A Cointegration-based cartel screen for detecting collusion

Kurdoglu, Berkay and Yucel, Eray

Turkish Competition Authority, Ihsan Dogramaci Bilkent University

26 July 2022

A Cointegration-Based Cartel Screen for Detecting Collusion

Berkay Kurdoğlu Turkish Competition Authority Economic Research and Analysis Division P: +905544685751 E: bkurdoglu@rekabet.gov.tr	Mustafa Eray Yücel Ihsan Dogramaci Bilkent University Department of Economics P: +905325435888 E: eray@bilkent.edu.tr

PRELIMINARY VERSION FOR COMMENTS & CRITICISMS

Abstract

In this article, we propose a new empirical screen for detecting cartels, using the cointegration as our basis of modeling. The proposed screen is capable of identifying potential cartel behavior, indicating the strength of price adjustment among firms, and providing a basis for assessing structural change. The screen is applied to the Turkish cement market for an initial demonstration of use; we obtain promising results.

Keywords: Antitrust; Cartel; Detection; Empirical screen

JEL Classification: D43; L41

1. Introduction

ICT developments have recently eased the formation and execution of cartel arrangements and challenged the competition authorities to screen them (OECD, 2017, 23-24). Since the operation of cartel arrangements resorts to ICT at an increasing rate, traditional-reactive tools of competition law such as complaints, external information, and leniency programs remain under question, as emphasized crucially by Friederiszcik and Maier-Rigaud (2008).

On the other hand, survival and duration of a non-competitive formation, while not easily identifiable with traditional tools, do relate to market outcomes (price level, market share, profit margin and other possible indicators) well (Levenstein and Suslow, 2006; Abrantes-Metz and Metz, 2019, 3). It is salutary that economics equips us with proper numerical techniques to relate those market outcomes back to the non-competitive practices that might have caused them and establish reasonable doubt in antitrust investigations (Verbach and Franck, 2013, 3). In that, econometric approaches have recently made up a sizable portion of these efforts to enhance the legal evidence base in official/judicial processes.

Despite the increasing ability of corporations to form cartels via ICT tools and of hiding themselves from competition authorities, it is still hard for them to veil the impacts of their actions on market indicators (OECD, 2017, 19; Abrantes-Metz and Metz, 2019, 4-6). In that, there is vast room for cartel screening techniques to measure sector anomalies and to report reasonable doubt (OECD, 2013, 7). These cartel screening techniques are now in progress, reflecting the complementary role of economic techniques in competition analysis, as pointed out by Ginsburg and Fraser (2010, 14).

The spectrum of quantitative antitrust analysis covers impact assessment of price decisions, description of the relevant product and geographical market, counterfactual analysis, measurement of market concentrations and power, and the assessment of the dominant position. In this context, red-flagging of collective behavior, meeting of minds/concurrence of wills, concerted practice/action and tacit collusion receive some special attention, as this class of behaviors are seen as observable manifestations of an anti-competitive stance by businesses. In the same spirit, in this article, we propose a new empirical screen for detecting cartels, using cointegration as our basis of modelling. The proposed screen is capable of identifying potential cartel behavior, indicating the strength of price adjustment among firms and providing a basis for assessing structural change. The screen is applied to the Turkish cement market in order to demonstrate the novelty a strength of the analysis; we obtain promising results.

In the remainder of the paper, Section 2 reviews the literature and Section 3 describes our methodology and computational approach. Finally, after presenting an actual sector data implementation of the proposed approach in Section 4, Section 5 concludes.

2. Literature

The earlier literature on cartel screening can be considered under two broad categories, namely the structural cartel screens and behavioral cartel screens. While the former approach is industry-based and focuses on the sectors prone to collusion through specific characteristics like entry barriers, type of product, and concentration index, the latter is market-based and investigates the actual economic activity of undertakings. However, the structural approach primarily identifies the markets with ideal conditions for anti-competitive behavior (see Grout and Sonderegger, 2005 for more detailed explanations). Therefore, the likelihood of false positives could be comparatively high in structural paradigm, and empirical tools for exploring structural traits are less likely to be effective in detecting cartels (Harrington, 2008, 214).

Many cartel screening methodologies have been developed and proposed in the literature on competition economics, particularly in procurement markets. From these studies aim to research bid-rigging conspiracies in private/public auctions, Porter and Zona (1993, 1999) revealed that the offers of competitive firms in the procurement markets differ statistically from the offers of the cartel member undertakings and the correlation coefficients between the bids of the cartel member undertakings are considerably high. Bajari and Ye (2003) observed that it is possible to quantitatively identify non-competitive bids by calculating the posterior probability of competition or coordination in asymmetric bidding models using over-cost prices. Froeb et al. (1993), on the other hand, examined the price movements of a bid-rigging cartel in the collusion and competition period and estimated the “but-for price” that would be valid if the cartel did not exist, and found that the markups in the cartel period were between 23.1% and 30.4%. In one of the recent studies that pertain to the behavioral screening approach in auctions, Wachs and Kertetsz (2019) presented a novel network approach based on joint bid tendencies and bilateral interactions of undertakings as a cartel scanning method for procurement markets.

As Crede (2019) highlighted, most behavioral cartel screening procedures chiefly designed to detect anomalies may be related to anti-competitive actions in the public auctions, nevertheless, progress in the screening methodologies outside of the procurement market is still considered a blooming area, and its experiential toolbox is limited due to the lack of institutional and academic experiences. Peculiarly in the last decade, the adoption of the behavioral cartel screening approach has ceased to be limited to procurement markets, and various quantitative methods that represent a substantial part of the competition economics literature have begun to be applied in investigating competition/antitrust law concerns emerged in large numbers of different sectors.

