Collusion and Price Transmission: Evidence from the German Retail Gasoline Market

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Abstract

I study the effect of collusion on price transmission in the German retail gasoline market. I identify collusive pairs of brands by correlating the brand identity of nearby stations with prices. Comparing the price transmission of collusive stations with non-collusive stations, I find no difference in how they react to either increases or decreases in the crude oil price. This result stands in contrast to a popular theory claiming that gas stations collude by limiting their reactions to decreases in input prices.

1 Introduction

Gasoline makes up a significant share of households' expenditures. Because of the importance of the gasoline price to household budgets, concerns have been raised about the ways in which gas stations exercise market power, including by colluding with rival firms. A frequent concern is that gas stations engage in positive asymmetric price transmission (positive APT), that is, they raise the retail gasoline price faster in response to increases in the crude oil price than they lower it when the crude oil price falls. This phenomenon, labeled *rockets and feathers*, has been shown empirically in multiple gasoline markets.

While this issue has attracted much attention from both scholars and the general public, there is no consensus on what the underlying mechanism or appropriate policy response is. A popular hypothesis holds that the rockets and feathers phenomenon is a way in which gas stations collude with each other. In the absence of the possibility for explicit communication, sellers have incentives to find other means of coordinating on a price higher than that which corresponds to the competitive equilibrium. This *oligopolistic coordination hypothesis* (OCH), using terminology from Borenstein et al. (1997), claims that when input prices decrease, the previous period's competitive price becomes a natural collusive price. The collusive price can then be maintained until one firm deviates or input prices rise.

In this paper, I test a straightforward prediction of this theory: that gas stations which collude with their competitors react slower to decreases in the input price than do

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gas stations which do not collude. This is the first paper in the literature to test directly for an effect of collusion on price transmission. Previous work has been focused on a link between market power and collusion. However, unless the source of market power is collusion between competitors, the OCH makes no claim on what direction such a link would go.

To test the oligopolistic coordination hypothesis, I propose a new method of identifying gas stations that are colluding. My method exploits station-level variation in the brand of neighboring stations and its correlation with retail price. I identify pairs of brands that charge higher prices when their stations are close to each other, and show that this is likely a result of collusion. These gas stations face a coordination problem in charging a price above the competitive one, and limiting the reaction to decreases in input prices constitutes one method of doing so.

I run the tests on data from German gasoline stations over a two year period starting in 2014 and ending in 2016. I find that stations with coordinated market power display the same price transmission dynamics as other stations, undermining the oligopolistic coordination hypothesis.

The next section summarizes related literature. Section 3 provides the relevant market background. Section 4 gives an overview of the data sets I use, along with descriptive statistics. Section 5 presents the method I use for identifying collusive stations. In section 6, I describe the econometric techniques used to estimate the price transmission dynamics. Section 7 discusses the theoretical predictions of the oligopolistic coordination hypothesis. Section 8 presents the results. Section 9 offers a brief discussion and conclusion.

2 Related Literature

The literature on asymmetric responses to cost shocks in the retail gasoline market goes back at least to Karrenbrock (1991), who rejected the null hypothesis of symmetric responses by gasoline retailers to the price of wholesale gasoline.

Since then, there has been a flurry of academic papers analyzing possible asymmetries in the response of gasoline prices to changes in wholesale and crude oil prices. Notably, Borenstein et al. (1997) finds an asymmetric response of both wholesale gasoline prices to crude oil prices and of retail gasoline prices to wholesale prices. The authors put forward three hypotheses as to what underlying mechanisms could explain the patterns observed. The first one of these is what they refer to as the oligopolistic coordination theory. According to this theory, similar to the seminal work of Green and Porter (1984), gas stations move between phases characterized by collusion and competition. A fall in the input price may produce an opportunity to enter a collusive equilibrium where the price that was the competitive equilibrium price in the previous period becomes the collusive price in the current period. In this paper, I refer to the hypothesis that this is a mechanism through which operators of gas stations tacitly collude *the oligopolistic coordination hypothesis.* This paper aims to contribute to the body of work testing this hypothesis empirically.

The two additional hypotheses presented by Borenstein et al. (1997) involve (1) asymmetries in the cost of inventory adjustments arising from the constraint that inventories cannot be negative and (2) asymmetrical incentives for consumers to engage in costly search for better prices when the price at one station rises compared to when it falls.

Other researchers have proposed alternative, sometimes related mechanisms by which this positive APT may arise.

Two important contributions of theories which, similarly to the third one of Borenstein et al. (1997), rely on consumer search costs were made by Tappata (2009) and Yang and Ye (2008). These two papers present distinct models of price competition between firms where consumers have imperfect information about the prices charged by sellers. In equilibrium, a consumer's incentives to search is different in the case where they observe rising prices compared to the case where they observe falling prices. As a consequence, firms will react asymmetrically to input price increases compared to decreases.

Different mechanisms behind APT have different policy implications. For this reason, an empirical literature has emerged which attempts to test the differing empirical predictions of the different mechanisms.

Several authors have investigated a link between market power and price transmission. These papers posit that since collusion is a source of market power, a link between market power and asymmetric price transmission suggests that collusion is the underlying cause of the rockets and feathers phenomenon. A weakness in these papers, which this paper attempts to correct for, is that the sources of market power investigated are typically unrelated to collusion.

The typical approach to testing for a link between market power and price transmission has been to use an error correction model to estimate the cumulative response function of how a change in the input price affects the output price over time. In many papers, the response to a positive cost shock and a negative one is estimated separately, and the difference is compared across stations with different degrees of market power.

Deltas (2008) uses US data to show that markets where the wholesale-retailer margin is higher exhibit greater positive APT.

Balmaceda and Soruco (2008) undertake a similar analysis using Chilean data and obtains result in the same direction but fail to reject the null hypothesis of no difference in APT between high margin and low margin stations.

Loy et al. (2018) investigate the same question as above with data from Austria. The authors find mixed evidence on the effect of local market power on the asymmetry of price transmission, with different measures of local market power having opposite effect on the asymmetry.

Oladunjoye (2008) asks a similar research question in the context of the US wholesale gasoline market. The author finds mixed results on the effect of market concentration on the asymmetry of the response of wholesale gasoline prices to crude oil price shocks.

Verlinda (2008) uses data on wholesale gasoline prices and gasoline prices from Southern California. The author investigates the hypothesis that local market power impacts the asymmetry of price transmission by interacting station-level characteristics with the lagged cost variables and autoregressive terms in an error correction model.

In a meta-analysis, Perdiguero-Garcia (2013), concludes that more competitive segments of gasoline markets tend to exhibit less price asymmetry.

