What fuel prices can tell us: DOE Price Monitoring Data in Competition Enforcement and Consumer Welfare

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Retail fuel prices can influence the decisions of both regulatory institutions who are safeguarding the market, and the individual Filipino who needs to gas up. Conscious of this importance, the Department of Energy (DOE) faithfully monitors the prices of retail fuel, and yield an impressive amount of price data. These efforts are already a strong foundation to meet DOE's monitoring directive, but it has potential for applications that it has never been used for, especially in the field of competition policy.

In this paper, we explore the role of the DOE price monitoring scheme in PCC's antitrust work through applying October 2018 – April 2019 Metro Manila DOE price data in a preliminary cartel screen. We find that while there are clusters of stations who adjust their prices similarly, the size and station members of these clusters vary weekly. Throughout this exercise, we find stations with relatively extreme price changes which can be cheaper alternatives for consumers if they were informed of it. We also find that the data's reliability is challenged with missing data, and a limited sample size. To respond to these findings, we forward recommendations to widen and systemize the monitoring's sample, address nonresponse in data gathering, report price information at a station level, and tap underused station data for further studies.

Price Monitoring Policy

The DOE's monitoring role has been clear since the advent of deregulation. Section 14 of the Downstream Oil Industry Deregulation Act of 1998³ explicitly mandated the agency to "...follow the movements of domestic oil prices." In the landmark law's implementing rules and regulations⁴, Section 18 frames DOE's monitoring powers to be pursuant of promotion of retail competition and anti-trust safeguards. Both goals are anchored in the deregulation law -- Section 7 and 10 directs DOE to "...promote fair trade and prevent cartelization, monopolies, combinations in restraint of trade, and any unfair competition," and "...to achieve the social policy objective of fair prices," while Chapter III enshrines anti-trust safeguards and forms a DOE-led task force with information gathering powers. Furthermore, the Price Act⁵ mandates the monitoring of LPG and Kerosene prices as well as exercise direct price regulation in cases of emergencies through the national price coordinating council, of which the DOE Secretary is part of.

https://www.doe.gov.ph/sites/default/files/pdf/issuances/2018 compendium volume 3 downstream.pdf

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³ RA 8479 An Act Deregulating the Downstream Oil Industry and for Other Purposes https://www.officialgazette.gov.ph/1998/02/10/republic-act-no-8479/

⁴ Department Circular No. 98-03-004

⁵ RA 10623 An Act Amending Certain Provisions of RA 7581 (Price Act)

In 2001, the DOE announced in a memorandum that it intends to require oil companies to give prior notice for price adjustments and re-echoed its role as a price monitor, stating that it must monitor domestic prices and "assess its reasonableness," This was actualized 4 years later following the release of operational guidelines in Department Circular No. 2005-08-007. While a step towards price monitoring, in implementation the announcements from the mother oil companies acted more as suggested adjustments. Prevailing prices in actual retail stations do not necessarily follow it, and still change to take into account local market conditions.

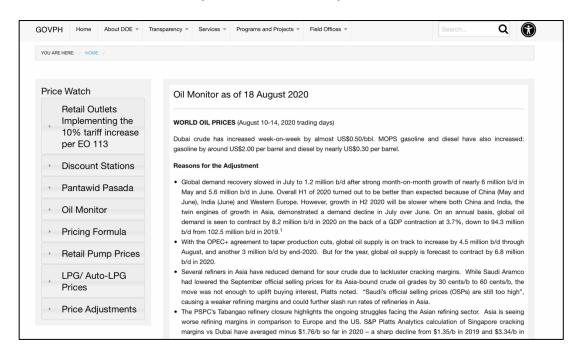


Figure 1: DOE Price Monitoring Website8

It was in the late 2000s that the DOE, through its Oil Industry Management Bureau (OIMB), began monitoring actual prevailing prices of retail gas and diesel products around the country. The price monitoring scheme was said to be initiated in response to public concerns on increasing prices. ⁹ The OIMB also relies on the resulting data for ad hoc studies on the market. ¹⁰

Figure 1 shows how the DOE is currently fulfilling its price monitoring mandate by maintaining its online Oil Price Monitor, which can be accessed through the DOE website. The page releases

⁶ Memorandum Circular No. 2001-05-002

https://www.doe.gov.ph/sites/default/files/pdf/issuances/2018 compendium volume 3 downstream.pdf

⁷Department Circular No. 2005-08-007

https://www.doe.gov.ph/sites/default/files/pdf/issuances/2018 compendium volume 3 downstream.pdf

