consumers. Hence, the two variables of interest are simultaneously determined within the model, causing P_{it} to be correlated with ϵ_{it} in Eq. (8) and, likewise, Q_{it} to be correlated with η_{it} in Eq. (9). To correct for the biases, we apply two stage least squares (2SLS). We use the wholesale price as an instrumental variable for P_{it} in the demand equation. In the supply relation, the variables included in $\boldsymbol{z}$ are used as instrumental variables for Q_{it}.

We use the wholesale price as an instrument for P_{it} because the wholesale price is the main input cost for gasoline and is hence a valid instrument.[23] Further, there is no obvious direct relationship between the cost of input factors and the quantity demanded in the retail market, implying that the wholesale price is uncorrelated with ϵ_{it}. This instrument thus generates exogenous variation related to P_{it} which we can take advantage of when estimating the impact of the retail price on quantity demanded. Q_{it} is instrumented by the $\boldsymbol{z}$ variables; namely the average disposable income, the average disposable income squared, the size of the local population and the regional supply of public transportation. These variables are all good candidates as they directly influence gasoline consumption through a positive income or

[21] The variables included in $\boldsymbol{w}$ have an impact on a seller's marginal costs. Consequently, by using P_{it} as the left hand side variable we can estimate the supply relation without knowing marginal costs.
[22] In order to estimate the equations and impose market clearing, we assume that prices clear the market, allowing us to treat Q_{it} as the equilibrium quantity. We believe this is a reasonable assumption to make since the Swedish retail market is not under governmental regulation neither at the demand, nor the supply side during the sample period.
[23] Swedish oil companies are price takers in the European gasoline market. The correlation between the instrument and the endogenous variable is as high as 0.881.

negative substitution effect, and through the fact that an increase in the population increases the demand for cars and fuel. However, they have no clear partial effect on the retail price or factors determining sellers' marginal costs, therefore being uncorrelated with η_{it}.

Data differ in various dimensions. The main variables Q and P vary from day to day and between stations. *Wholesale price* varies from day to day. Station characteristics are fixed over time, but have significant variation across stations. The remaining independent variables vary across either municipality or county, but are fixed over time.[24] In order to use all within and between variation across different dimensions, we use pooled OLS as an estimation method (Baltagi and Griffin, 1983). First, we estimate Eq. (8) using two-stage least squares in order to find the best linear combination of instrumental variables. Next, we use the estimated parameters from Eq. (8) to calculate Q^*. Finally, we estimate Eq. (9), again using two-stage least squares.

[24] One exception is *population*, which is quarterly numbers.

6. Empirical results

6.1 Market power in the Swedish retail gasoline market

Demand

Results for the demand equation (8) together with elasticities are presented in Table 4.[25] All four $\boldsymbol{z}$-variables come in significant, both alone and through the interaction terms, confirming empirically that they can be used for identifying markup in the supply relation. Due to the interaction terms, parameter values and corresponding signs give little direct intuition. Elasticities are therefore a better measure in order to gain intuition, and to validate the chosen demand variables to interact with price.

The average price elasticity is estimated to be -0.72 and is significant, implying that gasoline demand is downward sloping and inelastic to responses in fuel price. The income elasticity is positive, significant and slightly larger than one (1.11), meaning that gasoline is a normal good.[26] Results are within the range of elasticities found in other demand studies.[27] Further, as ε_Y is higher than ε_P, holding all other factors fixed, the demand for gasoline will increase for proportional increases in income and price.

The elasticity of public transportation proposes that better access to public transportation lowers the gasoline demand with a negative significant elasticity of -0.44. Hence, public transportation is a substitute for car travel, although not a perfect one. The population elasticity is marginally positive, though not significant. Being careful in interpreting a low insignificant number, this still suggests that the number of licensed drivers rises with population, which in turn increases the gasoline consumption. Contrary to expectations, although elasticities are small, the effect of the *number of stations* is positive, while the effect of the *distance to competitor* is negative. Larger markets typically have more stations, which suggests higher market demand. Likewise, in a dense market, the distance to the closest competitor is lower than in less dense markets, where the distance between outlets is larger. This we attribute to our control for market size, which is defined at the regional level, and thus very likely too wide to

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[25] Consider the simplified demand equation; $Q = \alpha_0 + \alpha_1 P + \alpha_z Z + \alpha_{PZ} PZ$. Then, the elasticity of Z is given by $\epsilon_Z = (\alpha_Z + \alpha_{PZ} P)(Z/Q)$, where we use sample means of P, Z and Q.

