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Market Share Dynamics as A Collusion Clue: A Look at The European Heavy Vehicle Industry

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ABSTRACT

This article explores how changes in market shares can subtly signal collusive behavior among companies, focusing specifically on the well-known European heavy vehicle cartel. We used economic analysis tools, including methods to spot sudden shifts and changes in market patterns, to see how market shares behaved when competition was healthy versus when companies were secretly colluding. Our findings show that during the cartel's active period, the market experienced unusual stability and deliberate re-distribution of market shares. We also saw what we call "umbrella effects," where companies not part of the cartel actually benefited. These patterns clearly stray from what you'd expect in a truly competitive market and perfectly match what economic theories predict about cartels. Ultimately, this research highlights that analyzing market shares can be a powerful tool for competition authorities. Especially when combined with advanced economic models and machine learning, it can help them uncover and prevent anti-competitive practices, protecting consumers and ensuring fair markets.

Keywords: Cartel detection, market shares, collusion, European heavy vehicle industry, structural breaks, econometric screening, competition policy, umbrella effects.

INTRODUCTION

Cartels, those secret agreements between competitors, are a real problem for our economy, causing significant harm to consumers and making markets less efficient [8]. When companies secretly agree on prices, production levels, or how to divide up customers, they essentially stop competing. This allows them to rake in extra profits, but it comes at the expense of everyone else. The tricky part, though, is actually finding these hidden agreements. Companies involved in cartels are incredibly good at keeping their secrets, using everything from quiet understandings to complex ways of exchanging information, making direct evidence incredibly hard to come by [6, 28]. The situation gets even more complicated in markets where only some companies are part of the secret deal—what we call "partial cartels" or markets with a "competitive fringe." Here, some players are colluding while others are still trying to compete, creating a messy and often confusing market dynamic that's tough to unravel [11, 23, 25, 30, 31, 38].

For a long time, finding cartels mostly relied on direct evidence, like someone blowing the whistle or a company asking for leniency in exchange for information. While these sources are invaluable, they're always a step behind, usually surfacing only after the market has already been significantly damaged. But as collusive tactics become more sophisticated and even use technology to hide, we urgently need smarter, proactive tools. We need ways to spot suspicious market behavior just by looking at the data we can observe [7, 28]. Among the many economic clues available, market shares have long been considered a potentially strong indicator of secret collusion. The idea is simple: in a truly competitive market, how much of the market each company holds is always shifting. It reflects constant rivalry, new ideas, and smart business moves. But if market shares become unusually stable, rigid, or fluctuate in strange ways, it can hint at an underlying agreement among competitors. They might be trying to keep a certain market structure or divide the market in a way that avoids real competition [21]. Such patterns could mean that cartel members are cutting back on production, allowing non-members to gain ground, or that there are explicit agreements among the colluders to share the market.

This article dives deep into how analyzing market share changes can serve as a powerful clue for spotting collusion. We'll draw on real-world insights from the well-known European heavy vehicle sector cartel. This particular case, involving some of the biggest truck manufacturers, is a perfect real-life laboratory because its collusive period is thoroughly documented, and the legal battles that followed brought many details to light. By carefully examining how market shares shifted in this sector, both during competitive times and under the cartel's influence, we aim to provide solid proof for what economic theories predict about market behavior in cartelized markets. What's more, this study also aims to show how this kind of market share analysis can be put into practical use as a smart screening tool. It can significantly boost the ability of competition authorities to find, investigate, and stop anti-competitive agreements. Our contribution here is to help us better understand how unusual market share patterns can become actionable signals for collusion, thereby helping to develop more effective and data-driven ways to spot cartels.

METHODS

To effectively detect collusion by analyzing market share dynamics, we need a comprehensive approach that combines advanced economic screening techniques with a detailed understanding of the specific industry. The basic idea is that when companies collude, their market shares will behave differently than they would in a truly competitive environment. They'll show observable patterns that deviate from normal market fluctuations.

Cartel Screening Methodologies: A Closer Look

The development of "screens for conspiracies" has truly changed how we detect cartels. These methods allow us to find secret collusive activity even when there's no direct, obvious evidence [3]. These screens primarily look for statistical oddities in market data—things that just don't make sense if the market were truly competitive.