⁸ Downloaded on August 25, 2020 (DOE Oil Monitor) https://www.doe.gov.ph/oil-monitor?ckattempt=1
⁹Informational interview, 2020

¹⁰DOE conducts studies on an as-needed basis, and also releases an annual downstream oil situationer. Some of these reports are published in the DOE website here: https://www.doe.gov.ph/downstream-oil/advisory?q=downstream-oil/research/ioprc-report-2012; https://www.doe.gov.ph/downstream-oil/advisory?q=downstream-oil/oil-supply-demand-2019

weekly reports on weekly announced price adjustments, and factors that affect price, such as world crude oil prices and foreign exchange. Price relevant policy announcements (such as tariff guidelines), and the pricing formula used prior deregulation are posted here. There are also links that contain irregularly updated discounted stations for public utility vehicles, weekly reports of prevailing prices of LPG and fuel from the price monitoring scheme.

Fuel Prices Monitoring Scheme

The monitoring is nationwide, covering provincial cities identified to have high economic activity, and all cities in the National Capital Region (NCR). Stations surveyed are from a random sampling, stratified by fuel company and city. The sample is further narrowed to the stations the DOE regional offices can reach by phone. To preserve comparability, the list of monitored stations remain unchanged, apart from eliminating closed stations. The DOE regional offices are tasked to operationalize data gathering. These offices call retail fuel stations from Tuesday through Thursday.

Observed prices of each monitored station are not publicly reported. Instead, the prevailing prices of each product are aggregated to a range per city, and per brand (Figure 2). Prices of brands with less than five stations are aggregated under the "Independent" column. These ranges are what is eventually reported on the DOE website. Under "Common Price", prices that occur the most and more than once among brands are also shown. If no two similar prices among two or more stations of different brands are observed, common price is marked as #N/A.

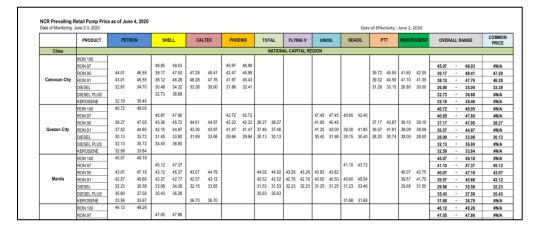


Figure 2: NCR Retail Price Monitoring¹¹

Behavioral Price Screens

Price monitoring efforts can be used for antitrust and fair pricing goals which the deregulation law had intended, and which are now pursued by the PCC following the passage of the Philippine Competition Act in 2016. However, the summary data as shown in **Figure 2** is not enough to

Screenshot from NCR Prevailing Retail Pump Price as of June 4, 2020 https://www.doe.gov.ph/sites/default/files/pdf/price watch/petro min 2020 june 02.pdf

measure the extent of price similarity, which is precursor finding to support a hypothesis of collusion.

Price fixing is an agreement among two or more firms to raise, lower, or stabilize prices in order to restrict competition and earn higher profits. These could be horizontal agreements between competitors selling the same product, or vertical agreements between suppliers and distributors. When firms do this, they no longer compete, and the result is often less innovation in products and higher prices for consumers. Price fixing that limits competition is prohibited under the Philippine Competition Act.

Screens identify markets where cartels such as price fixing agreements are likely, and point to where competition authorities like the PCC should further investigate. Screens are broadly classified as either structural or behavioral. The former examines market traits conducive to cartel formation, such as how different product characteristics are, how concentrated a market is, and how stable market demand has been. Meanwhile, the latter focuses on industry price and quantity data.¹²

The OIMB price data enables a behavioral screen. What price behaviors do behavioral screens look for? Markers of high cartel likelihood include reduced or low price variance across firms and customers, a series of steady price increases preceded by steep price declines, strongly correlated firm prices, and high uniformity across firms in other dimensions of price, including the prices for ancillary services.¹³ Past applications of behavioral screens on retail fuel markets outside the Philippines assessed local retail price responses to international crude oil prices,¹⁴ retail margin increases,¹⁵ local retail margin comparisons with national or foreign margins,¹⁶ and price leadership of firms through focal price points.¹⁷

Aside from screens that detect cartels, price monitoring data also allows the study of vertical relationships, and how these affect competition. Various researchers have studied the influence

¹² Harrington, J.E. (2006). Behavioral Screening and the Detection of Cartels. In *European Competition Law Annual* 2006: Enforcement of Prohibition of Cartels. Retrieved from:

http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.63.4196&rep=rep1&type=pdf

