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Abstract

Wholesale electricity markets have several features that increase the likelihood of collusion, including frequent interaction, multimarket contact, and a high degree of information transparency. As a result, screening techniques for detecting collusive agreements are desired. In this paper, we survey the existing literature on collusive screens and collusion in electricity markets. We discuss key features of non-competitive behaviour to be reflected in screens and suggest directions for improved screening in this industry. In particular, there is considerable potential to include machine learning and data mining techniques in screens in the electricity sector due to recent improvements in these methods.

Keywords: Screening Methods; Collusion; Electricity Markets
JEL Classification: L13, L40, L94, Q40

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1 Introduction

Collusion has been shown to arise in numerous industries worldwide. Collusive behaviour can result in higher prices and a reduction in output, a misallocation of resources across higher and lower cost technologies, and dynamic inefficiency regarding investment decisions.[1] Collusive "screens", designed to identify markets and firms where collusion is more likely or where behaviour appears to depart from non-cooperative behaviour, have begun to be adopted by antitrust authorities and government agencies. Screens can be used to identify which markets and firms should be subject to further scrutiny. Empirical screens have been employed in a range of industries, including gasoline, financial benchmarks, and metals.[2]

To be effective, collusive screens need to take into account the institutional detail and nature of competitive behaviour in the industries to which they are applied. Particularly for complicated industries, this requires a thorough understanding of equilibrium behaviour, and how collusion might manifest itself. One such industry is the electricity sector. Restructured electricity markets are often subject to ongoing scrutiny by government agencies regarding the exercise and abuse of market power.[3] While it would seem natural that screens designed to identify potential cases of collusion in electricity markets would be desired, relatively little attention has been given to this issue.

Recent cases have highlighted the potential for coordinated behaviour in electricity markets. In Alberta Canada, the Market Surveillance Administrator (MSA) in 2013 alleged that generators were bidding into the wholesale market in ways designed to reveal their identities and send signals to rivals (MSA 2013). These concerns ultimately resulted in restrictions

1. For a discussion of the implications of collusion, see Asker and Nocke (2021).

2. See Abrantes-Metz and Bajari (2009), Abrantes-Metz (2013), and Abrantes-Metz and Metz (2019) for further examples.

3. Goldman, Lesieutre, and Bartholomew (2004) and Twomey et al. (2005) provide thorough discussions of market power measurement in wholesale electricity markets. Graf et al. (2021) discuss methods used by regulators to mitigate this market power.

to publicly available information in the wholesale market (AUC 2017). In Italy, in 2012 three electricity generators were fined for collusion in the supply of ancillary services (Samà and Luchetta 2012). Studies have identified behaviour and market outcomes consistent with coordination in wholesale markets in the late 1990s in England and Wales (Sweeting 2007) and Spain (Fabra and Toro 2005).

The objective of this paper is to consider the development of collusive screens for use in wholesale electricity markets. First, we provide an overview of screens for collusion that are used in other industries. We then survey the theoretical and empirical literature on collusion in wholesale electricity markets, with a focus on features of collusive behaviour that might be exploited in screening.[4] Finally, we discuss how screens used in other settings may be adapted to identify coordination in electricity markets, and whether such methods could be employed using statistics regularly collected by monitoring agencies. A central theme of this review of the literature is that the additional complexity of restructured wholesale electricity markets creates difficulties for screening for collusion. This arises because predictions of non-cooperative behaviour and collusive models in this industry are less precise and empirical analysis is currently a frontier area of research. We provide suggestions on directions to guide future research and to design screens that are applicable to the electricity sector that can be implemented by regulatory agencies and/or market monitors.

The remainder of this paper proceeds as follows. Section 2 surveys the economic literature on collusive screens. Section 3 provides basic background on electricity markets, and summarizes the theoretical and empirical literature on collusion in these markets, drawing lessons from this literature for the development of screening tools. Section 4 discusses existing market monitoring and existing and potential applications of collusive screens in the electricity sector. Section 5 concludes.

4. Collusion has been discussed in other segments of the industry beyond wholesale. See for example Matsukawa (2019) for a discussion of possible collusion in retail electricity markets in Japan. Screening for collusion in retail electricity markets is discussed in Pires and Skjeret (2023).

2 Screening Methods to Detect Collusion

In economics, collusion generally refers to dynamic strategies employed by firms to allow them to earn profits greater than those available in a non-cooperative equilibrium. Key problems faced by firms attempting to collude are the potential for participating firms to cheat on the agreement (e.g., by undercutting the collusive price to increase short-term profits), the potential for entry by new firms that will disrupt the collusive behaviour, and the difficulty in asymmetric firms (with different technologies) reaching an agreement on price and market share allocations (Asker and Nocke 2021). Collusive strategies typically address the first issue through punishment mechanisms in which firms that "cheat" on the agreement are punished through aggressive competitive behaviour in future periods.

Collusion can be explicit, involving direct communication between the firms in order to set prices and allocate market share, or it can be tacit, in which case firms indirectly come to a mutual understanding of the strategies that will be used to prevent cheating and sustain higher profits without explicit meetings or other communication. The distinction between explicit and tacit collusion can be important for policy; while explicit collusion is generally subject to antitrust laws, tacit coordination may not be or may be more difficult to prosecute (particularly in the absence of conduct designed to facilitate coordination).

As discussed in Harrington (2008), Abrantes-Metz and Bajari (2009), Doane et al. (2015), and Imhof, Karagök, and Rutz (2018), preferred collusive screens are based on economic theory together with empirical evidence that the behaviour screened for is consistent with collusion or inconsistent with non-cooperative behaviour. Many of the predictions on which collusive screens are based come from economic models of collusion that rely on certain assumptions; in a setting where those assumptions are violated, the screens would be inappropriate. The most reliable screens rely on models of the specific industry in question or empirical studies of past conspiracies in that industry.

Typically, antitrust authorities use collusive screens as a proactive tool at a preliminary stage of analysis (Friederiszick and Maier-Rigaud 2008). Screens are considered a "first pass" at identifying conduct inconsistent with non-cooperative behaviour; it need not follow that the conduct identified violates competition law. Therefore, screens that are straightforward to use and automate, and rely on limited data, are favoured. In addition, a goal in the design of collusive screens is to minimize the number of errors; a useful screen will be unlikely to wrongly tag non-cooperative behaviour as collusive agreements (type I error), or fail to identify cartels in full swing (type II error).