One of the fundamental approaches is the "variance screen for collusion" [4]. This screen works on the principle that during periods of collusion, prices might become less volatile because companies are coordinating to keep them high and stable. Applying this same logic to market shares, a variance screen would suggest that secret agreements, especially those involving dividing up the market or setting production limits, could lead to unusual stability or rigidity in companies' market shares. In a competitive market, companies are constantly fighting for customers, which naturally causes market shares to shift and change. But under collusion, companies might quietly or openly agree to maintain their current market share proportions or stick to pre-set quotas. This takes away the incentive for aggressive competition, leading to an unnatural level of stability in market shares compared to a baseline of healthy competition [21]. On the flip side, some collusive strategies, particularly in "partial cartels," might actually lead to more volatility for companies outside the cartel if the cartel tries to control them, or if market shares are secretly reallocated among the cartel members.

Another powerful and widely used tool is the identification of "structural breaks" in time series data [5, 20]. A structural break means there's been a significant, sudden change in how the data is behaving, which can often correspond to when a cartel starts or ends. For example, a company's market share might follow a certain trend and show a certain amount of variation during a competitive period, then suddenly shift to a different trend (perhaps becoming more stable or showing a new growth path for a specific group of companies) during a collusive period, and then shift again after the cartel breaks up. Bai and Perron work on multiple structural change models [5] is particularly relevant here. Their method can automatically find multiple breakpoints within a time series, without needing to know when they happened beforehand. This is incredibly important for finding cartels, because the exact start and end dates of these secret agreements are almost never known in advance. Each breakpoint we find can then be examined as a potential sign of a change in market behavior, like a cartel forming, breaking down, or even changing its strategy significantly [15]. The statistical significance of these breaks, often checked using F-tests or information criteria like BIC, gives us a solid, quantitative reason to believe a market regime has changed.

Beyond these established methods, the field of cartel screening is rapidly evolving, now incorporating machine learning (ML) techniques [7, 27, 32, 42, 43]. ML algorithms are fantastic at processing huge amounts of data and spotting complex, non-linear patterns. This makes them a very promising avenue for more sophisticated cartel detection. These techniques can be "trained" using historical data from known cartel cases and competitive periods to learn the specific characteristics of collusive market behavior. For market shares, ML models could identify subtle correlations, trends, and deviations that traditional economic methods might miss. For instance, they could detect complex patterns of market share "stickiness" or coordinated shifts that strongly suggest hidden agreements, even when there's a lot of noise or other confusing factors in the data. Using ML goes beyond just flagging anomalies; it can potentially predict the likelihood of collusion, offering competition authorities a more proactive way to screen markets.

Market Share Analysis: The Economic Logic

The fundamental reason we can use market shares as a clue for collusion is rooted in how companies' strategic interactions change when they move from competing to colluding.

In a competitive market, companies' market shares are naturally dynamic. They're constantly being influenced by many factors:

- New Ideas and Products: Companies that introduce better or new products can gain market share.
- Pricing Strategies: Aggressive pricing, discounts, or special promotions can cause temporary or lasting shifts in market share.

- Cost Efficiency: Companies that are better at managing their production or distribution costs can offer more competitive prices and grow their market presence.
- Demand Changes: Shifts in what customers prefer, broader economic conditions, or regional demand can alter where companies stand in the market.
- Marketing and Sales: Good advertising, expanding sales networks, or better customer service can help a company get more customers.
- New Entrants and Exits: When new, innovative companies enter the market, or struggling ones leave, market shares naturally rearrange themselves.

However, under collusion, these dynamics change fundamentally. The main goal of a cartel is to reduce competition and maximize their combined profits. This usually means secretly coordinating on how much to produce or how to divide up the market. This coordination can show up in market shares in several ways:

- Market Share Stability or Rigidity: To keep the cartel agreement stable and prevent anyone from cheating, members might openly or quietly agree to maintain their current market share proportions or stick to pre-determined quotas. This reduces the urge for aggressive competition, leading to an unnatural level of stability in market shares compared to a baseline of healthy competition [21].
- Deliberate Re-allocation: In some cartels, especially those dealing with different types of products or operating in different regions, companies might agree to simply divide the market among themselves. This leads to deliberate shifts in market shares that aren't driven by who's better at competing, but by the secret agreement itself [12, 13, 14, 16, 17].
- Incomplete Cartels and the "Competitive Fringe": Many cartels aren't "complete," meaning they don't include every company in the market. The presence of a "competitive fringe" (companies not part of the cartel) creates complex dynamics [11, 23, 25, 30, 31, 38]. When cartel members limit their production and raise prices, they create a "price umbrella." Under this umbrella, companies on the fringe can also raise their prices (though still below the cartel's) while expanding their production and gaining market share [34, 39]. This happens because some customers will switch from the higher-priced cartel members to the relatively cheaper (though still inflated) fringe companies. Cartels might try to control this fringe expansion using various tactics, like "rent-sharing" (bribing fringe companies not to grow too much) or even trying to exclude them from the market. But even these tactics often leave their own observable marks on market shares [33]. Economic theory, as discussed by d'Aspremont et al. [22] and Shaffer [47], generally predicts that this competitive fringe will grow in size when the cartel acts as a price or quantity leader.

Econometric Techniques: How We Applied Them

To make our market share analysis work in practice, we used specific economic modeling techniques:

1. Using Regression to Find Trends and Breaks:

A good starting point for spotting changes in market share dynamics is a simple linear model, like this:

$so_t=\beta_0+\beta_1\delta_t+\epsilon_t$ (Equation 5)

Here, so_t represents the combined market share of the "outsiders" (companies not in the cartel) at a given time t. We calculate this as the ratio of outsider registrations (q_{ot}) to total registrations ($q_{ct}+q_{ot}$). The dummy variable δ_t is set up like this:

$\delta_t=\{0 \text{ if } t\leq k; 1 \text{ if } t>k\}$ (Equation 6)

In this equation, k is our best guess for when the cartel ended (for example, the official date the cartel was terminated). If β_1 turns out to be a statistically significant negative number, it would mean that the outsiders' market share significantly and consistently dropped after the cartel broke up. This would perfectly match the "umbrella effect" theory. We also check for "serial correlation" in the errors (using the Breusch-Godfrey test) and look at a "cumulative sum of residuals" (CUSUM) plot (Figure 3). If the errors tend to be positive during the cartel period and negative afterward, it suggests that our simple model (without the dummy variable) consistently underestimated market share during collusion and overestimated it later. This would imply that outsiders indeed held a larger average market share while the cartel was active.

2. The Bai-Perron Structural Break Test:

To find the exact points where these shifts happened, without guessing beforehand, we used the Bai-Perron algorithm [5]. This method is a more advanced version of the simple dummy variable approach because it can find multiple unknown breakpoints. The model looks like this:

$y_t=\beta_0+\sum_{i=1}^{n}\beta_i D_{it}+\epsilon_t$ (Equation 7)

Here, D_{it} are dummy variables that mark the different segments created by the n breakpoints. The algorithm works by repeatedly searching for the best number and location of these breakpoints, aiming to minimize the "sum of squared residuals" (SSR) or optimize information criteria like the Bayesian Information Criterion (BIC) [5]. The best break date for a single break (k_1) is found by:

$k_1=\arg\min_{k\in[t_L,t_U]}[SSR(k)]$ (Equation 8)

Here, t_L and t_U define the acceptable range for the sample (for instance, we need at least 15% of the data at each end to make sure our estimates are reliable). Finding breakpoints that line up with known or suspected cartel periods gives us strong statistical evidence that market behavior has changed.

3. The Synthetic Control Method:

To make sure our findings were truly due to the cartel and not just other factors (like regional cost changes or new regulations) that might affect market shares, we used a synthetic control approach [1, 2]. This method creates a "synthetic" control group that acts like a stand-in for the market we're studying. This stand-in group closely matches the characteristics of the cartelized market before the cartel broke up, but it wasn't exposed to the cartel's influence.

For our study, the bus market, where no collusion was detected, served as a good control. Truck and bus manufacturers often share many production components, face similar emission regulations, and are affected by the same big economic trends. This makes the bus market a believable comparison. The method works by assigning specific weights (wi) to the output of each company in the bus market. These weights are chosen to make the pre-cartel output patterns of the bus market as similar as possible to those of the truck market:

wi=argminx∈R+||qic−xqib|| (Equation 9)

Here, qij is a vector representing a company i's output in market j before the cartel ended. The synthetic CV market is then built by combining these weighted bus registrations:

Qcs=[w1Q1b…wnQnb] (Equation 10)

By comparing how market shares changed in the real truck market with how they changed in our synthetic control (and the bus market itself), we can isolate the true impact of the cartel breaking up. If the market share changes in the truck market were indeed caused by the cartel, we shouldn't see similar changes in our synthetic control or bus markets.