13 Id.

¹⁴ Sen, A. (2003). Higher prices at Canadian gas pumps: international crude oil prices or local market concentration? An empirical investigation. In *Energy Economics*, 25(3): 269-288. Retrieved from: https://doi.org/10.1016/S0140-9883(02)00097-X

¹⁵ Byrne, D.P. & de Roos, N. (2010). Learning to coordinate: A study in retail gasoline. In *American Economic Review*, 109(2): 591-619. Retrieved from: https://doi.org/10.1257/aer.20170116; and Organization for Economic Co-operation and Development. (2013). Ex officio cartel investigations and the use of screens to detect cartels. Retrieved from: http://www.oecd.org/daf/competition/exofficio-cartel-investigation-2013.pdf

¹⁶ Hong Kong Competition Commission. (n.d.). Study of the auto-fuel retail market. Retrieved from: https://www.compag.gov.hk/en/reference/fuel.pdf

¹⁷ Byrne, D.P. & de Roos, N. (2019). Learning to coordinate: A study in retail gasoline. In *American Economic Review*, 109(2): 591-619. Retrieved from: https://doi.org/10.1257/aer.20170116; and Lewis, M.S. (2015). Odd prices at retail gasoline stations: Focal point pricing and tacit collusion. In *Journal of Economics & Management Strategy*, 34(3). Retrieved from: https://doi.org/10.1111/jems.12103

of vertical supply restraints,¹⁸ company ownership and affiliation of stations,¹⁹ and resale price maintenance²⁰ on price levels in US and Canada markets. This is a relevant inquiry in Philippine retail petroleum as well, where the way stations set prices vary depending on whether it is company owned, dealer owned, or independent.

Even prior to the passage of the PCA, there have been recurring public concerns regarding a cartel in the retail fuel market due to the similarity of the announced weekly price adjustments across the companies. ²¹ We employ a preliminary screen on the OIMB price monitoring data to detect if there are retail stations who constantly adjust by the same price level every week. We refer to a group of more than 50% of observed stations with the same adjustment as a *cluster*. These clusters would support the possibility of an anti-competitive price fixing agreement among the retail stations and aid deeper investigation.

Price Monitoring Data Analysis

Description of the Data

In this policy paper, we investigate the utility of the DOE price monitoring raw data to build a cartel behavioral price screen, for retail fuel. We utilize a dataset covering 27 weeks, from October 4 to December 12, 2018, and from January 3 to April 30, 2019. During this period, 203-205 stations of 7 oil companies were monitored. We note that 2 Shell stations were dropped from the sample beginning 2019, but 1 Flying V new station was added. The number of stations observed on each day vary among companies (**Table 1**). Shell, Petron, and Caltex have the most observations per week, with Unioil, Flying V, Seaoil and Total having noticeably less than 10 stations monitored.

¹⁸ Cooper, J.C., Froeb, L.M., O'Brien, D., & Vita, M.G. (2005). Vertical antitrust policy as a problem of inference. In *International Journal of Industrial Organization*, 23: 639 – 664. Retrieved from: https://doi.org/10.1016/j.ijindorg.2005.04.003

¹⁹ Hastings, J. (2004). Vertical Relationships and Competition in Retail Gasoline Markets: Empirical Evidence from Contract Changes in Southern California. In *American Economic Review*, 94(1): 317-328.Retrieved from: https://www.jstor.org/stable/3592781

²⁰ Cooper, J.C., Froeb, L.M., O'Brien, D., & Vita, M.G. (2005). Vertical antitrust policy as a problem of inference. In *International Journal of Industrial Organization*, 23: 639 – 664. Retrieved from: https://doi.org/10.1016/j.ijindorg.2005.04.003 and

Isaac Brannon, J. (2003). The effects of resale price maintenance laws on petrol prices and station attrition: empirical evidence from Wisconsin. In *Applied Economics*, 35(3), 343–349. doi:10.1080/00036840210150857

²¹ GMA News Online. (2008, July 19) DOE-DOJ task force to quiz oil firms on P3/liter diesel hike. Retrieved from: https://www.gmanetwork.com/news/news/nation/107969/doe-doj-task-force-to-quiz-oil-firms-on-p3-liter-diesel-hike/story/;

Official Gazette. (2011, September 19) Govt. task force to probe alleged collusion by oil firms to hike oil prices - Roxas. Retrieved from: https://www.gmanetwork.com/news/news/nation/107969/doe-doj-task-force-to-quiz-oil-firms-on-p3-liter-diesel-hike/story/

Rivera, D. (2017 November 18) DOE forms team to probe oil price hikes. *Philstar Global*. Retrieved from: https://www.philstar.com/business/2017/11/18/1760258/doe-forms-team-probe-oil-price-hikes

The observed stations are located in all 17 cities in NCR. Most of these stations are in Quezon City, Manila, and Pasig. Notably, Unioil, Flying V, Seaoil, and Total are only observed in at most 6 out of the 17 covered cities.