One of the most notable contributions to the practical use of behavioral cartel screening is made by Abrantes-Metz et al. (2006). Researchers focused on the frozen fish cartel that operated in the United States between 1984 and 1989 and observed that the price variance decreased significantly during the settlement periods. Thus, similar empirical studies that put the "price volatility" notion in the center have commenced attracting more attention with this seminal academic work. Esposito and Ferrero (2006), a critical case study on the subject, also found that the variance for price-fixing conspiracies in the motor fuel and baby food sectors in Italy decreased and argued that low price variance was more likely to indicate an anti-competitive signal in the case of existing high barriers to entering the market. Jimenez and Perdiguero (2011) delved deeply into the links between price volatility and market structure by examining the gasoline prices for the Canary Islands in Spain and came to the conclusion that price volatility is low in islands where competition is relatively weak. Bolotova et al. (2006) used ARCH (Autoregressive Conditional Heteroskedasticity) family models to inspect the volatility pattern of prices in the cartel and non-cartel periods of the international Citric Acid and Lysine cartels operating from 1991 to 1995. They found solid shreds of evidence for the Lysine cartel and confirmed that the volatility has decreased but did not reach statistically significant results for the Citric Acid cartel. Maintaining a similar approach, Kurdoglu (2021) deployed ARMA-ARCH models to research thoroughly the price, profit margin, and markup of a past cartel case in Turkey and concluded that volatility reduced significantly with the cartel period in all the parameters. Providing an authentic perspective to the related literature by using Markov Switching Models, Bejger (2012) analyzed the price variance changes in the Indian cement industry between 1994 and

2009 and reached findings in parallel with the theory put forward. Finally, a more sophisticated (artificial intelligence-based) approach was introduced by Silveira et al. (2021), who tested the various statistical indicators like variance, standard deviation, and coefficient of variation in conjunction with supervised machine learning algorithms in order to verify the existence of retail gasoline cartel in Brazil. In line with the outcomes of the study, the authors stressed that conventional volatility analysis could still offer accurate and successful results, and blending new computational technologies with these methodologies may enhance the capability of the analysis horizon beyond recognition.

Variance-based screens can be easily implemented and require reasonable effort; nevertheless, they can fail when collusion does not contain all participants in the industry, price wars that might occur during the transition period, cartel prices depend on a dynamic parameter like exchange rates or unexpected supply/demand shocks that may stem from economic or political crises (Abrantez-Metz et al., 2006; Bolotova et al., 2006). In fact, Ordonez-de-Haro and Torres (2013) examined the Spanish food sector after the intervention of the Spanish National Markets and Competition Comission and observed that, contrary to the theory, price volatility decreased after the intervention even compared to the competitive period.

Structural break tests were proposed as complementary to variance-based tests by Harrington (2008) and Crede (2019), who argued that the cartel would cause an unexpected change in the pricing behavior of members and the instability of indicators such as average prices, profit margins, or markups in the market. At this latitude, Thrainsson (2012) suggested that the presence of the cartel and the inconsistency caused by it could be numerically uncovered through the instruments of structural break tests such as the CUSUM CUSUMSQ and Bai and Perron tests. Furthermore, structural break screens can also be a handy tool for determining the beginning date of collusion, which is an important issue when calculating overcharge (Thrainsson, 2012, 25-27; Crede, 2019, 544). For an illustrative example study, Boswijk et al. (2016) estimated the start of the Sodium Chlorate cartel in Europe using structural break techniques to calculate cartel damage accurately. Crede (2019), one of the most recent and prominent studies, highlighted that OLS-based CUSUM tests in which demand, cost, or any external variable may be included in the data generating process of industry prices, unlike variance-based screens, could be successfully dating and detecting structural instability induced by cartels. The researcher managed to support his hypothesis with experimental studies on the pasta industry in Europe.

Despite having a common implementation on specifying the relevant product or geographic market in competition law cases, studies of a cointegration-based screening approach for collusion are rare (Bishop and Walker, 2010). Nevertheless, Gülen (1996) and Kisswani (2016) showed that long-run relationships among firms in an industry computed by the cointegration methods yielded promising results for detecting cartels. Both studies make use of the cointegration approach to illuminate the question of that: “Does OPEC act as a cartel?” in the background of the premise that indicating the statistically significant long-run relation between OPEC production and each member’s production may be a signal of cartel conduct yet they reach divergent conclusions. The former study provides the statistical confirmation of the cointegration between the OPEC and each member’s production level, whereas the latter reaches no evidence of cointegration between the production of the members and OPEC. We take cost and demand shifters into account to estimate bilateral cointegration relationships between every one pair of firm prices in the market and add the components of the time and geographical dimension to get more precise and accurate results so as to build up these approach that can be used in the process of cartel detection.

At the bottom line, as Abrantes-Metz (2014) put it forth, two important rules with respect to designing and applying a cartel screen are to be followed to obtain sensible results. First, any screen must be fitted to the industry under investigation to ensure proper identification. Second, quality data are to be used for good identification. Having these sustained, concrete signs of collusion (termed as collusive markers in Harrington's 2006 work) can be pinpointed. This is what we try to maintain in the subsequent sections.

3. Methodology

The computational approach that we propose in this paper is based on the notion of cointegration and error correction which are well-established in the earlier econometric literature along with several useful applications. A cointegrating relationship describes a stationary long-run relationship between two or more nonstationary variables and a short-run relationship between the changes of the same series, i.e., an error correction specification. While the established cointegration techniques outlaw the possibility of a spurious regression between the nonstationary variables, the Granger Representation Theorem ensures the existence of error correction dynamics. In a way, the existence of a cointegration relationship among a set of variables is indicative of the presence of equilibrating forces that keep the variables of concern to move together. In the context of this paper, prices of different business entities in the same sector are the nonstationary variables and our approach aims at revealing their possible collective movements. To give a consolidated view of cointegration, we shortly refer to the Engle-Granger (1987), Johansen-Juselius (1990) and Pesaran-Shin-Smith (1996 ve 2001) techniques here (see Hamilton, 2020 for a detailed consideration).

a. Fundamentals in a Nutshell

The Engle-Granger (1987) technique, which is the pioneering work on cointegration, maintains a two-step procedure to establish a long-term relationship and its associated short-term dynamics.

$\ln P_t{}^i = \propto_0 + \propto_1 \ln P_t{}^j + \hat{e}_t$	(1)
$\Delta \ln P_t{}^i = \beta_0 + \beta_1 \Delta \ln P_{t-1}{}^i + \beta_2 \Delta \ln P_t{}^j + \beta_3 \Delta \ln P_{t-1}{}^j + \gamma \hat{e}_{t-1} + u_t$	(2)

In Equations (1) and (2), $P_t{}^i$ and $P_t{}^j$ denote the prices at time t of firm i and firm j, respectively. Upon estimating (1), if the residuals $\hat{e}_t$ are $I(0)$, lnP_t^i and lnP_t^j are said to be cointegrated. Then, a short-term relationship between the rates of change of $P_t{}^i$ and $P_t{}^j$ is estimated via (2) which may host other explanatory variables (Lütkepohl ve Krätzig 2004, 110). At the end, the multiplicative inverse of the error-correction coefficient $(1/|\hat{\gamma}|)$ yields the adjustment period between prices.