Data Requirements

To make sure our economic analysis of the European heavy vehicle sector was solid, we needed detailed and complete historical data. Here's what was crucial:

- Monthly Vehicle Registrations: We needed data broken down by manufacturer and vehicle type (medium commercial vehicles weighing 6-16 tons and heavy commercial vehicles over 16 tons). Data from organizations like the European Automobile Manufacturers Association (ACEA) served as a good stand-in for actual sales volumes and were essential for calculating individual company and overall market shares. The data needed to cover a period before, during, and after the alleged cartel (for example, 2001-2017 for the European truck cartel) to allow for strong comparisons and to spot structural breaks.

- Company Information: We had to clearly identify which companies were part of the cartel and which were the "fringe" (non-cartel) members. This required careful cross-referencing with official findings from competition authorities.

- Pricing Data: Even though we didn't use this directly for market share calculations, price data (like gross list prices, discounts, or average revenue per vehicle) provided valuable context and helped confirm if "umbrella pricing" effects were present.

- Industry Context: Information about new companies entering or old ones leaving the market, major technological advancements (like new emission standards), big economic shocks (like financial crises), and relevant regulatory changes (like the introduction of the Euro currency) was vital. These factors can independently affect market shares and needed to be considered as potential confusing variables or to help explain any structural breaks we found.

Some practical challenges in gathering this data included making sure it was consistent across different manufacturers and over time, dealing with any missing data, and accurately categorizing companies into cartel and fringe groups. Using registrations as a stand-in for sales is generally acceptable, though it's important to remember that registrations might lag behind actual sales due to delivery times, especially during busy periods or economic downturns [44].

RESULTS

Our in-depth look at market share dynamics within the European heavy vehicle sector during the period when the cartel was active revealed clear patterns. These patterns strongly matched what economic theories predict about cartels, and they were distinctly different from what you'd expect in a truly competitive market.

The European Truck Cartel: A Quick Overview

The European truck cartel, a major case in antitrust history, involved six of Europe's biggest truck makers: DAF, Daimler, Iveco, MAN, Scania, and Volvo/Renault. This secret price-fixing agreement, which lasted for about a decade and a half (from 1997 to 2011), came to light when MAN decided to cooperate and applied for leniency on September 20, 2010. The cartel's activities covered the entire European Economic Area (EEA) market, focusing on medium (6-16 tons) and heavy (over 16 tons) commercial vehicles [16].

The companies involved secretly exchanged information and coordinated to increase their gross prices at the factory level. This was made easier by the introduction of the Euro currency, which led to harmonized price lists across the EEA for most of them. Cartel members regularly shared price lists, used digital "configurators" (tools for setting vehicle specs and prices), and worked together to reduce discounts. These discussions happened at both their headquarters and, after 2004, at the German subsidiary level [17]. While the European Commission didn't give an exact damage estimate, studies suggest that prices were overcharged by up to 7.6% on individual net prices. This translates to a staggering total damage of approximately €43.4 billion, clearly showing the huge negative impact this cartel had on welfare [18].

Importantly, this cartel wasn't all-inclusive; it faced competition from a "fringe" of American, European, and Asian manufacturers. This made it a perfect case study for understanding "umbrella effects" and how market shares behave in partial cartels.

Market Share Dynamics: What We Saw

Our analysis used monthly vehicle registration data from the European Automobile Manufacturers Association (ACEA) for the years 2001-2017, covering both medium and heavy commercial vehicles. Table 1 gives a quick summary of monthly registrations by manufacturer, clearly separating the former cartel members from the fringe members. It highlights that the cartel included the biggest players in the industry, which fits with theories about incomplete collusion. The fringe members included Japanese manufacturers (grouped together because of how the data was reported), smaller "Other" manufacturers, and companies from Europe (PSA, VW) and the US (GM, Ford).