Table 1: Number of Observed Stations Per City and Per Company

City.	Company						Station	
City	Shell	Petron	Caltex	Unioil	Flying V	Seaoil	Total	Count
Caloocan	4	2	3					9
Las Piñas	2	1						3
Makati	5	2	4					11
Malabon	2							2
Mandaluyong	2	1	1				1	5
	13							
	(2018)							
	11							29 (2018)
Manila	(2019)	6	7	1		2		27 (2019)
Marikina	4	3						7
Muntinlupa	4	1	2				1	8
Navotas	1		1	1				3
Parañaque	2	6	5	1				14
Pasay	2	1	1				1	5
								16 (2018)
Pasig	4	3	7	1	1 (2019)		1	17 (2019)
Pateros					1			1
Quezon	24	30	12	4	2	4	1	77
San Juan	2	1			1		1	5
Taguig	1	1	1					3
Valenzuela	3	2						5
NA					2			2
								204(2018)
Station Count	75	60	44	8	6	6	6	205(2019)

We note that per week, not all observed stations have reported prices in the datasets, even for petroleum products commonly sold (Table 2). Per week, an average of only 65.26% of monitored stations has recorded RON 91 prices during the observed period. For Diesel 1, an average of 65.31% stations have recorded prices. Standard deviation of the share of stations with actual entries show us that number of entries vary per week. Consultation with the DOE reveals that this is due to nonresponse during data gathering. The blanks could also be a result of data loss from the manual encoding process.

Table 2: Share of Stations with Reported Prices for RON 91 and Diesel

	Overall Share of Stations with Reported Prices (%)	Mean Share of Stations with Reported Prices Per Week (%)	Standard Deviation (%)
RON 91	65.26	65.46	6.21
Diesel	65.91	65.13	6.51

The OIMB price monitoring dataset records prevailing prices for four standard gasoline products, specifically gasoline with octane ratings (also referred to as Research Octane Number or RON) 100, 97, 95, and 91. Kerosene, and two diesel products with cetane ratings 50 and 55 are monitored as well. For the assessment we conduct here, we focus on the prices of RON 91, a gasoline product sold commonly across companies.

Ranges and Bouncebacks

We first look at the distribution of price changes of RON 91. We note that in the original dataset, the price changes range from a minimum of -6.3 to a maximum 6 pesos. **Figure 3** below show the spread of the price changes each week, indicating that the week-to-week standard deviation is typically bounded by 3 pesos. Focusing on the extreme week to week price changes of less than 3 and greater than 3, we note that these "large" price changes are both about 1% of the data overall.

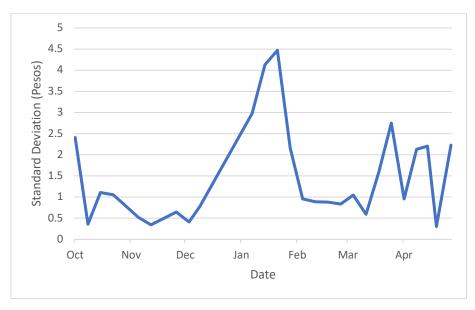


Figure 3: Standard deviation of RON 91 price adjustments over time

There are seventy-three (73) stations with these large price changes, some of them do these price changes multiple times in the seven-month dataset. There are two possibilities: First, these are true price changes and represent real price changes, a hallmark of competition that consumers are not well aware of. Second, these could be encoding errors; in which case we document them here to raise awareness.²²

We next check if the large changes in price are accompanied by large corrections which we call bouncebacks in price in the following week. All large price changes are expected to return to a common mean at some point because of arbitrage. We would check here if the price changes are reversed in the following weeks for these extreme price changes. If they are completely reversed the following week, then these price changes are most likely to be encoding errors. We summarize our findings in the table below. We find that only 8.4% fully recovered their price changes after two weeks.