Despite its value as the zero milestone of cointegration research, Engle-Granger technique is recently not very popular due to its limitation to two-variable cases. When the number of variables in a long-run relationship exceeds two, a proper treatment of them via Engle-Granger technique may not be viable, giving way to the Johansen-Juselius (1990) technique. Johansen-Juselius technique has its main strength in being able to define several long-run relationships among at least two nonstationary variables. Considering y_t as a vector of the nonstationary model variables, (3) and (4) describe the model dynamics as a Vector Error Correction model (VECM):

$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_k y_{t-k} + u_t$	(3)
$\Delta y_t = \Pi y_{t-k} + \Pi_1 \Delta y_{t-1} + \Pi_2 \Delta y_{t-2} + \cdots + \Pi_{k-1} \Delta y_{t-k} + u_t$	(4)

where Π and Π_i are defined as in (5) and (6):

$\Pi = \sum_{i=1}^{k} \beta_i - I_g$	(5)
$\Pi_i = \sum_{j=1}^{i} \beta_j - I_g$	(6)

In order to find the number of independent cointegrating relationships, the test statistics in (7) and (8) are defined based on the eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_g$ of Π:

$\lambda_{trace}(r) = -\mathrm{T} \sum_{i=r+1}^{g} \ln(1 - \hat{\lambda}_i)$	(7)
$\lambda_{max}(r, r+1) = -\mathrm{T} \ln(1 - \hat{\lambda}_{r+1})$	(8)

where r stands for the number of cointegration vectors under the null hypothesis (H_0). Intuitively, a more negative $\hat{\lambda}_i$ increases the values of the test statistics in (7) and (8). As each eigenvalue corresponds to a different cointegration vector, the number of eigenvalues that significantly differ from zero turns out to be the number of significant cointegrating relationships. In that, while the Trace test considers the null hypothesis of ‘up to r cointegrating relationships’ (against one), the Maximum

Eigenvalue test considers that of 'r cointegrating relationships' (against $r+1$). Upon testing for cointegration, estimation of VECM and calculation of the adjustment period are straightforward.

As also put forth by Wassell and Saunders (2000), Johansen-Juselius technique have some conceptual difficulties against the mathematical advantages it has. First, not every estimated cointegrating relationship has a clear economic interpretation. Second, it is not possible to isolate the correction dynamics of a variable of concern, due to the vector approach maintained. Finally, the requirement for the involved variables to be integrated at the same order might be restrictive for practitioners. Against the background of Engle-Granger and Johansen-Juselius techniques, the methodology of Pesaran-Shin-Smith maintains a more liberal stance as to the degree of integration of the involved time series.

In the Pesaran-Shin-Smith technique, an ARDL model can be estimated for a variable x_1 among the g variables $(x_1, x_2, \ldots, x_g)$ which are not necessarily of the same order of integration. Having specified the most suitable ARDL model, through Akaike Information Criterion (AIC) or Schwarz Information Criterion (SIC), the error-correction specification of (9) can be written:

$$\Delta x_{1t} = \alpha_0 + \alpha_1 \Delta x_{1,t-1} + \alpha_2 \Delta x_{2,t-1} + \alpha_3 \Delta x_{3,t-1} + \cdots + \gamma_1 (x_{1,t-1} + {}^{\gamma_2}/_{\gamma_1}\, x_{2,t-1} + \cdots + {}^{\gamma_g}/_{\gamma_1}\, x_{g,t-1}) + u_t \qquad (9)$$

The Bounds test offered by Pesaran, Shin and Smith (2001), then, considers $H_0: \gamma_1 = \gamma_2 = \cdots = \gamma_g = 0$ (no cointegration at all) against its alternative $H_1: \exists \gamma_i \neq 0$ (presence of at least one cointegrating relationship). If the F-statistic of the test is exceeding the upper critical value of PSS, presence of cointegration is concluded, where the opposite conclusion is reached when the F-statistic falls short of the lower critical value of PSS. Otherwise, a conclusion is reached based on the individual degrees of integration of the variables involved. As shared by Haug (2002) as well, PSS (2001) provides a good deal of flexibility in modeling, especially for small samples.

b. The Proposed Computation Approach

As the previous section suggests, a common denominator of the cointegration analysis is the researcher's ability to write and estimate a short-term (short-run) error correction relationship between the variables of analytical concern. In this section, we base our analysis of potentially collusive behavior on the time series of the prices of businesses in the same sector. Briefly, a statistical co-movement of these prices are indicative of reasonable doubt, if not purely solid evidence, for a collusion.

At the beginning, a short-term relationship for the variables can be written as in Equation (10):

$$\Delta lnP_{it} = \propto_0 + \propto_1 \Delta lnP_{i,t-1} + \propto_2 \Delta lnC_{it} + \propto_3 \Delta lnC_{i,t-1} + \propto_4 \Delta lnD_{it} + + \propto_5 \Delta lnD_{i,t-1} + \beta_0 \Delta lnP_{jt} + \beta_1 \Delta lnP_{j,t-1} + \gamma \left(lnP_{i,t-1} + \theta_1 lnC_{i,t-1} + \theta_2 lnD_{i,t-1} + \theta_3 lnP_{j,t-1} \right) + u_t, t = 1,2,\ldots,T. \quad (10)$$

where P_{it} is the price of firm i in period t, P_{jt} is the price of firm j in period t, C_{it} is the average cost of firm i in period t and D_{it} is the average demand in period t. After estimating Equation (10), a significant estimate of γ (i.e., $\hat{\gamma}$) suggests the existence of an error correction dynamic between P_{it} ve P_{jt}, that is, a long-run comovement of the two. In the same setup, the multiplicative inverse of the absolute value of $\hat{\gamma}$, which is $1/|\hat{\gamma}|$, measures the speed of adjustment.

After estimating Equation (10) for every pair of businesses in a sector, a full list of the estimates of γ is obtained. Denoting the corrective effect of firm j on firm i as $\hat{\gamma}_{ij}$, and marking their statistical significance via an indicator function $I(\hat{\gamma}_{ij})$, one has a rich set of information with regard to potential collusive behavior for the period $t = 1,2,\ldots,T$. At the end, this is used for finding the patterns in relation to firm size (market share), geographical location, time period and other feasible combinations of these. Thus, we also enable to assess the power of the cointegration relationship with regard to undertakings relative market share; interpreting the existence of a structural break considering any, suspicious or not, time interval; prioritization of competition concerns in a geographical latitude especially can be beneficial for organizing the dawn raids performed by the competition authorities.

4. Empirical Analysis: A Demonstration on the Turkish Cement Sector

In this section, the proposed economic method is applied to the Turkish cement sector, which is one of the vital sectors that has been closely monitored by the Turkish Competition Authority.