Finally, screens should be difficult for firms to fool or work around. One concern is that once firms learn that certain screens are being used, they may find ways to continue to collude without violating the screen (Ortner et al. 2021). If it becomes public that an agency screens for coordination using a particular source of public information, for example, then colluding firms may adapt by making use of other information sources. Likewise, screens for particular forms of market allocation or punishment may simply force firms to adopt other methods. The best screens will be those that are difficult to beat without incurring substantial additional costs.[5]

The economic literature differentiates between structural and behavioural screens for collusion (Harrington 2008). Structural screens consider whether market structure is such that collusion would be profitable, whether that collusion would be easy to sustain, and the ease at which an agreement could be reached. The market structure features that are expected to make collusion more likely have been the subject of an extensive literature, dating back to Stigler (1964); representative market features include market concentration, the degree of product differentiation and cost heterogeneity, and demand volatility and growth.[6]

5. See Harrington (2008) Section 6.3 for discussion.

6. For overviews of this literature see for example Church and Ware (2000) and Ivaldi et al. (2003). Abrantes-Metz and Bajari (2009) note the use of structural screens in Europe to identify "high-risk" industries which would be subject to a more detailed analysis.

Notably, electricity markets frequently exhibit market features that are expected to make collusion more likely and sustainable, including frequent interaction and a high degree of transparency.

In contrast, behavioural screens identify behaviour that departs from expected non-cooperative conduct. Behavioural methods for testing or screening for collusion vary in their complexity, ranging from simple statistics and indicators to more complex econometric analysis. However, while more complex approaches may be suitable as methods of testing specific allegations of collusion, Aryal and Gabrielli (2013) and Imhof, Karagök, and Rutz (2018) emphasize that their usage as *ex-ante* (preventive) screening tools may be less effective compared to simpler screening techniques.

One set of simple behavioural screens looks at price levels and asks whether prices are higher than expected under non-cooperative behaviour. This can involve identifying periods when price levels increase abruptly without cost or demand justification. Such a structural break may occur for observable reasons (such as the formation of a trade association or the introduction of regulatory changes that enhance or reduce the likelihood of collusion). In addition, such screens may look for structural breaks with an unknown start date that signal the beginning or end of a cartel. These methods must take the unknown start date into account in statistical testing (Hansen 2001; Crede 2019). One can also make use of comparison markets, asking whether prices differ from those in markets believed to be competitive. As discussed by Abrantes-Metz and Bajari (2009), these methods have been used by antitrust agencies such as the FTC in screening retail gasoline prices. Of course, conduct may differ across the candidate and control markets for reasons other than collusion, making it important to choose control markets carefully or to control for these differences.

Other simple behavioural screens identify geographic areas or time periods where the variation in price (either across firms and outlets or over time) has been reduced. To justify such a screen, empirical studies of known cartels that involved reductions in price dispersion or volatility are cited; examples include Genesove and Mullin (2001), Abrantes-Metz et al. (2006), Bolotova, Connor, and Miller (2008), and Silveira et al. (2021).

Related to variance screens are screens that look for increases in price uniformity or rigidity, clustering of prices or bids, or a lack of independence of prices or bids controlling for cost, demand, and market structure information publicly available to the firms.[7] The argument is that improbably uniform, clustered, or correlated prices or bids may be used for purposes of coordination.[8] Screens and tests of this sort are used by antitrust practitioners as well as in academic studies of collusion (Dijkgraaf and Gradus 2007; Lima and Resende 2021). For example, the U.S. Department of Justice indicates that behaviour suggesting the possibility of price fixing includes identical prices, particularly when "prices stay identical for long periods of time, prices previously were different," and "price increases do not appear to be supported by increased costs."[9] Abrantes-Metz et al. (2012) consider clustering of individual Libor quotes to test for manipulation of the Libor rate by particular banks.

Within the context of procurement auctions, proposed screens look at the distribution of bids. For example, Huber and Imhof (2019) consider the use of the coefficient of variation, skewness, and kurtosis of the distribution of bids, as well as statistics based on the difference between the lowest and second lowest bids; these screens are then applied to bid-rigging cartels in Switzerland.[10]

Other methods of looking for "improbable" patterns in bids or prices that may indicate

7. In auction settings, for instance, the prediction that once costs and other relevant observable variables are controlled for, bids of different firms should be independent has been applied as a screen by Porter and Zona (1993, 1997), Bajari and Ye (2003), and Ishii (2009) to auctions in school milk contracts and highway construction repair contracts.

8. Note however that uniform or clustered prices can also reflect intense competition in a setting with homogeneous products.

9. Antitrust Div., U.S. Department of Justice, Price Fixing, Bid Rigging, and Market Allocation Schemes: What They Are and What to Look For, available online at https://www.justice.gov/atr/file/810261/download.

10. In the context of retail electricity prices in Norway, Pires and Skjeret (2023) argue that higher moments of the distribution of prices (skewness and kurtosis) are better screens for partial cartels that do not involve all of the firms in a market.

an attempt to coordinate have been applied in certain settings. Benford's Law, which concerns the frequency with which different digits appear in numbers, is used to screen for manipulation of the Libor rate in Abrantes-Metz, Villas-Boas, and Judge (2011). Christie and Schultz (1994, 1999) focus on the lack of odd-eighth quotes by Nasdaq market makers. Following the allegations of an aluminum cartel, Samà (2014) applies Benford's Law to the price of aluminum traded on the London Metal Exchange. The "Screening for Cartels" tool developed by the UK's Competition and Markets Authority for use in public procurement auctions incorporates Benford's law, as well as screens based on the number of bidders, the presence of outlier bids, and similarity in bids (including text similarity and word count); see Sanchez-Graells (2019) for a discussion and critique.

Some approaches look for time series behaviour predicted by economic models of collusion. Such behaviour includes the switching in and out of price wars predicted by Green and Porter (1984), or the countercyclicality of margins of Rotemberg and Saloner (1986). The timing of price wars and their role in collusion has been the subject of empirical attention in a large number of industries, including airlines (Zhang and Round 2011), railroads (Porter 1983), bromine (Levenstein 1997), and wholesale electricity (Fabra and Toro 2005).

Some collusive screens will use data other than prices. For example, some screens are based on market share data, looking either for market shares that are improbably stable (which could signal an attempt to maintain coordination), or market shares for an individual firm that exhibit negative correlation over time, as firms alternate having the lowest price or winning bid, or when deviations from collusion (increasing market share in the short term) are met with subsequently reduced market shares.[11] Importantly, however, both market share stability and 'bid rotation' in an auction setting can have non-collusive explanations; see Porter (2005) for discussion.