[26] When testing the hypothesis H_0: ε_Y=1, we reject the hypothesis at the 1% level. Thus, the income elasticity is significantly higher than 1.

[27] See e.g. the survey by Basso and Oum (2007), as well as Johansson and Schipper (1997) and Baltagi and Griffin (1983) for OECD-countries and Yatchew and No (2001) for Canada.

Table 4: 2SLS estimation results of Eq. (8) and corresponding elasticities.

Variable	Coefficient
P	127,819.8***
	(16,169.0)
Y	8,796.3***
	(1,086.4)
Y^2	-10.024***
	(1.243)
Public transportation	742.88***
	(154.71)
Population	-119.53***
	(16.368)
Number of stations	10.114***
	(0.761)
Distance to competitor	-70.268***
	(3.382)
Self-service	2,185.6***
	(33.97)
P × Y	-594.20***
	(73.642)
P × Y^2	0.678***
	(0.084)
P × Public Transportation	-52.219***
	(10.518)
P × Total number of stations	8.110***
	(1.103)
Constant	-1888145.9***
	(238,490.8)
ε_{P}	-0.719**
	(0.245)
ε_{Y}	1.117***
	(.0425)
$\varepsilon_{\text{Public transportation}}$	-0.442***
	(0.022)
$\varepsilon_{\text{Population}}$	0.007
	(0.007)
$\varepsilon_{\text{Number of stations}}$	0.097***
	(0.007)
$\varepsilon_{\text{Distance}}$	-0.025***
	(0.001)
Observations	64,497
R-squared	0.112
Day of the week dummies	YES
Month dummies	YES
Region dummies	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors of elasticities are calculated using the delta method. Sample period is 1 January 2012 to 31 December 2012.

fully account for all cross-market differences. The local market effects instead turn out through our elasticities for distance to competitors and number of stations.

Focusing on the interaction terms, we see that coefficients are strongly significant, which is important in order to identify the coefficient of Q^* in the supply equations. In total, the demand function behaves well and proposes plausible predictions.

Supply

Turning to the supply relation, baseline estimation results of Eq. (9) are presented in Table 5. All variables come in significantly and with anticipated signs. The marginal effects are difficult to interpret directly and we have therefore provided elasticities in the table as well. Marginal costs are increasing in Q, but only marginally (elasticity=0.002).

Table 5: 2SLS estimation results of Eq. (9) and corresponding elasticities.

Variables	Coefficients
Q	0.000006***
	(0.000001)
Wholesale price	1.066***
	(0.005)
Q*	0.005***
	(0.0003)
Carwash	0.075***
	(0.003)
Self-service	-0.095***
	(0.023)
Constant	8.982***
	(0.037)
ε_{Q}	0.002***
	(0.0004)
$\varepsilon_{\text{Wholesale price}}$	0.389***
	(0.002)
$\varepsilon_{\text{Carwash}}$	0.002***
	(0.00006)
$\varepsilon_{\text{Selfservice}}$	-0.002***
	(0.0006)
Observations	60,888
R-squared	0.843
Month dummies	YES
Region dummies	YES
Brand dummies	YES
Contractual form dummies	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors of elasticities are calculated using the delta method. Sample period is 1 January 2012 to 31 December 2012.

Increases in the wholesale price also raises costs (elasticity=0.39), but due to the high data frequency and only one year of data we do not find full pass-through. The station amenity variables both influence costs; self-service reduces costs (elasticity=-0.002), whereas car-wash facilities increase costs (elasticity=0.002).[28]

Scrutinizing the markup parameter, the model predicts λ to be significant and larger than zero, but very low. An estimate of 0.005 suggests that Swedish gasoline retailing is not a pure competition market. This is in line with several other studies that find that despite high upstream concentration, the retail level does experience competition, e.g., Houde (2012), Manuszak (2009) and Slade (1987). This suggests that even though the market is highly concentrated as there are few brands present in the Swedish market, there is sufficient competition between sellers at the retail level.[29]

However, in the baseline model we do not identify to which extent potential effects on the firms' markup level depend on station characteristics. The literature points in particular to three groups of station characteristics that might influence the level of market power locally; (i) local competition level, (ii) station amenities and (iii) brand identity and contract forms. We will look at these groups in turn below.

