Using machine learning to detect international cartels : an interorganizational analysis

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Research interest

Cartels have a detrimental impact on the entire economic fabric, including the final consumers. Consequently, public authorities in many countries and regions, including the European Union, employ methods to detect and punish cartels, continuously striving to enhance these methods.

Currently, there are two primary methods for fighting cartels: investigations and leniency. However, despite being crucial and effective, leniency only accounts for half of the detected cartels in Europe (Jaspers, 2020). Therefore, there is a pressing need to develop new, efficient methods for detecting cartels. The development of such methods serves a dual purpose. First, it shortens the duration of cartels by detecting them before their natural expiration, thus reducing their adverse impact on the economy. Second, it has a positive ex-ante effect by deterring the formation of cartels (Connor, 2011).

The introduction of leniency policies has underscored the necessity and relevance of developing and implementing various methods to dismantle cartels. Presently, the focus should shift towards enhancing the efficiency, targeting, and cost-effectiveness of investigations. Additionally, combining multiple innovative techniques is beneficial for increasing the accuracy of predictions and curtailing cartel activities.

This paper aims to complete this reflection on the creation of new, easily replicable models that competition authorities can use to detect cartels. While existing models primarily concentrate on analyzing price distribution in cartel markets, our study offers a fresh perspective by emphasizing the role of interorganizational relationships between companies, particularly the influence of organizational similarities, in the formation and sustainability of cartels.

In addition to the theoretical implications regarding the role of interorganizational similarities in cartel formation, this research also holds practical applicability. By employing easily collectible indicators, the proposed methodology presents a nearly cost-free innovation for competition authorities. There are two primary potential uses for competition authorities. Firstly, it can be combined with other screening techniques to enhance prediction accuracy. Secondly, it can be used independently when there is already a suspicion of a cartel, aiding the decision-making process regarding whether to initiate an investigation. In essence, it assists in allocating investigative resources more effectively.

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Background

Bid rigging cartels

Until now, algorithms have mainly been used to detect bid-rigging cartels, where different companies coordinate their offers in procurement auctions. Such situations are particularly susceptible to collusion among participants (Marshall and Marx, 2009). Earlier studies, such as Porter and Zona (1993), Howard and Kaserman (1989), and Zona (1986), have used regression methods to evaluate the impact of bid-rigging in public procurement.

Other methods have been employed to detect collusion in auction markets by examining the dispersion of overall bid distributions (Ballesteros-Perez et al., 2015) or the lowest bids (Signor et al., 2021). However, these approaches have limitations. They only consider market-related and auction-related features to explain collusion patterns. Additionally, determining firm costs ex-ante, which is crucial for assessing deviations in auction prices, can be challenging.

More recent research has incorporated machine learning techniques to detect collusion in auctions. The main advantage of these techniques is that they require minimal information about the auction to generate accurate patterns (Rodriguez et al., 2022). For example, Huber and Imhof (2019) develop a model based on a dataset of Swiss construction bid-rigging cartels, achieving an accuracy rate of 86%. Similarly, Razmi et al. (2021) use a dataset from the electricity market and employed a CART and SVM algorithms to differentiate between cartel and non-cartel situations based on market equilibrium scenarios. The variables used to train the algorithm were all market-related, including marginal cost of generators, bid price of generators, Lerner index for different generators, market share of each producer with load demand, and Herfindahl Hirschman index of the market with each load demand.

Although these models have achieved good accuracy results, they are not easily replicable. They cannot be easily applied to any sector, as implementing them requires in-depth knowledge of the specific market structure. Furthermore, bid-rigging cartels, while involving collusion between firms and being anticompetitive, represent a narrower scope compared to most cartels.

Cartel screening

Although such attempts are still rare, a few works have tried to develop tools to detect cartels, and not only bid-rigging, based on market patterns that could indicate the presence of collusion. Examples include the works of Porter (2005), Harrington (2006), and Lorenz (2008). In the latter study, the methodology is based on the underlying assumption that cartels result in market disturbances. Thus, detecting such disturbances in typical market processes can indicate the presence of cartels in specific markets. The article tests this method on the German cement market, which has faced multiple convictions for price-fixing.

Screening methods have been developed to identify the presence of cartels in a market, and these methods are referred to as "screening." According to Abrantes-Metz and Bajari (2009), a screen is a statistical test used to detect collusion in a market. Competition authorities often use screening methods to identify potential cartels based on market anomalies. For instance, the existence of higher price rigidity in the case of collusion has been theoretically (Athey et al., 2004) and empirically (Jimenez and Perdiguero, 2012) demonstrated. Price dispersion is another characteristic that can be utilized for collusion detection (Connor, 2005).

