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Screening for partial collusion in retail electricity markets

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ABSTRACT

Starting from a theoretical model of coalition formation, we analyse which price markers are more adequate to identify clues of partial cartels. Based on the theoretical model, we argue that measures of the shape of a distribution (such as kurtosis and skewness) can complement centrality measures (such as the mean and the dispersion of the distribution of prices) to screen for potential partial cartels. We apply these price markers to price data from the Norwegian retail electricity market.

1. Introduction

A partial cartel is a cartel where only a subset of all firms in a given industry have a collusive agreement, i.e. some firms are inside the cartel while others are outside. In turn, in a full cartel all firms in an industry are cartel members. Partial cartels are more ubiquitous than full cartels (see Gomez-Martinez, 2017); however, the literature on cartels has primarily focused on full cartels.

The cartel screening literature tries to identify abnormal price behaviour patterns in the data that can be consistent with cartelization (see Harrington, 2008). Like the literature on cartels, the screening literature has also focused more on full cartels. However, as argued by Harrington (2008), screening tools for full cartels might not be the most appropriate for partial cartels, given that the economic incentives and the economic structure of partial cartels are different from full cartels. In addition, most of the existing screens in the literature were developed ad-hoc without ground on economic theory.

In this paper, we aim to give the following contributions to the literature on cartel screening. First, to develop price markers that are better suited to screen for partial cartels. Second, to develop screening tools grounded on a rigorous theoretical framework. In particular, we propose screens that are based on a theoretical model of coalition formation extended from Deneckere and Davidson (1985). Third, to apply these screen methods to the electricity retail market in Norway. These three objectives of the paper are discussed in more detail below.

In terms of the first objective, to develop price markers for partial cartels, as mentioned above, most screening methods are developed for full cartels. Based on a theoretical model of partial cartels/coalitions, we propose two statistical measures that are better suited for partial cartels, skewness and kurtosis, than the measures developed for full cartels, i.e. mean, and dispersion of the distribution of prices, (standard deviation and coefficient of variation).

The reason for using the mean of prices in full cartels is obvious: the formation of a cartel is expected to increase mean prices. Similarly, it is frequently argued that collusive prices in a full cartel have lower dispersion than what would be observed in competitive markets (Abrantes-Metz and Bajari, 2009). However, changes in measures of centrality and dispersion need not only indicate changes in the intensity of competition and/or cartelization. Changes on both the supply and demand side may also explain changes in measures of centrality and dispersion of prices. For instance, an increase in costs can result in an increase in mean prices. Also, when prices vary seasonally, mean and dispersion of prices can also fail to capture abnormal behaviour in prices. For example, if mean prices of electricity increase during winter months: is this because a new cartel was formed, or because of increased consumption due to a particularly cold winter? Furthermore, in a partial cartel, outside firms set lower prices than the colluding firms, dampening the impact on mean price – and variance of price – compared to the effect on mean price and variance of price when a full cartel is formed. This reduces the power of statistical tests to detect the formation

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(or breakdown) of partial cartels compared to the formation of a full cartel.

Measures of skewness and kurtosis can help control for some of these external factors (such as costs increases) and seasonality, as long as these shocks do not affect firms asymmetrically. To control for these external factors is particular important in partial cartels, since not all firms active in the market are part of the cartel. Bos et al. (2018) use a similar approach in a related setting. They argue that effective cartel enforcement will reduce the number of cartels with high and low overcharges. They test this empirically using data on legal and illegal cartels, finding that there is less mass in the tails of the overcharge distribution, compared to illegal cartels.

In terms of the second objective, we develop screens based on theory of collusion formation. This contrasts with much of the existing literature, where screens are only loosely based on economic theory. We start with the theoretical model of coalition formation by Deneckere and Davidson (1985), modifying this to allow for greater heterogeneity between firms, in particular in prices. Using this framework, we generate hypotheses about both competitive and partial collusive behaviour in markets. One advantage of having the theory of coalition formation as a foundation is that we can better discriminate between price patterns expected to be observed in competitive and in partially collusive markets.

In terms of the third objective, we apply the screens developed to the Norwegian electricity retail market. The choice of the Norwegian electricity market was driven by three reasons. First, the Norwegian retail electricity market is characterized by high levels of concentration. For instance, in some regions the dominant regional retailer has a market share higher than 60%. Second, industry experts/analysts and the regulator have aired concerns about a specific type of contract, a mixture of spot-price and fixed-price contracts, known as Standard Variable Price contract, or SVP-contract (The Norwegian Energy and Water Directorate NVE, 2010). These concerns have also found voice in the Norwegian media (see for instance, Sparre, 2012). The Norwegian regulator has pointed out that this contract is opaque in the way it sets prices to consumers, and can therefore lead to collusion activities.[1] Third, the possibility of a full cartel in the Norwegian electricity market is not very likely. The Norwegian retail electricity market is very fragmented regionally. For example, some firms operate only in one region. This fragmentation makes it more difficult to find a full cartel agreement that satisfies all actors, in all regions since they face different regional competitive realities. Second, some firms are publicly owned. Given the level of public and media scrutiny of public firms in Norway, this makes their participation in a full cartel more difficult. Third, and very important, entry and exit is relatively easy in the Norwegian market (see von der Fehr and Hansen, 2010). The deregulation of the Norwegian electricity market in the early 1990s reduced barriers to entry, and in subsequent years, the Norwegian regulator has worked to reduce these barriers even further. Low barriers to entry are known to make it more difficult to maintain a full cartel.

[1] In Norway, electricity prices vary from region to region. The spot price for each region is calculated by NordPool based on demand and supply. NordPool is the central market exchange in Scandinavia where retail firms buy electricity and electricity producers sell electricity. Consumers buy electricity from retailers, and they can choose between three main types of contracts. First, spot price contracts. This follows the NordPool spot price for the region where the consumer lives plus a mark-up. Second, fixed price contracts. This contract also varies from region to region, and consumers have a fixed price for a given period, usually one or three years. Third, the above-mentioned SVP price contract, which is a mixture of spot price (again plus a mark-up) and future-fixed price for the region where the consumer lives. For most SVP contracts is however unclear how the final price is set, i.e. what are the weights of the spot price and the future price on the final price. This opacity is what leads to concerns by the industry experts, the regulator, consumer agencies and the media.

We then test for dubious observations of prices in regional electricity markets in Norway looking for structural breaks in the data and analysing the price strategies of insiders and outsiders. We find two periods where the observations of prices do not seem to comply with competitive behaviour. Analysis of the market conditions during these periods did not reveal any exogenous shocks that could explain the price observations, for example weather conditions that could cause extreme price patterns in an electricity market primarily based on hydropower, as the Norwegian. However, these results cannot be used as evidence of cartelization, since as mentioned above, screens are subject to false positives and cannot be accepted as proof in court. In any case, our exercise highlights that price markers can help to identify what can be considered “not normal” occurrences in the price data that can support further investigation by competition authorities.

The rest of the paper is organized as follows. In the next section, we review the existing relevant literature. We examine the economics of tacit collusion, theories of partial cartels, and cartel detection using screens. In Section 3, we present the theoretical framework. In Section 4, we describe the data used in this paper. In Section 5, we present the empirical strategy. Section 6 documents the results of the empirical analysis. Section 7 concludes.

2. Literature review

In this section, we briefly review the literature on partial cartels and screening methods. This will serve as a starting point for the development of screening methods for partial cartels in the next section.

2.1. Economics of partial cartels

The main question analysed in the partial cartel literature is whether there exist market configurations where a subset of firms can operate profitability in equilibrium as a partial cartel (i.e. making more profits than being outside the partial cartel), while at the same time there are firms outside of the cartel acting profitability on an individual basis (i.e. making more profits than being inside the partial cartel).

Selten (1973) was an early and important contributor to the work on partial cartels. With the use of a model of quantity leadership, he showed that a partial cartel could be stable in equilibrium. Later, d’Aspremont et al. (1983) analysed partial cartels using a price-leadership model. Donsimoni et al. (1986) and Shaffer (1995) built on this work by discussing the equilibrium properties of a partial cartel. Spulber (1989) analyses partial cartels using a quantity-leadership model with a Cournot fringe. Bos and Harrington (2010, 2015), in turn, study partial collusion with capacity constraints.

The general result from this literature on partial cartels is that in equilibrium, a subset of firms finds it profitable to collude (the cartel members), while at same time another subset of firms finds it profitable to not collude (outside/competitive fringe firms).

A related literature examines the incentives for firms to form coalitions. In particular, Deneckere and Davidson (1985) examines firms’ incentives to form coalitions under Bertrand competition. They show that it may be optimal for a subset of firms to form a coalition even when some firms act independently outside the coalition. Of particular interest for our case is that insiders set a higher price than outsiders.[2] This contrasts with the models discussed in the previous paragraph, where insiders and outsiders set identical prices. In Section 3, we apply this framework to partial cartels with the intention to derive predictions about the density of prices. If all firms maximize profits individually, observed prices should be low, and price dispersion (if any) should be small. If a partial cartel is formed, we expect two groups of prices: a group of high prices (for insiders) and a group of low prices (for

[2] Bos and Harrington (2010, 2015) also show, in a partial-cartel context, that outsider firms may set prices marginally below those of the cartel members.

outsiders).

2.2. Cartel detection using screens

In the last decade a growing literature on screening tools has been developed. One reason for this interest is that efficient tools for detecting cartels may create significant welfare gains, because the costs of collusion are acknowledged to be substantial (see OECD, 2002). Another reason is that that screening tools have proved successful in many other areas when it comes to detecting illegal behaviour, e.g. tax evasion (Nigrini, 1996), credit-card or insurance fraud (Harrington, 2008) and insider trading (Ewerhart et al., 2007; Pirrong, 2004). Obviously, screening methods require price-data (or quantity-data) from many firms over time. This can be challenging to collusion cases, where typically there are fewer observations, than in tax data, credit card or insurance fraud and insider trading. However, and as our case illustrates, more and more large data sets are available. Therefore, we can envisage that in the future, screen methods can also become more and more relevant for studying collusion with price data.

According to Harrington (2008), an effective competition policy to fight collusive behaviour requires: (i) efficient detection of cartels, (ii) prosecution of cartel members and (iii) optimal penalization of cartel members (see also Cabral, 2005; Houba et al., 2018). For a long time, economic theory has played a central role in penalizing cartel members. For instance, welfare losses due to collusive behaviour are often measured using economic theories of damage (Fisher, 2006). However, as argued by Harrington (2008), economic theory is rarely used when cartel members are prosecuted or when it comes to detecting cartels. Harrington argues that screen methods can be very helpful in this stage, that is, when it comes to detect cartels.

The screening literature can be divided into ex ante and ex post analysis (see Imhof, 2017a). It is important to note that ex ante and ex post analysis usually use the same type of data, and apply the same type of screens. The only difference is that ex post analyses screen for collusion using price data where it is known that cartels were active, while ex ante analyses screens for collusion using price data where only suspicion but no proof of collusive behaviour exist.

It is important to stress that screens cannot be used in court as a proof of a collusive behaviour, since competition law in most jurisdictions requires proof of open communication between cartel members. In addition, as is the case with all statistical tests, there is the possibility of false positives and/or false negatives. However, the literature on screens has shown that these tests are quite powerful in identifying cartels.

Since screens cannot be used as a proof in court, it can be asked what the value of ex ante screens is. We argue, following Harrington (2008) that ex ante screens can be important for competition authorities for two reasons. First, screens are a tool that can help to identify a cartel at an early stage. Second, screens can act as a deterrent to new cartels. Accordingly, members of a cartel – aware of the fact that price screens may trigger further investigations by competition authorities, must behave more cautiously.

In this sense, as defended by Motta (2004), Competition Authorities should not restrict their actions against collusion to ex post analysis, since this reduces not only the tools available to detect collusion, but also the possibility of pre-emptive action. Furthermore, many markets have become more transparent over time in what concerns prices, which makes it possible to establish and maintain cartels even without overt communication between firms (see Andersson and Wengström, 2007). Accordingly, screening methods applied ex ante can give regulators better tools to signal red flags on collusive behaviour of any type of collusion, either open or tacit collusion.