11. Examples of relevant economic theory are Athey and Bagwell (2001), Skrzypacz and Hopenhayn (2004), and Athey and Bagwell (2008).

The increased availability of data along with advances in data analytics have opened up new possibilities in the usage of screening techniques to detect collusion, such as the use of machine learning algorithms combined with statistical analysis.[12] As discussed by Kleinberg et al. (2015), Athey and Imbens (2019), Rabuzin and Modrusan (2019), and Garcıéa Rodrıéguez et al. (2020) machine learning is a promising way to solve prediction policy problems, i.e., where collusive behaviour is the outcome we want to predict.

One approach to applying machine learning to the identification of collusion is through the application of supervised classification algorithms; see for example Huber and Imhof (2019), Wallimann, Imhof, and Huber (2022), Huber, Imhof, and Ishii (2022), and Silveira et al. (2022).[13] These studies consider industries where cartels were known to occur (typically because of previous competition cases) and for which the cartel timing and location are also known; data on both collusive and non-cooperative time periods and markets are used to train machine learning algorithms to predict instances of collusion on test data. The papers within this literature will use conventional screening variables and different machine learning algorithms to predict when and where collusion occurs. The authors can then identify which variables are most important in predicting collusion, and which algorithms and decision rules are most effective. These studies can provide evidence regarding the relative effectiveness of the different basic screens described above.

As a recent example, Silveira et al. (2022) evaluate the ability of different screening variables and supervised machine learning algorithms to identify collusion in retail gasoline markets in Brazil. The standard deviation and coefficient of variation of weekly station-level prices within a city are found to be the most powerful predictors of collusion. Huber and Imhof (2019) find in the context of Swiss procurement cartels that the coefficient of variation and the distance between the lowest and second lowest bids (normalized by the

12. Recent discussion of the potential application of machine learning to cartel screening can be found in Harrington and Imhof (2022) and Abrantes-Metz and Metz (2018).

13. See Izenman (2008) for details about supervised and unsupervised machine learning algorithms.

average distance between all adjacent bids) are the most effective screens.

In many industries or markets, however, there will not exist instances of known collusion that can be used to train machine learning algorithms. Huber, Imhof, and Ishii (2022) employ data on bid-rigging cartels in both Switzerland and Japan, and ask whether a machine learning algorithm trained on cartel data for one country can be effective at predicting collusive behaviour in the other country. The results suggest that the ability of a model trained in one jurisdiction to identify collusion in another can depend upon the algorithms employed. Hence, variables that are good predictors of collusion in one industry or market may be less effective in others.

The possible use of machine learning techniques in detecting collusion without labeled data (that is, without a training data set in which collusive and non-collusive observations are identified, say because of a prior legal case), is explored in Silveira et al. (2023). The authors study data on road maintenance auctions in Brazil, and combine supervised and unsupervised machine learning techniques to propose a screening method for unlabeled data, i.e., for detecting *ex-ante* cartels. In particular, the authors use cluster analysis to 'label' the data, and then employ machine learning techniques with different screening variables to predict collusive auctions.[14]

To summarize, there is a robust and active literature that develops and employs structural and behavioural screening tools to detect collusion across various industries. The screens are often tailored to capture specific features of the industry in question. In the subsequent sections, we will turn our attention to the electricity sector and describe how collusion and non-cooperative behaviour have been modeled, detail challenges with traditional screening methods, and summarize existing screening methods in the electricity sector and potential

14. As another approach without labeled data, Wachs and Kertész (2019) propose a network-based framework to screen bid rigging cartels. Cohesion and exclusivity are used to map firms' interactions and understand how cooperative behaviour and trust arise as ideal conditions to sustain collusive agreements in different bidding markets.

opportunities for improvement.

3 Collusion in Electricity Markets

3.1 Restructured Electricity Markets and Non-cooperative Models

Before discussing collusion in wholesale electricity markets, it is useful to review the basic features of these markets, and how non-cooperative behaviour in this industry has been modeled in the economic literature.[15] Prior to the 1990s, electricity markets around the world consisted of vertically integrated regulated utilities, subject to cost-of-service regulation, that generated electricity, transported it through transmission and distribution lines, and sold it to consumers. Beginning in the 1990s, jurisdictions began restructuring the electricity sector through vertical separation, introducing competition at the wholesale and retail levels, while maintaining regulation at the transmission and distribution levels.

The cornerstone of restructured electricity markets is the wholesale market, operated as a multi-unit auction in which firms submit offers indicating the quantities they are willing to supply from their generating units at different prices; the system operator combines these offers into a market-wide "supply curve" and dispatches energy in order of least-cost. Typically these markets occur hourly, although other frequencies exist. There can be important differences in the details of wholesale markets across jurisdictions. A market may yield a single wholesale price that applies to all suppliers across a jurisdiction or large zones, or it may yield many different local marginal prices at a nodal level, as a response to the potential for congestion (Weibelzahl 2017). Firms may submit simple offer schedules, consisting of a series of price-quantity blocks, or they may submit more complex bids that include start-up and ramping costs and constraints (Herrero, Rodilla, and Batlle 2020). Wholesale market bids may be subject to "bid mitigation", restricting bid levels near estimates of marginal cost

15. See Pfeifenberger, Spees, and Schumacher (2009) for detailed discussion of different market designs.

as a method of addressing potential market power (Graf et al. 2021).

Firms typically interact in other markets in addition to the real-time wholesale market. This may include submitting offers into day-ahead markets and markets for ancillary services to balance short-term fluctuations in supply and demand (Wolak 2021). Generators trade more broadly in financial forward markets, where forward contracts are financial arrangements that secure a pre-specified quantity of electricity in advance of the market at a fixed price; it has been shown that forward commitments have important implications for the market power incentives of firms in the spot market (Bushnell, Mansur, and Saravia 2008). Finally, because of concerns over the ability for short-term markets to promote investment, in some jurisdictions, long-term markets have been designed to compensate generators for their ability to generate (i.e., capacity) (Pfeifenberger, Spees, and Schumacher 2009).

