THE ENVIRONMENTAL AND INDIRECT FINANCIAL EFFECTS OF ROAD SPACE RATIONING: EVIDENCE FROM JAKARTA'S ODD-EVEN POLICY

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ABSTRACT

Road space rationing policies are often used by metropolitan areas as a tool to support pollution reduction efforts. Despite widespread use of these policies, causal inference studies on its pollution-reducing effects remain limited. This exploits the 2016 implementation of the Odd-Even Policy in Jakarta as a natural experiment in two ways. First, using air pollution data from weather and meteorological agency databases, it aims to estimate the causal effect of the policy on air pollution levels. This study employs the synthetic control method to estimate its main effect and a placebo study for robustness checks. The main findings show that the Odd-Even Policy reduced PM10 and CO concentration by 10.5 and 6.2 ppm, respectively. Second, the study also uses Yahoo Finance daily stock data to measure market reaction to the Odd-Even Policy. Using the market-risk event study methodology, the study finds a 5.4% cumulative abnormal return at the first public announcement of the policy.

Keywords: Odd-Even Policy, Synthetic Control, Placebo Study, Event Study, Pollution, Stock Price.

INTISARI

Kebijakan pembatasan ruang jalan sering digunakan oleh daerah metropolitan sebagai alat untuk mendukung upaya pengurangan polusi. Meskipun penggunaan luas kebijakan tersebut, penelitian inferensi sebab-akibat tentang efek pengurangan polusi dari kebijakan tersebut masih terbatas. Penelitian ini memanfaatkan implementasi Kebijakan Ganjil-Genap di Jakarta pada tahun 2016 sebagai eksperimen alam dalam dua cara. Pertama, dengan menggunakan data polusi udara dari basis data agensi cuaca dan meteorologi, tujuannya adalah untuk memperkirakan efek sebab-akibat kebijakan terhadap tingkat polusi udara. Penelitian ini menggunakan metode kontrol sintetis untuk memperkirakan efek utamanya dan sebuah penelitian plasebo untuk pemeriksaan kekuatan temuan. Temuan utama menunjukkan bahwa Kebijakan Ganjil-Genap mengurangi konsentrasi PM10 dan CO sebesar 10,5 dan 6,2 ppm, secara berturut-turut. Kedua, penelitian ini juga menggunakan data saham harian Yahoo Finance untuk mengukur reaksi pasar terhadap Kebijakan Ganjil-Genap. Dengan menggunakan metodologi studi peristiwa risiko pasar, penelitian ini menemukan kumulatif abnormal return sebesar 5,4% pada pengumuman publik pertama kebijakan tersebut.

Keywords: Kebijakan Ganjil Genap, *Synthetic Control*, *Placebo Study*, *Event Study*, Polusi, Harga Saham.

TABLE OF CONTENT

STATEMENT OF ORIGINALITY II
ACKNOWLEDGEMENTS III
ABSTRACT V
INTISARI VI
TABLE OF CONTENT VII
LIST OF TABLES IX
LIST OF FIGURES X
CHAPTER 1 1
INTRODUCTION 1
1.1 Research Background 1
1.2 Problem Formulation 5
1.3 Research Questions 5
1.4 Research Objective 6
1.5 Research Contributions 6
1.6 The Scope of Research 7
1.7 Systematical Structure of The Research 7
CHAPTER 2 9
LITERATURE REVIEW 9
2. 1 Driving Restriction Policies 9
2. 2 Effects of Pollution 10
2. 3 Environmental and Financial Factors Linkages 11
CHAPTER 3 13
DATA & METHODOLOGY 13
3. 1 Data 13
3. 1. 1 Measuring Air Quality in Jakarta *13*
3. 1. 2 Measuring Compensating Responses *14*
3.2 Empirical Strategy and Methodology 15
3.2.1 Synthetic Control *15*
3.2.2 Synthetic Control Placebo Study *20*
3.2.3 Market-Risk Event Study *21*
3.3 Definition of Variables 26
3.3.1 Synthetic Control *26*

3.3.2 Market-Risk Event Study *28*

CHAPTER 4 .... **29**

RESULTS AND FINDING **29**

4.1 DESCRIPTIVE STATISTICS 29
4.1.1 Synthetic Control *29*
4.1.2 Market-Risk Event Study *33*
4.2 SYNTHETIC CONTROL RESULTS 36
4.3 PLACEBO STUDY RESULTS 44
4.4 MARKET-RISK EVENT STUDY RESULTS 53

CHAPTER 5 .... **62**

CONCLUSION **62**

5.1 CONCLUSION 62
5.2 LIMITATION OF STUDY AND RECOMMENDATION 65

REFERENCES **68**

LIST OF TABLES

TABLE 1.1: TIMELINE OF KEY ROAD RATIONING POLICY IN JAKARTA 3
TABLE 3.1: EVENT STUDY TIMELINE 25
TABLE 4.1: SYNTHETIC CONTROL DESCRIPTIVE STATISTICS 30
TABLE 4.2: JAKARTA VS CONTROL PRE-TREATMENT AVERAGE 30
TABLE 4.3: AUTOMOTIVE STOCKS USED IN THE STUDY 34
TABLE 4.4: MARKET-RISK EVENT STUDY DESCRIPTIVE STATISTICS 35
TABLE 4.5: OPTIMAL WEIGHTS FOR PM10 SYNTHETIC CONTROL 36
TABLE 4.6: OPTIMAL WEIGHTS FOR CO SYNTHETIC CONTROL 37
TABLE 4.7: ALPHA AND BETA ESTIMATION 54
TABLE 4.8: MEAN ABNORMAL AND CUMULATIVE ABNORMAL RETURN 57

LIST OF FIGURES

Figure 3.1: Odd-Even Policy Map and Air Quality Sensor Coverage 14
Figure 4.3: PM10 AQI Plots for All Donor Pool Cities 31
Figure 4.4: PM10 AQI Plots for Jakarta vs Donor Pool Average 31
Figure 4.5: CO Plots for All Donor Pool Cities 32
Figure 4.6: CO Plots for Jakarta vs Donor Pool Average 32
Figure 4.7: Historical Price of Select Indonesian Automotive Stocks 35
Figure 4.8: PM10 Synthetic Control Results 39
Figure 4.9: CO Synthetic Control Results 40
Figure 4.10: PM10 Gaps for Actual and Synthetic Jakarta 41
Figure 4.11: CO Gaps for Actual and Synthetic Jakarta 42
Figure 4.12: PM10 Synthetic Control on Predictors 43
Figure 4.13: CO Synthetic Control on Predictors 43
Figure 4.14: Singapore PM10 Placebo Study 45
Figure 4.15: Bangalore PM10 Placebo Study 45
Figure 4.16: Weinan PM10 Placebo Study 46
Figure 4.17: Full Donor Pool Placebo Study for PM10 48
Figure 4.18: Full Donor Pool Placebo Study for PM10 Excluding Poor Fit Units 48
Figure 4.19: Bangkok CO Placebo Study 49
Figure 4.20: Hanoi CO Placebo Study 50
Figure 4.21: Full Donor Pool CO Placebo Test 51
Figure 4.22: Full Donor Pool PM10 P-Values 52
Figure 4.23: Full Donor Pool CO P-Values 53
Figure 4.24: Stock Beta Regression 55
Figure 4.25: Plot of Mean Abnormal Returns 58
Figure 4.26: Plot of Individual Mean Abnormal Returns 58
Figure 4.27: Plot of Mean Cumulative Abnormal Returns 59
Figure 4.28: Plot of Individual Cumulative Abnormal Returns 59
Figure 4.29: Historical Gaikindo Automobile Data 59

CHAPTER 1

INTRODUCTION

1.1 Research Background

Traffic congestion and air pollution are common issues faced by large cities around the world. Ambient air pollution is known to impose significant costs on society, causing 90 million cases of respiratory symptoms (Asian Development Bank, 2002) and reducing up to 2.3 years of life expectancy at current PM2.5 levels for Jakarta residents (Greenstone and Fan, 2019). A large source of ambient air pollution are motor vehicles, with vehicle exhaust emissions accounting for 32 - 41% of PM2.5 concentration in Jakarta (Vital Strategies, 2021). In response, policymakers have formulated traffic management policies designed to lower congestion and pollution, including high-occupancy vehicle lanes and road rationing policies. Many of the past implementations of these policies are in Asia or Latin America, either in permanent form such as in Bogota (1998), La Paz (2003), San Jose (2005), Honduras (2008), and Quito (2003), or temporary as found in Beijing (2008) and New Delhi (2015).

In August 2016, Jakarta implemented the first round of the Odd-Even Policy (OEP) based on licence plate numbers. This means that cars with odd-ending licence numbers are restricted from driving in select streets during even dates, and vice versa. In its first iteration, the policy was applicable to 9 road sections during 6AM - 10AM and 4PM - 8PM. Only privately owned cars are affected by this policy, with motorcycles, government-owned cars, and public transportation exempt. The policy was then amended in June 2022, increasing coverage to 25 roads and extended its duration by 1 hour to 6AM - 10AM and 4PM – 9PM. Initially, the OEP was established following the elimination of the "3-in-1" high-occupancy vehicle policy, which required all privately-owned cars to carry at least 3 individuals in order to drive through select roads. Introduced in 1992, the government deemed 3-in-1 ineffective in lowering congestion due to the prevalence of "jockeys", namely people who would get paid to become an additional passenger when entering 3-in-1 restricted areas. Regardless, this is rejected by Hanna et al. (2017), who found that the presence of "jockeys" created an additional marginal cost of entering 3-in-1 areas and thus lowered congestion. Initially, pollution reduction was not one of the goals of the OEP. However, in 2019 the DKI Jakarta Provincial Government passed Law No. 66, which formally stated air quality improvement as one of the goals of the OEP. Consider Table 1 for detailed timeline on the OEP.

If effective, the OEP is expected to lower pollution as people substitutes away from private vehicles towards public transportation during restricted days. On the other hand, it is possible for the policy's efficacy to be lowered by non-compliance and compensating public responses, such as people's decision to purchase an additional car. Existing literature on this subject have mixed findings, with little to no studies addressing behavioural responses to the policy.