In the empirical part of this paper, our application is in the tradition of ex-ante analysis of collusion, since no collusive practices have been proved in the Norwegian electricity retail market. However, as argued in the introduction, industry experts and the regulator have been concerned about the pricing behaviour for on particular type of contract, the SVP contract. Already in 2009, the regulator discussed the price level of SVP-contracts (NVE, 2009), this was maintained in 2019 (NVE, 2019). In addition, newspapers, industry experts, and consumer agencies (Forbrukerrådet, 2020) have advised consumers to not subscribe to this contract because of the high prices compared to other contract types, and the lack of transparency regarding how contractual details affect the price facing consumers (Matre and Svendsen, 2010; Lie, 2011; Sparre, 2012). For this reason, we focus on this particular type of contract in our empirical part.

As acknowledged by Imhof (2017a) most of the screening literature is based on ex post analyses. There are, however, important exceptions of ex ante studies (see Imhof, 2017a). For instance, Abrantes-Metz et al. (2012) use a measure of dispersion to test for collusive behaviour in the LIBOR-market, partly because the media (e.g. the Washington Post) reported that there were concerns about cartel pricing in this market. Jiménez and Perdiguero (2012) study the gasoline retail market in the Canary Islands. Their motivation was that five of the islands have gasoline retail oligopolies, while on two of the islands the gasoline retail market was operated as a monopoly. Bajari and Ye (2003), in turn, propose a method to detect bid-rigging cartels ex ante. Aryal and Gabrielli (2013) focus instead on first-price auctions in highway procurement in California. Imhof et al. (2018) develop a multi-step procedure to detect ex ante cartelization. In a similar vein, Huber and Imhof (2019) advocate the use of machine learning methods to detect cartels ex ante. Foros and Steen (2013), in turn, show that the dominant gasoline firms in Norway use a vertical restraint strategy that fixes prices at the headquarter level for independent retailers.

Turning to the screens tests used in the literature (whether ex ante or ex post), most collusive markers use data from auctions and retail markets, like market shares, bidding data, prices and/or cost data (for a review see Harrington, 2006 and Froeb et al., 2014).[3] For instance, auctions can be suspected of collusive behaviour if bids are highly correlated, or if bids do not reflect costs in the market (Bajari and Ye, 2003; Porter and Zona, 1993, 1999).[4] Regarding market shares, suspicion can arise if market shares are very stable or negatively correlated over time (Bresnahan, 1987; Hastings, 2004; Harrington, 2006).

In what concerns price data, it has been argued that time series price data can demonstrate the existence of collusion if, for example, prices fail to reflect costs or if it is observed a low variation in prices across time (Bolotova et al., 2008; Crede, 2019; Esposito and Ferrero, 2006; Seaton and Waterson, 2013).[5] For instance, a higher price accompanied by a reduction in the variation of prices is often pointed out as a collusive price marker. Harrington (2006) argues that it has been documented that cartel formation in many instances is characterized by a series of price increases followed by large price drops when a cartel breaks down.

Most screen markers, however, are developed in an ad hoc way, not based on the theory of collusion, making it difficult to tell which screens are more appropriate for a given market (see Harrington, 2008, and Ivaldi et al., 2007). One reason for this is that the theory of implicit collusion generates very general hypotheses about firm behaviour, which are difficult to translate into empirical measures of cartel detection.

[3] Screens have also been based on mathematical laws such as Benford's law (Abrantes-Metz et al., 2011; Giles, 2007). This law describes the regular distribution of digits in data. If a given price data set for a given market violates Benford's law, this can indicate collusive behaviour.

[4] Imhof (2017b), in turn, develops an econometric model to test for bid-rigging cartels.

[5] For other examples of price data used to identify collusive behaviour see Slade (1992); Boreinstein and Shepard (1996); Chevalier et al. (2003); Lorenz (2008); Lewis (2011); Lewis and Noel (2011).

As pointed out in Imhof et al. (2018), however, two theoretical models can provide justification for the use of some price screens.[6] First, Athey et al. (2004) show that in an infinitely repeated Bertrand game where costs are private information (and vary over time), demand is inelastic, and if firms are sufficiently patient, optimal collusion is characterized by price rigidity. Harrington and Chen (2006), obtain a similar result, showing that prices are less responsive to cost shocks (prices are more rigid) under a cartel than under competition to avoid cartel detection by buyers.

These two theories were developed assuming full cartels and are therefore less suited for partial cartels.[7] As argued in the introduction, if we want to test for partial collusion, screen tests developed from partial collusion theory would be more precise and can therefore complement screen tests based on the first and second moments. The theoretical model we develop highlights the importance of using the third and fourth moments to detect partially collusive behaviour.

In addition to this, there are further three reasons why the third and fourth moments are more adequate for partial cartels than for instance the first and second moments used usually to uncover full cartels.

First, the motivation to use mean and variance of prices in a full cartel is because when all firms are inside a cartel (i.e. full cartel), the mean of prices tends to increase, while the variance of prices tends to decrease. This is not necessarily the case under a partial cartel, since some firms stay outside the cartel and therefore keep lower prices than the insiders of the partial cartel. As a result, in a partial cartel, mean of prices do not necessarily increase and variance do not necessarily decrease. The third and fourth moments allow to correct for these types of patterns in the data.

Second, the third and fourth moments permit to control for seasonal prices. For example, if prices are seasonal, the mean of prices increase and decrease according to the high and low seasons. This need not be the case with kurtosis and skewness. Seasonality occurs in the Norwegian electricity market mainly due to the following.

During winter months, low temperatures increase demand elevating prices compared to the warmer summer months. Furthermore, the main source of electricity in Norway is hydropower. Inflow of water into reservoirs has a strong seasonal component. During the snow melting in spring/summer and the rainy autumn months, reservoirs are filled up, and the reservoirs stores water over the winter season. During the winter season, precipitation largely comes in the form of snow, and inflow of water into the reservoirs does not take place until the snow melting in the spring. Prices in the Norwegian electricity market vary with these two seasonal components. During summertime, demand is low, and reservoirs are being filled up, and prices are usually lower. During the wintertime, demand is high, reservoirs are emptier, and prices are therefore higher.

Third, the third and fourth moments also allow controlling for symmetric changes in the cost of production (i.e. changes that affect all firms in the same way). This is the case in the Norwegian retail electricity market, since the main component of costs for retail firms is the NordPool wholesale price (more on this below). As mentioned above, NordPool is the central market exchange in Scandinavia where retail firms buy electricity. This means that all electricity retail firms in the regional electricity price zones in Norway face the same price of electricity.

Summing up the discussion above, first most of the available screen methods for cartel detection are based on measures of centrality and dispersion (mean and standard deviation of prices). Second, these measures are usually not derived from economic theory. Third, the centrality and dispersion measures were developed having in mind full cartels (see for instance Abrantes-Metz et al., 2011). Fourth, the third and fourth moments allow to control for patterns of the data related with seasonality and costs of production.

Next, we present the theoretical model that will serve as a basis for the development of screens for partial cartels and for the empirical application (ex-ante) of these screens.

3. Theoretical background

Deneckere and Davidson (1985) formalize a market where products are differentiated, firms have constant marginal costs and the strategic variable is price.[8] As all firms in the Norwegian electricity retail market must specify the price (not output) in contracts regulating the relationship between retailers and end-users, the mode of competition is price competition. In addition, a large fraction of the cost of electricity retailers is the costs of purchasing electricity in the wholesale market. If a retailer sets a lower price, some consumers will switch to this retailer from other retailers.[9] One may therefore expect that wholesale prices are unaffected, and that the cost of increasing the number of consumers for a retailer is to a large extent constant.

Deneckere and Davidson (1985) analyse an industry with N firms, where $K < N$ firms decide to form a coalition. They find that in a price-setting oligopoly, forming a coalition of any size $2 \leq K \leq N$ is profitable for each coalition member, even when there are $F = N - K$ firms outside the coalition. When all firms set prices separately, they impose a negative pecuniary externality on each other. However, if firms decide to form a coalition, they will internalize the negative pecuniary externalities that their decisions have on other members.[10] As a result, F firms outside the coalition set low prices, and K firms inside the coalition set high prices.

We modify the model of Deneckere and Davidson (1985) in two ways. First, while Deneckere and Davidson (1985) use the demand specification outlined in Shubik and Levitan (1980), we use the demand

[6] For auctions, Bajari and Ye (2003) develop a method to detect bid-rigging cartels ex ante based on first-bid sealed auction theory with asymmetric bidders.

[7] Imhof et al. (2018) developed screens for partial cartels, but in the context of bid-rigging cartels in auction markets. Partial cartels in bid rigging include collusion in auctions that does not involve all firms and/or all contracts. Partial cartels in auctions differ from partial cartels in consumer markets. Not only is the theory of bid-rigging (partial) cartels different from the theory of (partial) cartels in consumer markets, but also the type of firm behaviour involved is different. Auction competition is related to the competition for specific contracts. Consumer market competition is associated with the competition for consumers on a regular basis. In particular, in auctions firms bid for a tender and collude in who wins the bid, i.e. the winning collusive firm bids lower, while the loser collusive firms bid higher. Collusive behaviour, in retail markets involve instead firms colluding to set higher prices.

[8] While electricity clearly is a homogeneous product, differences in contractual arrangements between retailers imply that one may regard retail electricity contracts as differentiated products. In particular, retail electricity is differentiated along many dimensions such as type of contract (spot price, forward price, or mixed), associated services, type of energy used (renewable or non-renewable, green or not green and so on) and type of extra fees. As a result, different consumers face different contracts and different prices.

[9] In the empirical section, we show that in the Norwegian retail electricity market a substantial fraction of consumers indeed switch contracts as a response to price changes. This behaviour is somewhat different from other retail electricity markets in other countries. We can only speculate the reasons for this. First, this can be due in part to the fact that electricity prices are very often discuss in the news media since consumers are very sensitive to electricity prices. Second, the regulator has made the retail prices very transparent and easily available to consumers. Third, the regulator has made the change from one retailer to another very easy (e.g. a simple SMS is enough to change operator).

[10] One type of coalition formation is mergers, where the original merging entities cease to exist as separate entities and they create a new combined organization. Another example of coalition formation is the case where a subset of firms, explicitly or implicitly, form a cartel. As noted in Jacquemin and Slade (1989), a merger is an extreme form of cartel.

specification from Bowley (1924). Second, while in Deneckere and Davidson (1985), firms have the same cross-price effects, we assume that firms can have different cross-price effects.[11] With firms with different cross-price effects, we can have firms that set different prices. This is not the case in Deneckere and Davidson (1985), where all firms in a group (insiders or outsiders) have identical prices. In our model in turn insiders have different (high) prices, and outsiders have different (low) prices. The model presented in this section is therefore more suitable for empirical analyses, since in the real world we observe different prices between firms.

Accordingly, as in Deneckere and Davidson (1985), we argue that the own-price effect is stronger than the cross-price effects.[12] However, while in Deneckere and Davidson (1985), the cross-price effect between product i and all other products j ($j \neq i$) are identical, we assume that cross-price effects can differ. The rationale for asymmetric cross-price effects can be, for instance, geographical competition (see for instance Andree, 2012). In the Norwegian electricity market, many local (or regional) retailers have a large share of electricity consumers. Another reason for assuming different cross-price effects in this market, is the presence of contractual differences in retail contracts, like payment and invoice methods, additional services offered and marketing activities (see von der Fehr and Hansen, 2010).[13]

The model in this paper, like Deneckere and Davidson (1985), considers then Bertrand competition with differentiated products, and zero costs $c_i = 0$.[14]

The industry has 5 firms (similar results are obtainable when there are more firms in the industry). The demand function for product 1 is (see appendix A for the full demand specification):

$$q_1 = a - bp_1 + dp_2 + ep_3 + fp_4 + gp_5$$

where p_i is the price of product i, q_i is the quantity demanded given prices, p_i (with $i = 1, 2, 3, 4, 5$). We assume for simplicity that 'neighbouring' products, that is products 1 and 2, 2 and 3, 3 and 4, and 4 and 5 are the closest competitors. We capture this proximity with the parameter, d. For less closely related products, products 1 and 3, 2 and 4, and 3 and 5, the distance between these products is captured by the parameter e. In turn, the distance between even more distant products, products 1 and 4, 2 and 5 are captured by the parameter f. Finally, the distance between the two most distant products, products 1 and 5, is captured by the parameter g. As mentioned above, two reasons for having products that are more close or more distant competitors are spatial competition or differentiation on contractual agreements. We believe that these reasons occur in the Norwegian electricity market.