6.2 Sources of local market power

Local competition

To analyze the effects of local competition, we estimate modified supply relations (Eq. (9)) where we interact Q^* with variables that measure local competition. The variables are alternative measures of closeness to competitors. The first is *distance to competitor*, and the second is *station density*. Results are presented in Table 6. [30]

Both models perform in the same manner as our baseline model. The new interaction terms both suggest that local competition level influences market power. The larger the distance to the nearest competitor, the higher is the market power. Likewise, the more stations within the close vicinity, the less market power is attainable for the stations.

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[28] The instruments perform well in both models. The 1st stage adjusted R^2 of Eq. (8) and (9) are 0.999 and 0.689 for the demand function and the supply relation, respectively.

[29] According to Corts (1999), the CV models perform poorly only when the estimated market power as measured by λ is large (Genesove and Mullin, 1998). We find only a very modest level of market power.

[30] There are fewer observations used in the estimation of the models in Table 6 because information about distance to the nearest sellers is missing for some stations. We do not replace missing values in order to avoid smoothing effects. However, results are qualitatively the same when replacing missing values with the mean value for each distance variable in each county.

Table 6: 2SLS estimation results of Eq. (9) with inclusion of interactions between Q* and local competition measures.

	Distance to competitor	Station density
Q	0.000005***	0.000007***
	(0.000001)	(0.000001)
Wholesale price	1.062***	1.063***
	(0.006)	(0.006)
Q*	0.005***	0.008***
	(0.0002)	(0.0004)
Q*×Distance to competitor	0.001***	
	(0.0005)	
Q*×Station density		-0.001***
		(0.0001)
Carwash	0.086***	0.085***
	(0.003)	(0.003)
Self-service	-0.066***	-0.062***
	(0.023)	(0.023)
Constant	8.967***	8.951***
	(0.037)	(0.037)
Q* + Q*×Distance to competitor	0.005***	
	(0.0003)	
Q* + Q*×Station density		0.007***
		(0.0003)
ε_{Q}	0.002***	0.003***
	(0.0004)	(0.0004)
$\varepsilon_{Wholesale\ price}$	0.388***	0.389***
	(0.002)	(0.002)
$\varepsilon_{Carwash}$	0.002***	0.002***
	(0.00007)	(0.00006)
$\varepsilon_{Selfservice}$	-0.002***	-0.002***
	(0.0006)	(0.0006)
Observations	58,345	58,345
R-squared	0.843	0.843
Month dummies	YES	YES
Region dummies	YES	YES
Brand dummies	YES	YES
Contractual form dummies	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors of elasticities are calculated using the delta method. Sample period is 1 January 2012 to 31 December 2012.

Taking a closer look at the coefficients, we can get an idea of how sizeable the effect of local competition is. The *distance to competitor* coefficient is 0.001 and the interpretation is as follows: If the distance to the nearest rival of seller *i* increases by one km, seller *i*'s markup increases with 0.001. Hence, the total effect of *Q** for a station with a distance of one km to its closest rival is 0.005 + 0.001 = 0.006, and the effect is significant. Thus, this coefficient scales the markup according to the distance to the closest competitor. The average station in our sample is located 1.82 km from its closest competitor. The distance variable has, however, a rather high variation, and varies from 0.02 to 30 km across all stations in the sample. This implies for instance, that if we compare a station with no competitors closer than 5 km to a station with a next-door neighbour station, the baseline markup parameter from Table 5 is doubled. Obviously, though one should be careful with the interpretation when we are far away from the mean value, rural stations are typically a long distances away from their neighbours, and they will have substantially more market power than those who have close competitors.

This suggests that the longer the distance between outlets, the higher market power each seller will have because the fuel they offer is more horizontally differentiated from the consumers' point of view. Intuitively, a la Hotelling (1929), the further the distance to the closest competitor, the more consumers are in seller *i*'s "backyard" and hence regard seller *i* as the most preferred seller, other things equal.