Table 1.1: Timeline of Key Road Rationing Policy in Jakarta

Date	Event
16-May-16	3-in-1 policy eliminated First trial period: April 5th – 13th, 2016 Second trial period: April 13th - May 14th, 2016
20-Jul-16	Odd-even policy socialization period: June 28th - July 19th 2016 First trial, violators receive verbal warning: July 20th - August 5th, 2016. Second trial, violators escorted to exit road: August 8th – 29th, 2016
23-Aug-16	Official signing of the policy

Source: Jakarta Provincial Government (2022)

This study comprises two strategies. First, it aims to estimate the causal effect of Jakarta's OEP on ambient air pollution using a synthetic control procedure as in Abadie and Gardeazabal (2003). Specifically, this study will use a combination of other large metropolitan areas as a "synthetic" control city with similar characteristics to Jakarta prior to the OEP. The causal effect is thus inferred by comparing the evolution of this counterfactual Jakarta, i.e., what would have happened in the absence of the OEP, with actual data of Jakarta. Unlike past studies which focus only on the outcome variable, this study will analyse the mechanism of the causal effect. It will estimate the causal effect of the policy on congestion to assess whether reductions in pollution stems from lowered exhaust emissions and no other sources. Second, the study will investigate the impact on abnormal returns of automotive stocks as a behavioural response channel. The causal effect on stock prices will be estimated using the Event Study methodology, specifically using the Market-Risk Model.

Observational analysis of the OEP during its July - August 2016 trial shows a 19% decline in average commute duration and 30% increase in Trans Jakarta ridership, coupled with 16,086 counts of violations (Katadata, 2016). Nonetheless, observational analysis is insufficient to infer causality given it is subject to selection bias. There are several reasons as to why the synthetic control method is favourable in this case. First, the large and unique nature of the OEP means there are no single cities that can act as a control. Compared to road space rationing measures in other cities, Jakarta’s daily vehicle volume is significantly higher. Further, Jakarta’s OEP is also unique since it is immediately preceded by the 3-in-1 policy covering the exact same roads. Both features render it difficult to use a single city as a counterfactual. Second, high frequency pollution data tends to contain considerable noise and lack a discernible trend. This may lead to violation of the parallel trends’ assumption necessary for an unbiased difference-in-differences.

The economic mechanism that serves as the underlying premise of this study is as follows: Plate-based restriction of road space usage should initially limit the number of cars that travel at affected roads during OEP hours. Given so, individuals will be incentivized to purchase an additional car with an ending plate number different than what they currently own, as it is commonplace to customize plate numbers in Indonesia. If this is the case, demand for cars should increase, thereby increasing the sales of automotive car manufacturers. Stock market participants who engage in price speculation will expect automotive stock performance to improve, thereby acting on this information by purchasing automotive stocks. Further, this might further expand to derivative products of motor vehicles, such as spare part and tire manufacturers, given higher number of cars in circulation should increase higher demand for complementary goods.

1.2 Problem Formulation

The main problem that this research aims to tackle is the question of whether the OEP has pollution-reducing effects. Road traffic policy is one of many tools that a policymaker can use to lower air pollution. Given so, the Jakarta Provincial Government and governments of other cities such as Bogota, La Paz, and San Hose among others, have implemented road rationing policies as a tool to reduce pollution. Pollution is clearly a significant cost to society, as exposure to high levels of particulate matter in individuals' daily commute as found by Deryugina et al. (2016) can increase the likelihood of hospitalizations and medical spending. Thus, this begs the question on whether the OEP is effective in reaching its purported goal. In addition, the reaction of the market is also worth knowing, considering the seemingly large potential effect the OEP has on automotive stocks.

1.3 Research Questions

This paper aimed to answer the following research questions:

1. Does the implementation of the Odd-Even Policy in Jakarta have a causal effect on air pollution?
2. Does the Odd-Even Policy cause indirect effects on automotive stock prices?

1.4 Research Objective

As mentioned in the Research Question, this study aims to provide empirical evidence regarding the causal effects of the Odd-Even Policy on air pollution levels in Jakarta and automotive stock prices.

1.5 Research Contributions

This research aims to fill a literature gap from past studies. *First*, this study will enrich the literature by using the synthetic control method on high frequency data in evaluating the causal impact of the Odd-Even Policy. To the author's knowledge, little to no previous road rationing policy research employs synthetic control, let alone synthetic control on high-frequency data. *Second*, this study contributes to the literature by establishing a causal link between road rationing policies and air pollution, given that past studies focus mostly on congestion. *Third*, this study also adds to the literature insight on the Indonesian stock market's efficiency in capturing the Odd-Even Policy into automotive stock prices. This is important as it provides evidence on the market's compensating response to road rationing policy, an aspect that previous studies have rarely touched upon. *Fourth*, the findings of this study will provide policymakers insights on the efficacy of the Odd-Even Policy, which may serve as directional guidance on future policy iterations.

1.6 The Scope of Research

The paper will focus on two key areas. *First*, the paper will focus on the link between the Odd-Even Policy and air pollution. It does so by building an underlying framework of analysis to estimate the counterfactual air pollution levels using synthetic control methods. Note that the focus here is on air pollution as opposed to congestion, as multiple past studies have done analyses on air pollution, and this research aims to provide a new angle to the literature. *Second*, the paper will focus on the link between the Odd-Even Policy and the abnormal returns of automotive stocks. Similar as before, this will be based on a data-driven estimation of the counterfactual stock returns. Further, this provides insights on market expectations of customers' purchase of automotive products in response to the policy. As a whole, the results of the paper include the causal effect of the Odd-Even Policy on air pollution, and the compensating response of the market.

1.7 Systematical Structure of The Research

This study will be divided into five main sections.

Chapter 1. The Introduction explains the background, research problem formulation, research question, research contribution, and the scope of research.

Chapter 2. The Literature Review explains previous studies related to driving restriction and the effect of pollution on health.

Chapter 3. The Data and Methodology explains the sources of data used in research, empirical strategy and methodology, and definition of variables.

Chapter 4. The Results and Findings explain the descriptive statistics and results.

Chapter 5. The Conclusion summarizes the result of the study, explains the limitations and corresponding recommendations.

CHAPTER 2

LITERATURE REVIEW

2. 1 Driving Restriction Policies

Past studies examining the causal effect of driving restrictions mostly focus on congestion. Although some studies touch upon pollution, results remain mixed. Using regression discontinuity, Davis (2008) analysed hourly air pollutant data to examine Mexico City's one-day-per-week driving restriction, finding no evidence that air pollution was reduced. Evaluating the same policy, Eskeland and Feyzioglu (1997) used a time-series model and found instead that pollution and congestion increases in the long-run. This is attributed to the fact that most drivers respond by purchasing older, higher emission cars. Using traffic flow data, de Grange and Troncosco (2011) found that vehicle restrictions in Santiago failed to reduce congestion because of a short time window affecting only 4% of cars in the city. Using hourly carbon monoxide data, Gallego et al. (2012) found no evidence that driving restrictions reduced pollution, largely because of quick household responses of secondary car purchases particularly among the middle class.

Several studies have also found pollution-reducing evidence of driving restrictions. Carillo et al. (2016) found that driving restrictions in Quito significantly reduced ambient concentrations of carbon monoxide, attributing the success to strong reinforcement and low per capita incomes preventing households from purchasing an additional car. Wolff (2014) used a difference-in-difference model to estimate the pollution-reducing effects of the European low-carbon area policy, finding a slight reduction in PM10 concentration. Using station-level pollution data of PM10, Viard and Fu (2015) found that driving restrictions reduce pollution, but at the cost of lower working hours among self-employed workers. Kreindler (2016) used crowd-sourced traffic congestion data from Google Maps and found that the odd-even policy in Delhi produced a moderate reduction in congestion as many drivers switched to public transportation.

Past studies evaluating driving restrictions in Jakarta remain limited. Hanna et al., (2017) used Google Maps data to study the lifting of Jakarta's 3-in-1 policy, finding an increase in average travel time not only in former 3-in-1 roads but also in alternate roads due to spillover effects. Zulkarnain and Ghiffary (2021) studied the expansion of the odd-even policy using a regression discontinuity, finding no evidence for reductions of six major pollutants. A lack of external validity on past driving restriction studies coupled with little to none examining Jakarta's odd-even policy motivates this analysis.

2. 2 Effects of Pollution

A large literature also documents the costs imposed by air pollution on society. Chay and G reenstone (2003) exploited variations in pollution during a recession and found that reductions in total suspended particulates (TSPs) were associated with lower infant mortality. Exploiting daily variation pollution, Deryugina et al. (2016) found that exposure to PM2.5 increased hospitalizations, medical spending, and mortality. Using the value of a statistical life (VSL) approach, Small and Kazimi (1994) estimated that emissions from an average motor vehicle impose a $0.03 cost per mile in Los Angeles. Dockery et al. (1993) used a panel of adults across six U.S. cities for 16 years and found that exposures to SO4 and FP increased mortality significantly even when controlling for smoking, education, and occupational exposure. Further, Resosudarmo and Napitupulu (2004) estimated that air pollution in Jakarta will impose a cost of roughly 2.5% of the city's GDP in 2015 via increased incidences of asthma attacks, respiratory illnesses, and chronic bronchitis.

It is also important to note of potential endogeneity that may arise due to meteorological determinants of pollution. The literature suggests that PM10 and NO2 is strongly affected by atmospheric pressure, humidity, air temperature, and wind speed (Tian Et al., 2014; Filonchyk and Yan, 2018). Given so, failure to control for these meteorological factors might result in a biased estimate of the treatment effect.