Table 1: Monthly Vehicle Registrations: Summary Statistics

Firm	Obs.	Mean	Std. Dev.	Min.	Max.
Cartel					
DAF	204	3388	991	1545	9973
MAN	204	4094	1055	1875	10,241
Scania	204	2854	801	1157	6293
Volvo	204	3251	900	1097	7142
Renault	204	2646	789	906	5585
Daimler	204	6288	1374	3532	14,347
Iveco	204	4037	1111	2094	7628
Fringe					
Japanese producers (Honda, Suzuki, Toyota, Nissan, Mazda, Mitsubishi)	204	492	145	270	1193
VW	204	169	60	19	326
PSA	204	30	20	1	126
GM	204	35	39	0	264
Ford	204	67	31	11	214

Other (Daewoo, Hyundai, etc.)	204	732	199	295	1438

Economic Proof of Umbrella Effects and Market Shifts

To thoroughly test whether the cartel's collapse actually caused a drop in non-cartel members' market share, we used a two-step economic analysis.

Step 1: Finding Umbrella Effects (Equation 5)

Our first regression analysis, using Equation (5) with a dummy variable (δt) for the period after the cartel (assuming k=120, the official end date), gave us significant results (Table 2). The estimated coefficient for $\beta 1$ was negative and statistically significant (for example, -0.012*** with a standard error of 0.001). This confirmed that the market share of companies not in the cartel experienced a substantial and lasting reduction after the cartel ended. This finding directly supports the theory that fringe companies lost their "umbrella benefit" once the cartel stopped operating.

Table 2: Regression Estimates (Equation 5)

Coefficients	**(1)**	**(2)**
$\beta 0$	0.055***	0.060***
	(0.001)	(0.001)
$\beta 1$		−0.012***
		(0.001)
R2	0.00	0.304
Obs.	204	204

***p < 0.01, standard errors in parentheses.

Additionally, our analysis of serial correlation and the cumulative sum of residuals (CUSUM) (Figure 3) provided more evidence. The Breusch-Godfrey test strongly rejected the idea that there was no serial correlation, indicating that our simple model (without accounting for the cartel's effect) was missing something important. Figure 3 clearly shows this: the CUSUM of residuals for the model without the dummy variable (the solid line) steadily increased during the cartel period (2001-2010) and then sharply decreased after 2011. This pattern suggests that our model consistently underestimated the outsiders' market share during the collusion and overestimated it afterward. This implies that outsiders did indeed hold a larger average market share while the cartel was active. Adding the dummy variable significantly reduced this auto-correlation, showing that the dummy effectively captured a large part of this structural shift.

Finding Structural Breaks (Equation 7)

To avoid simply assuming when the cartel ended, we used the Bai-Perron structural break test (Equation 7) on the market share data over time. This test automatically finds significant breakpoints. Our analysis showed that the best fit for the data was obtained with four breakpoints (Figure 5, which illustrates how SSR and BIC change with the number of breaks). One of the most important breakpoints we found was September 2010 (Figure 4), which perfectly matches the month when MAN applied for leniency, essentially signaling the beginning of the end for the cartel. This strong alignment provides compelling statistical evidence that the observed shift in market share dynamics was a direct result of the cartel breaking down.

The other three breakpoints we identified were:

1. December 2003: This break might be connected to the slow recovery from the millennium recession. Our data suggests a drop in the combined market share of outsiders around this time, possibly indicating that cartel members

benefited more from the economic rebound, or that the cartel's influence became stronger.

2. March 2008: This breakpoint lines up with the start of the global financial crisis. Interestingly, during this period, the sales of companies outside the cartel seemed more resilient to negative demand shocks, leading to an increase in their combined market share (Figure 2a). This could be explained by the idea of countercyclical collusive pricing, as suggested by Rotemberg and Saloner [46], where cartels might keep prices higher during economic downturns, further benefiting fringe companies.

3. September 2014: This later break indicates a reduction in the fringe's market share. Even though the cartel officially ended earlier, its lingering effects or spirit might have persisted, with prices not immediately returning to fully competitive levels. This could also be influenced by former participants anticipating that post-cartel prices might be used to estimate damages in future lawsuits [30, 19].

Step 2: Proving Cause and Effect with a Control Group

To truly establish that the cartel was the cause of these changes and to rule out other factors (like regional cost changes or tariffs) that might independently affect market shares, we used a synthetic control approach. We chose the bus market as our control group because truck manufacturers also make buses, and both vehicle types share many production components, face similar emission regulations, and are affected by the same big economic trends.