While this literature has seen various contributions, no paper to date makes the crucial distinction between collusive and non-collusive sources of market power. Although the oligopolistic coordination hypothesis does predict a link between market power and APT, the link is specifically for collusion. For example, the theory makes no straightforward prediction about how the number of competing stations should affect APT, still most of the contributions listed above perform tests similar to this.

The main contribution of my paper is leveraging data on the geographical location and brand of stations to test specifically whether pricing patterns indicative of collusion are associated with limited responses to decreases in crude oil prices. My methodology in this paper most closely resembles that of Verlinda (2008).

While different in methodology, Bulutay et al. (2021) asks a similar research question to what I do in this paper. The authors perform a laboratory experiment where participants play a repeated oligopoly game with varying costs. Deviations from the Nash equilibrium prices were found to increase following negative cost shocks, consistent with tacit collusion as a driver of positive APT.

This paper also relates to a vast literature on competition and collusion between gasoline stations. Borenstein and Shepard (1996) find that margins appear to increase when demand is expected to increase, a finding which is consistent with tacit collusion. Slade (1987) tests empirically for collusion in the Vancouver gasoline market. Byrne and De Roos (2019) document how gas stations in Perth, Australia learn to coordinate with each other over time.

3 Market Background

In this section, I will list three characteristics of the German gasoline market that potentially differentiate it from other gasoline markets. These factors may impact the degree to which the results presented in this paper are likely to extend to other markets.

3.1 Price Transparency

Germany has had a policy of fuel price transparency since 2013. Gas stations are required to report their prices of the prices of three fuel types to the Market Transparency Unit for Fuel Prices (Markttransparenzstelle für Kraftstoffpreise), which then shares the prices with third party data providers for integration into consumer facing products such as GPS systems. This policy was implemented with the aim to reduce consumer search costs and boost price competition between stations.

This price transparency has multiple implications for this paper. First, my analysis uses price data that was available due to this policy. Second, all results presented in this paper are from a market characterized by a high degree of price transparency. Because popular hypotheses alternative to the oligopolistic coordination hypothesis rely on costly consumer search, the dynamics of price transmission may well be different in the German gasoline market compared to markets characterized by lower price transparency. Moreover, the policy not only makes it easier for consumers to find information about prices but also for gas stations to find the prices of rival gas stations. This may facilitate collusion as the time it takes to detect a deviation from collusion is shorter. To the extent that the transparency facilitates collusion, the results in this paper will reveal whether the collusion occurs through asymmetric price adjustments.

Frondel et al. (2020) investigated how the asymmetry of price transmission for gas stations in Germany differed before and after this policy was implemented. They found that while the price transmission asymmetry was positive before price transparency (consistent with rockets and feathers), it was negative after. The authors note that if the difference is due to the increased market transparency, then this is evidence in favor of the search cost hypothesis and proof of the benefits of increasing market transparency. On the other hand, Asane-Otoo and Schneider (2015) find negative APT between 2009-2013 and Asane-Otoo and Dannemann (2022) find positive APT between 2014-2018.

3.2 Algorithmic Pricing

Another aspect of the German retail gasoline market worth noting is that algorithmic price setting has been commonplace in recent years. Assad et al. (2024) show that this has led to higher prices through increased collusion. The price data in this paper ends before almost any stations had adopted algorithmic pricing according to Assad et al. (2024). For this reason, the collusion observed in this sample is not likely driven by algorithmic pricing.

3.3 Price Matching Guarantee

In 2015, Shell, the second-largest gas station operator in Germany, introduced a price matching guarantee for card-carrying members, promising to match the lowest prices from a set of nearby stations. The set was usually defined as the 10 nearest stations for Shell stations that are not on the highway and the four nearest stations for stations that are on the highway. Some exceptions were made for unbranded stations and other Shell stations. Cabral et al. (2021) show how this led to higher prices by facilitating collusion. While the policy appears to have had an impact on both coordinated market power and may also have had an impact on the dynamics of price transmission, this is not a potential source of bias for my estimation, but rather a potential mechanism through which the coordinated oligopoly hypothesis may operate.

4 Data

4.1 Primary Data Set

As mentioned in the previous section, my primary data set exists due to a policy by which all German gas stations have to report their prices in real time to a government body. I obtained historical data on all price changes of E5, a fuel that consists of 95% gasoline and 5% ethanol, occurring between June 8, 2014 and May 2, 2016 from Tankerkönig, a third party provider of this data.

The dataset consists of a list of all gas stations in Germany that were active during this time, complete with geographical coordinates, brand and other characteristics. Moreover, the data contains a complete list of all price changes that occurred during the period of study, including station identifier, date, time and the updated prices for E5, E10 and Diesel.

I remove observations corresponding to gas stations whose geographical coordinates are unavailable and price updates that are unreasonably high or low, keeping only prices between 0.01 and 10 Euros per liter.

Because my research question requires daily prices at the station level, I calculate daily time-weighted mean prices, assuming each station operates between 7 AM and 9 PM. This assumption is in line with what Assad et al. (2024) use in their analysis. I also remove daily mean prices at least five interquartile ranges from the daily median.

4.2 Population Density

Because population density is an important determinant of demand, I obtain population data from the German Statistical Authority (Statistisches Bundesamt). This data contains counts of the number of inhabitants in each square kilometer of Germany in 2021. While not overlapping perfectly in time with the price sample, I deem that the population distribution of Germany was likely similar enough in 2014-2016 to 2021 that this variable constitutes a useful regressor in the pricing function.