Table 3: Share of Stations with Large Price changes recovered by at least 90%

	Change after One Week	Cumulative Change after Two weeks
Share of Stations with at least 90%	5.4%	8.4%
return reversal		

Market Information and Consumer Welfare

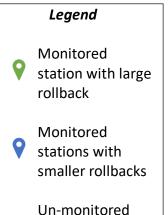
The dataset shows us that during instances of large price decreases in a station, most nearby stations would have smaller, more standard price decreases. We show in **Figure 4** an example of a large price rollback last April 4, 2019, where a monitored station decreased the price of RON 91 by 6.34 pesos. Meanwhile, the nearest monitored stations (about 4 km away, or a 9-minute drive by car) only decreased by 0.10 to 1.25 pesos. We also note here that there are stations nearer to the large rollback station that are not part of the monitoring, but could have smaller price decreases.

²² The possible encoding errors are not in the price adjustments per se, but in the price levels documented by the DOE Fuel Price monitoring team.

Price monitoring information could potentially increase price competition and benefit consumers, who could refer to the monitoring to look for cheaper prices. This would require releasing a disaggregated version of the current reports into station-level price data with station locations. Additionally, this can be further maximized if the price monitoring covered more stations a consumer can compare and choose from. As can be seen from Error! Reference source not found., surrounding the monitored station are many un-monitored stations. Because of the importance of local competition in explaining price differences, it would be important to monitor more than one station in a single street.



Figure 4: Stations with Large and Average Price Changes



stations

In some countries, this information is widely available to the public. A notable example is Western Australia's Fuel Watch website, where the public can see each station's current prices, prices for the next day, and street address (**Figure 5**). Stations in the state are required by law to notify the government of their daily prices 24 hours prior. The website allows users to filter the stations by product, location and brand, download historical prices, and subscribe to daily email alerts. Users have reported to have saved 2- 20 Australian dollars weekly because of the service.²³

Figure 5: Western Australia's Fuel Watch Price Search Interface²⁴

https://www.fuelwatch.wa.gov.au/fuelwatch/pages/public/quickSearch.jspx

²³ How Fuel Watch Works. Retrieved from:

https://www.fuelwatch.wa.gov.au/fuelwatch/pages/public/contentholder.jspx?key=works.html

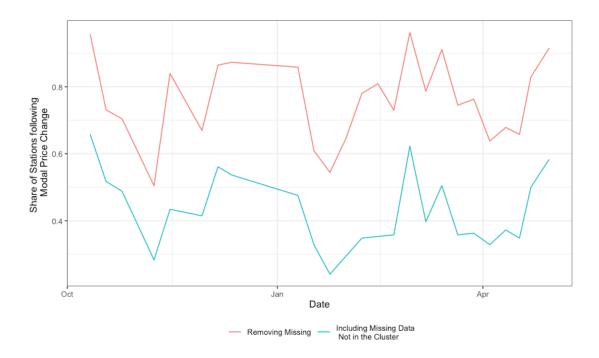
²⁴ Fuel Watch Price Search. Retrieved on August 28, 2020



Price Change Clusters

To calculate the price adjustment for each week in our sample, we subtract the prevailing price with the previous week's price. From analyzing these price adjustments, we document the extent of the price change similarity among stations in the price monitoring dataset for RON 91. We define price change similarity by introducing the notion of price (change) clusters. A price cluster is a proportion of stations which have the same price change. An equivalent way to view this is to calculate the modal price and calculate the proportion of stations which follow the modal price change.

Figure 6: Proportion of Stations in a RON 91 price adjustment modal price change



Error! Reference source not found.6 shows the share of stations following the modal price change. We note that the share changes over time, at a minimum of 50% to a maximum of over 95%. The variation shown here is compounded by changes in the stations which report from week to week. The blue line takes the number of stations as the denominator. We include it here, not as an estimate of the true share, but as an indication of how much information is lost given the week to week attrition of stations. Moreover, these figures don't break down the price cluster share by mother company and City. We turn our attention to these next.