Characteristics of the Turkish cement industry can be described in several fragments. First of all, the sector has an oligopolistic and static market structure owing to the entry/exit barriers created by high transportation and investment costs. In addition to economic entry barriers, market participants must also have an Environmental İmpact Assessment Report given by the Government. Second, the number of firms in the market is around 20; however, because of the high transportation costs and nature of the product, there is a high regionalization tendency. Therefore, the sector possesses a high proportion of regional concentrations and the mutual interdependence between virtually all undertakings in the market.

Generally, undertakings have more than one terminal in the country located in the different cities and regions and sell cement to more than one city, with transportation cost constraints, thanks to the homogeneity of the product. As a general information, two types of cement are produced, namely bulk and bagged; the former is sold in close-range; the latter can relatively travel long distances. In this framework, the most frequently sold cement type is bulk CEM I 42.5 in Turkey.

The sector receives many complaints in the competition law dimension and is often the subject to scrutiny. Furthermore, the Turkish Competition Authority prepared a comprehensive sector report that will be referred to in this study as TCA-CSR.

Although seasonality can be observed in the sector, especially during the summer months, the reflection of this seasonality on prices is realized to a very limited extent, as pointed out by TCA-CSR under qualitative and quantitative research.

Lastly, the cement sector is one of the locomotives of the Turkish economy. It is essential to emphasize that overall economic conditions affect the industry in many ways. For instance, cement prices and the inflation rate have a strong correlation in the case of the non-existence of collusion.

a. The Data

The data set is taken from the Turkish Competition Authority for the period running from January 2009 to August 2014, considering 68 plants operated by 19 firms. The first part of data set contains 2,101,472 sales invoices for the bulk CEM I 42.5 during the mentioned period. The invoice-based price data have been consolidated to a monthly frequency on the basis of sales volumes of plants and firms. The second part of data set contains the costs incurred and they are consolidated in a similar fashion to that of prices. Owing to the trade-secret nature of these data, names of firms and plants are masked prior to further analytical use or reporting.

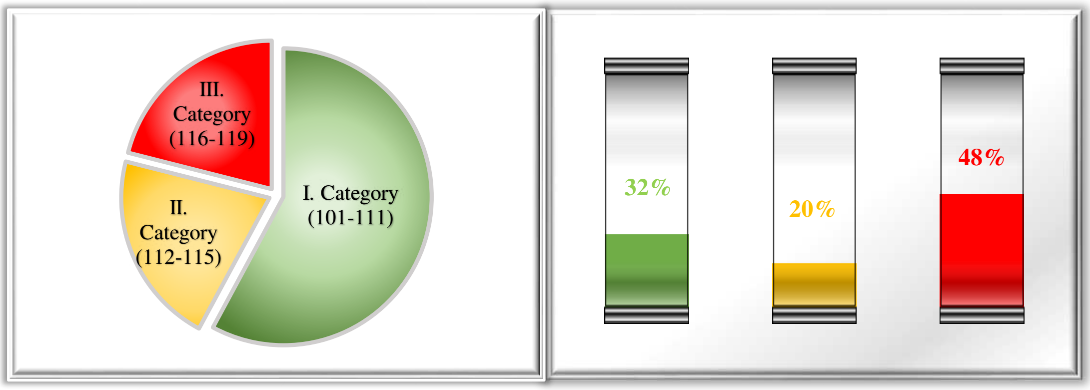
b. Implementation of the Proposed Method

Against the background provided above, we implement the method we proposed on the Turkish cement industry for the period from 2009 to 2014 using data at a monthly frequency. In our preliminary analysis, we have used the model for the countrywide cement industry without placing any emphasis on temporal or spatial dimensions, where we obtained a satisfactory analytical performance, i.e., we could pinpoint the possible concerted action of firms. Then, we implemented the modeling framework by paying attention to spatial and temporal dimensions. These preliminaries all resulted in tangible results. In order to save space, we report in this subsection the results of our temporal implementation.

In the first step, the undertakings (19 in total in the relevant market) have been divided into three categories according to their economic size. The first category represents "small-medium players" labeled 101 to 111 (including 111). The second contains "medium-large players" labeled 112 to 115. The third comprises "large-scale players" or leader firms in the market labeled 116 to 119.

The total market share of all three categories in the cement industry (calculated by total sales) and undertakings clusters in each category is exhibited in Figure 1.

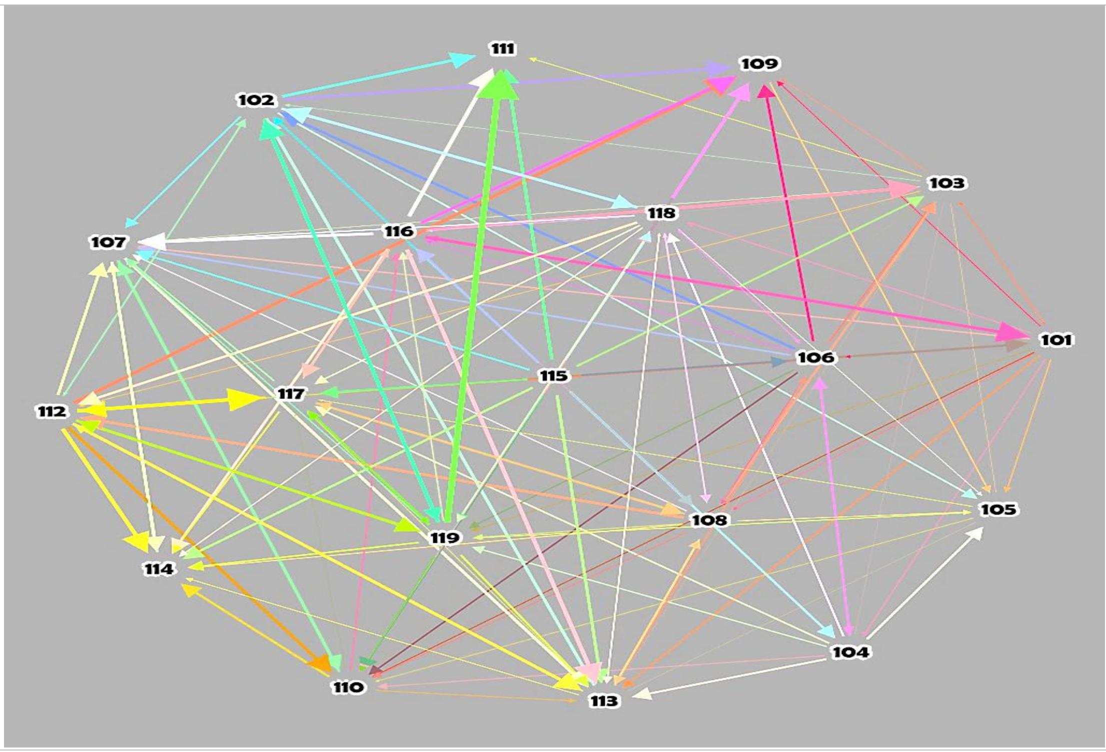
Figure 1: Total Market Share of Each Category



As seen In Figure 1, eleven undertakings are in the first category, whereas four are in the second and third categories. However, it is noteworthy that the undertakings in the first category have a total market share of 32% in the industry, 20% in the second category, and 48% in the third category. In this regard, the third category symbolizes almost half of the total commercial size of the Turkish cement industry.