As a result of the complexity of electricity markets, a variety of approaches have been taken to modelling wholesale electricity markets in the theoretical literature, with different degrees of tractability and realism; thus, it is useful to review these approaches before discussing how collusion is modelled in theoretical analyses of electricity markets.[16] One common modelling framework is the Cournot model, in which oligopolists who produce homogeneous products choose quantities simultaneously (Bushnell, Mansur, and Saravia 2008; Willems, Rumiantseva, and Weigt 2009); the market price then clears the market by equating total production to total demand. In a (non-cooperative) Nash equilibrium, firms exercise market power, with an equilibrium price above marginal cost; the degree of market power is generally declining in the number of firms in the market. As a result, the observation of market power cannot be taken as an indicator of coordinated behaviour.

The Cournot framework has been extended in the context of electricity to consider the interaction with other markets, including forward markets and ancillary services; see for example Allaz and Vila (1993) for the classic treatment of forward contracts in a Cournot

16. An overview of different modelling approaches can be found in Ventosa et al. (2005).

setting.[17] This modelling approach has been applied extensively in the empirical literature (e.g., Bushnell, Mansur, and Saravia (2008)). Despite abstracting from the realities of electricity markets in important ways, it has been found that Cournot models generally capture the exercise of market power well once forward contracts are accounted for (see for example Bushnell, Mansur, and Saravia (2008)).

An alternative modelling framework is the Supply Function Equilibrium (SFE) (Klemperer and Meyer 1989).[18] In this approach, firms choose supply functions, which specify the quantity they will supply at different prices. While the SFE approach has been argued to closely reflect reality given that firms submit supply functions in practice, it comes at the cost of significant analytical complexity. In general, SFE models can generate multiple equilibria, with different levels of market power; for example, in Klemperer and Meyer (1989) market power outcomes range from homogeneous products Bertrand to Cournot. It has been argued that the key advantage of the SFE arises in situations where firms submit offers that apply for an extended period of time (e.g., daily) where a wide range of demand is expected (Borenstein and Bushnell 1999; Baldick, Grant, and Kahn 2004).[19] Willems, Rumiantseva, and Weigt (2009) compare Cournot and SFE approaches in the context of the German electricity market, and conclude that which approach is more appropriate depends on the question being considered (e.g. short-vs-long term).[20]

17. Brown, Eckert, and Silveira (2023) provide a recent treatment of a Cournot model with both spot and ancillary service markets.

18. See Genc (2012) for a survey of the non-cooperative theoretical literature on electricity auctions with a focus on SFE. For a third approach, in which firms submit bids for their entire capacity, see Fabra, Fehr, and Harbord (2002).

19. Hortaçsu and Puller (2008) investigate market power in Texas's wholesale electricity market and consider a Share Auction model that serves as a generalization to the SFE model.

20. SFE models have also been extended to incorporate forward contracting; see Holmberg (2011).

3.2 Theoretical Literature on Collusion in Electricity Markets

While the theoretical literature on non-cooperative models of electricity markets is large, the literature considering coordinated behaviour is more limited. The majority of theoretical models of collusion have focused on infinitely repeated versions of standard oligopoly models such as Cournot and Bertrand competition, or models of single unit auctions. Only a small number of studies have looked at collusion in models more closely reflecting the reality of wholesale electricity markets, and even in those cases, models are simplified for tractability.

An important focus of the theoretical literature on collusion in electricity markets is on how market design influences the sustainability and profitability of collusion. Fabra (2003) analyzes a repeated game setting in which two symmetric firms submit the minimum price at which they are willing to supply their entire capacity, and finds that maximum sustainable collusive profits are greater in a uniform price setting than under discriminatory pricing. Ciarreta and Gutierrez-Hita (2006) study collusion under both supply function and quantity competition and find that whether collusion is sustainable under supply function competition depends upon the number of firms and the slope of the demand curve. Kremer, Weiner, and Winter (2017) find in the context of a dynamic auction model of a flow good (such as electricity) that collusion is more likely in higher frequency auctions.

Collusion may also involve interactions across markets. It has been argued that forward markets may increase the sustainability of collusion by reducing the gains from cheating; see for example Liski and Montero (2006) and Le Coq (2004). Liu and Hobbs (2013) develop a model of collusion with transmission constraints, suggesting that collusive firms might act to strategically manipulate congestion; such behaviour can create smaller congested markets where collusion can be profitable.[21]

21. The fact that firms generating electricity interact in multiple markets (such as wholesale, forward markets, ancillary services, retail, etc.) may increase the sustainability of collusion. See for example Bernheim and Whinston (1990).

For the purposes of developing collusive screens, an important theme of this literature is that collusion can involve strategies that are asymmetric across firms, as well as firms alternating roles. For example, Fabra (2003) demonstrates in a repeated uniform price multi-unit auction that for certain capacity levels, optimal collusion is most sustainable using strategies in which firms rotate roles, alternating between setting the collusive market price or offering at low prices that reduce the incentive to cheat on the collusive agreement; if the firm whose bid sets the market price attempts to undercut its rival, it will cause the equilibrium uniform price to fall dramatically.[22] Dechenaux and Kovenock (2007) generalize the model of Fabra (2003) to allow firms to offer quantities less than total capacity. In a uniform price auction, collusive strategies are shown to often entail offering a portion of supply at the collusive price, while the majority of the capacity is offered at a low price that reduces the incentive to undercut.[23]

Another important element of theoretical models of wholesale electricity markets is the potential for multiple non-cooperative equilibria with different degrees of market power, as noted in Section 3.1 above. It has been argued that coordination can be used to select among such equilibria in models of electricity markets, such as SFE models; Bolle (1992) argues that when multiple equilibria exist, coordination among firms to select the most profitable equilibrium should be viewed as a form of tacit collusion. More discussion of "collusive-seeming" equilibria can be found for example in McAdams (2002) and Wang and Zender (2002). Importantly, since under this form of coordination, firms are coordinating in order to choose a more-profitable static Nash equilibrium over a less-profitable one, such coordination would not be detected by considering whether firms are unilaterally maximizing their profits in response to their rivals' offers.

22. However, this conclusion is disputed in the presence of demand uncertainty by Benjamin (2016).

23. The potential for coordination in wholesale electricity markets to involve asymmetric strategies and alternating roles is also raised in Baziliauskas, Sanderson, and Yatchew (2011).