2. 3 Environmental and Financial Factors Linkages

There is a large body of literature documenting the linkages between environmental and financial factors, including asset prices. He, Zhao, and Zheng (2023) used 5-year panel data on China-listed firms and found that stocks headquartered in high-pollution cities had lower average stock returns due to worsening investor sentiment. Liu et al. (2021) analysed the effects of air pollution on stock prices using browser search activity as a mediating variable and found that increased investor attention on company's environmental footprint cause negative effects on returns for polluting companies but no effect on renewable energy companies. Heyes, Neidell, and Saberian (2016) found that a one standard deviation increase in PM2.5 concentration resulted in an 11.9% reduction in S&P500 same-day returns. In addition, using event study analysis James (1995) found that public disclosure of companies possessing toxic release in the U.S. resulted in a US$4.1M loss of stock value for affected firms. Furthermore, Xu, Wang, and Tu (2021) found that air pollution and congestion results in lower stock returns via psychological well-being as a mediating variable, finding that there is a negative correlation between air pollution and lagged daily stock returns, given it takes time for individuals to incorporate deteriorating air quality into their mood.

Despite numerous studies analysing the link between environmental and financial factors, there are minimal studies covering road space rationing and asset prices specifically. One seminal research on this topic is Jerch et al. (2021), who utilized microdata on housing transactions in Beijing and found that road space rationing caused an increase in housing demand near subway stations and thus shifted house ownership composition into high-income households, thereby causing an increase in home prices. The lack of studies analysing the link between stock prices and air pollution presents a research gap that this study aims to address.

CHAPTER 3

DATA & METHODOLOGY

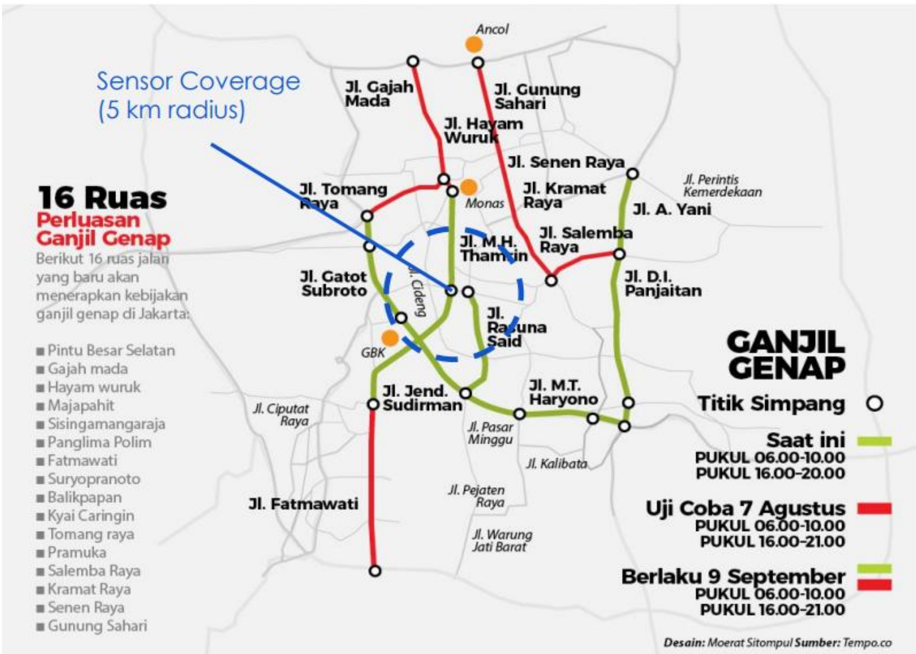
3. 1 Data

3. 1. 1 Measuring Air Quality in Jakarta

Air quality can be measured by different indicators. In Jakarta, the Provincial Government's Environmental Services Department measures air quality via ambient air quality monitoring stations located in five locations, namely in Bundaran HI, Kelapa Gading, Jagakarsa, Lubang Buaya, and Kebon Jeruk. These stations measure hourly concentration of particulates (PM10), Carbon Monoxide (CO), Nitrogen Oxide (NO), Sulphur Dioxide (SO2), Hydrocarbon (CH4, NMHC, THC) and ozone (O3). In addition to the government owned stations, the U.S. embassy in Jakarta owns the only PM2.5 station available in the city. The sparse number of stations across the city means that estimations of a treatment effect would be local to nearby areas, within the station's 5-kilometre detection radius (Urban Emissions, 2020).

This study will use two major pollutants as its main outcome variable, namely PM10 and CO. Monthly average concentrations for the three pollutants will be used for two years prior and after the full-effect policy date of August 30th, 2016, given that historical data for the pollutants remain limited to 2014. In particular, this study will employ data used from the Bundaran HI Air Quality station with a 5-kilometre radius as shown in Figure 1.1. The reason for this is because it is the only station with only Odd-Even roads within its coverage, which is the treatment group in this study.

Figure 3.1: Odd-Even Policy Map and Air Quality Sensor Coverage



Source: Tempo.co

3. 1. 2 Measuring Compensating Responses

Past studies have found additional purchases of vehicles as responses to odd-even driving restrictions (de Grange and Troncosco, 2011; Gallego et al., 2013). Previous approaches include using micro data on households within odd-even areas and tracking the number of cars they own over time. Given a lack of microdata availability for car ownership in Jakarta, this study will instead examine the demand side, namely changes to the abnormal returns of automotive stocks around the first public implementation of the policy. Stock prices of automotive manufacturers will be examined around a 20-day window before and after the first public implementation of the policy on July 20th, 2016. This is to evaluate whether the market is efficient enough to reflect all available information. If the OEP was perceived to have a positive impact on the automotive industry, then automotive stocks should have shown a positive performance relative to the market.

3.2 Empirical Strategy and Methodology

3.2.1 Synthetic Control

The main goal of this study is to examine the impact of the odd-even policy on air quality in Jakarta. Simple comparisons of air quality between Jakarta and other control states after the policy date is not feasible, given that it might not only reflect the impact of the odd-even policy but also other pre-OEP policy factors that have an influence on air quality (e.g., factory constructions). The synthetic control method solves this issue by creating synthetic Jakarta as a control. Abadie and Gardeazabal (2003) explains that synthetic control essentially models the counterfactual of the treatment city (i.e., Jakarta post-treatment in absence of OEP) as a weighted combination of other metropolitan areas selected to have similar characteristics with Jakarta prior to the treatment. Estimation of the treatment effect is then done by comparing the air quality evolution of the actual Jakarta and the synthetic Jakarta.

Formally, let J be the number of cities that serve as control for Jakarta during the odd-even policy period, namely 20 other metropolitan cities in the donor pool, and let $W = (w_1, \ldots, w_J)$ be a (J x 1) vector of nonnegative weights that sum to one. Thus, the scalar w_j ($j = 1, \ldots, J$) is the weight of city j in the synthetic Jakarta. Each unique value of W results in a different synthetic control for Jakarta, and thus the method aims to find a valid subset of control cities out of the 20 by finding an optimal weight. The weights here are selected to be optimal such that the synthetic control Jakarta most closely resembles actual Jakarta prior to the odd-even policy. Let X_1 be a (K x 1) vector of pre-OEP values of K air quality predictors for Jakarta (e.g. wind speed, temperature, etc). Let X_0 be a (K x J) matrix containing the same predictors for the J possible control cities. Let V be a diagonal matrix with nonnegative components. Thus, the diagonal elements of V will reflect the relative importance of the various air quality predictors.

$$\text{Choose } W = W^* \text{ such that } \min[(X_1 - X_0W)'V(X_1 - X_0W)] , \qquad \text{(eq. 1)}$$

$$\text{s.t. } w_j \geq 0 \ (j = 1, 2, \ldots, J)$$

and

$$w_1 + \ldots + w_J = 1$$

The algorithm thus chooses a vector of optimal weights W* to minimise eq.1 subject to the two constraints that the weights must be non-negative and sum to one. The W* vector thus contains the combination of non-OEP control cities that is most similar to Jakarta in terms of air quality determinants prior to the policy. Given that the value of W* depends on the set of predictors V, selection for predictor variables must be done based on knowledge of previous literature regarding the importance of air quality predictors (Abadie and Gardeazabal, 2003). In other words, the value of predictor variables for Jakarta during the OEP period is equal to the value of predictors for control cities during the OEP period multiplied by the optimal weights, as follows:

$$X_1^* = X_0 W^*, \qquad \text{(eq.2)}$$

To be certain that the estimated weights W* are reliable in producing the counterfactual, the difference between predictors in actual and synthetic Jakarta must be similar, meaning that eq.3 must be close to zero in the OEP period.

$$X_1 - X_1^* \qquad \text{(eq.3)}$$

Next, let Y_1 be a (T x 1) vector which contains the values of air quality indicators (e.g. PM10, CO, NO) for Jakarta during T time periods. Let Y_0 be a (T x J) matrix containing the values of air quality indicators for the control cities. Note that we cannot observe the true counterfactual. To estimate the treatment effect of the OEP, we thus estimate the counterfactual, namely what air quality would have been in Jakarta at the post-treatment period in absence of the OEP. The counterfactual evolution of Jakarta's air quality is thus calculated as follows:

$$Y_1^* = Y_0 W^* \qquad \text{(eq. 4)}$$

$$TE = Y_1 - Y_1^* \qquad \text{(eq. 5)}$$

In other words, the estimated counterfactual is equal to the values of air quality indicators for the control cities multiplied by the optimal weights. The treatment effect (TE) is thus the difference between air quality indicators in actual and synthetic Jakarta (eq. 5). Given this model, the treatment effect of the OEP can be estimated by looking at the relationship between air quality indicator gap (i.e., difference between actual and synthetic Jakarta) and the scale of the OEP. Given that the OEP has increased in scale over time, we should expect a widening gap since the initial launch of the policy.