One of the prominent characteristics of a market where collusion occurs is price variance, making it a commonly used screening criterion (Abrantes-Metz et al., 2006; Abrantes-Metz and Adanki, 2007; Harrington, 2008). However, the efficacy of variance screening is considered limited because its relevance may vary in specific market situations (von Blanckenburg et al., 2013). Empirical studies have also produced mixed results regarding price variance during a cartel, as it can either increase or decrease (Bolotova, Connor, and Miller, 2008).

In summary, Doane et al. (2013) emphasize the limitations of screening methods, highlighting that they may not be applicable in every market. Each industry possesses specific characteristics, and due to the scarcity of literature, it is assumed that models developed for one industry may not necessarily apply to other industries.

Proximity in alliances

Because cartels are by nature illegal, such organizations between firms cannot be coordinated through a formal contractual agreement (Suslow, 2005). Consequently, cartels tend to be unstable because each company may have an incentive to cheat on the agreed-upon rules in order to maximize its profits (Osborne, 1976; Dick, 1996). However, despite this constraint, cartels exist, indicating that these organizations can maintain coordination mechanisms based on informal control methods (Jaspers, 2017). From a social perspective, stability in cartels can be achieved through mutual trust (Leslie, 2004; Stephan, 2010). Trust emerges as one of the primary explanations for why companies can coordinate in the long run in illegal settings (see for example von Lampe and Johansen, 2006).

Extensive research in management has emphasized the importance of trust in interactions among members of an organization or between organizations for successful alliances (Parkhe, 1998; Nielsen, 2011; Cullen, Johnson, and Sakano, 2000). Trust is also a critical driver of alliance performance (Zaheer and Harris, 2006; Meier et al., 2015).

Culture plays a significant role in trust, and cultural distance negatively impacts relationships (Ng et al., 2007). Conversely, cultural proximity and compatibility contribute to the success of international alliances (Lane, Salk, and Lyles, 2001). We also know that other forms of proximity influence alliance success. Reuer and Lahiri (2014) have shown that, in the case of RD alliances, an increase in geographic distance between two companies reduces the likelihood of forming an alliance. These findings remain relevant despite technological advances. The bias toward geographic proximity in economic and financial transactions has been demonstrated in various contexts (Bodnaruk, 2009; Sarkissian and Schill, 2004; Martinez-Zarzoso, 2003). In this context, geographic proximity should be considered in terms of both physical distance and accessibility. For example, Ellis, Madureira, and Underwood (2019) demonstrate that when new flights are introduced, thereby enhancing accessibility between two destinations, funds from each location increase investments in companies from the other location. This phenomenon can be explained by the fact that proximity reduces uncertainty and facilitates coordination (Boschma, 2005).

Existing literature also suggests that companies are inherently embedded in an environment, including a social and societal context, which influences their behavior and organizational choices (see House et al., 2004, known as the GLOBE research group, for an extensive review of the topic). The nationality of a company should, therefore, partly explain its inclination to form a cartel with another company. Companies are likely to associate with firms located in culturally similar countries.

Additional biases may exist when a company selects partners for an alliance. Extensive research has demonstrated the existence of homophily in human behavior, which can be described as the tendency to associate with similar others (Ertug et al., 2022). In our context, this concept suggests that organizations sharing similar characteristics are more likely to form alliances in the case of a cartel. For example, in a network, highly embedded companies are more likely to form alliances with other highly embedded companies (Gulati and Gargiulo, 1999).

In the literature, homophily is generally associated with higher performance (Ertug et al., 2018) and greater trust (Ahlf et al., 2019), especially among individuals engaged in illegal activities (Flashman and Gambetta, 2014). This trust, once again, facilitates relationships between firms, making homophily a potential driver of cooperation and collusion.

Because organizations are inherently influenced by culture, and considering our previous discussions on homophily, we propose the hypothesis that proximity, particularly organizational proximity, plays a significant role in explaining the formation of cartels. Consequently, we will incorporate several indicators of proximity as explanatory variables in our algorithm. These indicators will be divided into two categories: company-related aspects and cultural environment-related aspects.

The company-related aspects will encompass variables such as differences in revenue, geographic distance, and age between companies. These factors provide insights into the similarities or differences between companies in terms of their financial performance, physical distance, and establishment time.

On the other hand, the cultural environment-related aspects will include variables such as the language spoken or individual preferences extracted from Hofstede's cultural classification in the country where the company operates. These variables capture the cultural proximity or compatibility between companies, which can influence their likelihood of forming a cartel.