3.3 Empirical Evidence

While there have been a large number of studies addressing the extent to which firms exercise market power in electricity markets, the possibility of collusion has received limited empirical attention.[24] A number of studies examining the exercise of market power test whether the degree of market power observed is consistent with non-cooperative behaviour, or is more suggestive of collusion. Examples include studies of California (Puller 2007), England (Wolfram 1999; Sweeting 2007) and Alberta Canada (Brown and Eckert 2022).[25]

Similarly, several studies test whether firms are playing non-cooperative best responses to the strategies of rival firms. For example, Hortaçsu and Puller (2008) study Texas's electricity market and use a structural model to compare observed offer curves to the unilateral profit-maximizing offer curve. Similar methods have been applied in Wolak (2000, 2007), McRae and Wolak (2012), and Reguant (2014) to study other questions and jurisdictions. However, these methods do not directly evaluate whether firms are colluding, or whether deviations from unilateral profit maximization have other explanations.[26] Further, recent work has highlighted the potential empirical challenges with this method (Brown and Eckert 2021). In addition, such approaches would be unable to detect coordination on higher-profit non-cooperative (collusive-seeming) equilibria.

A small number of studies have attempted to test predictions of models of collusion. Fabra and Toro (2005) study daily prices in Spain during 1998 to test whether prices alternate between price wars and collusive periods as predicted in Green and Porter (1984), and to

24. Market power studies have been carried out in numerous jurisdictions including California (Wolak 2003; Hodge and Dahl 2012), Alberta Canada (Brown and Olmstead 2017; Brown, Eckert, and Shaffer 2023), England (Wolfram 1999), Spain (Reguant 2014), and Australia (Wolak 2000; Jha and Leslie 2021).

25. In addition to econometric analyses of possible collusion in electricity markets, there exists experimental evidence looking at possible collusion in multi-unit uniform price auctions; see for example Goswami, Noe, and Rebello (1996), Sade, Schnitzlein, and Zender (2006), Bernard, Schulze, and Mount (2005), and Bolle et al. (2013). The focus of this literature is on how different auction frameworks affect collusion, as opposed to examining the nature of collusion.

26. For example, Hortacsu et al. (2019) find evidence that the extent to which firms deviate from unilateral profit maximization in Texas is associated with strategic ability and manager sophistication.

determine the triggers of price wars. The authors find evidence of two pricing regimes, and that the probability of a price war beginning depends upon the market shares and revenues of the two main market participants, and upon their contracting positions. A similar approach is taken in Sapio and Spagnolo (2016), which finds price regime-switching consistent with tacit collusion in Sicily over the period 2012 - 2014. Macatangay (2002) considers whether the two dominant firms in England and Wales were engaged in tacit collusion from April 1996 to March 1997. The author finds that the two largest firms behaved differently from other firms and that their offers were interdependent, supporting concerns about the presence of tacit collusion.

Regulatory or antitrust cases involving allegations of collusion in electricity markets have been limited. Collusion involving bid rotation in electricity markets has been observed in the context of Italy's ancillary service markets; see Samà and Luchetta (2012).[27] In 2012, three firms operating in the Campania region of Italy were fined for collusion in providing voltage support in 2010. From the perspective of collusive screening, this case has several important features. First, the cartel employed a bid rotation scheme, in which the firms alternated winning the voltage support auction. Second, the cartel involved a linkage across product markets; the firms were accused of not offering plants in a certain geographic area into the day-ahead market, in order to create demand for ancillary products from these plants which would then be supplied by the cartel. Finally, communication seems to have taken place through public information. As a result, given the delay in releasing information employed by the system operator, bids for one week displayed a relationship with bids from two weeks previous, as opposed to bids from the previous week. Communication through public information was also the basis of allegations of coordination in Alberta Canada, which will be discussed in the following section.

27. An example of possible collusion in the ancillary services market in Germany is discussed in Heim and Götz (2021).

3.4 The Role of Information and Transparency

Central to screening for collusion in electricity markets is the issue of information transparency. The degree of information transparency in restructured electricity markets is the subject of an important policy debate.[28] Companies have argued for a high degree of transparency, with large amounts of information being made publicly available in real-time. This argument has been supported by models of static competition. For example, Holmberg and Wolak (2016) find, in the context of a static multi-unit auction with private information, that increased transparency and public information increases competition.[29] In contrast, concerns have been raised that the availability of a high degree of granular information in real-time can facilitate coordinated behaviour (von der Fehr 2013). Delaying the release of electricity auction information to prevent collusion is also suggested in Rothkopf (1999).[30] Hendricks, McAfee, and Williams (2015) (page 519) note, regarding the efficiency and collusive effects of information transparency, that "a greater understanding of this trade-off is one of the big open questions in auction design."

A recent example in Alberta's wholesale electricity market highlights how information can be used to facilitate coordination. In each hour, firms submit price-quantity bids for each of their generation units that reflect their willingness to supply electricity. These bids can be adjusted up to two hours before the market clears. Historically, these offers were made publicly available ten minutes after the hour ended, with the identity of the units and firms removed, via the Historical Trading Report (HTR). In 2013, the Market Surveillance Administrator (MSA) alleged that firms were using information from the HTR to coordinate

28. For example, in 2013 the European Commission introduced regulations to increase transparency in European electricity markets, providing information on generation unit outages, asset-level production, and reporting on wholesale market transactions (EU 2013).

29. See also Valitov and Maier (2020), who find that private information on unplanned outages distorted intraday electricity prices.

30. A detailed discussion of the pros and cons of information transparency in electricity markets can be found in Niefer (2014).

on high prices (MSA 2013). The MSA's concern revolved around the use of "tagging patterns" where firms would price-up several large units and tag the offers to reveal their identity and indicate the intention to maintain these offers at high prices. This would allow other firms to price up their units without the fear of being subsequently undercut, creating a steep portion of the offer curve, followed by a large cluster at high prices within a narrow band. These allegations ultimately led to a hearing that resulted in the end of the publication of the HTR (AUC 2017).

Brown, Eckert, and Lin (2018) use data from Alberta's wholesale market and provide empirical evidence that firms could have used the unique bid patterns to identify the offers of specific large firms with a high probability. The analysis finds that certain firms adjust their offers after these bid patterns are disclosed in the HTR. Brown and Eckert (2022) extend this analysis to consider whether firm bidding behaviour was consistent with unilateral profit maximization when bidding patterns were being employed, and find that unilateral deviations could have increased expected profits.