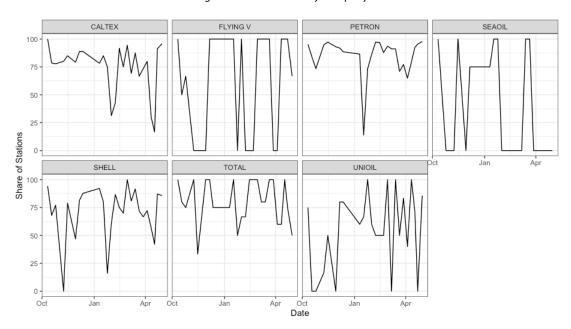


Figure 7: Cluster Share by Company²⁵

Figure 7 shows the companies that join in the price cluster per week in the sample. Aside from the message that not all companies have the same cluster share, and that this changes over time, its notable that the smaller firms have a much more variable estimated share. For a few weeks, the cluster share is zero for some stations. The reason for this is there are fewer stations sampled for smaller firms, and some of those samples did not regularly have price data. As a result, cross-company statistical tests to compare proportions would lack power. The company with the most number of stations observed (and with price submissions) is Petron and we are most confident in their cluster shares. We can see that the share variation is greatly reduced (except for one week in January 2019), with the cluster shares usually greater than 70%.

Likewise, we can cut the price adjustment data into cities, and calculate the price adjustment clustering for those markets. **Figure 3** shows the cluster shares by City. The most confidence we have is in Quezon City, because they have the most stations in our sample. The shares are almost always above 55%.

This clustering can be indicative of an agreement among companies to increase or decrease prices at a similar level. More incriminating evidence of a cartel are stations that are part of the cluster every week for a prolonged period. Otherwise, they are not dictated by a cartel agreement to adjust their retail price by a set amount, and are instead free to adjust by any independent amount.

The OIMB data can be used to identify stations that regularly adjust price at the cluster price adjustment levels. In the bar plot in Error! Reference source not found. Error! Reference source

²⁵ Includes only stations with price adjustment data.

not found.**9**, we count the distribution of station's weeks in they spent in the price adjustment cluster. There are 3 stations that were always (23 weeks) in a price adjustment cluster.²⁶

We trace the locations of the 3 stations which are always in a cluster (**Figure 10**). The stations are scattered across the capital rather than being concentrated in a geographical area, which would have been more conducive for a cartel.

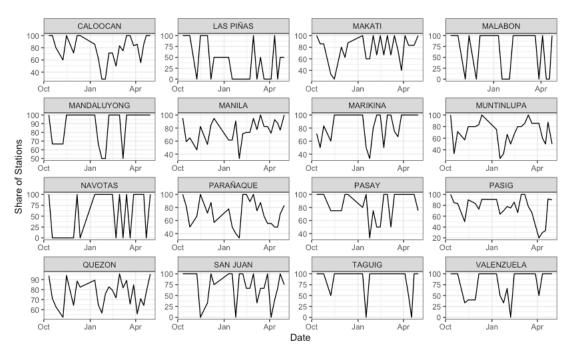
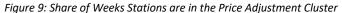
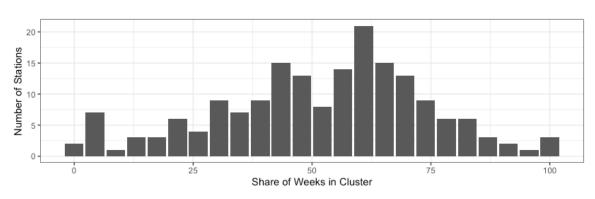


Figure 3: Share in a Cluster, by City





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²⁶ There are 23 weeks because 2 weeks do not have price adjustment data as they are the start of the observations in 2018 and the start of the year in 2019. This plot represents 180 stations with at least one price adjustment data. There are 206 stations in the dataset listed.

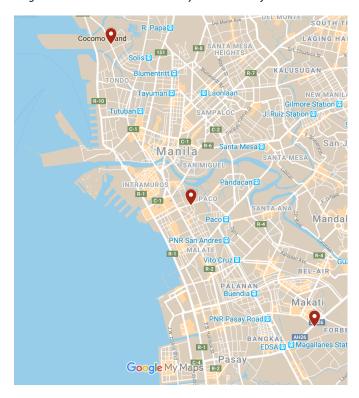


Figure 10: Stations which are Always in a Price Adjustment Cluster

The analysis can be repeated on the OIMB data's other time periods, product types, and cities. Its results can then determine whether deeper investigations should be pursued. If the price data also characterizes the firm, it can even inform the scope and starting point of an investigation.

Statistical Tests and Power

We have raised the "reliability" of our price cluster shares, including those broken into cities and brands. We have noted that missing data, either through non-submission of prices, or inconsistent monitoring, contribute to uncertainty in estimating price cluster shares. When we use price monitoring data as a behavioral screen, we are using them as statistical tests, to test for changes in the value of the statistics we calculated. However, if uncertainty is high, the reliability of the test in is question. The key factor behind the reliability of an estimate is the number of observations that have been used to calculate the shares.