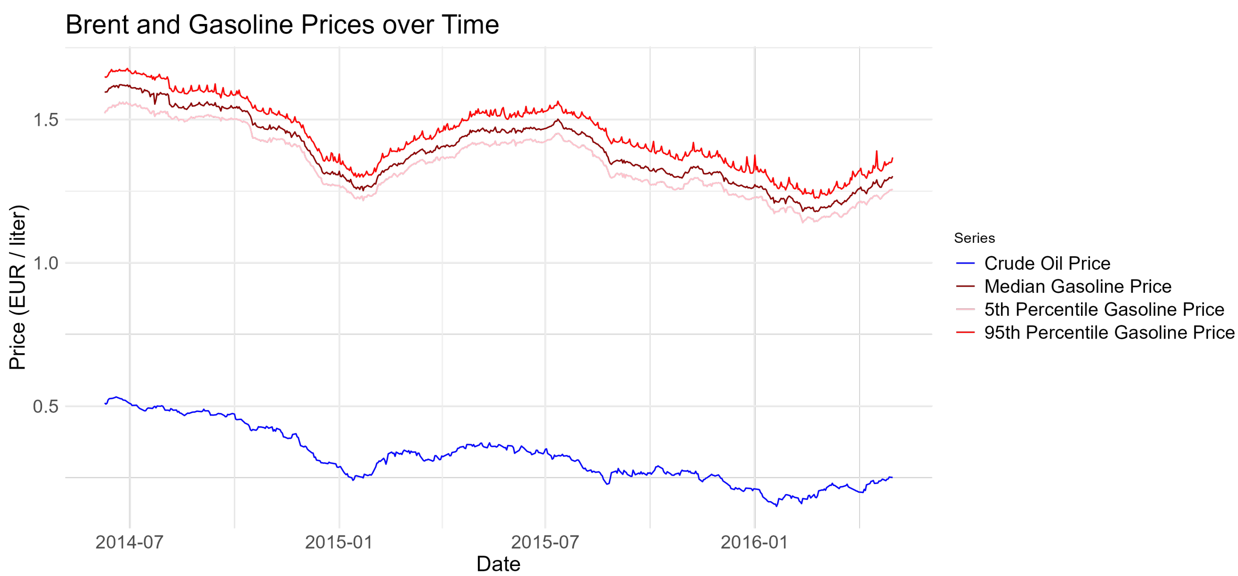
4.3 Input Prices

As a proxy for input prices, I obtain historical spot prices of Brent crude oil, the most commonly used commodity benchmark for oil in Europe, from the US Energy Information Agency. I also obtain historical EUR-USD exchange rates from the European Central Bank to calculate the oil prices in the same currency as gasoline prices.

Because the commodity spot market is not open on weekends and public holidays, I infer these assuming linear trends between the nearest trading days before and after.

4.4 Descriptive Statistics

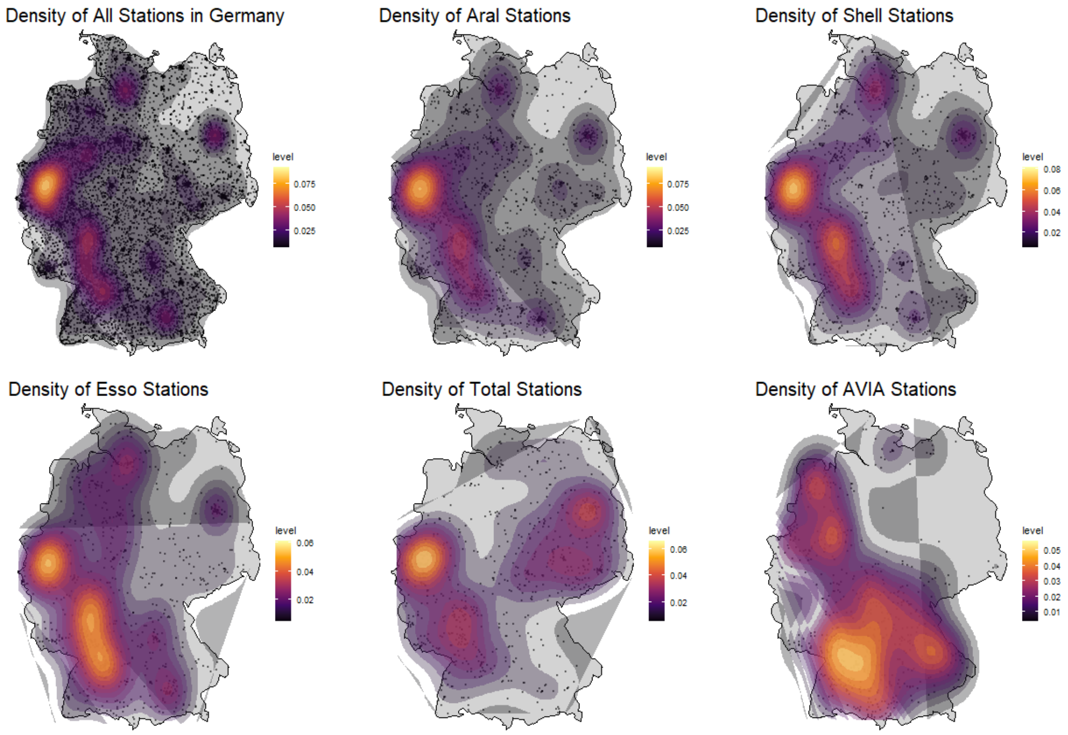
Below is a graph displaying the development of Brent crude oil prices as well as 5th, 50th and 95th percentile retail gasoline prices. The broad movements in the crude oil price are reflected in movements in the gasoline price. The sample contains both increases and decreases in the Brent crude oil price, and corresponding responses in the gasoline price. Over the whole sample, the price of Brent crude decreased from about 0.5 Euros per liter to about 0.25 Euros per liter.



The sample contains 14,706 gas stations. The five brands that operate the greatest number of stations are listed below, collectively making up 46% of all gas stations in Germany. These five brands will be the subject of particular attention in this paper, owing to their large market shares.

Brand	Number	Percentage
Aral	2329	16%
Shell	1783	12%
Esso	1047	7%
Total	867	6%
AVIA	734	5%

There is significant overlap in the geographical areas in which these brands have stations, with the clearest exception being that AVIA have no stations in Berlin and its surrounding areas.



5 Identification of Collusion

This paper uses a broad definition of the term collusion. The definition used is that a gas station colludes with another if the two stations are not jointly owned and it sets prices with some regard to the other stations demand. It is well known that repeated interactions between producers may lead to such behavior. Because the largest brands of gas stations repeatedly interact with one another not only across time but over multiple locations, I focus my analysis on how the pricing behavior of stations belonging to these brands varies with the brand identity of nearby stations.

My analysis of this question consists of two approaches, labeled the cross-sectional and the panel approach. The cross sectional approach has significantly higher statistical power in identifying collusion between particular pairs of brands. The panel approach investigates changes in prices after nearby openings. This approach has lower statistical power, but the benefit of implicitly controlling for a broader set of geographical covariates.

5.1 Cross-Sectional Approach

In the retail gasoline market, gas stations compete with physically proximal gas stations primarily along the dimension of price. Assume that each gas station sets prices as if it maximizes a weighted sum of gas station profits. In a competitive benchmark, each station puts a positive weight on its own profits and a zero weight on all other gas station's profits. Relative to this benchmark, positive weights on other stations' profits will lead to higher prices. By my definition of collusion, such positive weights could only appear from two sources:

- Joint ownership of stations. I label the market power that results from this joint ownership as *unilateral market power*.
- Collusion between gas stations.

This section will proceed by first showing evidence of the unilateral market power, then of the collusion.