Concerns over information and transparency have arisen in other industries as well. In 2012, the Federal Energy Regulatory Commission (FERC) issued a Notice of Inquiry into increasing transparency in U.S. natural gas markets (FERC 2012). Concerns raised by the U.S. Department of Justice led FERC to abandon plans to increase information disclosure (DOJ 2012; FERC 2015). There are a number of additional examples in the academic literature that consider industries including airlines (Borenstein 1998), concrete (Albæk, Møllgaard, and Overgaard 1997), retail gasoline (Lewis 2015), and FCC spectrum auctions (Cramton and Schwartz 2000). These examples demonstrate that information and transparency can play an important role in maintaining and facilitating collusion. Consequently, it is important to consider the information that is available to firms and how they might utilize this information when designing screens to monitor behaviour.

4 Application of Screens in the Electricity Sector

In this section, we turn to the application of collusive screens in the electricity sector. A first general note is that in many respects, wholesale electricity markets exhibit features that make collusion (tacit or explicit) more likely, including the high frequency of auctions, multimarket contact, and a high degree of public information and transparency. This in turn highlights the need to develop effective collusive screens.

It was emphasized in Section 2 that screens that are effective in some industries can be less effective in others. In this section, therefore, we discuss whether screening methods employed in other settings are useful in electricity markets. In addition, we discuss screening methods that have been employed in the electricity sector, as well as suggest other possible approaches. We take key lessons suggested by the theoretical and empirical literature, as well as past cases, to inform the design of these collusive screens.

It is worth noting that the potential for screening in the electricity sector may be greater than for other industries. In contrast to most other markets, electricity markets are typically observed by market monitoring agencies that have access to large quantities of data, and who monitor the exercise of market power.[31] Data monitored by agencies in the U.S., for example, include high-frequency information on demand (load), capacity, congestion, market prices, unit-level price-quantity bids, outages, etc. Such monitoring is employed in bid mitigation; in jurisdictions without bid mitigation, the excessive exercise of market power can trigger other regulatory actions depending on legislation and the nature of the conduct.

Different approaches to screening are categorized in Table 1, which also summarizes for each category the data requirements, analytical complexity, and compatibility with electricity markets. We discuss each category in turn.

31. For comprehensive surveys of market power monitoring approaches, see Goldman, Lesieutre, and Bartholomew (2004), Twomey et al. (2005), and Graf et al. (2021).

Table 1: Potential Screening Methods in the Electricity Sector

Screening Method	Data Requirements	Complexity	Pros	Cons
Structural Indicies: HHI, Concentration Ratio, Residual Supplier Indices, Pivotal Supplier	Low	Low-to-Medium	Identifies potential for market power, Can be used to regulate bids	Certain measures poorly captures market features, focuses on unilateral market power
Price Measures: Price/Bid Levels, Variance, Coefficient of Variation	Low	Low	Easy to implement, Captures broad trends, Identifies concerning bid characteristics	Poor fit with key market features, Difficult to control for confounding factors
Price-Cost Margins	Medium	Low	Directly measures market power execution	Measurement error in cost
Econometric Techniques: Unilateral Market Power Test, Structural Break Test	Medium-to-High	Medium-to-High	Tests if behaviour is consistent with unilateral market power, Grounded in economic theory, Control for key price drivers	Computationally intensive, Relies on modelling assumptions, Multiple equilibria challenges, Skewed price distribution
Machine Learning, Data Mining: Supervised and Unsupervised, Pattern Recognition	High	High	Leverage publicly available data, Identify communication	Heavy data requirements, Complex methods, May require historical examples of collusion

4.1 Structural Screens

The first category consists of structural screens, designed to highlight times and/or markets where collusion is more likely. As discussed in Section 2, such screens often consider simple measures including market concentration and market shares. While such measures are easily computed by market monitoring agencies using available data, it is widely recognized that standard concentration metrics (such as the HHI index) do not perform well in identifying the potential for market power in this industry; see Borenstein, Bushnell, and Knittel (1999). This arises because of the unique features of electricity markets, where supply must always equal demand at every moment, demand is highly inelastic, and electricity is costly to store. As a result, there can be periods of high demand (or tight supply) that can result in firms having considerable ability and incentive to exercise unilateral (non-cooperative) market power. This has resulted in the development of industry-specific measures of the potential for market power, such as residual supplier indices (measuring the extent to which a certain firm's available capacity is required to meet market demand).[32] Such indices are routinely

32. More formally, the RSI of a firm j in period t is given by the following formula $RSI_{jt} =$ (Total Available Supply$_t$ - Available Supply Controlled by Firm j)/Demand$_t$. Values below 1 indicate that firm j is needed

computed by monitoring agencies (Broehm et al. 2018).

Notably, the focus of market monitoring agencies is on detecting the potential for and exercise of market power, regardless of whether that market power is being exercised unilaterally or in a coordinated fashion with other firms. As such, the structural screens employed by such agencies typically are not designed explicitly to distinguish the potential for unilateral or coordinated market power. In some cases, structural screens have been adapted to reflect the possibility of market power through coordination, for example by considering whether a group of firms together are jointly pivotal; i.e. that their combined capacities are required to meet market demand.[33] Structural screens and their uses may be adapted further to reflect the lessons of the previous sections. This may include monitoring for negative correlations in market shares across firms resulting from alternating strategy roles, as well as looking at correlations in market shares across different product markets (e.g., wholesale and ancillary service markets).

4.2 Price-based Screens

Moving from structural to behavioural screens, the second category in Table 1 consists of screens based solely on prices. These include screens that consider price or bid levels, price variance over time or across firms, as well as higher order moments (Bolotova, Connor, and Miller 2008). Such approaches have low data requirements, particularly for market monitoring agencies that have access to all offers made by firms to the wholesale market. In addition, price-based screens are generally of low complexity. A key challenge in looking at equilibrium price levels or volatility over time is that wholesale electricity prices tend to exhibit frequent shocks and high volatility. Electricity demand is highly inelastic and is prohibitively costly to store in large quantities; as a result, increases in demand or outages

in order to clear the market.

33. For discussion, see for example Reitz et al. (2007).

in generation capacity can result in rapid and large price spikes, creating additional noise that can make identifying structural breaks challenging.