Indeed, the proposed methodology suggest an economic relation network, mainly because it focuses on all undertakings' bilateral pricing behavior. The network diagram, prepared to show the interactions in this intricate structure, is depicted in Figure 2.

Figure 2: An Interaction Network between Undertakings



Arrows in Figure 2 reveal statistically significant cointegration relationships (adaptation or adjustment) in prices for each player in the industry. As it can be deduced from the number of directional and bi-directional arrows, there is a strong connection between the pricing behaviors of undertakings in the industry on the whole.

In the phase of transforming the proposed method into a cartel screening technique, firstly, a "structural" breaking date is determined based on external information, notice, whistleblowers, abnormal market movements, etc. The second comparative analysis is made according to the chosen date before and after. In this way, the change in the cointegration relations and the level between the normal period and the suspected period can be examined.

For our case, when the average market price and average costs for CEM I 42.5 bulk cement in the Turkish cement sector are held under the microscope for the period being examined, we could clearly observe that the bond between price and cost weakened noticeably by 2013 when average market prices also had started to rise sharply. Figure 3 below provides the average market unit (ton) price (in Turkish Liras or TL) and cost series of CEM I 42.5 bulk cement with a vertical axis placed in 2013.

Figure 3: Average Price and Cost of CEM I 42.5 Bulk Cement, Jan'09-Aug'14 (TRY)

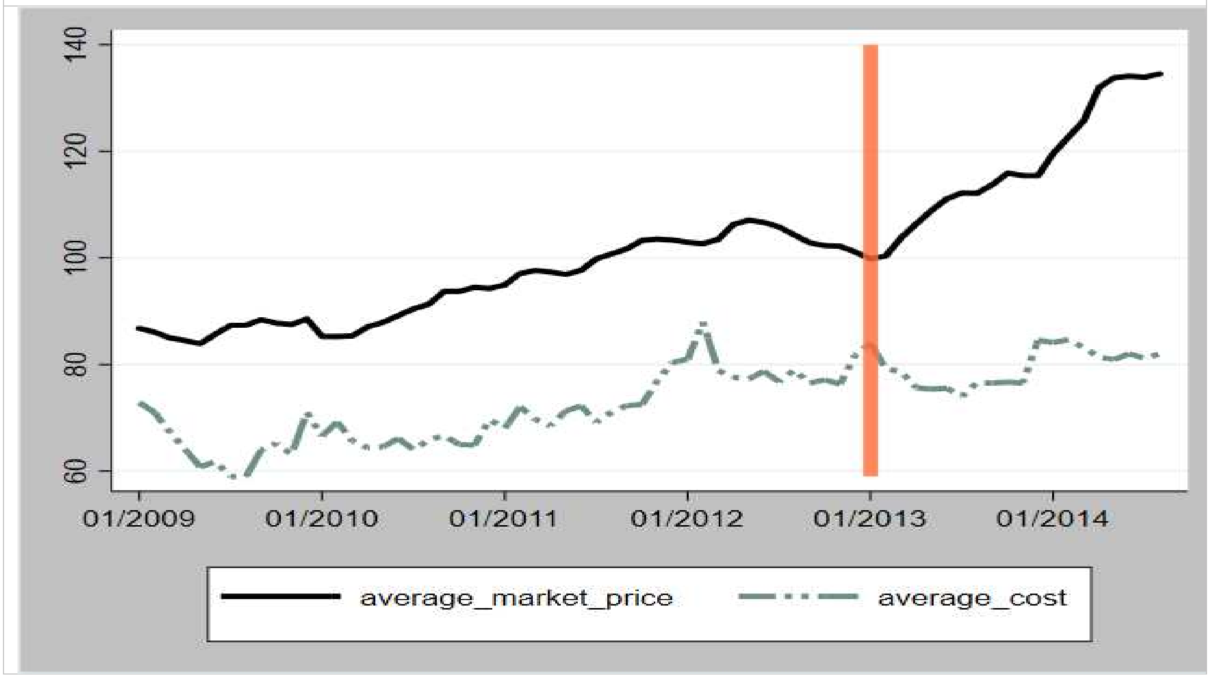


Figure 3 suggests the average price in the industry has soared since January 2013, while the average costs initially have a slight decline, and then for the rest of the period is relatively stagnating. Nevertheless, one might consider whether this price increase could steam from an economic crisis, inflation, or a substantial demand shift in the market. In this point, TCA-CSR enlightens the fact that none of them can adequately elucidate this upward-movement unrelated to costs. Therefore the period after 2013 can be coherently classified as a red-flagged zone.

We implemented our procedure for all combinations of undertakings pair regarding the before and after 2013, and we derived three matrices to illustrate each statistically significant cointegration relation and speed of adjustment coefficient between actual prices of undertakings. The matrices presented in Table 1 and Table 2 are respectively composed of adjustment coefficients belonging to the periods before and after 2013 and their difference.

Table 1: Inverted Adjustment Coefficients for Normal Period (Month)

	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119
101			2.5			3.2		3.3	2.4					4.6				3.8	3.5
102	10.3		6.2	7.2	2.8	7.6			10.1	5.9	8.0	3.6	9.1	7.5	2.5	6.9		6.8	
103	1.9	2.3		1.4	1.2	1.5	2.7	2.2	2.7	1.2		2.3	1.6		2.1	1.8	1.3	1.2	1.1
104			5.2							4.1									
105			1.9														1.3	0.9	1.2
106	4.2		4.5	4.3	1.4		7.3	2.3			4.8		4.9	8.3		1.8	4.4	1.9	2.7
107	4.9	3.3	2.9	4.6	2.5	3.4		4.0	4.8	4.8	4.7		4.9	4.4	3.5	4.2	5.0	3.9	3.9
108	6.3		5.0	2.7		3.1				5.0			6.0	6.0		3.1			
109	2.4				2.3					3.7	4.4	3.6	2.9	3.5	3.9		4.1		
110					1.4	2.3	5.3	2.4	5.6		2.7	6.5	1.7			3.0	1.4	1.7	1.4
111					0.8														
112	6.3	2.9	6.3	5.5		5.0		6.1	6.1	5.7	6.4		5.7	5.7	3.5	5.5	6.3	5.4	5.4
113	4.3	4.1	4.3	4.6	1.7	4.0	4.3	4.4	4.1	2.2	2.4	4.3		3.6	3.8	3.9	2.2	2.7	2.8
114	3.3			3.7				3.1		3.5	3.2	3.0				2.2	3.3	3.2	
115										6.1				8.8			7.6		7.5
116								8.8						5.7					
117	2.7	3.0	2.5	4.0	1.0	2.4	2.5	2.1	2.0		3.1	2.7	2.8	2.0	3.2	2.8		2.2	2.3
118	5.8			1.2	3.5	5.3	4.2	5.5			4.2	6.8	4.2	4.9		3.0	4.3		3.7
119	5.0	6.5	4.9	2.4		2.5	4.6	3.1	5.5		4.3	5.8	4.3	5.4	8.2	2.8	3.8	1.5	