To test whether gas stations on aggregate exercise unilateral market power, I regress the log of retail prices on a dummy variable, indicating whether the station shares brand identity with its nearest other gas station, and a rich set of controls:

$$\ln p^R_{ibt} = \beta \mathbb{I}(\text{Brand of Nearest Station}_i = b) + \gamma \mathbf{X}_{ibt} + \alpha_b + \alpha_t + \epsilon_{ibt} \tag{1}$$

If the set of controls is sufficiently rich, then the coefficient β will capture the causal effect of changing the brand identity of station i 's nearest station from a random other brand, to the same brand as station i. This claim relies on the assumption that any factor which affects the probability of sharing brand identity with the nearest station and is also correlated with prices is likely observable and can be included in the vector of controls, $\mathbf{X}_{ibt}$.

The set of controls that I include in $\mathbf{X}_{ibt}$ are: The number of stations within a 5, 10, and 15 kilometer radius, respectively, the number of inhabitants within a 5, 10 and 15 kilometer radius, respectively, in 2021, as well as these population density measures squared, the number of gas stations per million inhabitants in a 10 kilometer radius and a dummy variable of whether the nearest station is less than 50 meters away. α_b is brand fixed effects and α_t is date fixed effects. Standard errors are clustered at the brand and date levels.

The regressor of interest, $\mathbb{I}(\text{Brand of Nearest Station}_i = b)$, requires a distance metric to be well-defined. I propose three possible metrics and present a method for determining the most appropriate one to use. The three metrics are:

- The linear geographical distance, calculated using the Haversine formula and station coordinates.
- The distance of the shortest driving route, as given by the Open Source Routing Machine (OSMR).
- The duration of the shortest driving route, also given by the OSMR.

The procedure I use to determine which measure is more appropriate to use in this case is to test which measure most strongly determine higher prices. Since theory predicts that gas stations should charge higher prices when the nearest station belongs to the same owner, and gas stations with the brand identity at least in some cases share ownership, the coefficient on β in the regression below should be positive.

Table 1: Effect on Log Price of Having the Nearest Station Belong to Same Brand

	Dependent variable:			
	$\ln p^R_{ibt}$			
	(1)	(2)	(3)	(4)
Same Brand as Nearest, Linear Distance	0.005***			0.007***
	(0.001)			(0.002)
Same Brand as Nearest, Driving Distance		0.002***		−0.003**
		(0.0005)		(0.001)
Same Brand as Nearest, Driving Duration			0.002***	0.001
			(0.001)	(0.001)
Controls, Date FE & Brand FE	✓	✓	✓	✓
R^2	0.95473	0.95458	0.95459	0.95476
Observations	9126830	9126830	9126830	9126830

Note: *p<0.1; **p<0.05; ***p<0.0
Standard errors are clustered at the date and brand level

The results above indicate that the linear distance determines the cross price elasticity between two stations. This measure has the greatest coefficient and R^2 when it is used alone and it is the only measure associated with a positive significant price effect when the others are included. Because of these results, I will only use the linear distance in the remainder of the paper.

In addition to determining the appropriate distance metric, the table above reveals that on average, having the nearest station belong to the same brand leads to prices that are approximately 0.5% higher.

While local market concentration has a positive effect on prices on average, it may not be true that ownership correlates perfectly with brand. For example, there may be some brands that operate as franchises that give the individual station owners the control over prices, and all gas station profits, after paying a franchise fee. If this is true, two stations of such a brand may compete as fiercely with one another as if they belonged to different brands.

I choose not to focus on the particular legal organization of each brand, as this may reflect neither the level at which price setting occurs nor the objective function that prices seek to maximize. Moreover, Assad et al. (2024) highlight the difficulty in obtaining information about how German gas stations set prices in practice. A research assistant of the authors called 20 gas stations to ask them about their pricing, but abandoned the exercise thereafter when almost none gave informative answers.

Rather, I take an empirical approach to identify whether prices of one station are set with account for the effect on the demand of other stations of the same brand. For each of the five brands with the most stations, I run the a regression equivalent to the previous one, with only the sub-sample of stations belonging to that brand:

$$\ln p^R_{ibt} = \beta_b \mathbb{I}(\text{Brand of Nearest Station}_i = b) + \gamma \mathbf{X}_{ibt} + \alpha_t + \epsilon_{ibt} \tag{2}$$

Table 2: Effect on Log Price of Having the Nearest Station Belong to Same Brand, by Brand

	Dependent variable:				
	$\ln p^R_{ibt}$				
	Aral	Shell	Esso	Total	AVIA
	(1)	(2)	(3)	(4)	(5)
Same Brand as Nearest, Linear Distance	0.007***	0.007***	0.001	0.012***	−0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Controls & Date Fixed Effects	✓	✓	✓	✓	✓
Observations	1591715	1215444	716339	587108	472085
Note:	*p<0.1; **p<0.05; ***p<0.01				
	Standard errors are clustered at the date and station levels				

The null hypothesis of $\beta_b = 0$ is rejected for Aral, Shell and Total, while not rejected for Esso or AVIA. This result indicates that over the sample period, Aral, Shell and Total set fuel prices to maximize the sum of brand profits, while stations belonging to Esso and AVIA set prices to maximize the profits of each station individually. Total stations appear to be raise prices more when the nearest station is another Total station than Aral or Esso stations do in the same scenario. While this difference could be due to parameter uncertainty, it may also be due to Total's greater presence in former East Germany, which has lower population density and possibly different demand characteristics.

Next, I use an analogous method to identify collusion. For a pair of brands $a, b \in B = \{\text{Aral}, \text{Shell}, \text{Total}\}$, the brand-pair coefficients will be defined as:

$$\begin{aligned} &\mathbb{E}\big[\ln p^R_{ibt} | \text{Brand of Nearest Station}_i = a\big] - \\ &\mathbb{E}\big[\ln p^R_{ibt} | \text{Brand of Nearest Station}_i \notin B\big] = \beta_{ba} > 0 \end{aligned} \tag{3}$$

The parameters β_{ba} are identified with OLS in the regressions below, ran separately for the subset of stations belonging to each brand $b \in B = \{\text{Aral}, \text{Shell}, \text{Total}\}$:

$$\ln p^R_{ibt} = \sum_{a \in B} \beta_{ba} \mathbb{I}(\text{Brand of Nearest Station}_i = a) + \gamma \mathbf{X}_{ibt} + \alpha_t + \epsilon_{ibt} \tag{4}$$

Conditional on the same exogeneity assumptions as before, $\beta_{ba} > 0$ is only possible if gas stations of brand b puts a positive weight on the profits of stations of brand a, which is the definition of collusion used.