Further, screens that utilize a control group that is believed to be behaving non-cooperatively, to ask whether prices or price volatility has increased in one market relative to others, may be infeasible in many jurisdictions. At the market level, one could attempt to use a nearby jurisdiction; however, the substantial heterogeneity in regulations, market design features, demand levels and variation, and generation resource types and costs make this difficult. Within a market, it would be difficult to find firms whose behaviour is independent of the larger colluding firms. Small fringe firms have very different incentives and abilities to exercise market power from large firms. Further, it is difficult to argue that the behaviour of other non-colluding large firms would be unaffected by the presence of the collusive behaviour. More specifically, even if they were behaving non-cooperatively, their unilateral profit-maximizing strategies would likely be affected by the behaviour of the colluding firms. One possibility might be to monitor for changes in the price levels or volatility at specific nodes within a market with locational marginal pricing, to reflect the possibility of coordination to create local markets in which market power may be jointly exercised.

There is likely more scope for screens based on the individual price and quantity bids of different generators. For example, screens could be used to monitor for changes in the degree of clustering at high prices within the offer curve, particularly at the top of a large vertical segment of the offer curve. These types of screens are suggested by the theoretical literature, in which a steep vertical segment in the supply curve can be used to deter cheating (Fabra 2003). In addition, such screens would be consistent with the allegations in Alberta's electricity market where firms were alleged to have communicated and clustered their bids at high prices followed by a steep drop in the next offer prices (Brown and Eckert 2022). Measures of asymmetry regarding the firms' pricing below or above the vertical segment, and of alternating roles, are suggested by the theoretical literature. Correlations of offer prices of individual firms across product markets (such as wholesale and ancillary markets or forward markets) may detect attempts to manipulate one market in order to create the potential for market power in another.

4.3 Price-Cost Margins

A complication with the use of price-based screens is that prices may change over time for reasons other than competitive behaviour. One approach to controlling for other factors influencing prices is to look at price-cost margins, the third category in Table 1. This approach compares a firm's bid prices to the marginal cost of the unit. Such margins are frequently employed by market monitoring agencies as the first stage of a conduct-impact test, which considers whether firms have bid above a specified threshold above marginal cost, and then considers the impact of these high bids on market prices.[34] To address the possibility of coordinated conduct, an agency can simultaneously assess the impact of bids submitted by multiple firms that violate a given threshold. A challenge with this approach is that the use of a price-cost threshold to trigger further analysis generally leaves room for either unilateral or coordinated exercises of market power; as noted by Bushnell et al. (2013), page 13, "the approach's use of a bright line for impact may make it easier for market participants to unilaterally or through coordinated behaviour exercise market power while staying just below the impact thresholds that would trigger mitigation."[35]

Challenges with looking at price-cost margins also arise due to the potential for error in the estimation of marginal costs. If all cost components were known, short-run marginal costs can be readily estimated. However, generation unit characteristics are private information and firms have an incentive to overstate their costs. In practice, particularly in the design of bid mitigation mechanisms, market monitors have used historical bids to infer the underlying

34. Such a conduct-impact test can be triggered by structural indicators such as the RSI. See Adelowo and Bohland (2022) for a detailed discussion.

35. See also Graf et al. (2021) page 39.

costs. This approach has been shown to bias marginal cost estimates by a considerable margin (Adelowo and Bohland 2022). In addition, short-run marginal cost estimates often abstract away from other important cost components such as the cost of ramping up/starting up a generation facility. Ignoring these costs may lead to biased conclusions over the all-in costs of providing electricity.

4.4 Econometric Techniques

While price-cost margins control for changes in marginal costs, price and bid levels may vary for other reasons, such as changes in demand, import capacity, renewable generation, etc. The fourth category in Table 1 highlights the potential to use econometric techniques to control for these other factors. One approach to address other factors driving prices could be to employ econometric techniques discussed above in Section 3.3 to test whether firms' bids are consistent with unilateral profit maximization; such an analysis might estimate conduct parameters, or estimate residual demand elasticities to understand the unilateral potential and incentive for market power (Hortaçsu and Puller 2008; McRae and Wolak 2009). Such analyses may be prohibitively time and computationally intensive to be conducted on an ongoing basis as a screening tool, although Graf et al. (2021) suggest that ongoing market power tests that consider residual demand elasticity may become feasible in future with increases in computing capacity. In addition, such methods may be difficult to automate because of empirical challenges associated with the step-function nature of residual demand and non-concavities (Brown and Eckert 2021). Further, as noted in Section 3.3, such an approach would not flag coordination to achieve a more profitable noncooperative Nash equilibrium. Hence, at least at the present time, while such an approach may be reasonable as an *ex-post* analysis of allegations of collusion, it seems less feasible as an ongoing screen.

Another approach would be to use a reduced-form econometric approach that models the data-generating process that determines wholesale electricity prices. This involves developing a regression model that is a function of the factors that determine wholesale prices using periods where collusion is not suspected. In the electricity market context, this would involve key market factors such as demand, import capacities, renewable output, costs, unit outages/available capacity, etc. This model is then used to evaluate if there is a structural break in the data-generating process that determines wholesale prices. The existence of a structural break that cannot be explained by other factors can flag concerns of collusion.

This approach can serve as a potential screen to identify distinct changes in prices that cannot be explained by observable market factors. Such an analysis could be conducted at the market level, or using nodal prices in jurisdictions with locational marginal pricing. Crede (2019) use data from three European countries to evaluate the potential use of this approach in testing for cartels in the pasta industry. While this approach shows considerable promise in the electricity market context where it is critical to control for confounding factors, there are two key challenges that need to be overcome. First, there needs to be a period where it is believed that there is no cartel to serve as the baseline data-generating process. Second, wholesale prices are often rightward skewed with a relatively low modal price and infrequent high outliers due to price spikes. As a result, such screens would need to consider using methods developed in the time series literature to appropriately model these price spikes (e.g., Christensen and Lindsay (2009)).

4.5 Machine Learning and Data Mining

As noted above, electricity market monitors have a wealth of data.[36] This suggests a role for using recently developed machine learning algorithms which can leverage a large number of variables in order to predict instances of collusion; this is the fifth entry in Table 1.

Recent examples that apply machine learning to detecting collusion in electricity include

36. Note however that in some jurisdictions forward positions, which have been shown to be important for the incentive to exercise market power, may not be observable with precision even by market monitors. This suggests a potential need for enhanced monitoring of firms' forward positions.