By incorporating these proximity-related indicators, we aim to explore how organizational and cultural proximity contribute to the formation of cartels.

Methodology

Data Collection

We have created a comprehensive database comprising international cartels that have been identified and condemned. International cartel means that the companies in the cartel must be headquartered in at least two different countries. Our database is based on the OECD international cartels database, which relies on John Connor's Private International Cartels database which was acquired in 2017.

While the original database contains a larger number of entries, we have opted to reduce it to align with our specific research interests. Specifically, we have focused exclusively on companies involved in cartels and excluded governmental activities and associations. Although these entities may have indirectly participated in the cartel and are often considered facilitators of collusion, we have excluded them because their primary purpose in participating in cartels is not profit-oriented.

The database consists of 664 records, with each record corresponding to a company that has participated in a cartel. It is worth noting that a company may have participated in multiple cartels, and therefore, it is represented multiple times in the database. In total, we have identified 114 cartels, involving anywhere between 2 and 33 companies. The median number of companies per cartel is 4, and the average number is 5.8. The cartels' duration ranges from 2004 to 2017, and the first penalties were imposed between 2012 and 2019.

Dataset Creation

Our original database consists of 114 real cartel cases. However, in order to compare the organizational structure of cartels with non-cartels and classify them based on their distinctive characteristics, we need to create an artificial dataset of non-cartel cases.

To create this dataset, we employ a method called permutation testing. We shuffle the entries in our original dataset to generate randomized non-cartel cases. This technique allows us to assess whether the observed groups (cartels) exhibit significantly different characteristics compared to the outcomes expected by chance alone. Specifically, we aim to demonstrate that real cartels have significantly higher proximity indices compared to the non-cartel groups.

This approach is particularly suitable for studying cartels. Since the randomized non-cartels consist only of companies from our pool of convicted companies, we can be certain that these fabricated non-cartels do not actually exist. Indeed, when a company is convicted for participating in a cartel, it undergoes thorough scrutiny by competition authorities. Thus, we can be confident that the company has not been involved in any undisclosed cartel. This assurance is crucial to ensure that the non-cartel dataset does not include any genuine cartels, and vice versa.

To maintain consistency in the composition of non-cartels, we do not shuffle the dataset randomly. Instead, we assign each cartel a category based on the GICS classification of economic activities. Our original dataset is divided into 11 categories, and we shuffle the companies within each category to form new fictitious cartels.

By performing these permutations, we generate an additional 114 non-cartel cases. We then merge the original and fake datasets to create our final working dataset. Additionally, we encode a binary dummy variable: 1 represents a cartel group of companies, and 0 represents a non-cartel group. This dummy variable serves as our independent variable and will be utilized for classifying the groups of companies using our machine learning algorithm.

Experimental Setup

To ensure a fair analysis, we begin by standardizing our variables to eliminate any biases. Next, we randomly split our data into training and test subsets. The partitioning is carried out using the Scikit-learn library in Python. We allocate 70% of the data for training and reserve the remaining 30% for testing. The accuracy of the model is evaluated based on its ability to correctly classify the test subset.

Our objective is to assess the accuracy of various classification models. Based on prior research findings (Rodriguez et al., 2019), we anticipate that random decision forest models will yield superior classification results. Random decision forests are favored over decision trees because the latter are prone to overfitting, resulting in decreased performance and lower accuracy levels.

A random forest model operates on the principle of bootstrapping. It creates random subsets of the data and selects a subset of variables at each decision split. This process is repeated for each bootstrap sample, generating a decision tree for each sample. Once all the trees are constructed, their results are aggregated, and the algorithm generates a classification pattern that can be used to predict the classification of future inputs.

The model allows us to specify the number of individual trees in the forest. Modifying this parameter affects the model's accuracy and enables us to optimize classification performance. By computing accuracy for different values of this parameter, we can determine the optimal number of trees that achieves the highest accuracy. Other metrics such as the F1 score, precision, and recall can also be computed to assess the model's robustness across various aspects. The precision score, for instance, indicates the balance between false positives and false negatives. Depending on the specific objectives of applying the algorithm, certain parameters can be adjusted to fine-tune the classification (prioritizing flagging more company groups at the risk of potential false positives or ensuring minimal cartel omission).

Additionally, we can analyze the feature importance to identify the most influential organizational variables in explaining the decision to form cartels. This outcome will contribute to our theoretical understanding of the role of organizational proximity in cartel formation.

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