Table 3: Average European Market Shares, 2001-2017

Firm	**Market share (%) (Truck)**	**Market share (%) (Bus)**	**Firm**	**Market share (%) (Truck)**	**Market share (%) (Bus)**
DAF	12.0	1.6	Japan	1.7	0.3
MAN	14.6	9.0	GM	0.3	0.1
Scania	10.1	5.0	Ford	0.3	5.7
Volvo	11.5	7.7	VW	0.6	1.3
Renault	9.4	2.6	PSA	0.4	0.1
Daimler	22.5	30.0	Others*	18.1	2.6
Iveco	14.3	17.9			
Total	**94.4**	**73.8**	**Total**	**26.1**	**5.4**

Source: Own calculations based on ACEA registrations

*Registrations by smaller suppliers are grouped together as "Others" in the ACEA's registrations.

The synthetic control approach (Equations 9 and 10) allowed us to create a "synthetic CV market" as a counterfactual, based on weighted bus registrations. We then applied our regression analysis (Equation 5) to both this synthetic CV market and the actual bus market (Table 4). Crucially, the coefficient for β1 (which represents the change in outsider market share after the "treatment" or cartel's end) was not statistically significant for our synthetic CV control group (0.001 with a standard error of 0.001). For the bus market, it was actually positive (0.021***), suggesting an increase in non-cartel members' market share in that market after the treatment. This stands in stark contrast to the significant negative β1 we saw in the actual CV market.

Table 4: Control Group Regression Estimates

Coefficient	**Synthetic CV**	**Buses**

β0	0.042***	0.253***
	(0.001)	(0.004)
β1	0.001	0.021***
	(0.001)	(0.006)
R2	0.001	0.058
Obs.	204	204

***$p < 0.01$, standard errors in parentheses.

Furthermore, when we ran the Bai-Perron test for structural breaks on the control groups (Table 5), we found similar breaks in 2003 and 2008 (which make sense given economic conditions), but no significant break around September 2010 (when the cartel broke up) in either the synthetic CV or bus market. This strongly confirms that the observed decrease in outsider market share in the CV market was indeed a direct result of the cartel's demise, and not simply due to general differences between companies or other broad market factors.

Table 5: Breakdates

	Break dates				
CV	December 2003	March 2008	September 2010	September 2014	—
Synthetic CV	June 2003	Feb 2006	November 2008	July 2013	January 2012
Bus	June 2003	December 2005	November 2008	January 2012	June 2015

The Scania Case: Testing for Membership with Market Shares

The market share test we developed from this analysis offers a powerful way to figure out if an individual company was part of a cartel. The logic, as first proposed by Blair and Romano [9], is that a cartel member's production (and thus market share) would likely go down during the collusion, while an outsider's would go up. The European truck cartel provided a unique chance to apply this test to Scania, a company that denied its involvement despite being accused by the European Commission.

Table 6: Regression Estimates (Equations 11 and 12)

Coefficients	**(1)**	**(2)**	**(3)**	**(4)**
β0	0.035***	0.039***	0.06***	0.06***
	(0.01)	(0.01)	(0.001)	(0.001)
β1		−0.09***		−0.01***

		(0.01)		(0.001)
R2	0.00	0.43	0.00	0.30
Obs.	204	204	204	204

***p < 0.01, standard errors in parentheses.

Table 7: Individual Break Dates

	Break dates				**SSR**	**BIC**
Scania	December 2004	March 2008	Septembe r 2010	Septembe r 2014	0.32	-682.97
Cartel\Sca nia	December 2003	March 2008	Septembe r 2010	Septembe r 2014	1.05e-02	-1.38e+03
MAN	December 2004	March 2008	Septembe r 2010	Septembe r 2014	0.18	-799.90
DAF	December 2004	March 2008	Septembe r 2010	August 2014	0.30	-698.59
Daimler	Septembe r 2003	January 2008	July 2010	July 2013	0.10	-933.80
Volvo	Septembe r 2003	March 2008	July 2010	Septembe r 2013	0.38	652.11
Renault		February 2009		June 2015	0.40	-661.38
Iveco		January 2009		Septembe r 2014	0.15	-858.27

Putting these analyses together, they strongly contradict Scania's claim of not being involved. The drop in its market share during the collusion period and its subsequent recovery after the cartel broke up are very strong indicators of its role as a cartel member. This market share test is actually considered more robust than a simple output test because it's less affected by general economic cycles (since market shares naturally account for overall market size changes) and because an outsider might not be able to increase its production even if it gains market share due to capacity limits [33].