Statistical power is the ability of a statistical test to correctly detect a true change in the population data. Because we are working with probabilities, we are also measuring power in a statistical way; the probability that a test correctly identifies a true change in the population. This is related to the notion of Type I and Type II errors in hypothesis testing. Type I may be more familiar to the layman, as it gives you the probability that the true null hypothesis (usually of no change) is rejected. Researchers set this value to be 5%, which results in rejecting the null hypothesis only when the measured difference is high enough. Type II errors is related to statistical power. A Type II error is when we accept the null hypothesis of no effect, when the null hypothesis is wrong. When a researcher is setting a low Type I error, unless the test has sufficient

observations, then it inadvertently accepts a high Type II error. The test will tend to accept the null hypothesis of no change when that null hypothesis is false.²⁷ Setting a low Type II error is equivalent to increasing the statistical power of the test.

The fuel price monitoring data is a stratified dataset based by company and city in NCR. There are many tests we could do, but to illustrate the issues regarding statistical power in the context of testing for markers of collusion, we would like to compare companies' share per week, or test the changes in a company's share over time.

Let us consider the first problem first, comparing the price cluster shares between companies. Suppose that we have an indicator $z_{i,j,t}$, where $z_{i,j,t}=1$ if station i selling company j's fuel is part of the cluster in time t. Summing over the sample, this is a proportion of stations that are part of company j and part of the price cluster in time t. We can conduct a comparison test for $p_j=p_k$, where j and k are two different companies' proportion of being part of the price cluster. We can construct a 95% confidence interval on the difference of the two shares as $p_j-p_k \pm 1$

$$1.96\sqrt{\left(1-\frac{n_j}{N_j}\right)\frac{p_j(1-p_j)}{n_j}+\left(1-\frac{n_k}{N_k}\right)\frac{p_k(1-p_k)}{n_k}}.$$
 The term $\sqrt{\left(1-\frac{n_j}{N_j}\right)\frac{p_j(1-p_j)}{n_j}+\left(1-\frac{n_k}{N_k}\right)\frac{p_k(1-p_k)}{n_k}}$ is the standard error. The difference, or the expected effect size are within 1.96 standard errors,

95% of the confidence intervals drawn. The term $\left(1 - \frac{n_j}{N_j}\right)$ is called a finite population correction.

As the sample size n_j comes closer to N_j , the number of stations in the population, the lower the standard error. If the difference is beyond the size of the standard error, we are confident that the two estimates are statistically different from each other.

We can think of setting sample sizes to achieve a certain power level by assuming a certain effect size. The maximum standard error for estimates of shares for a given sample size n is $\frac{0.5}{\sqrt{n}}$, for p=0.5. Using the maximum possible standard error will give us a conservative choice for a sample size. Let us first assume that $n_j/N_j < 0.05$ when the finite sample correction is not used. The sample needed to achieve a power of 80% is 2.8 standard errors away from the estimate. This gives a sample size as a function of the effect size d; $d = 2.8 \frac{0.5}{\sqrt{n}}$, or $n = \left(\frac{2.8*0.5}{d}\right)^2$. The smaller d requires a larger sample to make sure the standard errors are small enough to rule out the Null Hypothesis. If the finite sample correction is included, the sample size calculation becomes $n = \left(\frac{2.8*0.5*fpc}{d}\right)^2$ and there is no longer a closed form solution for n. The sample size calculation becomes $n = \left(\frac{2.8*0.5*fpc}{d}\right)^2$ and there is no longer a closed form solution for n.

²⁷ As we will see, the other factor here is effect size, or the size of the change the test can reliability detect. The smaller the effect size, the harder it is to detect if the null hypothesis is true or false, for a given number of observations

²⁸ It is 2.8 because for the Null Hypothesis, it should be 1.96 (or 2) away from the estimate for a Type I error of 5%. To make sure that the estimate is 80% in the Alternate Hypothesis' confidence interval, i.e. 80% probability to accept the Alternative when the Null is wrong, it should be .8 standard errors further.

²⁹ For fixed N, d and p, the solution is a quadratic in n.

Let's consider some examples, based on these conservative power calculations. Based on scraped station location data for Shell, Petron and Caltex³⁰, Caltex has 69 stations in Metro Manila, Shell has 199 Stations and Petron has 213 Stations. The finite population correction for these companies applies. Based on computations with an assumed effects size of 10%, conservative estimates for sample sizes would be 51 For Caltex, and 100 for Petron and Shell.