There are several assumptions required for an unbiased estimation of the treatment effect (Shi et al., 2021). First, synthetic control only works if there are no other policies that may influence ambient air quality in the donor pool cities. If there are such policies, synthetic Jakarta might have a higher level of air quality than it should have, resulting in an underestimation of the treatment effect. Second, we assume that there is an independent causal mechanism. Essentially, this means that even though the distribution of air quality predictors X can vary across cities and time, the conditional outcome Y(0) | X only varies by time. In other words, knowledge of all air quality predictors X means that the location in which they are from becomes irrelevant for the distribution of the synthetic potential outcomes. Third, we must also assume that donors are sufficiently like Jakarta. This means that we cannot include cities that are vastly different in terms of environmental and socioeconomic characteristics to Jakarta. Fourth, we also assume that distributions of predictors are stable over time. Let S denote a subset of predictors with a distribution that differs only for the treatment of the city. Our assumption entails this distribution to be time-invariant, namely, to remain constant for all time periods. Lastly, we also assume that there exist no spillover effects between cities. Typically, large one-time policy changes such as OEP have the potential to affect both the treatment and control group. This implies that our donor pool must comprise cities whose air quality cannot be influenced by Jakarta's OEP, such as neighboring cities.

3.2.2 Synthetic Control Placebo Study

Standard errors and p-values are often used to measure uncertainty in econometric models. In the case of synthetic control, the use of aggregate data eliminates the uncertainty that typically arises from sampling. Uncertainty that arises in synthetic control studies arises from how well the synthetic control group matches the treatment group. To answer this question, researchers typically run a placebo synthetic control study, namely an iterative application of the synthetic control method to each city in the donor pool. This would yield a distribution of placebo gaps which can then be compared to the estimated gap for Jakarta.

A placebo study is often done in synthetic control research to verify whether the gap between actual and synthetic data occurs purely by chance or the inability of the model to estimate the counterfactual (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Abadie et al., 2015). Essentially, a placebo study involves applying the synthetic control method, namely the estimation of the air quality gap, Y_1 - Y_1*, to other (non-Jakarta) cities in the donor pool. These cities are those selected in the donor pool used to find the weights which synthetic Jakarta was constructed on. Given that none of these cities implements a driving restriction policy, it is expected for them to not experience a treatment effect. The goal of the placebo study is to compare the evolution of air quality of a city similar to Jakarta but without the OEP, to the evolution of air quality in its synthetic version also without the OEP. If the gap between Jakarta and its synthetic control is a noticeable outlier (i.e., significantly larger or smaller) compared to the gap of similar cities and their synthetic control, we can become more confident that our treatment effect is indeed caused by the OEP.

3.2.3 Market-Risk Event Study

Stock market event studies are empirical models used to estimate how stock prices change in response to a particular event (MacKinlay, 1997; Khottari and Warner, 2006). The treatment effect is the effect of the event, such as a news, policy, or corporate action, on the stock price. These studies typically focus on an event window, such as 20 days prior and after an event. The main goal of this method is to estimate the counterfactual, namely what the stock price would have been in absence of the treatment. Formally, let there be two groups of stocks: treatment (D = 1) and control (D = 0). Group membership here is kept constant over time, but it is not randomly assigned. We assume there to be one treatment stock, i.e., the stock supposedly affected by the event, and N control stocks.

Theoretically, this method is based on the Efficient Markets Hypothesis (EMH) and has been used to complement synthetic control studies (Abadie and Gardeazabal, 2003). The EMH states that prices reflect all relevant information that might affect the asset’s value. According to Fama (1991), market efficiency can be divided into three types: weak (all historical information is reflected in the current market price), semi-strong (all public information are reflected in the current market price), and strong form (all public and private information are reflected in the current market price). In this case, there might be evidence in favour of strong EMH if automotive stocks experience a price run up prior to the first public announcement of the OEP.

We define a range of time T_1 - T_2 as the event window, a short period of time before and after the event (defined as 0) which we will use to observe the stock price reaction. Specifically, our event window runs from May 23rd to July 25th, 2016. The period is formally defined as T_1 - 0, and the post-period is defined as 0 - T_2, where 0 is the first public announcement of the OEP on June 20th, 2016. Each of these periods are 20 days long, as is used by MacKinlay (1997). All potential daily return Y outcomes of our stock is thus as follows:

$$Y_{0,\,PRE},\ Y_{1,\,PRE},\ Y_{0,POST},\ Y_{1,POST}\ \mid D = 1 \qquad \text{(eq.6)}$$

$$AR\ = Y_{1,POST} - Y_{0,POST}\ \mid D = 1 \qquad \text{(eq.7)}$$

Our goal is to estimate the treatment effect (eq.7), often also called the abnormal return (AR). The problem here is that we cannot observe the counterfactual $Y_{0,POST} \mid D = 1$ from the data, which is what the return for the stock would be in the post-period in absence of the treatment. To estimate the abnormal return, we will use the market-risk adjusted model. First, let us consider the potential outcomes for control stocks i = 1, 2, … N, as follows:

$$Y_0^{i=1}{}_{,PRE},\ Y_1^{i=1}{}_{,PRE},\ Y_0^{i=1}{}_{,POST},\ Y_1^{i=1}{}_{,POST} \mid D = 0 \qquad \text{(eq.8)}$$

$$Y_0^{i=2}{}_{,PRE},\ Y_1^{i=2}{}_{,PRE},\ Y_0^{i=2}{}_{,POST},\ Y_1^{i=2}{}_{,POST} \mid D = 0 \qquad \text{(eq.9)}$$

$$\ldots$$

$$Y_0^{i=N}{}_{,PRE},\ Y_1^{i=N}{}_{,PRE},\ Y_0^{i=N}{}_{,POST},\ Y_1^{i=N}{}_{,POST} \mid D = 0 \qquad \text{(eq.10)}$$

From the potential outcomes of each control stock, we can only observe $Y_{0,\,PRE}$ and $Y_{0,POST}$ for each day in the event window. The market-risk adjusted model thus assumes that we can model the treatment stock's abnormal return (i.e. the counterfactual) as a function of returns of the N control stocks, as follows:

$$[Y_{0,\,POST} \mid D = 1] = [f(Y_0^{i=1}{}_{,POST},\ Y_0^{i=2}{}_{,POST},\ \ldots,\ Y_0^{i=N}{}_{,POST} \mid D = 0)] \qquad \text{(eq.11)}$$

Substituting eq.11 to eq.7 yields:

$$AR = [Y_{1,\,POST} \mid D = 1] - f(Y_0^{i=1}{}_{,POST},\ Y_0^{i=2}{}_{,POST},\ \ldots,\ Y_0^{i=N}{}_{,POST} \mid D = 0) \qquad \text{(eq.12)}$$

More specifically, the above f(.) function will be defined as the market return model. Under the market return model, daily returns for the treatment stock is modelled as a linear function of the weighted average return of the control group stocks which are typically the returns for a market index, as follows:

$$f\,(Y_0^{i=1}{}_{,\,POST},\, Y_0^{i=2}{}_{,\,POST},\, \ldots,\, Y_0^{i=N}{}_{,\,POST} \mid D = 0) = \alpha_i + \beta_i(w_i Y_0^{i=m}{}_{,\,POST}) \qquad \text{(eq.13)}$$

Where $w_i Y_0^{i=m}{}_{,\,POST}$ is the market capitalization-weighted return of the index.

In the above equation, w_i is the market capitalization weight of stocks in the market index i; $Y_0^{i=m}$ is the return for stock index, α_i is the stock's return when the market return is zero, β_i is the measure of volatility of stock i in relation to the market. Essentially, alpha indicates the return of a particular stock when the market returns are zero, and beta indicates the change in a stock's return given a unit change in the market return. We will thus estimate beta using linear regression of data within the estimation window, defined as a period T_0 - T_1 which lasts from 300 trading days prior up until 45 days prior to the event (MacKinlay, 1997; Gielens et al., 2008). Consider Table 3.1 below for a full timeline the study is concerned with:

Table 3.1: Event Study Timeline

Date	Notation	Event	Duration (Trading Days)
17-Feb-15 to 11-May-16	T0 - T1	Estimation Window	300
15-Jun-16 to 19-Jul-16	T1 - 0	Pre-period (Within Event Window)	20
20-Jul-16	0	Event Point	1
21-Jun-16 to 18-Aug-16	0 - T2	Post-period (Within Event Window)	20

Source: DKI Jakarta Provincial Government

In our case, the estimation window lasts from February 17th, 2015, to May 11th, 2016. If the market model can estimate the counterfactual well, we should expect zero abnormal returns in the pre-period within the event window as nothing should systematically occur prior to the event. The abnormal return is thus obtained by finding the difference between the stock's actual return and its market-model predicted return. In the case of the OEP, if the market anticipates automotive stocks to rise in value due to households purchasing more cars as a response, the average abnormal return of Indonesian automotive stocks should thus increase in the post-period of the event window. In addition to abnormal returns, event studies also often estimate cumulative abnormal returns (CAR) for each day in the event window. Consider the following:

$$CAR_{i=t} = AR_{i=1} + AR_{i=2} + \ldots + AR_{i=N} \qquad \text{(eq.14)}$$

In other words, cumulative abnormal returns for stock i at time t is equal to the sum of abnormal returns from t = 1 until t = N. his is done to account for the possibility that the event affects the market in a slow manner over time as opposed to a sudden price jump. Comparison of average cumulative abnormal returns of different sectors (i.e., 3 automotive stocks vs unaffected sectors) allows us to examine whether the purchasing additional vehicles are expected compensating responses by the market.

3.3 Definition of Variables

3.3.1 Synthetic Control

3.3.1.1 Outcome Variables

a. Particulate Matter 10 Air Quality Index (pm10):

   Air quality in cities is measured by an Air Quality Index (AQI) that is reported daily and takes a value of 0 – 500, with higher values indicating worse air conditions. An AQI on PM10 is a continuous variable that measures the level of particulate matter that is 10 micrometers or less in diameters. The source of PM10 typically include brake wear, fuel exhaust, re-suspension, road surface wear, industrial activity, and fires.

b. Carbon Monoxide Concentration (co):

   Concentration of Carbon Monoxide in the air, a continuous variable that is measured in parts per million (ppm). The source of CO typically includes fuel combustion, power plants, fires, and other machinery that burn fossil fuel.