Profits for firm i are:

$$\pi_i(p_1, \dots, p_N) = p_i q_i(p_1, \dots, p_N).$$

First order conditions are:

$$\frac{\partial \pi_i}{\partial p_i} = q_i(\bullet) + p_i \frac{\partial q_i}{\partial p_i} = 0, \vee i$$

As noted in Deneckere and Davidson (1985), entering a coalition is most beneficial when the substitutability parameters between coalitional products have intermediate values. When the substitution parameters are very small, products are unrelated and cartelisation will only provide small benefits, and conversely, when the substitution parameters are large, products are very similar and cartelisation of the market does not reduce the degree of competition significantly. Using the above demand specification and setting $a = 10$; $b = 0.9$; $d = 0.1$; $e = 0.09$; $f = 0.08$; $g = .0.07$, the equilibrium values for various market configurations are reported in Table 1. Results in Table 1 are robust to different parameter values.

Table 1 shows an example where a partial cartel with firm 1, 2 and 3 (as insiders) can emerge (with firm 4 and 5 as outsiders) and that this partial cartel is both internally and externally stable. To see that this partial cartel is internally stable note that insiders have higher profits inside the cartel (column 4, Cartel = 1,2,3) than under competition (column 2, Competition). For example, firm 1's profits under this partial cartel (Cartel = 1,2,3) equals 43,3 which are higher than the competitive profits for firm 1, 42,5. To see that this partial cartel is also externally stable, note that outsiders have no incentives to join the cartel. In fact, if firm 4 joins the cartel it gets profits 45,7 (column 5, Cartel = 1,2,3,4,) which are lower than firm 4 profits under Cartel = 1,2,3 (column 4), 45,8. And the same for firm 5 if it joins the cartel (see column 5, Cartel 1,2,3,5).

Furthermore, and very importantly, all prices differ. We see from the third column of Table 1 (Cartel = 1,2,3) a subset of low prices (7.01 and 7.14) by outside firms (firm 4 and firm 5, respectively) and a subset of high prices (7.83, 7.98, 7.97) by insiders (firm 1, firm 2 and firm 3, respectively).

We simulate the above market configuration 1000 times, adding a normally distributed error-term in the demand relation for both the competitive and partial cartel equilibria. Thus, we use the demand specification:

$$q_1 = a - bp_1 + dp_2 + ep_3 + fp_4 + gp_5 + \epsilon$$

where ϵ is random number, with zero mean and identical standard deviation for all demand specifications. We find the following density plots of prices (fig. 1). We can see from Fig. 1 that in a partial cartel (blue line) there are two sets of prices. The firms inside the partial cartel set higher prices than the firms outside the partial cartel. In a competitive equilibrium (red line), prices are clustered around a single price level. This price is lower than the price that collusive firms set under partial cartel. Then, when a partial cartel breaks up, we can observe a set of higher prices fall to the price levels set by the firms initially outside the partial cartel.

3.1. Partial cartels, skewness and kurtosis

Our version of the model of Deneckere and Davidson (1985), with a different demand function allowing for cross-price effects between firms, has some characteristics that can be helpful when screening for partial cartels. First, it identifies market structures where it is possible for otherwise identical firms to pursue different pricing strategies. Second, under a partial cartel one expects to observe a fraction of firms setting higher prices, and a fraction of firms setting lower prices. Third, if firms defect from an existing partial cartel/coalition, we expect the higher prices to fall to lower levels, while the lower prices remain relatively stable.

In this subsection, we will show that skewness and kurtosis can

[11] Cross-price effects are defined as $\partial q_i / \partial p_j$, where q_i is demand of firm i, and p_j is the price of firm j.

[12] Similarly, own-price effects are defined as $\partial q_i / \partial p_i$, where q_i is demand of firm i, and p_i is the price of firm i.

[13] There are other assumptions that could predict a distribution of prices around the high price (for firms inside the partial cartel) and the low price (for firms outside the partial cartel). First, firms could have different sizes and/or different costs of production (see Melitz, 2003). Second, consumers could be slow to switch contracts/suppliers, due for example to search costs (see Burdett and Judd, 1983; Stahl, 1989, 1996; Giulietti et al., 2014). Third, the market can have sophisticated and non-sophisticated consumers (see for instance, Kocas and Kiyak, 2006). Fourth, we could have products with different qualities (see Symeonidis (1999). Fifth, firms could compete in a spatial setting (see Anderson et al., 1989).

[14] We assume that $\boldsymbol{c_i = 0}$, not only because the same is assumed in Deneckere and Davidson (1985), but also because in Norway retail electricity firms face the same costs. Making $\boldsymbol{c_i = 0}$ is then the simplest way to capture this reality. Accordingly, all retail electricity firms in Norway face the same wholesale regional price of electricity since all of them buy electricity in the NordPool exchange. It is important to note that we could also generate firms with different prices if firms where heterogeneous in costs (as in Melitz, 2003.

Table 1
Emergence and stability of different cartel configurations.

Firm	Competition		Cartel = 1,2		Cartel = 1,2,3		Cartel = 1,2,3,4		Cartel = 1,2,3,5	
	profits	prices	profits	prices	profits	prices	profits	prices	profits	prices
1	42.501	6.872	42.727	7.315	43.3	7.829	44.198	8.417	44.037	8.322
2	43.87	6.982	44.12	7.42	44.697	7.98	45.598	8.625	45.428	8.527
3	44.333	7.019	44.982	7.07	45.218	7.972	46.104	8.662	45.929	8.562
4	43.87	6.982	44.46	7.029	45.815	7.135	45.694	8.527	47.754	7.284
5	42.501	6.872	43.02	6.914	44.222	7.01	46.307	7.173	44.103	8.222

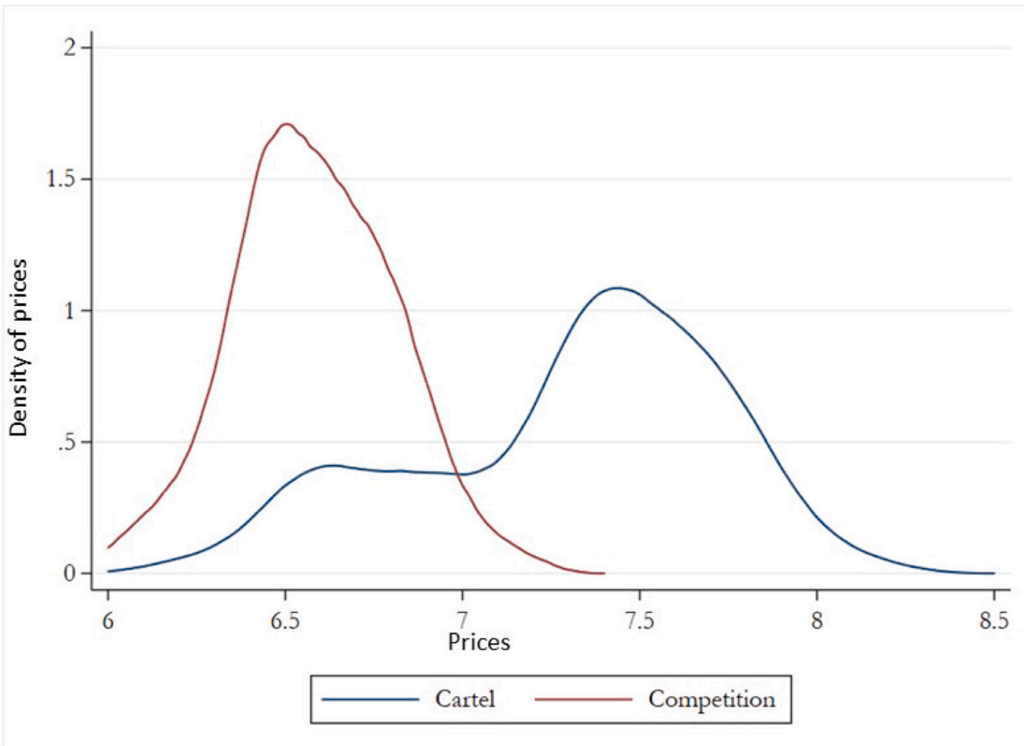

Fig. 1. Market density functions: partial cartel (blue line) competitive market (red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

contribute to capture these dynamics.[15] The first thing to note is that from Table 1 above, we can already see that skewness and kurtosis can capture a partial cartel and a breakdown of the partial cartel. In fact, from Table 1, the calculated skewness of prices shows an increase in skewness from − 0.52 to 0.05, indicating that the market goes from a partial cartel to a competitive equilibrium. Furthermore, kurtosis increases from 2.54 to 2.87 when the market goes from partial cartel to competitive, indicating that prices approach the mean of prices; that is, fewer prices are located more than one standard deviation from the mean.

More generally, skewness of prices provides additional information about collusive behaviour compared with only using measures of centrality of prices, such as the mean. For instance, increases in the mean of prices may be explained by an increase in costs. However, a change in mean prices accompanied by a change in skewness requires that firms are affected by these changes (costs) in an asymmetric manner. If a partially collusive market – characterized by some firms setting high prices, and other firms setting low prices – breaks down in a market where all firms set low (competitive) prices, we expect skewness to be affected. Furthermore, if more firms set a high price than a low price, skewness will fall relative to the competitive case. Conversely, if fewer firms set a high price than a low price, skewness will increase compared to the competitive outcome. Hence, the use of skewness, in addition to measures of centrality, increases the information available about the pattern of changes in prices.

Second, kurtosis of prices can also carry additional information compared with just using measures of dispersion such as variance, standard deviation, or the coefficient of variation. In particular, when firms have identical costs, a breakdown of partial collusive behaviour should have a significant effect on kurtosis. When a high fraction of observations is in the tails of the distribution, kurtosis will be relatively low, and as more observations approaches to mean of the distribution,

[15] Huber and Imhof (2019) and Imhof (2017a) also use skewness and kurtosis measures to screen for collusion but in a framework of bid-rigging auctions. In the lines of what we have argued in footnote 7, collusive behaviour in auctions is different from collusive behaviour in consumer markets (in bid rigging, the winning colluding firm sets lower prices than the other colluding firms; while in retail markets collusive firms agree to set higher prices). As a result, Huber and Imhof (2019) and Imhof (2017a) use the skewness and kurtosis measures in a different way from us. Huber and Imhof (2019) and Imhof (2017a) use kurtosis to analyse when bids converge, and skewness to analyse asymmetries in bids. In particular, Imhof (2017a) and Huber and Imhof (2019) observe the following behaviour of skewness and kurtosis when firms rig bids. First, the kurtosis is positive and increases in the case of bid rigging. Second, the skewness decreases in the case of bid rigging and is negative.

kurtosis will increase.

Third, when prices in a market fluctuates naturally from season to season (such as in the Norwegian electricity market), it is very difficult to detect collusive behaviour using only measures of mean and variance, because as noted above, price changes reflect both supply-side and demand-side factors. In other words, using skewness and kurtosis of prices, in addition to measures of centrality and variation, produces a more restrictive set of hypotheses. In cases where asymmetric shocks can be excluded, measures of skewness and kurtosis can then help to detect collusive behaviour.

The Norwegian retail electricity market fits well for using price markers based on kurtosis and skewness. First, electricity prices vary substantially because of the high share of hydro-based electricity production, making prices very sensitive to weather conditions. Second, wholesale electricity prices are determined centrally at the Nordic electricity exchange, NordPool, thus, cost shocks affect firms symmetrically (within regions). Furthermore, the NordPool price is publicly available, which means that costs are common knowledge for all retailers. This is important for sustaining collusive agreements, since it makes it more difficult for firms inside a cartel to alter prices arguing to other members that this is due to changes on the cost side.