In column (B), we interact Q^* with *station density*. The baseline estimate of λ is now 0.008, and slightly higher compared to the benchmark; however it is still small, but positive and significant. The interaction-term coefficient is negative, implying that if seller *i* faces an additional outlet within its neighbourhood (3 km radius), its market power decreases to 0.008 + (-0.001) = 0.007. One possible explanation to this is that the higher the station density, the more stations are within each consumer's reach and so each seller's good has more substitutes. Other things equal, increasing spatial competition thus reduces each seller's market power. However, the *station density* variable has less variation than the *distance to competitor* variable, with a minimum of zero, a maximum of 4, and an average of 2.4. This implies that the maximum scope for this variable (4×-0.001) is lower than for the *distance to competitor* variable. This gives some support to the findings of Hosken et al. (2008), namely that nearness to the closest competitor is more important than density.

In total, results indicate that raising the density of stations or lowering distance between sellers have a detrimental effect on each seller's markup and hence a positive effect on local competition. These findings are in line with those of Barron et al. (2004), Barron et al. (2007) and Clemenz and Gugler (2006).

Station Amenities

We move on to examine station amenities. From Table 1 we see that for our price and quantity observations, 31% of our sample have carwash amenities, 36% are self-service stations and 33% are full service stations without carwash. We want to examine to which extent these differences in service level affect market power. Using the full service stations without carwash amenities as reference category, we interact *Q** with *carwash* and *self-service* and estimate the supply relation (Eq. (9)). We present the results in Table 7.

Table 7: 2SLS estimation results of Eq. (9) with inclusion of interactions between Q* and station amenities.

	Station amenities
Q	0.000003**
	(0.000001)
Wholesale price	1.065***
	(0.005)
Q*	0.011***
	(0.001)
Q*×Carwash	-0.001
	(0.001)
Q*×Self-service	-0.010***
	(0.001)
Carwash	0.067***
	(0.003)
Selfservice	-0.088***
	(0.023)
Constant	8.991***
	(0.029)
Q* + Q*×Carwash	0.01***
	(0.0003)
Q* + Q*×Selfservice	0.0006**
	(0.0003)
ε_{Q}	0.001**
	(0.0004)
$\varepsilon_{\text{Wholesale price}}$	0.389***
	(0.002)
$\varepsilon_{\text{Carwash}}$	0.001***
	(0.00007)
$\varepsilon_{\text{Selfservice}}$	-0.003***
	(0.0006)
Observations	60,888
R-squared	0.846
Month dummies	YES
Region dummies	YES
Brand dummies	YES
Contractual form dummies	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors of elasticities are calculated using the delta method. Sample period is 1 January 2012 to 31 December 2012.

Again, we find signs, parameter magnitudes and significance as in our baseline model. The explanation power is marginally increased. Full service stations with no carwash have a markup (λ) of 0.011. Our results imply that there is no significant difference in markup for the full service stations with *carwash*. These have the same markup as the full service stations without carwash. On the other hand, the *self-service* stations have a significantly lower markup than the others. The interaction term between Q* and *selfservice* is significant and sizeable, suggesting that self-service stations have close to no markup. The estimate is still positive and significant at a 5%-level, but as low as 0.0006.

This suggests that market power increases with station service level. One explanation is that a seller might be able to charge a markup that covers more than the actual cost of providing service to customers. Our findings have some similarities to the results of Haucap et al. (2017), who show that carwash facilities affect retail prices positively, while stations without store facilities, tend to have lower prices.[31]

Our results are also in line with Eckert and West (2005) who find that station characteristics affect sellers' price setting, this as opposed to Hosken et al. (2008) who do not find any impact of station amenities on market power.

Brand identity and contractual forms

Several studies have argued that brand identity and contractual forms affect the stations' performance. In Table 8 we allow λ to vary with brand identity. Again, parameters, significance and elasticities are similar to those of our baseline model, and the explanation power is marginally increased.

Preem has a higher λ than the other brands (0.012), followed by OK-Q8 (0.01), Shell (0.009), Statoil (0.009), St1 (0.003), and lastly, Jet (-0.0005). All estimates except that of Jet are highly significant. This latter result is in line with the finding that self-service stations do not have any markup: Jet stations are all self-service stations. Related to this result, it is interesting to note that the other self-service brand, St1, has only one third of the markup as compared to the others, but here the positive markup estimate is significant. One possible explanation is that St1 and Shell have a common owner, and, as such, some of Shell's brand name effect potentially carries over to St1. Statoil has owned the Jet stations since 2008, but Jet has a very long prior history of being the low-price market challenger, suggesting that it is harder for Jet than St1 to increase its prices in 2012.