Notes: Figures indicated in the matrices demonstrate the inverse of the absolute value of the cointegration coefficient concerning the multiplication, which is referred to as a speed of adjustment in terms of months.

§

Table 2: Inverted Adjustment Coefficients for Suspected Period (Month)

	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119
101								1.2											
102			1.3	2.1			0.6	3.3	3.3		1.1	0.5			1.4			4.0	
103		0.7			0.7		1.0					1.1		0.5	0.8		0.7		0.7
104																			
105							2.8					2.6							
106		1.6	1.7	1.2			1.7	0.5	0.8	1.4	0.8		1.4		1.6			0.8	1.9
107	2.0			2.2	1.2	2.0			2.1	1.1			1.5	1.6	0.7	1.8		2.0	1.4
108			0.7	0.8			0.9		0.7	1.0	1.4			1.1				0.6	
109	1.0	1.6	1.5	1.2	1.3	0.7	1.3			2.1		1.3	1.5	1.2	1.5		2.0	1.2	
110		1.0			0.5		1.3					1.5	0.8				0.9		
111		2.6								1.6					2.1				
112	3.9			2.3	2.0	2.8	1.1	3.7	3.1		5.2		2.8	2.9	1.3	2.4	1.4	2.4	2.2
113		0.8	1.4	0.9	0.5		0.9			0.4				0.5	0.9	0.6	1.1		0.5
114			1.5	1.0	0.7				0.5	1.0			0.5			0.6			0.9
115				0.8	0.6					0.8						1.2	0.8	1.2	1.1
116		2.5		1.0								2.3	1.2	0.7	1.6				
117					0.6	1.6	0.7	1.4	1.2	0.4		0.9	1.0			1.2		1.4	
118	1.6	2.9		1.3	1.5	0.7			1.1	2.6		4.3	1.3	1.2	2.3	1.2			2.3
119		1.3			0.5		1.2			0.4	2.6	1.5			1.1				

Notes: Figures indicated in the matrices demonstrate the inverse of the absolute value of the cointegration coefficient concerning the multiplication, which is referred to as a speed of adjustment in terms of months.

Table 1 and Table 2 summarize the adjustment durations; i.e., the reciprocals of the coefficients of the error-correction terms, for the normal and suspected periods, respectively. For keeping the relevant relationship insight only, insignificant cases of adjustment are not reported in these tables. As seen in these adjustment durations vary between 0.8 and 10.3 months in Table 1, and between 0.4 and 5.2 months in Table 2. Table 3, then, displays the difference of the durations measured as “suspected minus normal”. Namely, the variation matrix illustrated in Table 3 provides the difference in power of price adjustment for each pair of firm prices considering the transition of the two periods in question. Therefore, positive figures in the table mean statistically significant augmentation of price harmony between firms in the suspected period, which is one can argue that the structural break that occurred may be related to collusion. Forward, there is also an opportunity to bundle firms that have the highest positive difference coefficient that may raise a red flag of anti-competitive behavior and separate them into a more detailed analysis or further investigation.

Table 3: The Variation (Difference) Matrix

	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119
101								2.1											
102			4.9	5.0					6.8		6.9	3.1			1.1			2.8	
103		1.5			0.5		1.7					1.2			1.3		0.6		0.4
104																			
105																			
106			2.8	3.2			5.6	1.8			4.0		3.5					1.1	0.8
107	2.9			2.5	1.4	1.3			2.6	3.7			3.4	2.8	2.8	2.5		2.0	2.6
108			4.3	1.9						3.9				4.9					
109	1.4				1.0					1.6		2.3	1.5	2.3	2.4		2.0		
110					0.9		4.0					5.1	0.9				0.5		
111																			
112	2.4			3.2		2.2		2.4	3.0		1.2		2.9	2.8	2.2	3.1	4.9	3.0	3.3
113		3.3	2.9	3.7	1.2		3.5			1.8				3.1	2.9	3.3	1.1		2.3
114				2.7						2.5						1.6			
115										5.3							6.9		6.4
116														5.0					
117					0.4	0.7	1.8	0.8	0.8			1.8	1.8			1.5		0.8	
118	4.2				2.0	4.6						2.5	2.9	3.7		1.8			1.4
119		5.2					3.4				1.7	4.3			7.1				

Notes: Figures indicated in the matrices demonstrate the inverse of the absolute value of the cointegration coefficient concerning the multiplication, which is referred to as a speed of adjustment in terms of months.

Moreover, we performed this method on the basis of categories and weighted all cumulative adjustment coefficients with turnovers of the undertakings to widen the analysis. Similarly, we could, therefore, extract the variation matrix for each category.

Table 4: Difference between Weighted Speed of Adjustment Coefficients Based on Categories for Before and After 2013 (Days)

	Normal Period			Suspected Period			Difference		
Categories	I	II	III	I	II	III	I	II	III
I	54	66	45	15	18	15	**39**	**48**	**30**
II	78	72	111	24	15	30	**54**	**57**	**81**
III	81	123	54	21	33	12	**60**	**90**	**42**

In Table 4, we present the weighted adjustment durations considering both the time periods (normal and suspected) and the three categories (low-mid scale, mid-scale, and high scale according to their annual turnover size) considered. As can be detected from Table 4, there is a sharp reduction in the adjustment durations, overall. The strongest decline, though, is observed in the price response of the third category which is the price-leader firms of the sector reside in. Similarly, the first and second categories also show the same indications. So, Table 4 is indicative of increasing price adaptation between firms and a possible red flag for anti-competitive behavior considering the suspected timeline.