3.3.1.2 Predictor Variables

c. GDP per Capita (gdpcap):

   Quarterly Gross Domestic Product per Capita for each city in the donor pool, measured in current US dollars.

d. Gust Speed (gustspeed):

   Gust is a sudden increase of wind above the average wind speed. Gust commonly lasts for 20 seconds or less and is measured in kilometers per hour. To qualify as gust, wind must temporarily peak above 30 kilometer per hour after accelerating at a rate of 17 – 19 kilometer per hour.

e. Wind Speed (windspeed):

   The speed of wind moving past a certain point, measured in kilometer per hour. Wind speeds may vary due to differences in atmospheric pressure as wind moves from high to low pressure areas.

f. Air Temperature (temp):

   Measure of how hot or cold the air is measured in degrees Celsius. Higher temperatures imply that the air is hotter, and vice versa.

3.3.2 Market-Risk Event Study

3.3.2.1 Outcome Variables

g. Jakarta Stock Exchange Daily Return (JK_Daily_Return):

Day-on-day percentage change in closing price of the Jakarta Stock Exchange Composite, a market capitalization-weighted index of all stocks listed in the Indonesian stock exchange.

3.3.2.2 Predictor Variables

h. Stock Daily Return (Daily_Return)

Day-on-day percentage change in closing price of each individual stocks such as ASII, AUTO, GJTL, IMAS, MASA, MPMX, and SMSM.

CHAPTER 4

RESULTS AND FINDING

4.1 Descriptive Statistics

4.1.1 Synthetic Control

The main data used in this research is the air quality indicators of PM10 and CO. As shown by the dataset's descriptive statistics in Table 4.1, the average city in the sample has a PM10 AQI of 55.3 and a CO concentration of 9.9 ppm over the study period. The average PM10 AQI value is of moderate magnitude on a 0 - 500 AQI scale, indicating that the sample is neither skewed left or right.

To assess whether the control cities are suited for Jakarta, researchers typically conduct a simple comparison of pre-treatment averages. As shown by Table 4.2, the pre-treatment average PM10 of Jakarta is similar in magnitude to the control group, namely the average of the 20 control cities, with an AQI of 55.2 and 54.8 respectively. For CO, the pre-treatment value is quite different with Jakarta and the control group having 25.8 and 20.2 ppm for CO, respectively.

Table 4.1: Synthetic Control Descriptive Statistics

Descriptive Statistics

Statistic	Unit	N	Mean	Std. Dev.	Min.	Max.
City	Number	1,078	11.50	6.35	1.00	22.00
PM10	ppm	1,078	55.29	30.85	8.65	217.61
CO	ppm	1,078	9.99	7.47	1.58	49.48
Temperature	Celsius	550	67.07	15.71	22.89	89.72
Wind Speed	Kmph	550	7.08	4.72	0.65	88.20
Gust Speed	Kmph	550	4.79	4.73	-	29.78
GDP	US$ Million	94	232,175.70	192,937.80	21,546.92	1,026,340.00
GDP per Capita	US$ Thousand	94	53.76	72.96	4.65	33,222.00
Population	Million	110	7.82	7.98	0.49	37.47
Population Density	Thousand per Sq km	110	5.85	7.67	0.04	29.13

Source: Government Statistical Agency, World Bank.

Table 2.2: Jakarta vs Control Pre-Treatment Average

Jakarta Pre-Treatment Average

Statistic	Unit	N	Mean	Std. Dev.	Min.	Max.
PM10	ppm	25	55.22	9.87	32.20	72.21
CO	ppm	25	25.78	3.92	17.65	32.33
Temperature	Celsius	25	83.35	1.42	80.86	86.60
Wind Speed	Kmph	25	6.72	1.01	5.26	9.59
Gust Speed	Kmph	25	0.21	0.29	-	0.97
GDP per Capita	US$ Thousand	3	12.41	1.13	11.22	13.47

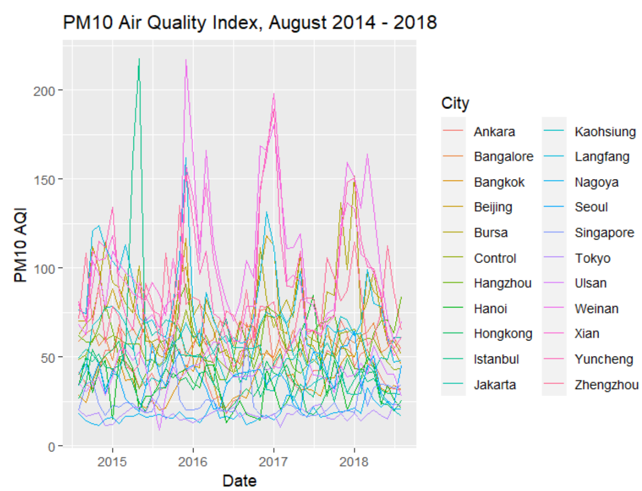
Control Pre-Treatment Average

Statistic	Unit	N	Mean	Std. Dev.	Min.	Max.
PM10	ppm	25	54.77	8.09	41.49	76.47
CO	ppm	25	10.23	1.39	8.69	14.35
Temperature	Celsius	25	67.07	10.83	50.37	82.15
Wind Speed	Kmph	25	7.08	0.91	5.90	10.71
Gust Speed	Kmph	25	4.79	0.55	3.91	6.30
GDP per Capita	US$ Thousand	3	36.45	7.54	27.77	41.32

Source: Government Statistical Agency, World Bank.

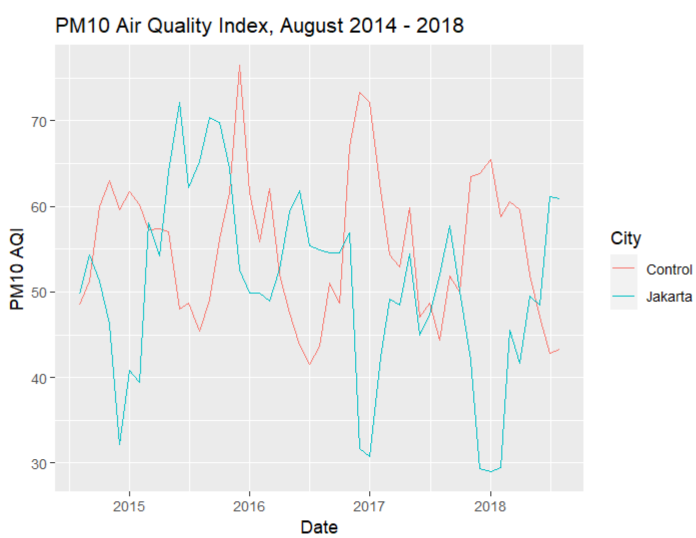
Jakarta and the control group have quite similar pre-treatment averages for wind speed and temperature, whereas there is a greater degree of variance for wind gust speed and GDP per Capita. To see a clearer comparison of the main outcome variables across the study period, consider Figure 4.3 below.

Figure 4.3: PM10 AQI Plots for All Donor Pool



Source: Government Statistical Agency.

Figure 4.4: PM10 AQI Plots for Jakarta vs Donor

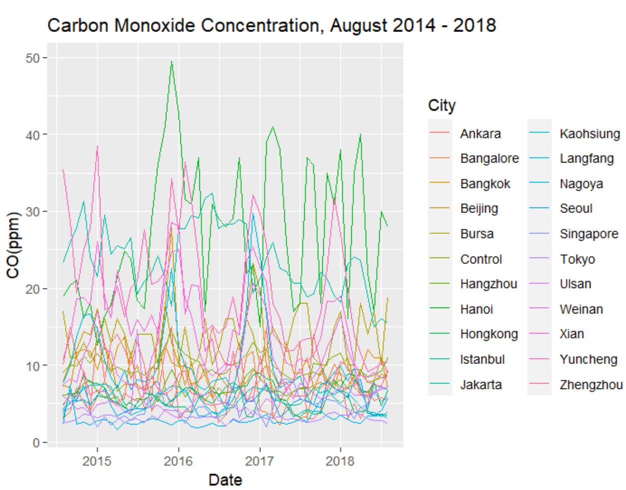


Source: Government Statistical Agency.

As shown by the Figure 4.3, Jakarta's PM10 AQI value is in the middle of the range, with the average of the two being roughly the same over the study period. Figure 4.4 shows that in some years, Jakarta has a higher AQI than the control cities whereas it is lower in other years. We can see that in mid to late 2016, there was a sharp decline in PM10 AQI in Jakarta, which is expected from observational analysis of the data. The average in the control cities instead increased, verifying that there was a lack of large-scale exogenous factors that affected PM10 levels.

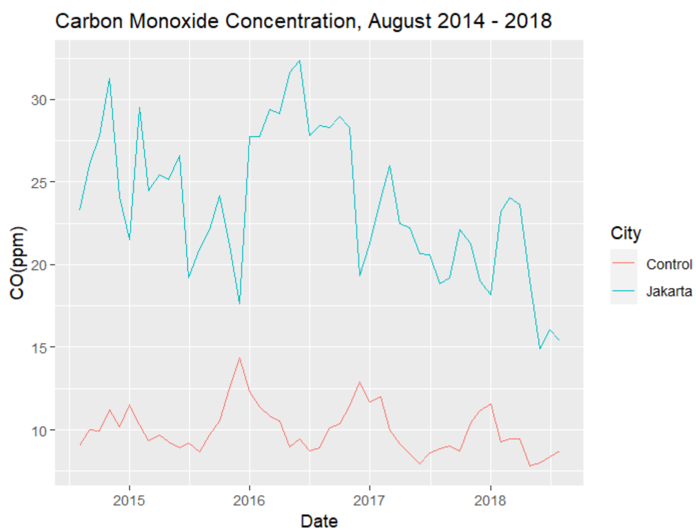
In the case of CO as shown by Figure 4.6, we can see that Jakarta is consistently higher than the average control city throughout the study period. Unlike PM10, observational analysis does not show any drop in Jakarta's CO levels around the policy period of mid-2016. The next section will go further than observational analysis by using causal inference methods.

Figure 4.5: CO Plots for All Donor Pool Cities



Source: Government Statistical Agency.

Figure 4.6: CO Plots for Jakarta vs Donor Pool Average



Source: Government Statistical Agency.