Table 3: Effect on Log Price of Having the Nearest Station Belong to Different Brands

	Dependent variable:		
	$\ln p^R_{ibt}$		
	Aral	Shell	Total
	(1)	(2)	(3)
Nearest Station Brand Aral	0.008***	0.006***	0.003***
	(0.001)	(0.001)	(0.001)
Nearest Station Brand Shell	0.006***	0.009***	0.003***
	(0.001)	(0.002)	(0.001)
Nearest Station Brand Total	0.001	0.007***	0.013***
	(0.001)	(0.002)	(0.002)
Controls & Date Fixed Effects	✓	✓	✓
Observations	1543666	1180771	574029

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at the date and station levels

The table reveals that five of the six ordered pairs of brands can be considered collusive according to the definition above. Moreover, for every pair $b, a \in B$ such that $b \neq a$, $0 < \hat{\beta}_{ba}$ and $\hat{\beta}_{ba} < \hat{\beta}_{bb}$. In other words, all estimates are positive and the diagonal elements are greater than the off-diagonal elements. This indicates that collusive pairs of brands, while able to raise prices, are not able to raise price by as much as they would under joint ownership. This is consistent with imperfect coordination between colluding brands, as would be, for example, in a model in the style of Green and Porter (1984), where pairs of brands alternate between collusion and price wars.

It is reasonable to expect that collusion would be symmetric. Brand b should collude with brand a as much as brand a colludes with brand b. In the table above, collusion appears not perfectly symmetric. While Aral and Shell collude symmetrically with one another, both pairs which include Total appear to collude asymmetrically. A plausible reason for this asymmetry is that brands observe imperfectly how much another brand colludes with them. This could explain both the asymmetry and the imperfect nature of the collusion observed.

5.2 Panel Approach

A valid concern about the cross-sectional approach presented above is that there are unobserved geographical factors that affect both prices and the distribution of brands of stations. To complement this approach, I employ a difference-in-difference design to investigate how prices of one gas station change after a nearby station opens, and how the change depends on the brand of the opened station. The strength of this approach is that unobserved geographical factors are implicitly controlled for. The main weaknesses of this approach relative to the cross-sectional approach are twofold: First, it is possible that the opening of a nearby station correlates with changes in costs or demand beyond the direct competitive effect that the estimation attempts to capture. For example, the gas station might open around the time when there is expected to be a surge in demand. To the extent that this is true, it is likely to bias the estimates upward. Second, this approach has far lower statistical power than the cross-sectional approach as the ratio of openings to total stations is low.

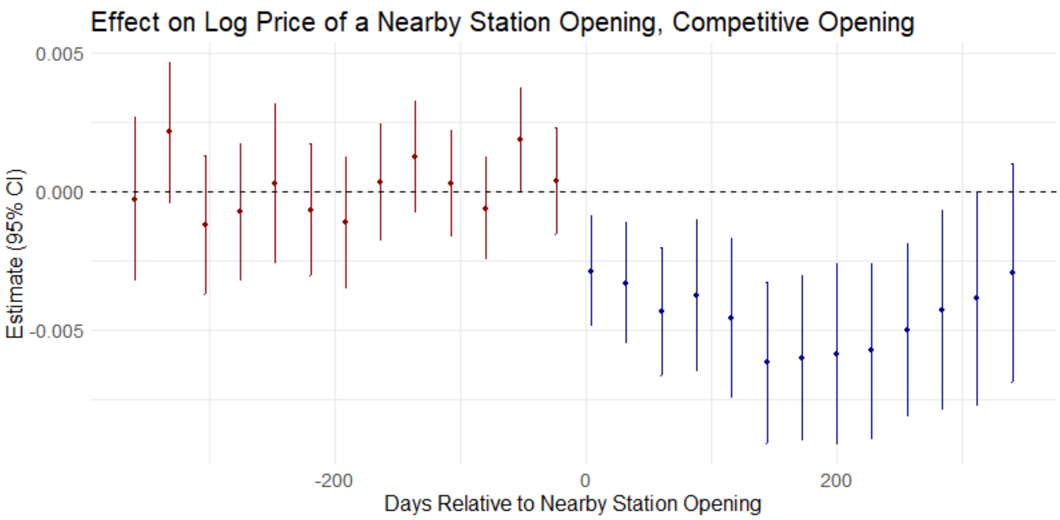
To measure openings, I assume that if a gas station's first price change occurs at least 12 weeks after the beginning of the sample, then that gas station opened at that time. For computational tractability, I limit the sample to daily prices every fourth Monday. I use the difference-in-difference estimator presented in Callaway and Sant'Anna (2021) and run the procedure separately for three different categories of stations defined by the brand of the station and the nearby station that opens, as the main question of interest is whether the brand combination impacts prices.

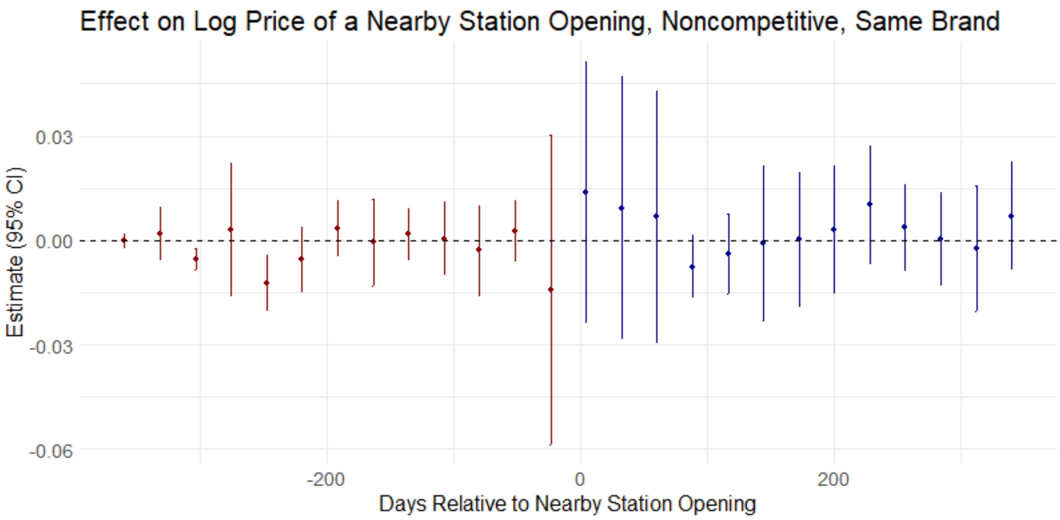
- **Competitive Openings:** Stations that do not belong to either of the other two categories presented below.
- **Noncompetitive, Same Brand:** Stations that belong to one of the brands Aral, Shell or Total and the station that opens belongs to the same brand.
- **Noncompetitive, Collusive:** Stations that belong a brand b whose nearby opening belongs to brand a such that in table 5.1, the coefficient β_{ba} is positive and significant at at least the 5% level and $a \neq b$.