Out of the seven geographical regions of Turkey, three of them are more dominant in case of competition concerns. These regions are, respectively, Mediterranean, Marmara, and Central Anatolia as TCA-CSR accentuated. This information allows room for adding geographic dimension to our analysis for prioritization and more detailed inquiry. From this point of view, the average adjustment coefficients for these regions before and after 2013 and their difference are calculated and given in Table 5 daily.

Table 5: Difference between Weighted Speed of Adjustment Coefficients Based on Categories with Geographical Dimension for Before and After 2013

	Normal Period	Suspected Period	Difference (Day & Percentage)	
Mediterranean	151	52	99	66%
Marmara	63	23	40	63%
Central Anatolia	80	21	59	74%

Finally, our geographical classification of the adjustment durations (for the Mediterranean, Marmara, and the Central Anatolia regions of Turkey) reveals that the speed of adjustment has substantially increased in the suspected period. In that, in terms of difference by day, the Mediterranean is the conspicuously first area of anti-competitive concerns that may arise. However, if we switch our focus to differences calculated by the percentage, Central Anatolia comes to the center. By this means, the Mediterranean and Central Anatolia can be subject to the further investigations and may become a top priority in the respect of the probability of anti-competitive conduct.

5. Discussion

The development of quantitative techniques in competition law and economics has received considerable attention in recent years since it finds novel ways to improve our understanding of competition in the market and can take the analysis horizon one step further. Cartel screening is one of the prominent areas where these numerical techniques are being used effectively and pro-actively. However, the question of how one designs a functional and flexible screening method using statistics or econometrics is still an important matter of debate. For instance, Abrantes-Metz et al. (2006) and Bolotova et al. (2006) propose a (price) volatility-based methods like standard deviation, variance, and ARCH-GARH, whereas Crede (2019) recommends structural break tests such as OLS-CUSUM and OLS-MUSUM to scan the sector and detect signals may be considered as a red flag that may be related an anti-competitive behaviors. Nevertheless, all methodologies to enhance the optimal screening background has advantages and disadvantages depending on their theoretical/empirical characteristics and adopted perspective.

From the perspective of Abrantes-Metz et al. (2006) and Bolotova et al. (2006), the decrease in price variance with the mean price increase may indicate the presence of a cartel. Nonetheless, in specific situations, especially in the presence of demand/supply shocks and in the price war periods of cartels, the volatility can increase in contrast to expectations. On the other hand, an unexpected structural break in the market may be revealed by a well-configured data (price) generating process could be a key element of cartel screening, as Crede (2019) supports. Although this method may successfully determine an anticompetitive concern or risk in a sector, it can not specify or give a hint at which market players can be part of a cartel or collusion because the analysis is performed for market level although this method may successfully determine an anticompetitive concern or risk in a sector, it can not specify or give a hint at which market players can be part of a cartel or collusion because the analysis is performed for the market level. So, the proposed methodology in this paper tries to derive lessons from these prominent numerical ideas and overcome possible issues with the help of cointegration processes.

The proposed technique's first and most path breaking plus is its division element that provides an opportunity to identify possible colluders concerning bilateral price relations. In this way, one may exclude other undertakings and focus solely on suspected pairs of undertakings. The more certainty ensured it could be easier to zoom in on connections between numbers and actions in the legal processes. In parallel to the structural break test procedure, price equations between undertakings can be modified by objective or subjective factors that correlate with the current situation. The flexibility characteristics of these methods allow eliminating the effect of exogenous (inflation, currency flows, economic crisis, demand/supply, political changes, etc.) and endogenous factors (average cost, average market price.). Moreover, the aim of prioritization can be reached in the case of geographical application of the technique, and it also could be helpful to shed light on sectoral dynamics for informative purposes even if it is applied without a break (for the entire timeline).

In contrast to variance-based cartel screening methodologies, which can serve as a real-time and dynamic approach for determining possible red flags that may be associated with anti-competitive behavior, the cointegration procedure we propose is retrospective. This means that there should be adequate data and time to perform the analysis correctly. Another challenge that may steam from the using cointegration approach for detecting cartels is the need for a correctly designed configuration to estimate prices. The design of the price equations in which cost, demand, competitor price, and other exogenous parameters are included is paramount.

One may also ask about how the cointegration level between two competitors' prices should be interpreted and what is the benchmark of the comparisons. For instance, what level of the cointegration between prices may indicate anti-competitive behavior or vice versa. At this point, focusing on the specific patterns between undertakings and linking up with legal evidence if they exist can be seen as a reasonable solution and needs a case-by-case approach. However, it is not certain whether there is a statistically significant cointegration relationship. Lastly, the choosing process of the breakpoint is a crucial element in questioning the existence of a structural break between bilateral price movements in the market. Hence, other structural break tests such as Bai and Perron and CUSUM can be helpful with the aim of picking the most accurate date unless there is not a suspected foreknown date that can be obtained from dawn raids or leniency programs.

6. Concluding Remarks

In today's world, cartel organizations are more intelligent and complicated than they were in the past. Compliance programs have benefited by enlightening to boundaries of competition law and increasing awareness of undertakings in numerous sectors. Nevertheless, some may presume on this awareness and wield of efficient camouflage for their anti-competitive cooperations instead. At this point, competition economics and its numerical toolbox took on the stage and began showing its potential to all competition law ecosystems. Since legal evidence for anti-competitive behavior is getting hard to find, market outcomes of the anti-competitive behavior on the market are much more difficult to be covered, as Levenstein and Suslow (2006) pointed out.

Economics has numerical techniques that theoretically put forward reasonable suspicion of anti-competitive behavior through these indicators observed in industries and attract attention on a case-by-case basis (Verbach and Franck, 2013, 3). In the current study, the construction of a new econometric technique based on cointegration, which is specific to detect cartels through the pricing behavior of undertakings and which is not directly included in the competition economics literature, and the experimental applications of this technique carried out through real market data.

The developed technique is expected to prepare a numerical understanding on which undertakings or clusters of undertakings in a sector engage in long-term collective pricing behavior that can be associated with a cartel or anti-competitive behavior. In addition, when the designed technique is applied to undertakings in different sectors or regions, it also provides the opportunity to prioritize the size of competitive concerns that price trends can determine.

The proposed econometric procedure differs from other economic methods used in cartel screening, as it allows for making an assessment specific to each undertaking subject to the analysis. However, it has its disadvantages and setbacks stated in the study, like the need for efficient design of price equations and accurate break dates.

For empirically testing the cointegration approach as a cartel screening, one of the most prominent (cement) cartel cases in Turkey was selected. The dataset used in the study also was based on a sector inquiry and related investigation led by the Turkish Competition Authority. The analysis conducted in the study provides solid statistical results right along with parallel assessments made in Turkish Competition Authority's decision and previous sector inquiry about relevant market's dynamics and existing competition concerns.