[31] If we only include the carwash interaction, we find some evidence of higher market power for the carwash stations.

Table 8: 2SLS estimation results of Eq. (9) with inclusion of interactions between Q* and brand identity dummies.

	Brand identity
Q	0.000006***
	(0.000001)
Wholesale price	1.066***
	(0.005)
Q*	0.009***
	(0.0003)
Q*×Preem	0.004***
	(0.001)
Q*×Okq8	0.001**
	(0.0005)
Q*×Shell	0.001
	(0.001)
Q*×Jet	-0.009***
	(0.0004)
Q*×St1	-0.006***
	(0.001)
Carwash	0.060***
	(0.003)
Self-service	-0.091***
	(0.023)
Constant	8.972***
	(0.029)
Q* + Q*×Preem	0.012***
	(0.0005)
Q* + Q*×Okq8	0.01***
	(0.0004)
Q* + Q*×Shell	0.009***
	(0.0009)
Q* + Q*×Jet	-0.0005
	(0.0003)
Q* + Q*×St1	0.003***
	(0.0005)
ε_{Q}	0.002***
	(0.0004)
$\varepsilon_{\text{Wholesale price}}$	0.389
	(0.002)
$\varepsilon_{\text{Carwash}}$	0.001***
	(0.00007)
$\varepsilon_{\text{Selfservice}}$	-0.002***
	(0.0006)
Observations	60,888
R-squared	0.845
Month dummies	YES
Region dummies	YES
Brand dummies	YES
Contractual form dummies	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors of elasticities are calculated using the delta method. Sample period is 1 January 2012 to 31 December 2012.

The finding of higher Preem margins is at first glance surprising all the time they have less than half the market share (14%) of both Statoil/Jet (35%) and OK-O8 (28%). However, Preem has a similar market share in terms of the number of stations as OK-Q8 and Statoil/Jet and has a significantly higher market share for diesel.[32] In our sample, Preem is also different in terms of which type of retail stations are represented. Even though commissioned stations are common in all the companies running full-service stations (Swedish Competition Authorities, 2013), in our sample, Preem only operates commissioned agent stations. The other five brands' stations are all typically fully vertically integrated outlets.[33] Thus, a potential explanation for the higher Preem markup is the contractual form they have chosen. Unfortunately, we are not able to distinguish between the brand identity effect and the contractual form effect since no other brands are using commissioned agent contracts in our sample. It is, however, not unreasonable to attribute some of this Preem-effect to the contractual form given their smaller market share.

Combining local competition, station amenities and brand identity

We learned above that three characteristics stand out. First, local competition, both measured by closeness to the next gasoline station and by the local density of stations, matters to the amount of market power extracted by the gasoline stations. Second, station amenities are important, especially whether the station is fully serviced or not. Third, we saw that Preem stands out, experiencing significant higher markups than the others, which might be due to their different contact structure in our sample, operating only commissioned agent stations.

Now we combine these three characteristics, local competition, station amenities and controlling for Preem, in the same models. Since local competition is controlled for in two different fashions (refer Table 6), In Table 9 we estimate two supply relations, one where we interact Q^* with *distance to the closest competitor* and the other two characteristics, the other interacting Q^* with *station density* and these other two characteristics.

As before, the models have similar predictions as the baseline model when it comes to magnitudes for cost parameters and elasticities. The models also have higher explanatory power than the baseline model in Table 5.

[32] OK-Q8, Preem and Statoil/Jet had between 600 and 700 stations in 2012. They also sold around a third of the diesel in Sweden in 2012 (Swedish Competition Authorities, 2013).

[33] We have 38 Preem stations in our sample, making up 21% of the sample. The remaining 142 stations are run by the other five brands, whereof as many as 136 are fully vertically integrated (96%). In our sample we only see 2 franchised and 4 independent stations, out of which 6 are OK-Q8 brands.

Table 9: 2SLS estimation results of Eq. (9) combining local competition, station amenities and brand identity/contractual form.