It's important to note that while our individual structural break tests, showed consistent breakpoints around the cartel's end for most cartel members (Daimler, Volvo, MAN, DAF), some companies like Iveco and Renault showed different patterns. This reminds us that market shares can still fluctuate within a cartel, for example, if the cartel decides to re-distribute production among its members for efficiency reasons. However, a consistent decrease in a company's market share during a period of collusion, especially when the overall market is growing or stable, is a significant "red flag" for participation. An outsider operating under a "price umbrella" would generally be expected to gain, not lose, market share. So, while a cartel member might sometimes "pass" the test (a

Type I error), a truly non-cartel member is highly unlikely to "fail" it (a Type II error). This makes the test a reliable indicator for participation, as seen in Scania's case, where our analysis supported the European Commission's finding of its involvement [35].

DISCUSSION

Our findings from the European heavy vehicle sector case provide strong and clear evidence that market share dynamics are indeed a very valuable "collusion clue." The distinct changes we observed during the cartel's active period—specifically, an unusual stability or deliberate re-distribution of market shares among the colluding companies, along with the appearance of "umbrella effects" that benefited companies outside the cartel—offer powerful indirect proof of coordinated anti-competitive behavior. These patterns aren't random; they perfectly align with what established economic theories predict about how cartels operate, especially in markets dominated by a few large players [29].

Policy Implications: Making Cartel Law Enforcement Stronger

The ability to analyze market shares as a screening tool is incredibly important for competition authorities. It offers practical applications both before a cartel is confirmed (ex-ante) and after (ex-post) in enforcing cartel laws.

Proactive Behavioral Screening: In the early stages of trying to find cartels, unusual market share behavior can act as a critical "red flag." It signals potentially suspicious market conduct that deserves a much closer look. If a group of leading companies in an industry consistently or suddenly sees their combined market share drop, and this can't be explained by normal competitive reasons (like a new competitor, a rival's superior innovation, or significant cost disadvantages), it's a strong sign of collusion. This is because, as our study showed, cartel members typically cut back on production to raise prices, which naturally means they lose market share to their competitive rivals. This kind of pattern can help competition agencies use their limited investigation resources more effectively, directing their attention to industries or companies where collusion is more likely. The fact that market share data is relatively easy to collect, especially compared to finding direct evidence, makes it even more practical as an initial screening tool.

Determining Membership After the Fact: Beyond just initial screening, analyzing market shares can be incredibly useful during the prosecution phase, especially when trying to figure out who was actually part of the cartel and who wasn't. The Scania case perfectly illustrates this. When a seller claims to have been an outsider to a cartel, but their market share patterns (like a drop during the collusion period followed by a recovery after the cartel broke up) don't match what a competitive fringe company would normally do, it puts a significant burden on that company to provide other, legitimate explanations for those patterns. While market share dynamics alone might not be enough to prove collusion in court, they can be compelling enough to strengthen the case for participation, supporting the findings of competition authorities. As we discussed, this test is particularly good at identifying cartel members (meaning it has a low "Type II error" rate), because it's very hard for a genuine outsider operating under a "price umbrella" to explain a sustained loss of market share.

Combining advanced economic techniques like structural break analysis [5, 20] and synthetic control methods [1, 2] significantly boosts the reliability and trustworthiness of market share screens. These methods allow for a more rigorous assessment of whether observed market share patterns are statistically different from what you'd expect in a competitive market, providing a quantitative basis for suspicion. Furthermore, the rapid progress in machine learning applications for cartel detection [7, 27, 32, 42, 43] promises to make these screening capabilities even more refined. ML algorithms can spot even more subtle and complex patterns in market shares that traditional linear models might miss. They can process huge amounts of data and potentially offer predictive insights into collusive behavior, going beyond just finding anomalies.

Limitations and Things to Keep in Mind

While analyzing market shares is incredibly useful, it's really important to remember its limitations and what to watch out for if you're relying solely on it to find cartels.

First, market share stability or rigidity can also happen due to perfectly legitimate business reasons. These include:

- Strong Brand Loyalty: Well-established brands with loyal customers might naturally have stable market shares.
- Unique Products: Companies offering very different products or serving niche markets might face less direct competition, leading to stable market positions.
- Efficient Operations: Companies that are consistently better at producing, managing their supply chain, or distributing their products might naturally maintain or even grow their market share without any collusion.
- Barriers to Entry: High regulatory hurdles or needing a lot of money to start a business can limit new companies from entering, leading to a more stable market structure even without collusion.
- Network Effects: In industries where a product becomes more valuable as more people use it (like social media platforms), dominant companies can naturally have stable, high market shares.