At the bottomline, the cointegration-based econometric technique designed to analyze the long-term pricing patterns of undertakings from a competition law perspective, and its complementary sub-models, can be an effective numerical method that can be used in various analyzes, especially the detection of new generation cartels that try to lose their traces in today's digitalized world.

References

Abrantes-Metz, R. M. (2014). Recent successes of screens for conspiracies and manipulations: Why are there still sceptics? Antitrust Chronicle, 10(2), 1–17.

Abrantes-Metz, R. M., Froeb, L. M., Geweke, J., & Taylor, C. T. (2006). A variance screen for collusion. International Journal of Industrial Organization, 24(3), 467–486.

Abrantes-Metz, R. M., & Metz, A. D. (2019). The Future of Cartel Deterrence and Detection. Antitrust Chronicle.

Bajari, P., & Ye, L. (2003). Deciding Between Competition and Collusion. The Review of Economics and Statistics, 85(4), 971-989.

Bejger, S. (2012). Cartel in the Indian Cement Industry: An Attempt to Identify It. Economics Discussion Paper No. 2012-18.

Bishop, S., & M. Walker (2010), *Economics of EC Competition Law, Sweet & Maxwell*, London.

Bolotova, Y., Connor, J. M., & Miller, D. J. (2006). The impact of collusion on price behavior: Empirical results from two recent cases. International Journal of Industrial Organization, 26(6), 1290–1307.

Boswijk, P., Schinkel, M. P., & Bun, M. (2016). Cartel dating. Tinbergen Institute Discussion Paper No. 16-092/VII.

Crede, C. J. (2019). A Structural Break Cartel Screen for Dating and Detecting Collusion. Review of Industrial Organization, Vol:54, s.543-574.

Engle, R., & Yoo, B. (1989). Cointegrated Economic Time Series: A Survey with New Results. Working Paper No: 8-89-13.

Engle, R., & Granger, C. (1987). Cointegration and Error Correction: Representation Estimation, and Testing. Econometrica, Vol:55, No:2, s.251-276.

Engle, R., & Granger, C. (1991), Long-Run Economic Relationships: Readings in Cointegration, Oxford University Press, Oxford.

Esposito, F. M., & Ferrero, M. (2006). Variance screens for detecting collusion: An application to two cartel cases in Italy. Mimeo.

Friederiszick, H. W., & Maier-Rigaud, F. (2008). Triggering Inspections Ex-officio: Moving Beyond a Passive EU Cartel Policy. Journal of Competition Law and Economics, Vol:4, No:1, s. 89-113.

Froeb, L., Koyak, R. A., & Werden, G. J. (1993). What is the effect of bid-rigging on prices? Economics Letters, 42(4), 419-423.

Gülen, G. (1996). Is OPEC a Cartel? Evidence from Cointegration and Casuality Tests. The Energy Journal, 17(2), 43-57.

Ginsburg, D. H., & Fraser, E.M. (2010). *The Role of Economic Analysis in Competition Law*. (ed.) I. McEwin, Getting The Balance Right: Intellectual Property, Competition Law and Economics in Asia.

Grout, P. A., & Sonderegger, S. (2005). Predicting Cartels. Office of Fair Trading.

Haug, A. (2002). Temporal Aggregation and the Power of Cointegration Tests: A Monte Carlo Study, Oxford Bulletin of Economics and Statistics, 64(2), 399-412.

Hamilton, J. (2020). *Time Series Analysis*. Princenton University Press.

Harrington, J. (2006). Behavioral Screening and the Detection of Cartels. 11th EU Competition Law and Policy Workshop, Florence.

Harrington, J. (2008). "Detecting Cartel", P. Buccirossi, *Handbook of Antitrust Economics* (p.213-252), MIT Press, London.

Jimenez, J.L., & Perdiguero, J. (2011). Does Rigidity of Prices Hide Collusion. Review of Industrial Organization, 41(3).

Johansen, S., & Juselius, K. (1990). Maximum Likelihood Estimation and Inference on Cointegration – With Applications to the Demand for Money. Oxford Bulletin of Economics and Statistics, 52(2), 169-210.

Kisswani, K.M. (2016). Does OPEC Act as a Cartel? Empirical Investigation of Coordination Behavior. Energy Policy, No:97, s.171-180.

Kurdoglu, B. (2021). The Economic Analysis of Cartels Pricing Behavior: An Empirical Study of One of the Turkish Cartel Case. Competition Journal, 22(1), 6-54.

Levenstein, M. C., & Suslow, V. Y. (2006). What Determines Cartel Success? Journal of Economic Literature, 44, 43-95.

Lütkepohl, H., & Krätzig, M. (2004). *Applied Time Series Econometrics*. New York: Cambridge University Press

OECD (2013). Ex Officio Cartel İnvestigations and The Use of Screens to Detect Cartels. Policy Roundtable.

OECD (2017). Algorithms and Collusion: Competition Policy in the Digital Age.

Ordóñez-de Haro, J. M., & Torres, J. L. (2014). Price hysteresis after antitrust enforcement: Evidence from Spanish food markets. Journal of Competition Law and Economics, 10(1), 217–256.

Pesaran, M.H., Shin, Y. & Smith, R. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. Journal of Applied Econometrics, 3(16), 289-326.

Porter, R.H., & Zona, J.D. (1993). Detection of Bid Rigging in Procurement Auctions. Journal of Political Economy, 101(3), 518-538.

Porter, R.H., & Zona, J.D. (1999). Ohio School Milk Markets: An Analysis of Bidding. The RAND Journal of Economics, 30(2), 263-288.
Silveira, D., Vasconcelos, S. P., Resende, M., & Cajueiro, D. O. (2021). Cartels, Won't Get Fooled Again: A Supervised Machine Learning Approach for Screening Gasoline. Energy Economics, 105(1).
Thráinsson, V. (2012). Market Screening for Collusion by Detecting Structural Breaks in Market Behavior - Dynamic Pricing Model for the Icelandic Gasoline.
Verbach, P. A., & Franck, J-U. (2013). Actions Speak Louder than Words: Econometric Evidence to Target Tacit Collusion in Oligopolistic Markets. University of Munich Discussion Paper No. 2013-8.
Wachs, J., & Kertész, J. (2019). A network approach to cartel detection in public auction markets. Sci. Rep.9.
Wassell, C. S., & Saunders, P.J. (2000). Time Series Evidence on Social Security and Private Saving: The Issue Revisited. Unpublished Manuscript, Central Washington University, Washington.