4.1.2 Market-Risk Event Study

In running the Event Study method, we are using daily returns data of seven automotive stocks and comparing them against the daily returns of the Jakarta Stock Exchange (JKSE) Composite Index. As described by table 4.3 below, the study uses seven automotive stocks to evaluate the impact of the OEP across manufacturing and distribution of vehicles, tires, and spare parts. These seven stocks are chosen given they have been within the top ten of highest market capitalization automotive stocks in the Stock Exchange at the time of the policy, excluding several stocks that experienced temporary suspension during the study period (i.e., PT Indo Kordsa Tbk and PT Garuda Metalindo Tbk) to prevent unbiased estimation of the counterfactual.

Table 4.3: Automotive Stocks Used in the Study

Company Name	Ticker	Main Business Line
PT Astra International Tbk	ASII	Car and motorcycle manufacturing and distribution
PT Astra Otoparts Tbk	AUTO	Spare part manufacturing and distribution
PT Gajah Tunggal Tbk	GJTL	Tire manufacturing and distribution
PT Indomobil Sukses Internasional Tbk	IMAS	Car and motorcycle manufacturing and distribution
PT Multistrada Arah Sarana Tbk	MASA	Tire manufacturing and distribution
PT Mitra Pinasthika Mustika Tbk	MPMX	Car distribution
PT Selamat Sempurna Tbk	SMSM	Spare part manufacturing and distribution

Source: Indonesia Stock Exchange

Table 4.4 below shows the mean daily return on the daily adjusted closing price of each alongside the minimum and maximum prices within the study period. We can see that on an average of daily adjusted closing price basis, ASII, GJTL and MPMX experienced a price increase in the study period, whereas AUTO, IMAS, MASA, and SMSM experienced the contrary. Interestingly, GJTL and MPMX in one of the days experienced a roughly 25% appreciation in adjusted closing price, which is a quite significant increase on a daily basis. ASII appears to be the most actively traded stock with an average daily trading volume of 34.7 million shares, with IMAS being the least traded at an average volume of 70.2 thousand shares.

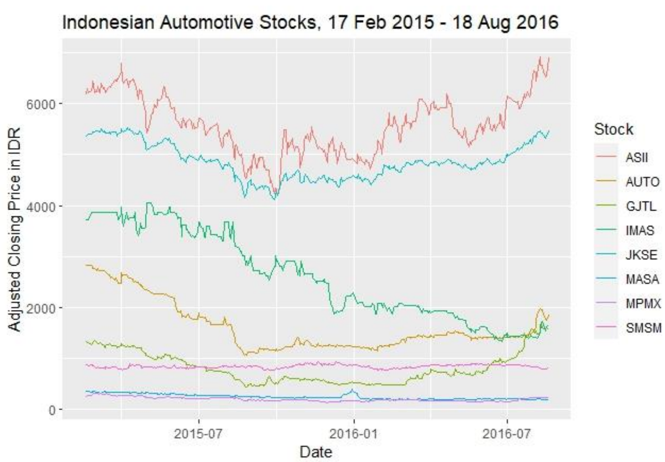
Table 4.4: Market-Risk Event Study Descriptive Statistics

	Mean Return	Min Return	Max Return	Mean Volume
ASII	0.06%	-8.58%	11.27%	34,748,081
AUTO	-0.09%	-9.00%	9.09%	242,107
GJTL	0.02%	-9.65%	25.00%	5,949,510
IMAS	-0.14%	-10.26%	12.75%	70,241
MASA	-0.13%	-10.00%	20.09%	608,960
MPMX	0.01%	-10.00%	25.00%	1,976,303
SMSM	-0.04%	-5.20%	8.70%	792,163

Source: Yahoo Finance

Figure 4.7 shows a clearer historical trend of the selected stocks' daily adjusted closing prices. We can observe that most stocks experienced a downward trend from February to September 2015, from which point most began to appreciate except for IMAS. In the implementation month of OEP in July 2016, we can see that most stocks experienced an increase in their price, suggesting that observational analysis indicates a potential positive impact on stock prices.

Figure 4.7: Historical Price of Select Indonesian Automotive Stocks



Source: Government Statistical Agency.

This will be verified further by estimating the counterfactual prices in absence of the policy by regressing each stock's returns against the JKSE. The above chart also shows that the JKSE in general has directional similarity with all the seven stocks, although perhaps at a higher degree of correlation for ASII and GJTL. This is expected given the cyclical nature of consumer discretionary stocks such as automotives, as people tend to purchase more vehicles when the economy does well, and vice versa.

4.2 Synthetic Control Results

The main synthetic control command was run on the data, with August 1st 2014 to July 30th 2017 as the pre-treatment period. Essentially, the synthetic control algorithm will model Jakarta as a weighted average of the other control cities in the treatment period. The optimal weights are then used to predict the counterfactual in the post-treatment period.

Table 4.5: Optimal Weights for PM10 Synthetic Control

PM10 Predictors			
	Unit	**Min Weight**	**Max Weight**
PM10	%	38.30%	38.30%
Gust Speed	%	21.51%	21.51%
Wind Speed	%	16.65%	16.65%
Temperature	%	15.15%	15.15%
GDP per Capita	%	8.39%	8.39%
Total		100.00%	100.00%
Predicted Loss		1.63%	1.63%

Source: Government Statistical Agency.

Table 4.5 above shows the synthetic control results for PM10 as the outcome variable. According to the model, using the pre-treatment period of August 2014 to July 2016 as the optimization period, the optimal set of weights to model Jakarta is Singapore (17.16%), Bangalore (81.34%), and Weinan (1.47%). This set of weights are chosen such that the Root Mean Square Prediction Error (RMSPE) is minimised, at a value of 10.6. In addition, as shown by the optimal weight vectors, PM10 is modelled as a function of gust speed (21.51%), wind speed (16.65%), temperature (15.15%), and GDP per Capita (8.39%), with the remaining weights allocated to itself. As found in the literature, meteorological factors are good predictors of PM10 with no single factor holding an overwhelmingly large contribution.

Table 4.6: Optimal Weights for CO Synthetic Control

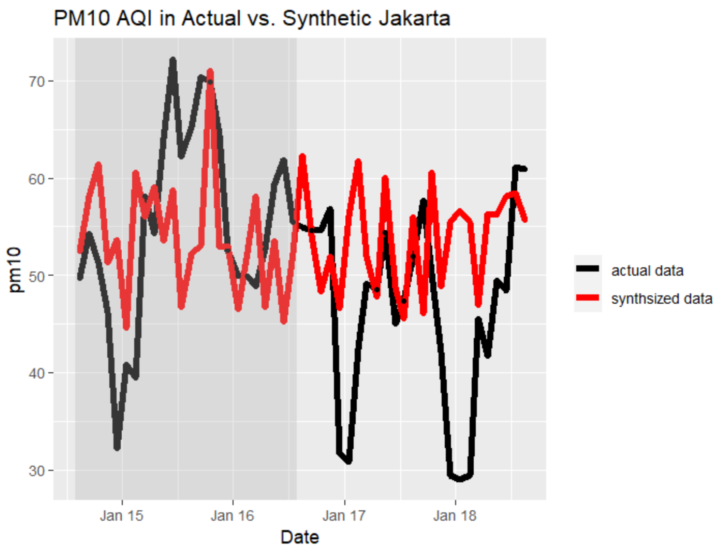
CO Predictors			
	Unit	**Min Weight**	**Max Weight**
CO	%	0.48%	8.35%
Gust Speed	%	18.02%	37.48%
Wind Speed	%	15.30%	8.35%
Temperature	%	8.35%	37.48%
GDP per Capita	%	57.84%	8.35%
Total		100.00%	100.00%
Predicted Loss		2.14%	8.77%

Source: Government Statistical Agency.

In the case of CO as an outcome as shown in Figure 4.6, the optimal set of weights to model Jakarta is Bangkok (27.69%) and Hanoi (72.31%), which generates a minimised RMSPE of 9.45. Further, the optimal weight vectors indicate that CO is modelled as a function of gust speed (18.02%), wind speed (15.30%), temperature (8.35%), and GDP per Capita (57.84%), with the remaining weights allocated to itself. Compared to PM10, non-meteorological factors hold a significantly smaller weight in predicting CO values, implying stronger correlation with GDP per Capita.

As shown by Figure 4.8, the pre-treatment fit is quite good for PM10 with only a slight deviation in mid-2015. In the post-treatment period, the PM10 plot suggests that synthetic Jakarta would have had a higher PM10 trend than the actual data (i.e., the counterfactual), averaging at 55 and 44.5 respectively. This suggests that the OEP had a negative causal effect on PM10 AQI levels, in other words, the policy successfully reduced PM10 concentration. We can see that synthetic Jakarta continued to have higher PM10 levels than actual Jakarta until May 2018 when the former was overtaken.

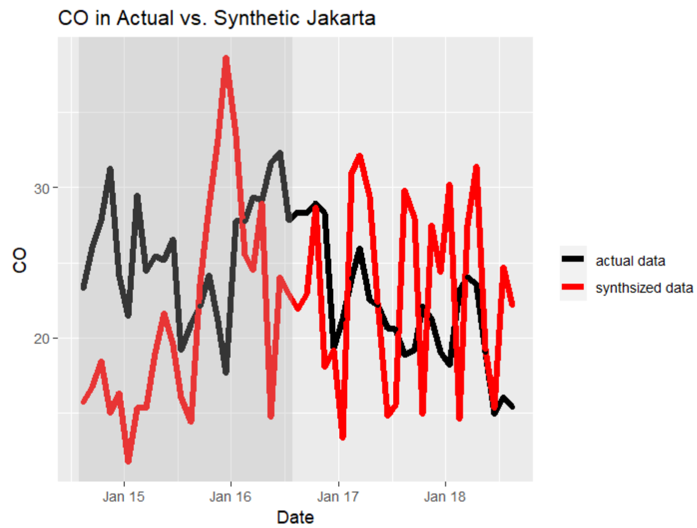
Figure 4.8: PM10 Synthetic Control Results



Source: Government Statistical Agency

In the case of CO as shown by Figure 4.9, the pre-treatment fit is not as well, with synthetic values prior to January 2015 deviating significantly from actual data. Consequently, the synthetic Jakarta values in the post-treatment period does not track actual data as closely as in the case of PM10. On average, actual is slightly lower than synthetic data at 17.1 and 22.3 ppm respectively, suggesting a negative causal effect. However, the deviations are relatively high, resulting in a noisy result that makes the findings less causally persuasive.