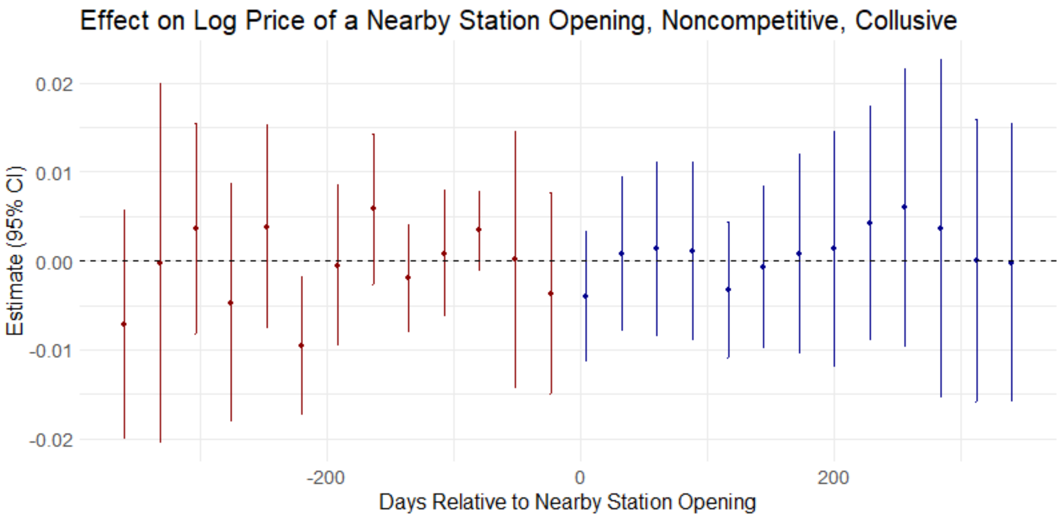
Below I detail the frequencies of nearby openings in each category, along with the frequency of nearby closings, defined analogously. The low number of openings associated with a particular brand pair highlights why this approach is limited in its capacity to estimate whether a particular pair of brands is collusive. Rather, this exercise should be thought of as a validation exercise for the cross-sectional methodology. Similarly, I document the low number of closings to justify my decision of considering only the effect of openings.

	Number of Events
Competitive	719
Noncompetitive, Same Brand	8
Noncompetitive, Collusive	21
Total Number of Nearby Openings	748
Total Number of Nearby Closings	15

Below, I present the event study estimates for openings in each of the three categories, along with aggregated ATT estimates.







Category of Opening	Competitive	Same Brand	Collusive
ATT Estimate	-0.00436	0.00387	0
Std. Error	(8e-04)	(0.00476)	(0.00343)
95% Confidence Interval	[-0.00592, -0.0028]	[-0.00547, 0.01321]	[-0.00674, 0.00673]

The competitive openings show a pattern of a reduction in prices following a nearby opening, consistent with reasonable priors. The magnitude of the price decline is approximately 0.44% and statistically significant.

The non-competitive openings produce noisier estimates, as would be expected with smaller sample sizes. The pre-trends appear less convincingly constant compared to that of the competitive openings. Taking the estimates at face value, there is no indication of a decline after an opening in either noncompetitive case, and neither is statistically significantly different from zero.

The evidence above indicates that the effect of a nearby station opening on prices is dependant on the brand pairing of the new station and the stations around it. In particular, it bolsters the hypothesis that the five ordered pairs of brands that were identified as collusive by the cross sectional section approach indeed do take into account the effect of its prices on each others' demand.

6 Estimation of Price Transmission

The standard approach to estimating price transmission in the literature is with an *error correction model*. The model is chosen for its flexibility in accommodating for a broad set of price transmission patterns. In the regression equation, changes in the retail price of gasoline depend on three terms: (1) current and lagged changes in the input price, (2) lagged changes in the gasoline prices, and (3) deviation from the long run equilibrium price. These three sets of regressors are denoted in the regression equation below:

$$\Delta p_{i,t}^{R} = \tau_i + \underbrace{\sum_{j=0}^{n} \beta_j \Delta p_{t-j}^{CO}}_{(1)} + \underbrace{\sum_{j=1}^{n} \gamma_j \Delta p_{i,t-j}^{R}}_{(2)} + \underbrace{\lambda(p_{i,t-1}^{R} - \phi p_{t-1}^{CO})}_{(3)} + \varepsilon_{i,t} \tag{5}$$

Where $p_{i,t}^{R}$ denotes station i's retail gasoline price on day t and p_t^{CO} denotes the price of crude oil that day. Δ is the first differences operator, such that $\Delta p_t^X = p_t^X - p_{t-1}^X$. In practice, part (3) of the right hand side is implemented by including $p_{i,t-1}^{R}$ and p_{t-1}^{CO} as regressors. To obtain a consistent estimator of ϕ, I divide the coefficient on p_{t-1}^{CO} by that on p_{t-1}^{R}.

The model above can be generalized to allow for asymmetric transmission of input costs by having separate terms for positive and negative price changes.

$$\begin{aligned} \Delta p_{i,t}^{R} = \tau_i + & \overbrace{\sum_{j=0}^{n} \beta_j^{+} \Delta p_{t-j}^{CO+} + \sum_{j=0}^{n} \beta_j^{-} \Delta p_{t-j}^{CO-}}^{(1)} + \\ & \underbrace{\sum_{j=1}^{n} \gamma_j^{+} \Delta p_{i,t-j}^{R+} + \sum_{j=1}^{n} \gamma_j^{-} \Delta p_{i,t-j}^{R-}}_{(2)} + \underbrace{\lambda(p_{i,t-1}^{R} - \phi p_{t-1}^{CO})}_{(3)} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

Where:

$$\Delta p_t^{X+} = \max\{0, \Delta p_t^X\}$$
$$\Delta p_t^{X-} = \min\{0, \Delta p_t^X\}$$

Cumulative responses to changes in the price for crude oil are the objects of interest. The cumulative response function CRF_t is defined as the expected cumulative change in the gasoline price from a one unit permanent change in the price of crude oil after t periods, starting at the steady state $p^{CO}_{t-1} = p^{R}_{i,t-1}/\phi$. In the asymmetric specifications, I allow for distinct response functions to a one unit decrease versus a one unit increase.

The lag length n is chosen by minimizing the Akaike information criterion on the symmetric specification. This procedure selects a lag length of 6. This is used for all specifications presented in section 8.