In the following section, we outline the data and market characteristics of the Norwegian retail electricity market in detail.

4. Data

In this section, we describe the Norwegian retail electricity market and present some descriptive statistics of the data we use in this study.

The main source of electricity in Norway is hydropower. Hydropower depends heavily on precipitation, and inflow of water to reservoirs. For example, the coastal region of Bergen, which is known for being one of the rainiest regions of Europe, has usually lower electricity prices than other regions in Norway, especially the region of Oslo where there is much less rain.

This means that during rainy years/seasons, prices are lower than in years/seasons with less rainfall. The prices obviously also depend on demand, and demand of electricity is higher during winter and lower in the summer. Due to this, the usual pattern of prices is the following. In winter due to more demand and snow and ice, prices are higher. In the beginning of spring with the melting of snow and ice (which increases the amount of water in reservoirs), more rainfall, and higher temperatures (i.e. lower demand), prices decrease. Prices are usually kept at a lower level during summer and then start to increase at the end of the summer, because there is less water in reservoirs (less rainfall in summer) and temperatures start to fall, which increases consumption. This pattern is somewhat balanced in early autumn since there is usually more rain in this time of the year. As the winter sets in (meaning more snow and ice and lower temperatures, and therefore more demand) prices rise, starting again the whole cycle.

As mentioned in the previous section, NordPool is the exchange responsible for setting regional wholesale electricity prices, the main cost component for retailers, thus, the NordPoool price is the main determinant of the retail prices for consumers. The Norwegian retail market for electricity is regional, which means that different regions can have different prices. The majority of entities are private, but there are still some companies owned by municipalities (i.e. they are public owned). These companies are an inheritance from the period before market liberalization. The market started to be liberalized in 1991, and it was fully liberalized in the period we analyse in the paper. This means that even municipal electricity companies compete in equal terms with private companies.

We obtained the data from the Norwegian Competition Authority on retail electricity prices for all retail firms for the years 2010–2015 (these prices are now governed by strompris.no). This dataset on retail prices is highly detailed. For all contracts, we have information about geographical coverage, allowing us to determine which municipality each contract applies. Furthermore, we have information about all price changes for the years 2010–2015. There are three main types of contracts in our dataset: spot price contracts, fixed price contracts and SVP contracts. In this paper we focus on SVP contracts for the reasons we enumerated above.

As mentioned in the introduction, SVP contracts are a hybrid type of contract based on both spot price and fixed price contracts. However, the link between the wholesale spot price and the SVP price is imperfect because the retailers must inform the regulator about changes in prices 14 days ahead of prices being changed.

The way firms set the final price in the SVP contracts is, furthermore, not public information. Due to this, the regulator has over the years paid particular attention to these contracts and industry experts have on several occasions advised consumers to not subscribe to these contracts. These concerns could be downplayed if the SVP contract was not important in the Norwegian electricity market. However, this is not the case, since according to NVE this type of contract covers about 40% of the household market and almost a quarter of the industrial market (NVE, 2010). This is also our motivation for analysing the SVP contracts.

We also use data on daily regionally differentiated prices for the wholesale electricity market exchange, NordPool. The wholesale prices are regionally differentiated and the differences are determined by regional transmission constraints; see Bjørndal et al. (2013). In addition, we use data on certificate prices, which is a cost component for retailers in the Norwegian retail electricity market (more on this below).

Although electricity delivered to households from various retailers is clearly a homogeneous product, the contracts specifying the relationship between households and retailers differs significantly. One difference between contracts is the one already mentioned, i.e. that some contracts are spot price contracts, others are fixed price contracts and others are SVP contracts. But there are other differences between contracts. First, retailers differ when it comes to relative size of the fixed and variable parts of the SVP-contract. A retailer setting a fixed and variable part of the SVP-contract to attract households consuming 30.000 kWh annually, may differ from the fixed and variable part of the SVP-contract another retailer uses to attract households consuming 10.000 kWh per year.

Third, contracts can also differ when it comes to aspects relating to payment and invoice. Some contracts require prepayment of the electricity bill, while others have different payment options. Furthermore, some contracts require email, SMS or internet invoicing, while others have different types of invoicing choices. Fourth, contracts also vary in terms of services offered and marketing strategies pursued. Regarding marketing activities, some retailers focus on selling local electricity, others market their electricity as clean/environmentally friendly hydro-based electricity, while others market their electricity as the cheapest in the market. Hence, although the market consists of firms setting prices, and that electricity is clearly a homogeneous product, it should not be expected that the price per kWh is identical between retailers. For more discussion on contract and market characteristics, see von der Fehr and Hansen (2010).

Another important aspect in the Norwegian retail electricity market is that consumers change contracts often, compared to other electricity retail markets in other countries (see Giulietti et al., 2014). This relatively high number of contract changes in the Norwegian electricity market started in the year 2002/2003. During the winter of that year, prices increased to very high levels (NVE, 2014), forcing many consumers to change operator. This has possibly broken a psychological barrier in consumers to change contracts, which was further incited by the regulator, since change of operator was soon after that made costless and effortless. As already mentioned above, a text message is enough to change operator. It is also very easy for a consumer to see which operator offers the cheapest price where they live, since all prices were posted on the internet, now at strompris.no (and these are also discussed in the media on a regular basis, and Norwegian are avid consumers of news and newspapers). Historically, we observe that consumers tend to change contracts during the first quarter (winter months), when prices are relatively high. However, and as observed in Fig. 2, it seems like other factors, apart from prices, have also contributed to contract changes in the Norwegian retail electricity market.

As mentioned above, consumers in the Norwegian retail electricity market have several of contracts to choose from, and there are many competing retailers selling contracts with different characteristics. Many retailers operate in all municipalities (they operate on a national basis), while some smaller retailers only operate in parts of Norway. As observed in Table 2, there are many contracts and retailers. In addition to the three types of contracts mentioned above, retailers also sell non-standard contracts.[16]

Table 3 shows that retail prices vary considerably. First, the average price levels differ regionally during the period we analyse. Second, there are large variations in prices over time. In addition, the existence of transmission constraints between regions in Norway creates significant regional price differences during periods of cold and dry weather.

We now discuss the major cost components for the retailing firms. The largest cost component for a retailing firm is, as we have already mentioned, the wholesale electricity price that is set by NordPool. Hence, this cost is common knowledge for all the firms. There has been considerable variation in wholesale prices in the period 2010–2015, see Fig. 3 below. Prices are generally lower in the Western and Southern regions, where a large share of production entities are located.

Fig. 3 highlights again a typical seasonal price pattern in hydro-based electricity markets such as the Norwegian one: low prices during the early summer months (lower consumption due to higher temperatures), price increases in the late summer (due to lower levels of water in reservoirs) and high prices during the winter months (due to higher consumption, low temperatures, and low rainfall due to snow and ice). The price in the period analysed varied between NOK 27 per MWh and NOK 682 per MWh (mean price was NOK 280 per MWh). Fig. 3 relates to the region of Bergen, but similar patterns exist in the other price regions.

In addition to the variation in prices over time, there are also variations among the price zones/regions in the market, highlighting the regional nature of the electricity prices in Norway (the regional nature of prices is not just an artificial administrative procedure, but is due to scarce transmission capacity between different regions). While some regions export electricity, other regions import electricity. When transmission capacities are binding, price differences occur, and import regions have higher prices than export regions. This is illustrated in Fig. 4, which shows price differences between Bergen and the other regions analysed. The Bergen price zone is a net producer, since there is large reservoir capacity (and is a rainy region). In contrast, the Oslo price zone is usually a net import region, since demand is high and water reservoir capacity is restricted.

Fig. 4 shows that in the winter of 2010 the price difference between Tromsø and Bergen was about 900 Norwegian Kroner per MWh (note that zero in the vertical axis means that there are no differences in prices between Bergen and the other regions). In other periods, Bergen has still lower prices than the other regions since it continued to be a net producer of electricity. However, the difference in the other periods was not so large. The maximum price difference in these other periods was about 200 Norwegian Kroner per MWh (in the spring of 2014), which is still substantial, given that the price in Bergen during the spring of 2014 was about NOK 250 per MWh.

The final major cost component for retailers is the certificate price, see Amundsen and Mortensen (2001). To incentivize increased production of electricity from renewable sources, the Norwegian and Swedish authorities have introduced a mandatory certificate market. Production of electricity from certified renewable producers in Norway is accompanied by certificates, and retailers are obliged to purchase a certain percentage share of the electricity they sell to consumers from these certified producers. Due to this market, the cost borne by retailers depends on three factors: (i) the regional spot price; (ii) the wholesale price of electricity from NordPool; and (iii) the percentage share that retailers must purchase from certified production entities. A retailer selling electricity has the following per unit of electricity cost (e.g. kWh):

$$c^R = p + \alpha p^{GC},$$

where c^R is the cost for the retailer, p is the regional spot price, p^{GC} is the price of green certificates and α is the percentage share of overall electricity sold by retailers from certified producers. The price of certificates was not very high during the period under analysis. The required percentage share was also low in the first years after the introduction of the certificate system, and thus the impact from the certificate price was not large in our sample.

5. Empirical strategy

Based on the predictions from our theoretical model, our empirical strategy has three stages. First, we calculate a range of weekly statistical measures that describe the shape of the distribution of prices. We focus on price markers describing the shape of the distribution of prices, such as skewness and kurtosis, because we have argued that these can be helpful in detecting price-fixing behaviour in partial cartels. However, we also show results for other price markers such as mean, standard deviation, and coefficient of variation. Second, we test for structural breaks in these data series. We statistically analyse the time series properties with the intent to identify possible structural breaks in the data and if so, to determine the dates when the shape of the distribution of prices changes significantly from what is regarded as normal. Third, we compare the price strategies of insiders and outsiders. This exercise can help us to check if insiders had different price strategies prior to events that look like a partial cartel breakdown, and what occurred after these events.

5.1. Screening measures: kurtosis and skewness

In this sub-section, we discuss the screening measures, kurtosis and skewness. In the empirical part in the next section, we also look at other screening measures used in the screens' literature (mean, standard deviation, and coefficient of variation). Here we restrict the discussion to kurtosis and skewness, since the other measures have been discussed elsewhere (see for instance Abrantes-Metz et al., 2012). In appendix B, we show the mathematical formulas for all the screening measures used in this paper (i.e. kurtosis, skewness, mean, standard deviation, and coefficient of variation).

In what relates to skewness and kurtosis, note first that a normal distribution will have a skewness of 0 and kurtosis of 3. Skewness measures the lack of symmetry of a given distribution. A negative value will in most instances indicate that the mean (and median) is higher than the mode. For our purpose, this implies that the distribution of prices is skewed upwards, that is, many firms set high prices, while a few sets low prices.

Providing qualitative interpretations of the observed changes in skewness is not straightforward. In our dataset, a negative skewness may occur for two different reasons. Either the tail on the left (low prices) is longer than the tail on the right (high prices), or the tail on the left is fatter than the tail on the right. We know that a symmetric distribution has zero skewness and a mean equal to the mode. However, the opposite does not need to be true; that is, one may observe zero skewness coupled with a mean that is different from the median. On may also observe a distribution of prices with zero skewness with a long thin tail in one direction and a short fat tail in the other direction. The tails on both sides may then cancel out, but the distribution is clearly asymmetric.

A similar concern exists when interpreting changes in kurtosis. Most

[16] Non-standard contracts are contracts that are neither spot price contracts, fixed price contracts nor SVP contracts. These contracts are a very small share of all contracts.