	Distance to competitor	Station density
Q	0.000005***	0.000008***
	(0.000001)	(0.000001)
Wholesale price	1.062***	1.062***
	(0.005)	(0.005)
Q*	0.009***	0.017***
	(0.0003)	(0.0005)
Q*×Distance to competitor	0.0004***	
	(0.0001)	
Q*×Station density		-0.002***
		(0.0001)
Q*×Self-service	-0.009***	-0.011***
	(0.0003)	(0.0004)
Q*×Preem&Commisioned	0.003***	0.003***
	(0.001)	(0.001)
Carwash	0.072***	0.070***
	(0.003)	(0.003)
Selfservice	-0.067***	-0.057**
	(0.023)	(0.023)
Constant	8.995***	8.982***
	(0.030)	(0.030)
Q* + Q*×Distance to competitor	0.009***	
	(0.0003)	
Q* + Q*×Station density		0.014***
		(0.0004)
Q* + Q*×Selfservice	0.00001	0.006***
	(0.0003)	(0.0004)
Q* + Q*×Commisioned	0.012***	0.02***
	(0.0005)	(0.0006)
ε_{Q}	0.002***	0.003***
	(0.0004)	(0.0004)
$\varepsilon_{\text{Wholesale price}}$	0.388***	0.388***
	(0.002)	(0.002)
$\varepsilon_{\text{Carwash}}$	0.002***	0.002***
	0.00007	(0.00008)
$\varepsilon_{\text{Selfservice}}$	-0.002***	-0.002***
	(0.0006)	(0.0006)
Observations	58,345	58,345
R-squared	0.846	0.846
Month dummies	YES	YES
Region dummies	YES	YES
Brand dummies	YES	YES
Contractual form dummies	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors of elasticities are calculated using the delta method. Sample period is 1 January 2012 to 31 December 2012.

All the interactions between Q^* and the station characteristics are significant in both models, and Q^* is even more precisely estimated than in the baseline model. In sum, both the models in Table 9 perform better than the baseline model, suggesting that we can estimate the markup more precisely when we also account for the different sources of market power.

The baseline estimate of Q^* in the *station density* model is higher in this combined model than in all the other models. Also, the *distance to the closest competitor* model suggests a high baseline estimate of Q^*. When looking at the marginal effects of the characteristics measured through the interactions with Q^*, these have the same signs as above.

Looking at local competition effects, the effect of *distance to closest* competitor effect is still significant, but smaller in magnitude than what we found in Table 6. The model with *station density* suggests a higher negative marginal effect. However, given the variance in these two continuous characteristics (distance and density), the potential influence on market power is still highest from *distance to the closest* competitor.[34] The station amenity measured through the self-service interaction exactly cancels the baseline effect in the model with *distance to the closest competitor*, whereas in the *station density* model we find some significant market power also for self-service stations. The effect of being a Preem and commissioned agent-run station is still significant and positive, and the marginal difference between these commissioned agent-run stations and the other brands' fully vertically integrated stations is increased as compared to Table 8.

We find a clear result: local station characteristics significantly affect the degree of market power for the local gasoline station. To illustrate our results, we construct estimates for two stations with different characteristics. First, from our *distance to the closest competitor* model: Compare a Preem-owned commissioned agent operated full-service station with average distance to its competitor (1.82 km), with one of the other brands' self-service stations, typically vertically integrated, competing with a next door neighbour. The "Preem station" has an estimated markup (λ) of 0.013, the "other station" has no markup (estimated $\lambda = 0.000008$).[35] Second, from our *station density* model: Compare a Preem-owned commissioned agent operated full-service station with an average density of stations (2.4) within a vicinity of three kms, to another brand's vertically integrated self-service station that has four stations within

[34] Remember that the variance in the *distance to competitor* is 0.02 to 30 km whereas the *station density* variable only varies between 0 and 4 stations.

[35] Estimated λ for the "Preem station" from the *distance to competitor* model: Baseline (0.009) + Distance to competitor (0.0004×1.82) + Self-service (-0.009×0) + Preem&Commissioned (0.003×1) = 0.0127. Estimated λ for "the other station": Baseline (0.009) + Distance to competitor (0.0004×0.02) + Self-service (-0.009×1) + Preem&commissioned (0.003×0) = 0.000008.

three kms. The “Preem station” has an estimated markup (λ) of 0.015, the “other station” has a marginally negative markup (estimated λ = -0.002).[36] In sum, though we should be careful when comparing small numbers, local station characteristics influence market power to such an extent that in some local markets, a station will be able to extract market power, whereas in others the competition will remove this possibility.