7 Theoretical Predictions

A station i belonging to brand $b \in B$ is considered collusive if its nearest station belongs to brand $a \neq b$ with $a \in B$ such that the null hypothesis $\beta_{ba} \leq 0$ is rejected. Denote the set of such stations by C.

The OCH predicts that colluding gas stations will limit how fast they react to a decrease in the oil price. This can be formalized as the set of inequalities:

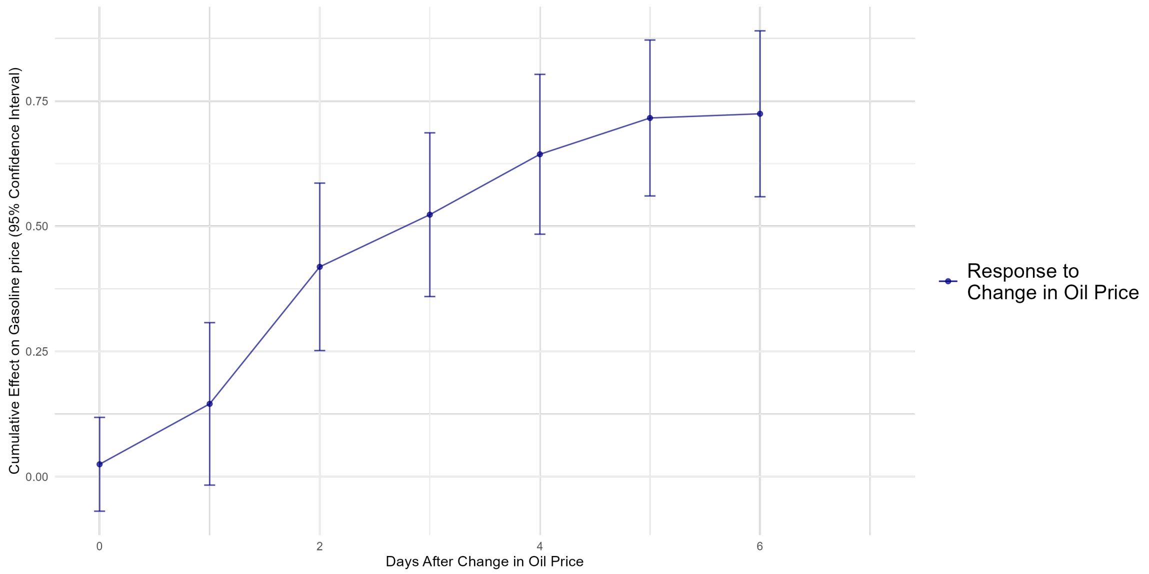
$$\begin{aligned} &\mathbb{E}\big[CRF^{-}_{i,t}|i \in C\big] - \mathbb{E}\big[CRF^{-}_{i,t}|i \notin C\big] < 0 \text{ for some } t \\ &\mathbb{E}\big[CRF^{-}_{i,t}|i \in C\big] - \mathbb{E}\big[CRF^{-}_{i,t}|i \notin C\big] \leq 0 \text{ for all } t \end{aligned} \tag{7}$$

8 Results

I limit my sample to those stations that belong to one of the brands Aral, Shell and Total, as the only stations that qualify for my definition of unilateral or coordinated market power belong to these brands.

8.1 Average Price Response

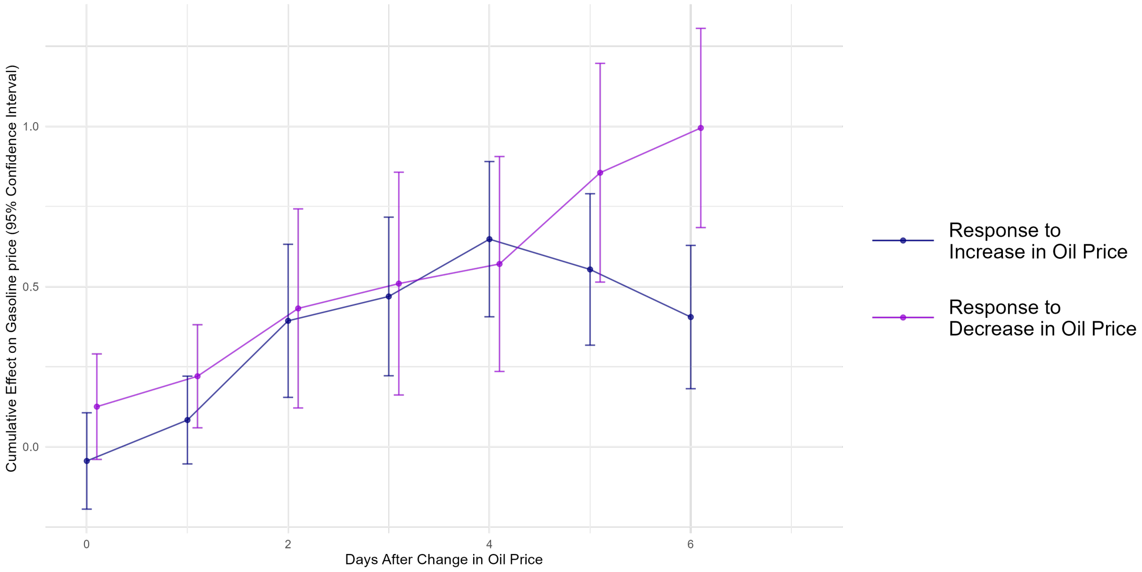
I first run the symmetric specification in equation 5, to examine how fast a cost shock is transmitted into gasoline prices.



The figure shows that a change in the crude oil price starts having an effect on retail gasoline prices within one or two days and continues to have an effect for at least 10 days thereafter. The transmission is fastest in the first few days and tapers off thereafter.