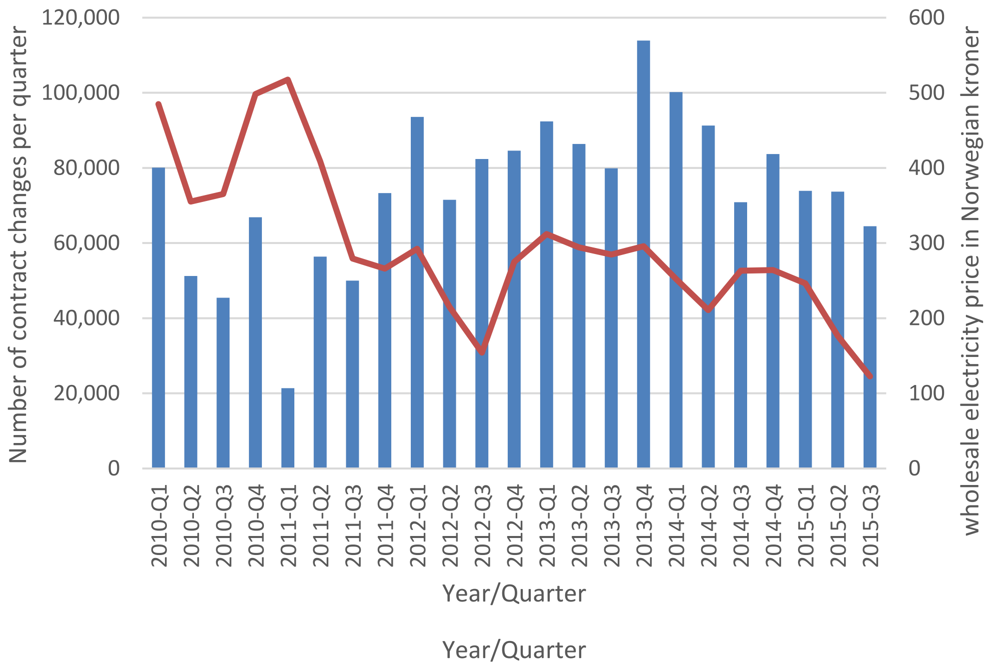

Fig. 2. Number of contract changes per quarter (blue columns, left axis) and wholesale electricity price in Norwegian kroner (orange line, right axis). 1 NOK ranged between about €7,3 and €9,6 in the period analysed. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 2
Contracts in the major markets analysed. Year: 2010. Data for all 52 weeks of the year 2010, for all four markets.

	Contracts per retailer				
City	**Retailers**	**Contracts**	**Maximum**	**Minimum**	**Average**
Bergen	29	58	7	1	2.00
Oslo	33	65	7	1	1.97
Trondheim	28	48	6	1	1.71
Tromsø	24	45	6	1	1.88

Table 3
Retail Prices 2010–2015. Data for all 52 weeks of the year 2010, for all four markets.

	Retail price			
	Average	**Standard deviation**	**Maximum**	**Minimum**
Bergen	40.34	12.72	89.16	22.87
Oslo	39.90	12.76	88.74	22.23
Tromsø	39.92	12.79	90.17	22.52
Trondheim	40.17	12.70	90.67	22.87

often, kurtosis is interpreted as the flatness of a distribution. However, Westfall (2014) demonstrates that changes in kurtosis primarily reflect changes in the tails of a distribution. For our work, this implies that a decrease in kurtosis should be interpreted as either: i) more price observations in the tails of the distribution, or ii) more price observations farther out in the distribution. Hence, the measure of kurtosis provides additional information about the dispersion of prices. One may argue that kurtosis measures the joint weight of both tails of the distribution relative to the weight of the rest of the distribution.

A constraint of using our approach is that kurtosis and skewness require a substantial number of observations. A large sample is advisable to calculate skewness and kurtosis, because the measures of kurtosis and skewness can vary with sample size for small samples (see for instance Cox, 2010 and Piovesana and Senior, 2018). Only for larger samples, the measures of kurtosis and skewness do not vary with sample size. It is however difficult to say what is the minimum sample size needed since this can vary from dataset to dataset. However, many retail markets are characterized by having numerous participants and are thus good candidates for using the method proposed in this article. This is also the case of the Norwegian retail electricity market. Another concern is that the measures of kurtosis and skewness are sensitive to outliers. However, this is also the case with the other screen measures, such as mean, standard deviation and coefficient of variation.

5.2. Structural breaks

Above, we outlined measures that describe the shape of the distribution of prices, and measures that detect the degree to which the distribution of prices deviate from the normal distribution. These measures identify relevant patterns in time-series data when screening for collusion. When one or more of the time series changes abruptly, there is a structural break in the time series of the data. We use the Wald test to test for structural breaks. The Wald test can be estimated in two ways. First, to test for structural breaks without imposing a date for when the break occurs. Second, to test for structural breaks imposing pre-defined dates.[17] Usually, the predefined dates are chosen by considering some special event that occurred at a particular date, or by visual inspection of the data. The tests of structural breaks tend to be more precise when the date of the break is pre-defined. As will see below this is also the case in our sample.

5.3. Price strategies of insiders and outsiders

While the measures above can help to detect suspicious distributions of prices in the market, they do not clearly show the price strategies of insiders and outsiders. We therefore complement the analysis above by examining how price strategies vary between insiders and outsiders. We do this by examining the density of price distributions before and after

[17] Both tests are analysed using post-estimation commands in Stata (sbsingle and sbknown) after regressing the time-series variable on lagged variables.

Fig. 3. Regional wholesale prices, Bergen region, 2010–2015. NOK per MWh.

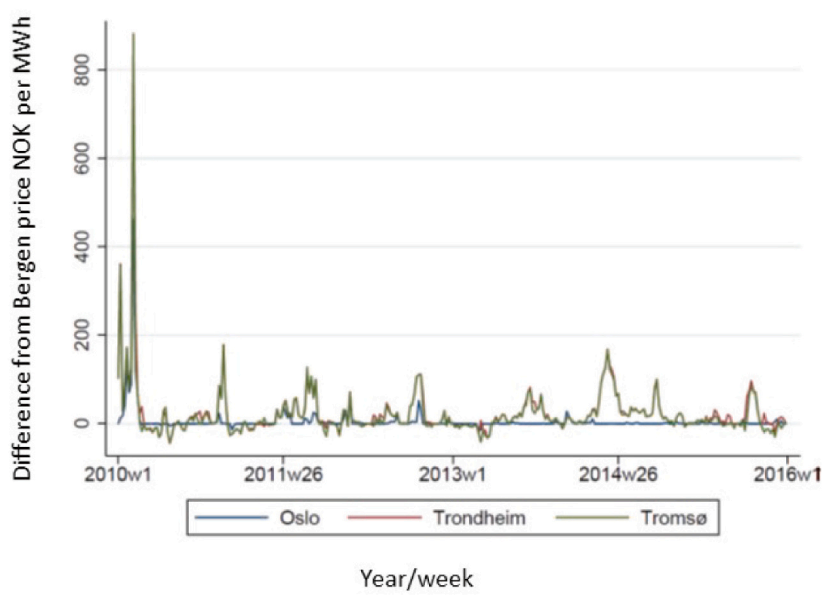

Fig. 4. Wholesale price differences from Bergen price, 2010–2015. NOK per MWh.

events that look like a partial cartel breakdown.

6. Results

In this section, we first visually inspect the changes in the screening measures outlined above. We then test for structural breaks. We conclude by analysing the price strategies of insiders and outsiders.

6.1. Screening measures

Fig. 5 shows the mean and standard deviation of prices, Fig. 6 shows the coefficient of variation, and Fig. 7 shows the kurtosis and skewness.

In Fig. 5, we observe that the variation in the mean and standard deviation of prices is large. The retail prices in the four markets are partially determined by costs; that is, the wholesale price and the certificate price. The standard deviation of prices also varies in the period analysed. Increases in wholesale electricity prices contributes to the changes in both mean prices and standard deviation of prices. This is not surprising since electricity prices, especially electricity generated by hydropower, as in Norway, vary seasonally: higher prices in winter and lower prices in summer. Because of this seasonality, as we have argued above, it is very difficult to find suspicious price patterns with only centrality and dispersion measures.

As for the mean and standard deviation of prices, the coefficient of variation (Fig. 6), defined as the ratio of the standard deviation to price, is also volatile over the sample period, and it is therefore also difficult to identify a suspicious pattern in the data.

In contrast to the mean, standard deviation, and coefficient of variation of prices, by visually inspecting the time series of retail prices for each municipality with kurtosis and skewness, we identify some extreme periods where the shape of the distribution of prices deviates from the normal levels observed in other weeks (see Fig. 7). The common pattern

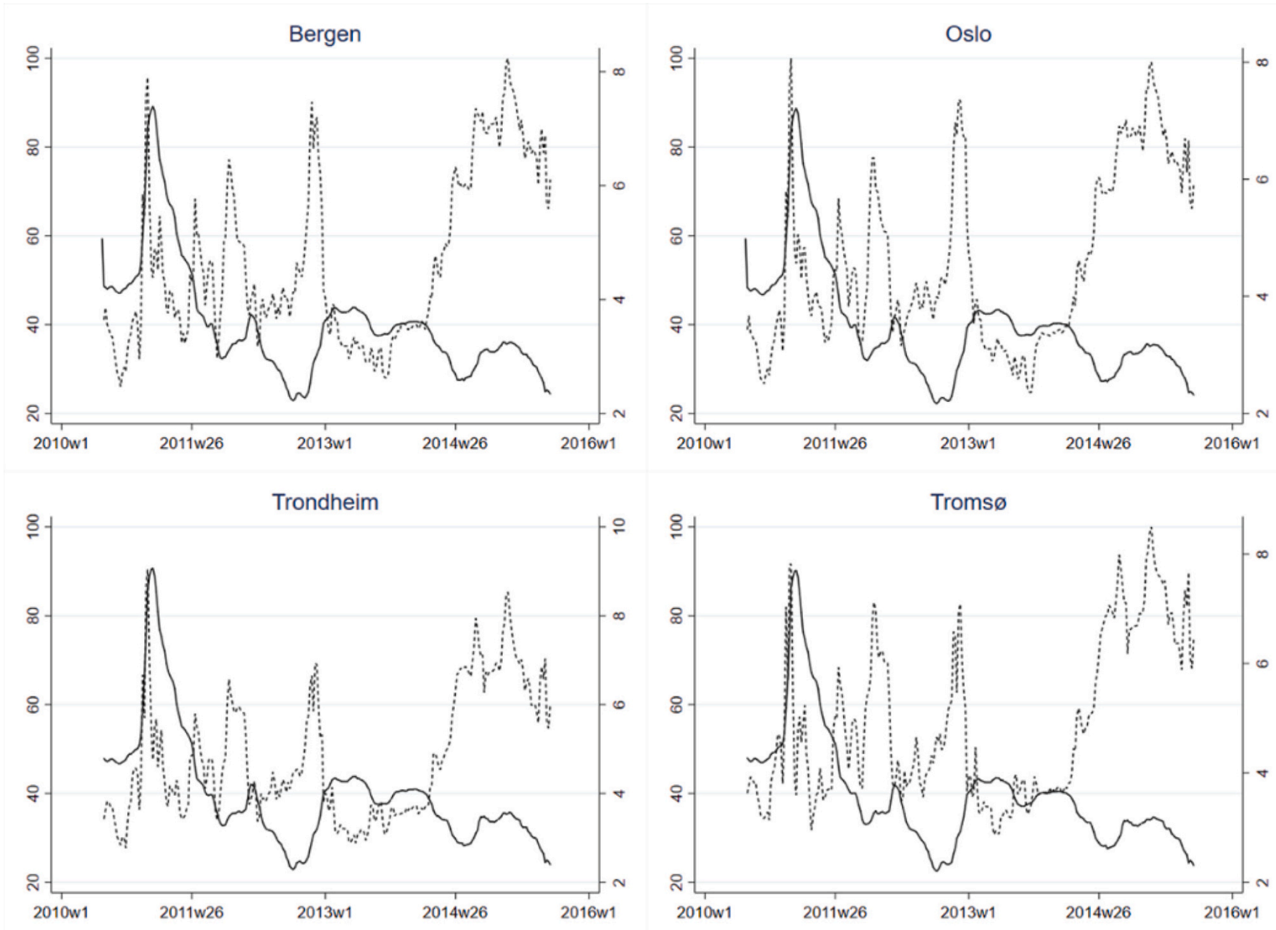

Fig. 5. Mean (solid line, left axis) and standard deviation (dotted line, right axis) of prices for selected regions, 2010–2015.

in all regional markets may well be explained by the fact that a large fraction of the firms sells contracts in all municipalities, and hence, face the same competitors in all markets.