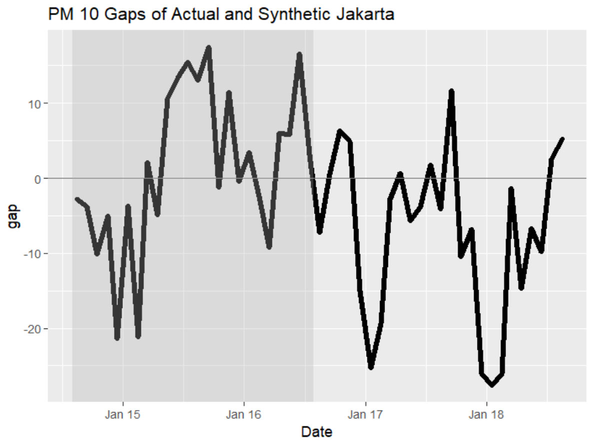
Figure 4.9: CO Synthetic Control Results



Source: Government Statistical Agency

Consider Figure 4.10 and 4.11, which plots the difference between actual (Y1) and synthetic (Y1*) Jakarta or more formally, Y_1 - Y_1* for PM10 and CO respectively. As shown by the figure, the gaps for PM10 averages at around -10.5, indicating a negative causal impact from the policy, which shows the OEP’s pollution reduction effect. The average value of the gaps is -4.2 for CO, a far smaller impact in terms of magnitude. However, the CO gaps data is far less convincing than PM10, given higher fluctuation in the former. The treatment effect for PM10 appears to be larger in January due to significant drops in PM10 levels shown by actual data. This is expected as PM10 comes mostly from vehicle combustion and factories which decline in activity post-holiday season. This is also evident in CO, although to a lesser extent.

Figure 4.10: PM10 Gaps for Actual and Synthetic Jakarta

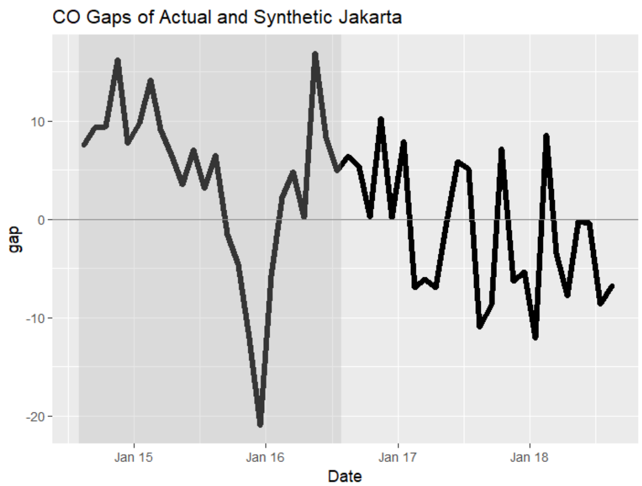


Source: Government Statistical Agency.

In addition to the main outcome variables, synthetic control was also run on the predictor variables as shown by Figure 4.12 and 4.13 for PM10 and CO respectively. The purpose of this is to assess the ability of the algorithm to match in the treatment period based on pretreatment data. The closeness of match between actual and synthetic data varies for each variable. Evidently, the match is poor for GDP per Capita due to the low number of observations, given that it has a quarterly frequency.

For gust speed, the match is poor in the case of PM10, and tracks actual data quite well until a deviation in mid-2015 in the case of CO. The same result is evident in the case of temperature, with closeness of match shown in certain time periods but high deviations in another.

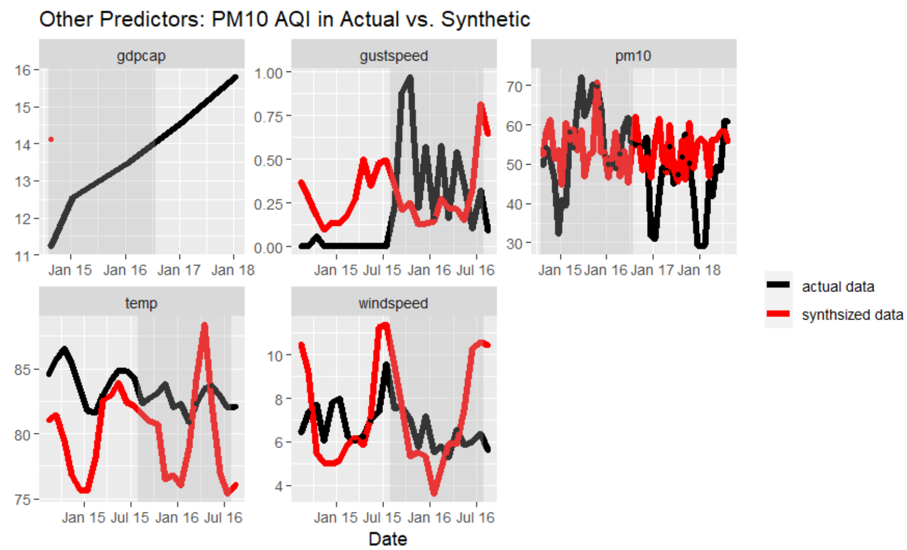
Figure 4.11: CO Gaps for Actual and Synthetic Jakarta



Source: Government Statistical Agency.

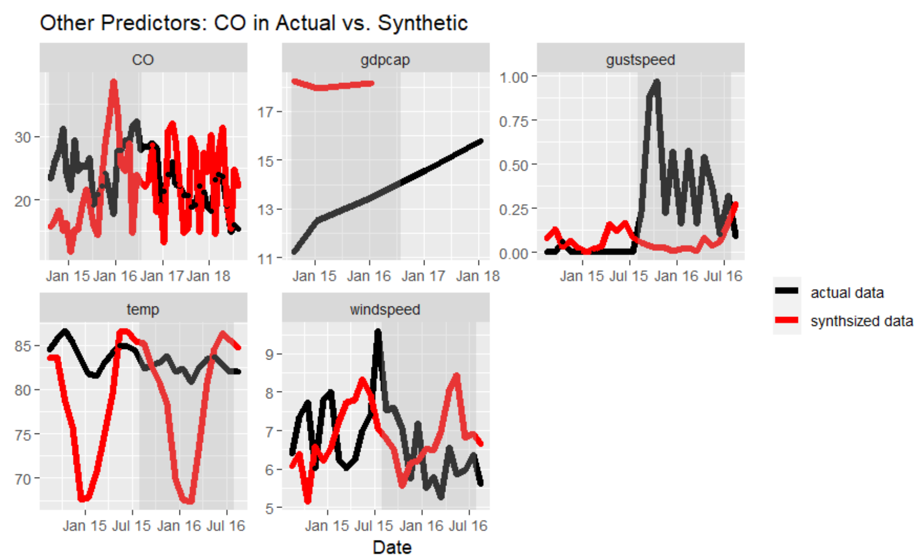
Wind speed however has relatively good fit in the case of both predictors, with a generally identical trend in pre- and post-treatment periods. Despite the predictors showing various degrees of match, the outcome shows considerably better match. Most likely this is because meteorological factors have a greater dependence on geographic location as opposed to pollutants. Countries that are located near the equator are generally higher in temperature and thus have lower atmospheric pressure and wind speeds. Regional differences of countries in the donor pool thus might generate different levels of closeness for each predictor. These results should not be a problem for the purposes of this study, given that the main outcome variables show good fits. In past synthetic control studies, attention is given to predictors only in the case when main outcome variables show poor pre-treatment fit (Abadie and Gardeazabal, 2003), which is not evident in this case.

Figure 4.12: PM10 Synthetic Control on Predictors



Source: Government Statistical Agency.

Figure 4.13: CO Synthetic Control on Predictors



Source: Government Statistical Agency.

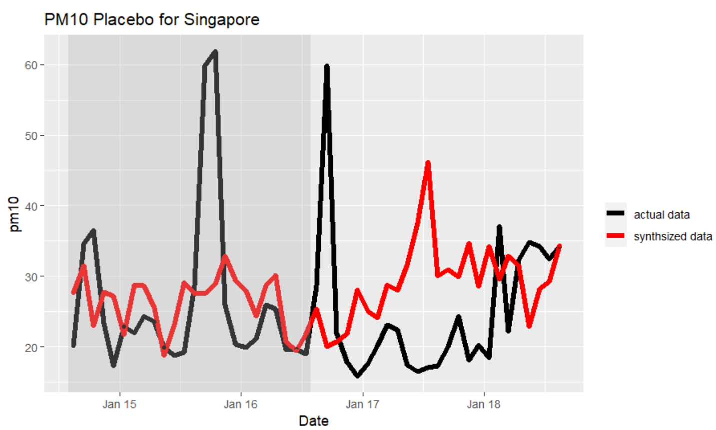
4.3 Placebo Study Results

Given that our synthetic control results indicate a negative causal effect, i.e., OEP did cause pollution to decrease, the question remains about whether the gap shown in Figure 10 has a causal link with the OEP or is just the outcome of the algorithm's inability to properly model the counterfactual, i.e., occurring by happenstance. To answer this concern, a placebo study will be run by using the same algorithm that computes the gap in Figure 10 in a similar city that did not implement OEP in the study period. Comparison of that city's actual data and its synthetic version should yield no indication of a causal effect for the method to be deemed reliable, given that neither has OEP implemented.

In conducting this Placebo study, we will choose cities that were chosen by the algorithm to model Jakarta in the post-treatment period. For PM10 the cities are Singapore, Bangalore and Weinan whereas for CO they are Bangkok and Hanoi. In addition to being the cities that yield the optimal weights, these locations are highly similar with Jakarta in terms of geography with most being tropical countries located near the equator with Weinan being the exception.