7. Concluding remarks

Endowed with detailed consecutive daily micro data at the gasoline station level from Sweden on both prices and quantities we estimate a structural model to uncover the degree of competition in the retail market. We apply a Bresnahan-Lau (1988) model utilizing detailed knowledge on each station’s (i) brand identity and contractual arrangements, (ii) station amenities and (iii) local competition factors. We analyze how all these three factors impact on the competition level.

The paper addresses a relatively large but still non-conclusive empirical literature on how competition in gasoline retailing relates to local station characteristics. Micro data at the station level on both quantity and price have typically been hard to obtain, restricting previous research to mainly study aggregate data and reduced form models. Our approach is thus different from the majority of previous literature, both due to the richness of our data, and because we can combine several local station characteristics within the same model.

Our demand estimates suggest an inelastic gasoline demand, which is in line with other studies of gasoline markets. The Bresnahan-Lau approach requires adding interaction terms between exogenous demand side variables and the retail price in the demand specification. We use local income, local population and supply of public transportation in the region in these price interactions. They all come in significant, and produce reasonable and significant elasticities. The income elasticity suggests a normal good, and an increased supply of public transportation reduces demand, suggesting substitutability, both elasticities also being significant. The interaction term with local population size is significant, and the elasticity proposes a marginal positive demand effect, though not significant.

[36] Estimated λ for the “Preem station” from the *density* model: Baseline (0.017) + Station density (-0.002 × 2.4) + Self-service(-0.011 × 0) + Preem&commissioned (0.003 × 1) = 0.0152. Estimated λ for “the other station”: Baseline (0.017) + Station density (-0.002 × 4) + Self-service (-0.011 × 1) + Preem&commissioned (0.003 × 0) = -0.002.

Using the information from the demand estimates, we identify market power through our estimated supply relations. We find that retailers do exercise some market power in the Swedish market on average, but despite the high upstream concentration also in Sweden (C4=99%), the market power is very limited on the downstream level.

Despite the very modest findings of market power, the competitive level varies significantly with local retail station characteristics such as the degree of local competition, station amenities and brand identity/contractual form. We show that the degree of market power varies with both the distance to the nearest station and the local density of gasoline stations. A higher level of service tends to raise a seller's market power, in particular we find that self-service stations have close to no market power. Finally, contractual form and brand identity are also found to matter, but we are not able to distinguish the effects fully in the sense that the only brand in our sample (Preem) that operates commissioned gasoline stations (and only such stations) also have a significantly higher markup than the other brands that predominantly have fully vertically integrated stations.

Swedish Competition Authorities stated in 2013 (p.128) "*…the stations' gross margins naturally vary over time and depend on the local competition pressure.*". We find a clear result reflecting this observation: local station characteristics significantly affect the degree of market power for the local gasoline stations. We show that differences in local station characteristics, even within the scope of the variation in our sample, have a large effect on local market power. The results show that the magnitude of these local differences implies that in some local markets, a station will be able to extract market power, in other markets the local competition factors will remove this possibility.

Hence, not only do we establish the effects of differences and importance in local station characteristics on market power, our results also indicate that local differences in station characteristics can more than offset the average market power found in our baseline models.

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NHH has a long reputation for its high academic level and contributions to the international research community. A large number of our faculty hold a PhD from institutions outside of Norway, in particular top US universities. This creates a diverse and stimulating academic environment.

The PhD student body is made up of around 100 men and women working within different fields of specialisation. The programme encourages close interaction between students and faculty in a social/academic climate where students are regarded as junior colleagues.

The PhD programme offers courses over a wide range of topics within six specialisations: Accounting; Economics; Finance; Management Science; Professional and Intercultural Communication; and Strategy and Management. The programme aims at giving the graduate a solid training in performing high quality scientific research in these areas, making use of state of the art empirical and theoretical techniques. This prepares the student for employment in national and international policy institutions, within research centres, business enterprises, and for the international academic job market. The entire programme is held in English. It runs over three years, with the first year consisting primarily of course work. The next two years are then devoted to independent research and the writing of a doctoral thesis, under the supervision of an advisor appointed from the NHH faculty.

NHH

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