There are two suspicious periods: late December 2012 and late summer of 2013. We observe a significant drop in skewness in late December of 2012, especially for the Trondheim and Tromsø regions. The normal level of skewness during the sample period is about zero, while during the periods identified as suspicious, skewness dropped to well below −2. There are also periods of low skewness in the late summer of 2013. In addition, the same periods were also characterized by a significant increase in kurtosis. The increase in kurtosis was particularly large in late December in Tromsø and Trondheim, while the increase in kurtosis was very large in late summer of 2013 in Bergen and Oslo. While the level of kurtosis in the sample period mainly varied between 2.5 and 3.5, we also observed values between 8 and 10.5 in the extreme periods.

6.2. *Structural breaks*

Next, we test for structural breaks (Tables 4 to 9). We consider both the case of unknown dates (Tables 4 to 8) and the case of known dates (Table 9). Furthermore, we test for structural breaks using the measures of centrality and dispersion (mean, standard deviation and coefficient of variation) and the measures of shape (kurtosis and skewness). Mean, standard deviation and coefficient of variation are shown in Tables 4 to 6, respectively. Kurtosis and skewness are shown in Tables 7 and 8.

First, we test for structural breaks in mean prices at unknown dates (Table 4). The test for structural breaks in mean prices identifies week 15, 2011 as a break point. This coincides with a strong increase in NordPool prices for all regions, prices were about NOK 400 per MWh in most of the year 2010, until late 2010 and early 2011 when prices increased to levels between about NOK 500 per MWh and about NOK 600 per MWh. Hence, the increases in retail prices are to a large extent a result of high wholesale prices being passed on to end-users. That is, the screen test signals suspicious behaviour, when in fact costs increased to higher levels.

The estimated structural break in the standard deviation (Table 5) for the region of Bergen is significant and occurs in the same week as the identified structural break in kurtosis. For the other regions, the test is not statistically significant.

Table 6 shows the results of the structural break tests with unknown dates for the coefficient of variation. The test identifies early summer 2014 as special observations. However, this is much later than the period of low prices during the late summer of 2013. The increased coefficient of variation results from weeks with a simultaneous reduction in the price of electricity and an increase in the standard deviation. We also note that the increase in the coefficient of variation identified in Table 6 in week 23 of 2014 is determined by a joint increase in the standard deviation and a decrease in the price level.

We now test for structural breaks with unknown dates in kurtosis (Table 7). For the northern regions, the tests confirm that there was a significant change in the shape of the distribution of prices during these late weeks of 2012. In the southern region, tests for unknown structural breaks confirm significant changes in kurtosis in the late summer of 2013. In particular, in the southern part of the market, the test identifies a decrease in kurtosis in week 39, 2013, but it does not identify an increase in kurtosis during week 28, 2013. While the structural break is highly significant for the cities of Bergen and Oslo, the identified breaks

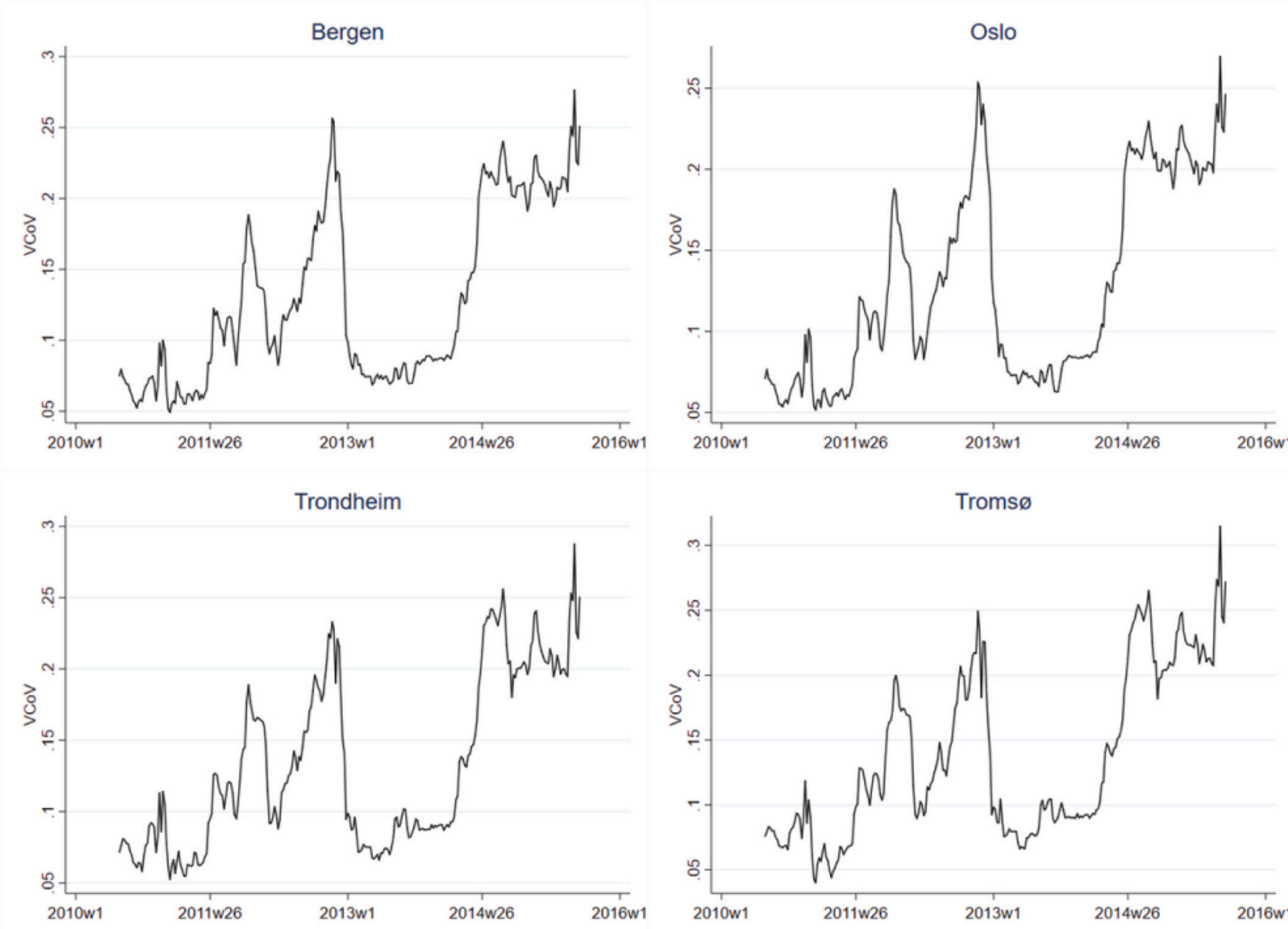

Fig. 6. Coefficient of variation of prices for selected regions, 2010–2015.

for Trondheim and Tromsø are not significant.

Whereas the Wald test with unknown dates for kurtosis identifies a decrease in kurtosis during week 39 in 2013 for the southern regions, the test for skewness detects an increase in skewness for these regions during week 28 in 2013. Hence, the test with unknown dates for the southern regions identifies both the start and the end of the period of dubious price observations: the start when testing skewness and the end when testing kurtosis. However, for the northern regions this test only identifies weeks 36 and 43 in 2012 as the most influential structural breaks.

When testing for structural breaks with known dates (i.e. using information about extreme observations), the tests provide stronger results (Table 9). We see that both the increase and decrease in skewness and kurtosis are significant at the 5% level. We also see that the extreme observations in week 52 of 2012 constitute a highly significant structural break. Moreover, when we analyse the two sets of observations in the summer of 2013, the increase observed in week 28 and the decrease observed in week 39, the test identifies these two periods as strong candidates for a possible structural break.

The tests for structural breaks with known dates confirm what one observes using visual inspection; in particular, that there are two periods in our dataset where the pricing of electricity contracts changed abruptly. The changes are statistically significant. Moreover, the observed changes can be explained by the theory of coalition formation. According to this theory, the price observations (i.e. the price decreases) during the late summer of 2013 resemble what a coalition breakdown would look like. Note that in a hydro-based power market, prices are usually lower during the early summer because of lower demand and full dams. However, in the autumn, prices usually begin to increase because of increased consumption (lower temperatures). The observed decrease in prices occurred when prices were expected to start rising and cannot be explained by factors on the supply side.

6.3. *Price strategies of insiders and outsiders*

There is another clue from the theory of coalition formation that we can further investigate to confirm our results. The theory of coalition formation shows that different subsets of firms choose different pricing strategies: those inside the coalition choose higher prices, and those outside choose lower prices. We do not expect that after the breakdown of a partial cartel, prices will change in the same manner for the two groups of firms. Accordingly, only the firms inside the cartel should reduce prices significantly, while the firms outside the cartel will reduce prices only marginally. To check this, we plot the density functions of prices before and after the decrease in prices in the summer of 2013 (see Fig. 8).

First, from Fig. 8, we see that prices in the period prior to the episode during the summer of 2013 can be characterized as “twin peaks”. This is consistent with the predictions from our modification of the theory of coalition formation by Deneckere and Davidson (1985), where a subset of firms set relatively high prices, while another subset of firms set relatively low prices (see Fig. 1 above).

Second, there is a change in the shape of the price data during the period where most prices decreased. In particular, during this period, which appears to involve a breakdown of a partial cartel, prices change

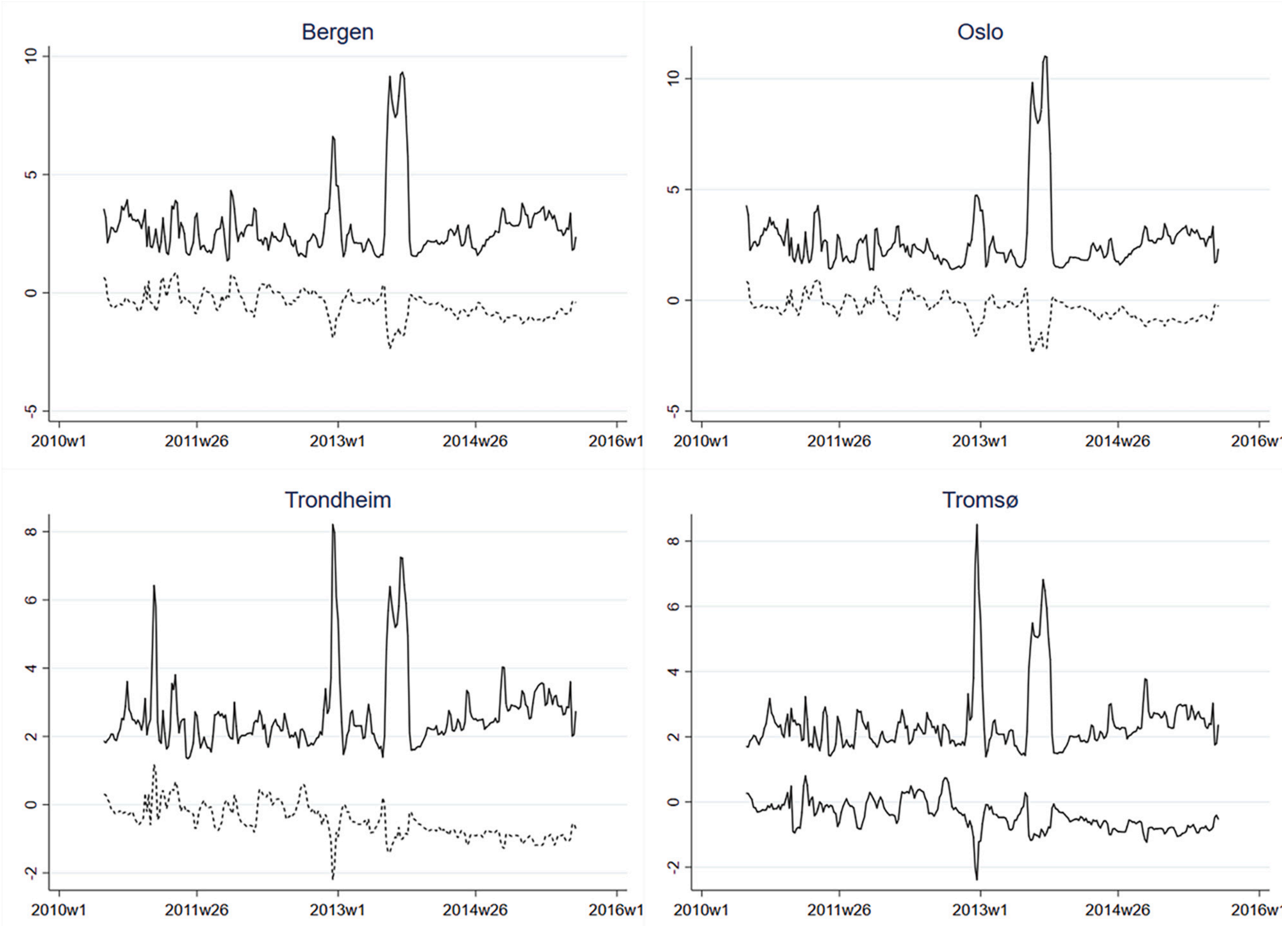

Fig. 7. Kurtosis (solid) and skewness (dotted) of prices for selected regions, 2010–2015.