The second comparison is holding the company's station constant and comparing its proportion over time. There are two possibilities. First, the samples are randomly determined every period, and the approximations in the earlier paragraphs carry over. Second, if the price monitoring is a true panel, then we would follow the same sample over time. This would generally lead to different errors because each station would likely exhibit persistence in its pricing behavior. The errors would be smaller (larger) if each unit being compared over time is positively (negatively) correlated.

Recommendations

With the passage of the Philippine Competition Act, the PCC is now partners with the DOE in fulfilling antitrust and consumer welfare mandates in fuel markets. The OIMB has done good and worthwhile work in monitoring fuel prices. As we have exhibited in the paper, their work is vital for preliminary behavioral screens and understanding the current market. Throughout the conduct of this preliminary screen, we realize that a few changes to the methodology and scope of the price monitoring would further increase the impact and applications of OIMB's work, especially to regulators like the PCC. We share our recommendations here.

1. Widening and systemizing the sample of monitored stations

The underrepresentation of stations hampers the detection of price clusters among these companies. We discussed how current sampling for NCR could further improve its statistical power. In the station count summarized in **Table 1**, we learn that several minor companies are not monitored at all in some NCR cities. Even outside the NCR, the OIMB monitoring covers a range of one to five retail stations per city in the provinces. As a result, some cities only have data on one to two out of the more than seven different fuel companies.

Constrained sampling is a crucial problem for the conduct of cartel screens. In areas where the DOE only monitor prices of one or two fuel companies, a price screen would not be able to detect an agreement across multiple brands. Low statistical power implies a higher likelihood of false negatives on any statistical cartel screens. Lastly, the low sample sizes are especially vulnerable to nonresponse, which will further decrease the actual sample monitored per week.

To address this, the OIMB could consider widening its sample size to fully be representative of companies and cities, and to increase the ability of tests conducted on the data. The DOE can do this through accurately updating its list of stations, and consultations with statisticians for the

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³⁰ From their official websites.

sampling. All changes to the sampling, including the removal or inclusion of stations in the future, should be documented and published online, for the easy reference of consumers, researchers, and future OIMB administrations.

2. Strategizing for nonresponse

We talked about how many of the weeks in the dataset have no entry due to record loss or non-response (**Table 2**). Together with poor sampling, missing entries also affect a screen's uncertainty.

The problem of nonresponse could be addressed even with limited resources. We recommend boosting the OIMB's efforts with a well-documented non-response callback system. The OIMB could also explore foregoing hand-enumerated questionnaires, and instead require sample stations to self-report to their respective DOE regional offices in a digital format, similar to the DOE's nationwide price adjustment announcement system, and the system employed in the paper's Western Australia price watch example.

Alternatively, if the DOE can allocate resources and expertise for a more fully automized system, we fully support and appliand it.

3. Reporting firm-level, station information

In its current form (as shown in **Figure 2**), the online public reports are incompatible for the PCC's antitrust price fixing screens. The cluster detection shown in this paper used manually encoded firm-level data rather than the publicly reported price ranges. The online public report is also incompatible for informing consumers of cheaper gas station options and location. We would not be able to reveal the lower priced stations like we mapped in **Figure 3** using only the reported ranges.

Instead of the current format, an interface showing each station's prices and the full street address and coordinate information would be necessary for screens, and consumer information. We can learn from the efforts from other jurisdictions, such as the Western Australia price watch model we shared.

4. Utilizing untapped station information for research

Aside from screens and consumer information, the data enables research about the market. The DOE recognizes this, as they use the data for their annual situationers and ad hoc studies. We argue that there is potential to encourage a wider scope of study. We enumerated examples of studies on price fixing screens, and ownership effects on prices in other countries' downstream markets. Price monitoring data can be used for similar inquiries for the Philippine market.

However, to achieve this breadth of research, the price monitoring data should have more station and market information – such as type of station ownership/dealership. The suggested information can be obtained and recorded from the DOE's existing registration and renewal processes for gas stations, and should be organized in a digitally accessible way.

Conclusion

There is a wide opportunity to build on retail fuel price monitoring processes and augment current methodologies. The goal is retail fuel price datasets that are representative, informative, and easily accessible for multiple applications that benefit the public.

After the abolishment of government price interventions through the Downstream Oil Industry Deregulation Act of 1998, the OIMB has evolved to a guardian of safety, quality, and market information for consumers. With its current functions, the Bureau can position itself as a invaluable data gathering body not only for consumers, but also for academic researchers and market regulators like the PCC.