So, market share screens should never be used on their own. They must always be combined with other economic indicators (like price levels, profit margins, and how much production capacity is being used) and a deep understanding of the specific industry's competitive landscape, its history, and any major outside events that might affect it.

Second, the presence of a "competitive fringe" or the formation of "partial cartels" can make interpreting market share data much more complicated [11, 23, 25, 30, 31, 38]. As we discussed, the dynamics in these markets might not be as straightforward as in a cartel where everyone is involved. While we generally expect the fringe to gain market share, the cartel might use clever strategies (like "rent-sharing" or targeting specific competitors) that could hide or change these expected patterns. The exact nature of the secret agreement (e.g., just fixing prices versus dividing up the market or limiting production) also affects how market shares are impacted.

Third, companies might strategically try to manipulate market share data or their activities to avoid being caught. For example, a cartel might deliberately allow some artificial market share fluctuations to make it look like they're competing, or they might engage in "conscious parallelism" where they align their behavior without any explicit agreement, making it harder to prove collusion based solely on market shares. This means we need sophisticated analytical methods that can tell the difference between real underlying collusive behavior and just a superficial attempt to look competitive [26].

Finally, the availability and quality of data can be a practical hurdle. Getting detailed, consistent, and reliable company-level data on sales, production, and market shares over long periods is often tough, especially for private companies or in less transparent markets. Combining data from different sources or dealing with missing information can introduce errors and hide the actual signs of collusion.

CONCLUSION

To sum it all up, the European heavy vehicle sector cartel provides a compelling and rich real-world example that clearly shows how powerful market share dynamics can be in the complex world of finding cartels. The distinct changes we observed during the cartel's active period—like the move towards more stable market shares, deliberate re-distribution, and the "umbrella effects"—offer strong indirect evidence of companies secretly working together against competition. These findings not only confirm long-standing economic theories but also highlight how practical and essential market share analysis is for competition authorities.

As competition authorities around the world continue to face the tough challenge of finding increasingly sophisticated and hidden collusive schemes, constantly improving and refining tools that rely on market shares will be absolutely crucial. When these tools are enhanced with advanced economic modeling (like structural break analysis and synthetic controls) and cutting-edge machine learning, they can significantly boost our ability to identify, investigate, and ultimately stop anti-competitive practices, thereby protecting competitive markets and ensuring consumers get a fair deal.

Looking ahead, future research in this vital area could focus on several key directions:

- More Dynamic Models of Cartel-Fringe Interaction: Developing more sophisticated economic models that explicitly consider the strategic back-and-forth between cartel members and the competitive fringe. This would involve modeling how specific cartel strategies (like pricing, production limits, or trying to exclude competitors) directly influence how fringe companies' market shares respond over time, potentially helping us tell the difference between various types of partial cartels.
- Predicting Across Different Industries: Conducting studies that compare different industries to see how well market share volatility and patterns can predict collusion in various contexts. Different industry structures, product types, and how sensitive demand is to price changes might require different ways of analyzing market shares.
- Combining Multiple Clues: Further research into the best ways to combine market share analysis with other behavioral and structural clues (like how prices move together, profit margins, how much production capacity is used, or bidding patterns) within a single detection framework. This could involve creating combined indicators or advanced statistical models that merge multiple signals to generate more accurate and reliable predictions of collusion.
- Machine Learning for Complex Patterns: Deeper exploration into using advanced machine learning techniques (like deep learning or reinforcement learning) to spot even more subtle and complex market share patterns that indicate collusion, especially in markets with lots of fast-changing data. This could include developing algorithms that can detect "mimicry" or clever collusive strategies designed to avoid simpler detection methods.
- Digitalization's Impact on Market Shares: Investigating how the increasing shift to digital markets and the availability of very detailed online data might change market share dynamics. This would also involve looking at how this affects the effectiveness of current and new market share-based detection tools.

By pursuing these research paths, the field of cartel detection can continue to grow, providing competition authorities with increasingly powerful and nuanced tools to fight anti-competitive behavior in our constantly evolving global economy.

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