Table 4
Wald test for structural break in mean prices, unknown dates.

City	Date	Statistic	*p*-value
Bergen	2011, week 15	10.0021	0.0946
Oslo	2011, week 15	9.8223	0.1016
Trondheim	2011, week 15	17.6556	0.0034
Tromsø	2011, week 15	17.6454	0.0035

Table 5
Wald test for structural break in standard deviation, unknown dates.

City	Date	Statistic	p-value
Bergen	2013, week 39	22.6099	0.0003
Oslo	2011, week 45	8.7126	0.1568
Trondheim	2014, week 23	10.0725	0.0920
Tromsø	2014, week 24	13.0873	0.0262

Table 6
Wald test for structural break in coefficient of variation, unknown dates.

City	Date	Statistic	p-value
Bergen	2014, week 18	9.8127	0.1020
Oslo	2014, week 23	21.2522	0.0007
Trondheim	2014, week 23	17.6787	0.0034
Tromsø	2014, week 23	15.5204	0.0090

Table 7
Wald test for structural break in kurtosis, unknown dates.

City	Date	Statistic	p-value
Bergen	2013, week 39	22.6099	0.0003
Oslo	2013, week 39	50.1266	0.0000
Trondheim	2012, week 48	6.7601	0.3197
Tromsø	2012, week 52	12.0127	0.0413

Table 8
Wald test for structural break in skewness, unknown dates.

City	Date	Statistic	p-value
Bergen	2013, week 28	9.7413	0.1050
Oslo	2013, week 28	8.4924	0.1706
Trondheim	2012, week 43	21.8768	0.0005
Tromsø	2012, week 36	15.5154	0.0090

from having two peaks to having only one. This new peak is around the price level that outside firms were setting before the possible breakdown of the partial cartel. This means that there was a collapse in the prices set by the firms inside the potential partial cartel. Thus, our price data contains the changes suggested by the theory of coalition formation.

Some other issues deserve to be highlighted. First, there was a fall in mean prices in the summer of 2013. Hence, this period is identified as being dubious, and there may have been a breakdown of a partial cartel. In addition, the decrease in retail prices cannot be explained by falling wholesale prices. In fact, the wholesale prices were stable (or increased slightly) in this period. Second, the fall in skewness indicates that the

Table 9
Wald test for structural breaks for skewness and kurtosis, known dates.

		Kurtosis		Skewness	
		Chi2	prob > chi2	Chi2	prob > chi2
Bergen	2013, week 28	12.8826	0.0016	7.1371	0.0282
	2013, week 39	11.4436	0.0033	8.9728	0.0113
	2013, weeks 28 & 39	115.9421	0.0000	63.7214	0.0000
	2012, week 52	1.6201	0.4448	2.0384	0.3609
Oslo	2013, week 28	10.9813	0.0041	5.8913	0.0526
	2013, week 39	9.2575	0.0098	7.1278	0.0283
	2013, weeks 28 & 39	158.2453	0.0000	89.7844	0.0000
	2012, week 52	4.9253	0.0852	1.7702	0.4127
Trondheim	2013, week 28	6.4226	0.0403	15.0320	0.0005
	2013, week 39	6.6609	0.0358	20.1963	0.0000
	2013, weeks 28 & 39	43.3965	0.0000	33.3892	0.0000
	2012, week 52	0.0302	0.9850	10.1430	0.0063
Tromsø	2013, week 28	6.0039	0.0497	9.5012	0.0086
	2013, week 39	7.0727	0.0291	13.3968	0.0012
	2013, weeks 28 & 39	44.5410	0.0000	36.8534	0.0000
	2012, week 52	12.0127	0.0025	10.6613	0.0048

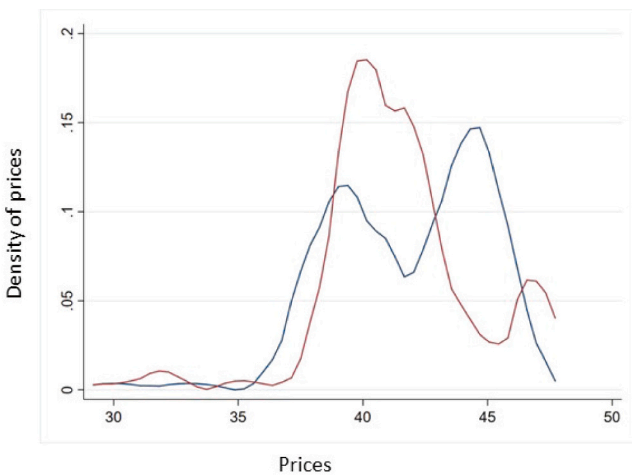

Fig. 8. Density plot of prices for Bergen, 2013, weeks 25 and 26 (blue line, before) and weeks 30 and 31 (red line, after). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

distribution of prices is skewed upwards. That is, the left tail (low prices) was either decreasing compared to the mean, or more price observations were in the left tail. If the latter explanation is true, this is an indication of a breakdown of a partial cartel. Finally, the strong increase in kurtosis indicates that there were large changes in the tails of the distribution of prices, which implies that a larger fraction of the price observations is located in the tails. Furthermore, because the standard deviation is relatively low in the sample period, the price distribution must be peaked and narrow. This is also expected following the breakdown of a partial cartel.

7. Conclusion

In this paper, we have developed screens intended to uncover partial cartels, cartels where only a subset of the firms in a market collude. A screen is a statistical tool used to detect patterns in data that can be consistent with collusive behaviour.

Most screens used in the literature are based on measures of centrality and/or dispersion, e.g. the mean and variance of prices. To a large extent, these screens are not rigorously founded on theories of collusion. Furthermore, most of these screens were developed to analyse full cartels, that is, cartels where all firms in the market collude.

We argue that using the third and fourth moments to uncover partial cartels, may complement existing price screens by creating screening methods able to differentiate between modes of competition. Our tools are based on a theoretical model, theory of coalition formation (with insiders and outsiders). By using this framework, we show that the third and fourth moments of market prices can differentiate between the shapes of the distribution of prices when firms act on a stand-alone basis (competition), and when a subset of firms act as a partial cartel.

Furthermore, we argue that kurtosis and skewness can complement measures of means and dispersion when it comes to detecting partial cartels by creating more robust screening tools. For example, when a full cartel is formed, all firms increase prices, and the mean of prices increases while the standard deviation decreases. When a partial cartel is formed only the cartel members increases prices, the firms that do not collude keep lower prices. As a result, in a partial cartel, mean of prices need not change much and the variance of prices do not necessarily decrease. In this situation, the third and fourth moments (skewness and kurtosis), can be a very valuable screen tool for detecting partial cartels. Hence, skewness and kurtosis reduce the number of false positives in these situations.

In addition, screens based on centrality measures may cause problems in markets characterized by seasonality in the prices, and when costs for firms change. In a seasonal market, mean prices increase in the high season and decrease in the low season. Applying screens resting on measures of centrality in this situation will most likely generate many alarms about collusive practises, not necessarily because collusion takes place but because prices increase due to the seasons. Similarly, when costs in a market increase, mean prices increase, even without collusion. In these cases, skewness and kurtosis can screen price increases caused by cost increases (or seasons) and price increases caused by the formation of a partial cartel.

These markers were then applied to the Norwegian retail electricity market. In particular, we have screened a contract, that on numerous occasions has been pointed out as very expensive and not transparent, the SVP-contract, a hybrid contract that combines fixed-prices and spot-prices. We identified two periods—the end of 2012 (for northern regions) and late summer of 2013 (for southern regions)—where the third and fourth moments of the distribution of prices was consistent with a breakdown in a possible partial cartel. We looked at this suspicious pattern of prices with two other pieces of evidence. First, the suspicious periods are also identified using formal statistical tests of breaks of the time series. Second, we looked at the density of prices for the insiders and outsiders of the potential cartel, and showed that before the possible breakdown of a partial cartel, insiders had indeed higher prices than the outsiders.

As a caveat for our results, no evidence of collusion has been proved in the market we analyse. In addition, the Norwegian electricity market is characterized by high level of price transparency. As the tacit collusion literature shows, when markets are very transparent, it might be possible for firms to maintain collusive outcomes, even without overt communication (Motta, 2004). Competition law in most jurisdictions, however, require the existence of open communication for the courts to punish a cartel. In this sense, our results can be consistent with tacit collusion, with no open communication between firms.

Further, we are not able to explain the periods of a seemingly cartel breakdown with neither demand nor supply side factors. First, neither certificate prices nor wholesale spot prices changed in a manner that could explain the observed changes in retail prices in these periods. We have also not found any special climatic conditions in the aforementioned periods. Second, we are not aware of any changes on the demand side that can help explain the observed changes in the level of prices or the abrupt changes in skewness and kurtosis. Still, our exercise is only a screen, not hard evidence of collusion taking place. As is the case for all screens, the period of price changes could be a candidate for further investigation for competition authorities.

Finally, we believe that competition authorities should consider using measures of skewness and kurtosis (shape of distribution) when undertaking behavioural screening of markets. The measures of shape (kurtosis and skewness) can contribute to a more informative analysis of collusive practices; in particular, when the number of firms in the market is high, when prices vary substantially because of cost side and/ or seasonal conditions, and in the presence of partial cartels, where not all firms collude.

Credit author statement

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Appendix A. Demand specification

In this appendix, we illustrate the full demand specification used in the text, for similar demand specifications, see references in main text. The own-price effect for all products is for simplicity assumed to be identical. Cross-price effects between products i and j, and products i and k also differ. Direct demand for the five products, $i = 1, \cdots, 5$ is:

$$q_1 = a - bp_1 + dp_2 + ep_3 + fp_4 + gp_5$$

$$q_2 = a - dp_1 - bp_2 + dp_3 + ep_4 + fp_5$$

$$q_3 = a - ep_1 + dp_2 - bp_3 + dp_4 + ep_5$$

$$q_4 = a - fp_1 + ep_2 + dp_3 - bp_4 + dp_5$$

$$q_5 = a - gp_1 + fp_2 + ep_3 + dp_4 - bp_5$$

Appendix B. Screening measures

Let p denote the price variable, and $p_i = 1, \ldots, n$ the individual price observations for each firm. The mean of prices, $\bar{p}$, is defined as:

$$mean = \bar{p} = \frac{1}{n}\sum_{i=1}^{n} p_i.$$

The standard deviation, σ, is:

$$st.dev = \sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - \bar{p})^2}.$$

In turn, the coefficient of variation equals the standard deviation divided by the mean:

$$CV = \frac{\sigma}{\bar{p}}.$$

The measures of skewness and kurtosis are defined from the r'th moment of the mean of prices, m_r:

$$m_r = \frac{1}{n}\sum_{i=1}^{n}(p_i - \bar{p})^r.$$

We apply the standardized measures of kurtosis and skewness (Sydsæter et al., 2005). The coefficient of skewness is defined as:

$$skew = m_3 m_2^{-3/2}.$$

The coefficient of kurtosis is:

$$kurt = m_4 m_2^{-2}.$$

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106473.