Razmi, Buygi, and Esmalifalak (2020, 2021). A challenge faced by this approach, however, is a lack of historical cases of proven collusion that can be used in training samples, meaning that standard supervised learning approaches using labelled data (as discussed in Section 2) cannot be applied to determine which screening variables best predict collusion. To address this limitation, the authors first generate an artificial data set based on a model of a wholesale electricity market, which is then used to simulate collusive and non-collusive market outcomes. Machine learning algorithms are then trained on this simulated data. The effectiveness of this approach will depend on the ability of the simulation model to capture the key aspects of the market and equilibrium behaviour.[37] Likewise, other approaches rely on agent-based models or other structural modelling of non-collusive and collusive behaviour.[38]

Instead of focusing specifically on collusion, Sun et al. (2022) employ machine learning to predict "market power abuse" by generators in China. Lasso algorithms are used. The authors employ Lasso variable selection collinearity tests to reduce the number of predictors; the final list includes measures of the proportion of a generator's capacity that is bid at 'high' prices or is out-of-merit, the market clearing price, and market concentration. Alternatively, the approach of Silveira et al. (2023) to first cluster the data with unsupervised learning methods and then predict the clusters using supervised learning algorithms may be fruitful.

Another potential avenue for the use of recently developed data analysis tools in collusive screening in electricity markets is in the identification of abnormal patterns in pricing that might indicate coordination. As an example, Brown et al. (2023) apply standard supervised machine learning algorithms to the case of the HTR in Alberta (discussed in Section 3.4), by examining the extent to which firms could have correctly predicted which offers in the HTR come from key large rivals. The authors find that before the MSA report in August

37. For example, Razmi, Buygi, and Esmalifalak (2021) assumes firms bid linear supply functions.

38. See for example Tellidou and Bakirtzis (2007), Anderson and Cau (2011), Liu and Hobbs (2013), Shafie-Khah, Moghaddam, and Sheikh-El-Eslami (2013), Samadi and Hajiabadi (2019), Chang et al. (2021), and Subramanyam, Hayajneh, and Zhang (2022).

2013 about the tagging of offers, machine learning algorithms are able to correctly predict the identity of a firm associated with a particular price-quantity offer with a high degree of accuracy, based on characteristics of the offer; this accuracy falls dramatically after the MSA's report alleging that firms were using the HTR for communication purposes. These results provide support for the MSA's claims that firms could identify their rivals in the HTR data, and that they were "tagging" their offers in a way that made those offers identifiable. This analysis also demonstrates the potential for machine learning algorithms to identify patterns firms may be using in prices or bids for purposes of communication or collusion.

A possible direction for future research into the detection of communication is to incorporate data mining algorithms used for sequential or periodic pattern recognition (see Mooney and Roddick (2013) and Fournier-Viger et al. (2017) for recent surveys). Popular algorithms include GSP (Generalized Sequential Pattern) or PrefixSpan, which are designed specifically for sequential pattern mining and take into account the order and temporal nature of the events in the dataset (Srikant and Agrawal 1996; Pei et al. 2004). To date, while these techniques have been applied in a diverse range of settings, such as consumer purchase decisions, text analysis and crime data analysis, to our knowledge they have not been employed in collusion detection. At the other end of the spectrum are algorithms designed for anomaly and outlier detection.[39] Such approaches could be used to detect atypical bids or other behaviour that deviates from normal patterns, designed to communicate specific information or send particular signals. Beyond the detection of collusion, outlier detection algorithms may be more broadly useful to electricity market monitors wanting to identify short-term instances of anomalous market power.

A key challenge with machine learning techniques is that the methods can be complex

39. Algorithms include the One-Class Support Vector Machine, Isolation Forest and Local Outlier Factor, and Gaussian Mixture Model; see Chandola, Banerjee, and Kumar (2009) for a survey of this literature. Deep learning models, such as Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks, can be used for anomaly detection in time series data (Choi et al. 2021).

and require access to a considerable amount of high-quality data. Further, interpreting the results of machine learning algorithms is difficult because the internal mechanisms that determine the predictions (e.g., for the presence of collusion) are often hidden or unclear. For example, machine learning algorithms form predictions using an optimization process that adjusts the internal model parameters. This training process can involve complex mathematical optimization algorithms, making it difficult to trace how the model arrived at its final state. This can make it challenging for regulators and/or market monitors to develop *ex-ante* screens to detect collusion. While techniques exist to identify variables that are the most important predictors in such algorithms, further consideration should be given to how best to articulate the specific predictive rules being used.

Overall, while electricity markets have certain advantages regarding collusive screening, there are particular challenges that would be faced in adapting methods from other industries, or that have been faced by previous studies screening for collusion in this industry. Structural screens commonly used elsewhere such as concentration measures are less effective in identifying the potential for market power in electricity markets. Industry-specific alternatives have been developed to account for the unique market features. Price-based screens face the challenge that equilibrium prices in electricity markets can be subject to considerable volatility due to demand and cost shocks. We suggest an alternative approach of reduced form econometric analysis to control for confounding factors to isolate periods of abnormally high prices. While price-cost margins are commonly constructed by market monitors, particularly as a tool in bid mitigation, they can be subject to measurement error and manipulation. The most potential to improve on existing methods for detecting collusion in electricity likely lies in the development of machine learning and data mining techniques. Promising directions for future research include the use of machine learning algorithms and pattern detection techniques to identify communication through public information.

5 Conclusions

Wholesale electricity markets have several features that increase the likelihood of explicit collusion. For example, there is frequent interaction, multimarket contact, and high degrees of information transparency. However, these features and others complicate the development of screens that (potentially) could detect such collusion. In this paper, we survey the literature on collusive screens; we then examine the theoretical and empirical literature on collusion in electricity markets and derive lessons from this literature regarding the development of screens for this industry. We provide suggestions on screening methods that can be pursued by market monitors and/or regulatory agencies.

A challenge in identifying effective screens for detecting collusion is tying those screens to theoretical models or empirical evidence for the industry in question or similar industrial activities. Unfortunately, wholesale electricity markets are unique in many respects, leading one to expect that screens suitable in other industries may be less so in electricity markets. The existing literature on detecting collusion in electricity markets suggests that effective screens will incorporate asymmetries in behaviour across firms, alternating strategic roles over time, connections between multiple markets, and the use of public information for coordination.

A key direction for the development of collusive screens in this industry is the continued use of machine learning algorithms. To date, attempts to use machine learning to predict collusion have been hampered by a lack of labeled data; time periods, and markets where collusion is known to have occurred, and that can be used to train the algorithm. Developments in unsupervised or "semi-supervised" methods are likely to increase the usefulness of machine learning for this purpose. More generally, data mining techniques designed to detect repeating patterns hold promise for screening, particularly in identifying abnormal behaviour for communications purposes.

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