8.2 Asymmetry

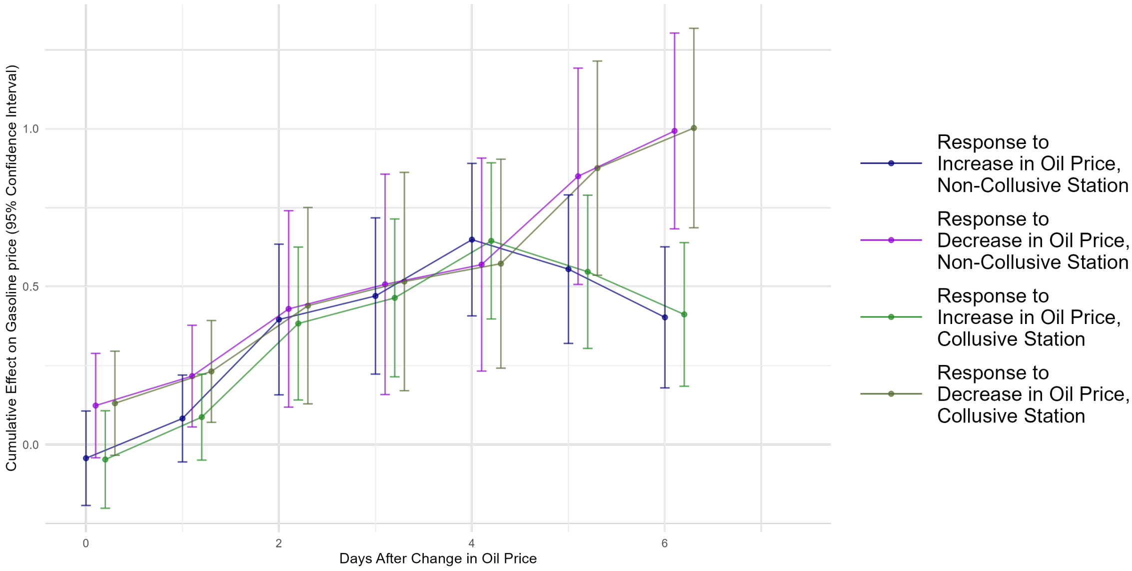
Next, I run the asymmetric specification represented by equation 6.



The figure shows a pattern indicative negative asymmetric price transmission. That is, prices fall faster in response to a cost decrease than they rise in response to a cost increase. This direction of asymmetry has been found in some previous work. Frondel et al. (2020) finds the same direction of asymmetry in a sample of German stations over a similar time span. Moreover, Bremmer and Kesselring (2016) find this direction of asymmetry during "times of generally falling crude prices" in a sample of US gas stations. The authors term this phenomenon *balloons and rocks*, in contrast to the more well known rockets and feathers.

8.3 Collusion and Price Response

In the graph below, I plot the positive and negative CRF-curves separately for collusive stations and non-collusive stations. Collusive stations are defined by the station-closest station brand pair. A station is labeled collusive if and only if its directional brand pair is one of the five that yielded positive and significant coefficients in the pairwise regressions presented in table 5.1.



The price transmission patterns of collusive stations tracks that of non-collusive closely, well within each others' confidence intervals. This is true for both positive and negative changes.

These results indicate that gas stations that collude do not do so by limiting their reaction to decreases in the oil price. This runs contrary to the predictions of the oligopolistic coordination hypothesis, which would have predicted a lower CRF_t^- curve for stations that collude.

9 Conclusion

This paper has investigated the effect of collusion on price transmission with the aim to evaluate the validity of the oligopolistic coordination hypothesis, which claims that firms collude by limiting how fast they reduce their retail prices when input prices fall. While I do find evidence that several pairs of brands exhibit collusive price patterns, I find no evidence that these stations react differently to changes in costs from other stations.

This paper should be considered an investigation into whether collusion is a sufficient, rather than a necessary, condition for positive APT. Whilst I have found that stations identified as collusive do not exhibit different price transmission dynamics than other stations, it is possible that in markets where positive APT is observed, it is still caused by collusion, potentially of a different nature.

Areas for future research in this field include testing if the results generalize to countries with lower price transparency or where positive APT is observed in aggregate. Moreover, the method I present for estimating collusion at the station level can be adapted to any market characterized by spatial competition where data is available of the geographical location of each vendor. This method can be used to answer different questions about collusion, not only about the means through which it is exercised, but also about its effects.

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Appendix

Derivation of the Cumulative Response Function

The econometric model is:

$$\Delta p_{i,t} = \tau_i + \sum_{j=0}^{n} \beta_j \Delta p_{i,t}^{CO} + \sum_{j=1}^{n} \gamma_j \Delta p_{i,t}^{R} + \lambda(p_{i,t-1}^{R} - \phi p_{i,t-1}^{CO}) + \epsilon_{i,t}$$

Define CRF_t as the expected change in the retail price resulting from a unit increase in the crude oil price, starting from a point where $p_{i,t-1}^{R} = \phi p_{i,t-1}^{CO}$.

Then, CRF_t depends on four objects: (1) The cumulative effect until the previous period CRF_{t-1} (2) The direct effect of the lagged change in the oil price (3) The indirect effect of lagged changes in the retail gasoline price and (4) the adjustment toward the long run equilibrium.

$$\begin{aligned}
CRF_0 &= \underbrace{\beta_0}_{(2)} \\
CRF_1 &= \underbrace{CRF_0}_{(1)} + \underbrace{\beta_1}_{(2)} + \underbrace{\gamma_1 CRF_0}_{(3)} + \underbrace{\lambda(CRF_0 - \phi)}_{(4)} \\
CRF_2 &= \underbrace{CRF_1}_{(1)} + \underbrace{\beta_2}_{(2)} + \underbrace{\gamma_1(CRF_1 - CRF_0) + \gamma_2 CRF_0}_{(3)} + \underbrace{\lambda(CRF_1 - \phi)}_{(4)} \\
&\dots \\
CRF_t &= \underbrace{CRF_{t-1}}_{(1)} + \underbrace{\beta_t}_{(2)} + \underbrace{\sum_{j=1}^{t-1} \gamma_{t-j}(CRF_j - CRF_{j-1}) + \gamma_t CRF_0}_{(3)} + \underbrace{\lambda(CRF_{t-1} - \phi)}_{(4)}
\end{aligned}$$

For the purposes of differentiating, we can factorize each CRF-term:

$$CRF_t = (1 + \lambda + \gamma_1) CRF_{t-1} + \sum_{j=0}^{t-2} (\gamma_{t-j} - \gamma_{t-j+1}) CRF_j + \beta_t - \lambda\phi$$

The derivative of a particular CRF_t with respect to a regression parameter θ is then given by:

$$\frac{dCRF_t}{d\theta} = \frac{\partial CRF_t}{\partial \theta} + \sum_{j=0}^{j-1} \frac{\partial CRF_t}{\partial CRF_j} \frac{\partial CRF_j}{\partial \theta}$$

Denote the gradient of CRF_t as:

$$\nabla CRF_t \equiv \begin{bmatrix} \frac{dCRF_t}{d\theta_1} \\ \dots \\ \frac{dCRF_t}{d\theta_k} \end{bmatrix}$$

Standard errors of CRF_t can then be computed using the delta method:

$$SE(CRF_t) = \sqrt{(\nabla CRF_t)' \Sigma_\theta (\nabla CRF_t)}$$

Where Σ_θ denotes the variance-covariance matrix of the regression parameters.