References

Abrantes-Metz, R., Bajari, P., 2009. Screen for conspiracies and their multiple applications. Antitrust 24, 66–70.
Abrantes-Metz, R., Villas-Boas, S., Judge, G., 2011. Tracking the libor rate. Appl. Econ. Lett. 18, 893–899.
Abrantes-Metz, R., Kraten, M., Metz, A., Seow, G., 2012. Libor manipulation? J. Bank. Financ. 36, 136–150.
Amundsen, E., Mortensen, J., 2001. The Danish green certificate system: some simple analytical results. Energy Econ. 23, 480–509.
Anderson, S., de Palma, A., Thisse, J.-F., 1989. Demand for differentiated products, discrete choice models, and the characteristics approach. Rev. Econ. Stud. 56, 21–35.
Andersson, O., Wengström, E., 2007. Do antitrust laws facilitate collusion? Experimental evidence on costly communication in duopolies. Scand. J. Econ. 109, 321–339.
Andree, K., 2012. Collusion in spatially separated markets with quantity competition. J. Ind. Compet. Trade 13, 309–318.
Aryal, G., Gabrielli, M., 2013. Testing for collusion in asymmetric first-price auctions. Int. J. Ind. Organ. 31, 26–35.
Athey, S., Bagwell, K., Sanchirico, C., 2004. Collusion and price rigidity. Rev. Econ. Stud. 71, 317–349.
Bajari, P., Ye, L., 2003. Deciding between competition and collusion. Rev. Econ. Stat. 85, 971–989.
Bjørndal, E., Bjørndal, M., Gribkovskaia, V., 2013. Congestion Management in the Nordic Power Market: Nodal Pricing Versus Zonal Pricing. Mimeo, SNF.
Bolotova, Y., Connor, J., Miller, D., 2008. The impact of collusion on price behavior: empirical results from two recent cases. Int. J. Ind. Organ. 26, 1290–1307.
Boreinstein, S., Shepard, A., 1996. Dynamic pricing in retail gasoline markets. RAND J. Econ. 27, 429–451.
Bos, I., Harrington, J., 2010. Endogenous cartel formation with heterogeneous firms. RAND J. Econ. 41, 92–117.
Bos, I., Harrington, J., 2015. Competition policy and cartel size. Int. Econ. Rev. 56, 133–153.
Bos, I., Davies, S., Harrington, J., Ormosi, P., 2018. Does enforcement deter cartels? A tale of two tails. Int. J. Ind. Organ. 59, 372–405.
Bowley, A., 1924. The Mathematical Groundwork of Economics: An Introductory Treatise. Clarendon Press, Oxford.
Bresnahan, T., 1987. Competition and collusion in the American automobile industry: the 1955 price war. J. Ind. Econ. 35, 457–482.
Burdett, K., Judd, K., 1983. Equilibrium price dispersion. Econometrica 51, 955–970.
Cabral, L., 2005. Collusion theory: where to go next? J. Ind. Compet. Trade 5, 199–206.
Chevalier, J., Kashyap, A., Rossi, P., 2003. Why don't prices rise during periods of peak demand? Evidence from scanner data. Am. Econ. Rev. 93, 15–37.
Cox, Nicholas J., 2010. Speaking Stata: the limits of sample skewness and kurtosis. Stata J. 10, 482–495.
Crede, C., 2019. A structural break cartel screen for dating and detecting collusion. Rev. Ind. Organ. 54, 543–574.
d'Aspremont, C., Jacquemin, A., Gabszewicz, J., Weymark, J., 1983. On the stability of collusive price leadership. Can. J. Econ. 16, 17–25.
Deneckere, R., Davidson, C., 1985. Incentives to form coalitions with Bertrand competition. RAND J. Econ. 16, 473–486.
Donsimoni, M.-P., Economides, N., Polemarchakis, H., 1986. Stable cartels. Int. Econ. Rev. 27, 317–327.
Esposito, F., Ferrero, M., 2006. Variance Screens for Detecting Collusion: An Application to Two Cartel Cases in Italy. Italian Competition Authority. Working Paper.
Ewerhart, C., Cassola, N., Ejerskov, S., Vallad, N., 2007. Manipulation in money markets. Int. J. Cent. Bank. 3, 113–148.
Fisher, F., 2006. Economic analysis and antitrust damages. World Compet. 29, 383–394.
Forbrukerrådet, 2020. Advarer mot ekstremt dyre strømavtaler. Date 30 (08), 2020. https://www.forbrukerradet.no/siste-nytt/advarer-mot-ekstremt-dyre-stromavtaler/.
Foros, Ø., Steen, F., 2013. Vertical control and price cycles in gasoline retailing. Scand. J. Econ. 115, 640–661.
Froeb, L., Sibley, D., Doane, M., Pinto, B., 2014. Screening for collusion as a problem of inference. In: Blair, Roger D., Daniel Sokol, D. (Eds.), The Oxford Handbook of International Antitrust Economics, Vol. 2. OUP, Oxford.
Giles, D., 2007. Benford's law and naturally occurring prices in certain eBay auctions. Appl. Econ. Lett. 14, 157–161.
Giulietti, M., Waterson, M., Wildenbeest, M., 2014. Estimation of search frictions in the British electricity market. J. Ind. Econ. 62, 555–590.
Gomez-Martinez, F., 2017. Partial Cartels and Mergers with Heterogeneous Firms: Experimental Evidence, UC3M Working Papers, Economics, No. 17-10, August 2017.
Harrington, J., 2006. Behavioral screening and the detection of cartels. In: Ehlermann, C.-D., Atanasiu, I. (Eds.), European Competition Law Annual, London. Hart Publishing.
Harrington, J., 2008. Detecting cartels. In: Buccirossi, W.P. (Ed.), Handbook of Antitrust Economics, Cambridge. The MIT Press, Massachusetts.
Harrington, J., Chen, J., 2006. Cartel pricing dynamics with cost variability and endogenous buyer detection. Int. J. Industr. Econ. 24, 1185–1212.
Hastings, J., 2004. Vertical relationships and competition in retail gasoline markets: empirical evidence from contract changes in Southern California. Am. Econ. Rev. 94, 317–328.
Houba, H., Motchenkova, E., Wen, Q., 2018. Legal principles in antitrust enforcement. Scand. J. Econ. 120, 859–893.
Huber, M., Imhof, D., 2019. Machine learning with screens for detecting bid-rigging cartels. Int. J. Ind. Organ. 65, 277–301.
Imhof, D., 2017a. Simple Statistical Screens to Detect Bid Rigging. Mimeo University of Fribourg.
Imhof, D., 2017b. Econometric Tests to Detect Bid-rigging Cartels: Does it Work? University of Fribourg Working paper SES N. 483.
Imhof, D., Karagok, Y., Rutz, S., 2018. Screening for bid-rigging: does it work? J. Compet. Law Econ. 14, 235–261.
Ivaldi, M.; Jullien, B.; Rey, P.; Seabright; P. and Tirole, J. (2007). The Economics of Tacit Collusion: Implications for Merger Control. The Political Economy of Antitrust, Emerald Group Publishing Limited.
Jacquemin, A., Slade, M.E., 1989. Cartels, collusion, and horizontal merger. In: Arrow, K. J., Intriligator, M.D. (Eds.), Handbook of Industrial Organization. North-Holland.
Jiménez, J., Perdiguero, J., 2012. Does rigidity of prices Hide collusion? Rev. Ind. Organ. 41, 223–248.
Kocas, C., Kiyak, T., 2006. Theory and evidence on pricing by asymmetric oligopolies. Int. J. Ind. Organ. 24, 83–105.
Lewis, M., 2011. Asymmetric price adjustment and consumer search: an examination of the retail gasoline market. J. Econ. Manag. Strateg. 20, 409–449.
Lewis, M., Noel, M., 2011. The speed of gasoline price response in markets with and without edgeworth cycles. Rev. Econ. Stat. 93, 672–682.
Lie, Ø., . Skor seg på dyr strøm. Teknisk Ukeblad. https://www.tu.no/artikler/skor-seg-pa-dyr-strom/246470. Teknisk Ukeblad.
Lorenz, C., 2008. Screening markets for Cartel detection: collusive markers in the CFD cartel-audit. Eur. J. Law Econ. 26, 213–232.
Matre, J., Svendsen, S., 2010. Rekordhøye strømpriser - denne uken dobles prisen: - Ikke velg feil priskontrakt på strøm. Verdens Gang (vg.no). https://www.vg.no/forbruker/i/JjgG7/rekordhoeye-stroempriser-denne-uken-dobles-prisen-ikke-velg-feil-priskontrakt-paa-stroem.
Melitz, M., 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica 71, 1695–1725.
Motta, M., 2004. Competition Policy: Theory and Practice. CUP, Cambridge.
Nigrini, M., 1996. A taxpayer compliance application of Benford's law. J. Am. Tax. Assoc. 18, 72–91.
NVE, 2009. Kvartalsrapport for kraftmarkedet, 1. kvartal 2009. Rapport 6/2009. Norwegian Water and Energy Directorate.
NVE, 2010. Leverandørskifteundersøkelsen, 4 kvartal, 2010. Leverandørskifteundersøkelsen, Norwegian Water and Energy Directorate.
NVE, 2014. NVEs årsrapport 2014, Norwegian Water and Energy Directorate.
NVE, 2019. KRAFTSITUASJONEN, Fjerde kvartal og året 2019. Report. Date: 30.08.2022. https://www.nve.no/media/9092/kraftsituasjonen_q4_2019.pdf.
OECD, 2002. Fighting Hard-Core Cartels: Harm, Effective Sanctions and Leniency Programmes. OECD Publishing.
Piovesana, A., Senior, G., 2018. How small is big: sample size and skewness. Assessment. 25, 793–800.
Pirrong, C., 2004. Detecting manipulation in futures markets: the ferruzzi soybean episode. Am. Law Econ. Rev. 6, 28–71.
Porter, R., Zona, J., 1993. Detection of bid rigging in procurement auctions. J. Polit. Econ. 101, 518–538.
Porter, R., Zona, J., 1999. Ohio school Milk markets: an analysis of bidding. RAND J. Econ. 30, 263–288.
Seaton, J., Waterson, M., 2013. Identifying and characterising price leadership in British supermarkets. Int. J. Ind. Organ. 31, 392–40.
Selten, R., 1973. A simple model of imperfect competition, where 4 are few and 6 are many. Int. J. Game Theory 2, 141–201.
Shaffer, S., 1995. Stable cartels with a cournot fringe. South. Econ. J. 61, 744–754.
Shubik, M., Levitan, R., 1980. Market Structure and Behavior. Harvard University Press, Cambridge, MA.
Slade, M., 1992. Vancouver's gasoline-price wars: an empirical exercise in uncovering supergame strategies. Rev. Econ. Stud. 59, 257–276.
Sparre, M., . Så mye taper du på ikke å ha flytende strømpris. Dagens Næringsliv (dn.no). https://www.dn.no/privat/privatokonomi/2012/09/18/sa-mye-taper-du-pa-ikkei-a-ha-flytende-strompris. Dagens Næringsliv.
Spulber, D., 1989. Regulation and Markets. MIT Press, Cambridge, Massachusetts.
Stahl, D., 1989. Oligopolistic pricing with sequential consumer search. Am. Econ. Rev. 79, 700–712.
Stahl, D., 1996. Oligopolistic pricing with heterogeneous consumer search. Int. J. Ind. Organ. 14, 243–268.
Sydsæter, K., Strøm, A., Berck, P., 2005. Economists' Mathematical Manual. Springer, London.
Symeonidis, G., 1999. Cartel stability in advertising-intensive and R&D intensive industries. Econ. Lett. 62, 121–129.
von der Fehr, Nils-Henrik M., Hansen, P., 2010. Electricity retailing in Norway. Energy J. 31, 25–45.
Westfall, P., 2014. Kurtosis as Peakedness, 1905–2014. RIP. The American Statistician, 68, pp. 191–195.