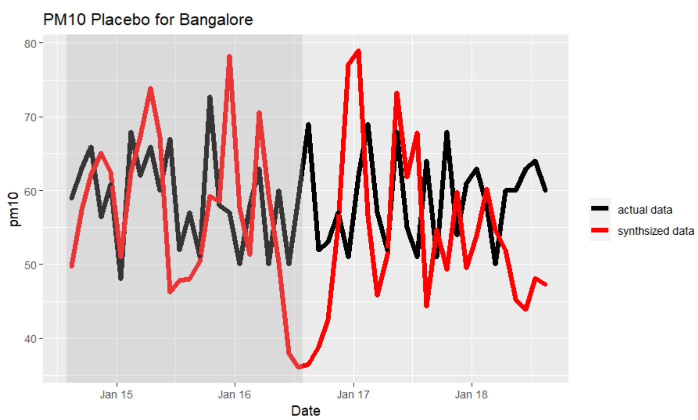
These locations are also similar in terms of population density and industrial activity, which are factors that have a significant bearing on air pollution. As shown by Figure 4.15 and 4.16, the weighted combination of cities in the donor pool (excluding Jakarta) reproduces PM10 AQI with a high degree of accuracy across pre- and post-treatment periods for Bangalore and Weinan respectively.

Figure 4.14: Singapore PM10 Placebo Study



Source: Singapore Statistical Agency.

Figure 4.15: Bangalore PM10 Placebo Study

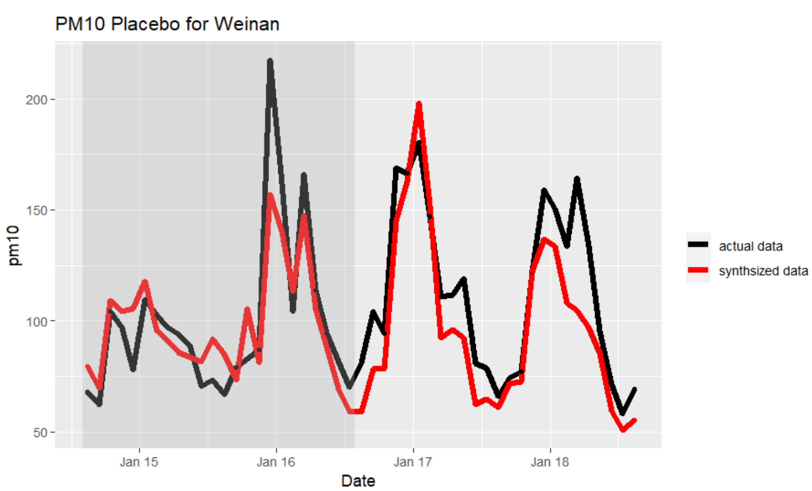


Source: India Statistical Agency.

For Singapore as shown by Figure 4.14, the accuracy of the synthetic reproduction lasts until mid-2016, after which actual Singapore starts to experience unusually high levels of pollution. One explanation for this is the 2016 Southeast Asian haze incident, where slash-and-burn farming practices in Sumatra and Kalimantan led to transboundary haze and smog to Singapore, even more so than Jakarta due to its proximity to the fire source.

The closeness of the match for Bangalore is particularly important for robustness, given its 81.34% contribution to synthetic Jakarta for PM10. As shown above, synthetic Bangalore reproduces actual data well with mid-to-late 2016 and early-to-mid 2017 as the exception. In short, the placebo studies for Bangalore and Weinan indicate that they did not experience any causal effect as their synthetic version did not deviate from actual data, which is in accordance with the hypothesis (i.e., no significant pollution-inducing event occurring in these locations should yield zero treatment effect). This is evidence in support of robustness, given little to no indication of false positives.

Figure 4.16: Weinan PM10 Placebo Study

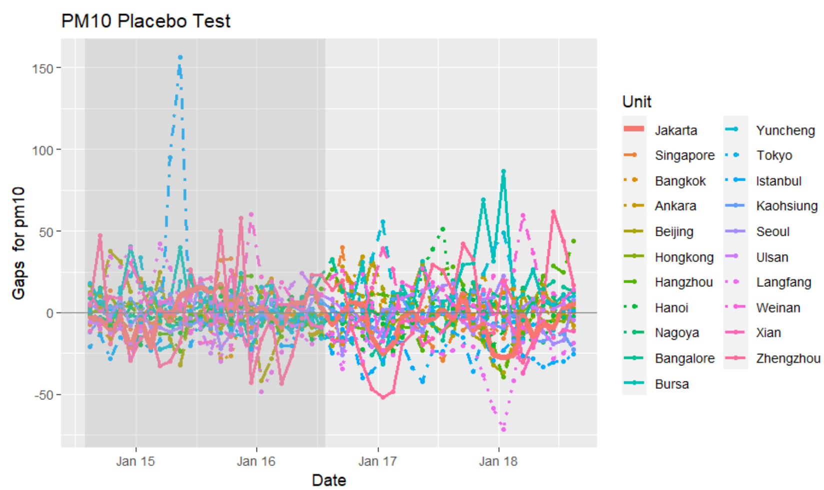


Source: China Statistical Agency

Given so, let us examine how the actual and synthetic version of each city in the donor pool compares to Jakarta for the case of PM10. Consider Figure 4.17, which plots the gaps between the actual (Y_1) and synthetic (Y_1*) version of each city, i.e., Y_1 - Y_1*. Shown by the thick red line, the gaps for Jakarta are located in the middle of the range. We can observe that the gaps for Jakarta are not a significant outlier, meaning that it is not more pronounced than other donor pool cities despite being the only city that experienced a road rationing policy change.

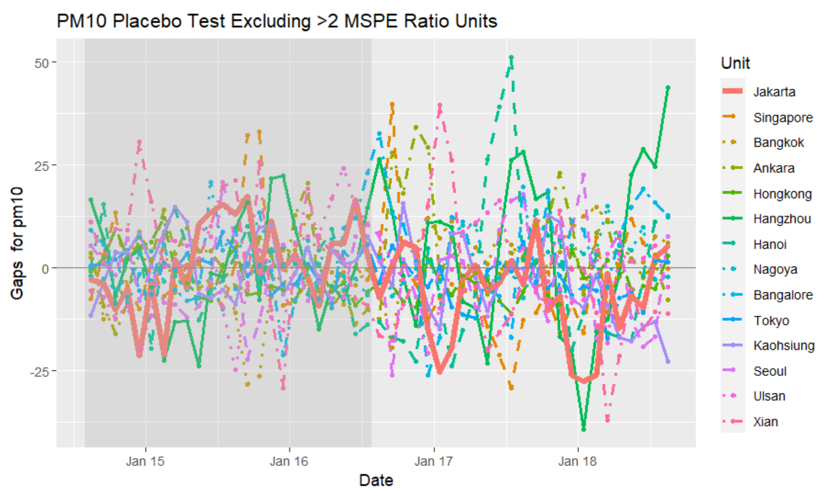
Given underlying noise in the data, we can rerun the placebo study but this time excluding cities with poor pre-treatment fits, which is defined by the MSPE ratio. In essence, this is simply the ratio between the pre-treatment MSPE of a control (i.e., placebo) unit to the pre-treatment MSPE of the treated unit. In synthetic control studies, not all donor pool units can be synthesised with a good fit under a placebo study. Although a large post-treatment gap is expected of these placebo units, these gaps are not caused by a treatment effect but rather a lack of model fit. Thus, Abadie, Diamond, and Hainmueller (2010) suggests excluding these units for the sake of investigating the effect of the original treated unit, with poor units being defined as those having a ratio of 2 to 20, although this is usually left to the discretion of the author. As shown by the right-hand side in Figure 4.18, the exclusion of placebo units with twice worse MSPE than the treated unit have made Jakarta appear as more of an outlier. The gap for Jakarta becomes more pronounced relative to remaining units, with Hangzhou being the only city with more pronounced fluctuations.

Figure 4.17: Full Donor Pool Placebo Study for PM10



Source: Government Statistical Agency

Figure 4.18: Full Donor Pool Placebo Study for PM10 Excluding Poor Fit Units



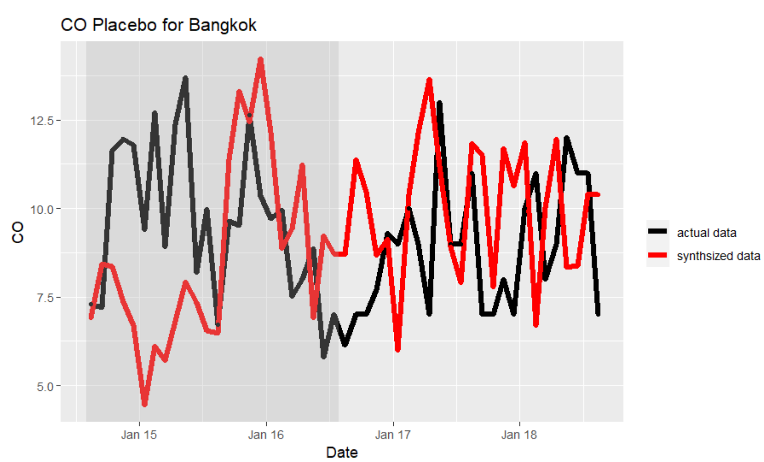
Source: Government Statistical Agency

The placebo result comparison with units that have good pre-treatment fits provides evidence that the negative causal effect shown in Figure 4.8 was robust.

Initially, this was not apparent when the comparison was done with every unit in the donor pool. However, this comparison is misleading as it is subject to noise from units that have poor pre-treatment fit.

In addition to PM10, we have also conducted placebo tests on CO as an outcome. As shown by Figure 4.19 and 4.20, there are mixed results to the wellness of fit for the donor pool cities. For Bangkok, the pre-treatment fit appears poor from August 2014 to June 2015 with synthetic Bangkok moving opposite to actual data. However, the fit started to improve from then on, with post-treatment values of synthetic and actual Bangkok showing virtually similar trends. As such, the placebo study indicates little to no treatment effect for Bangkok, providing evidence in favour of the model’s robustness.

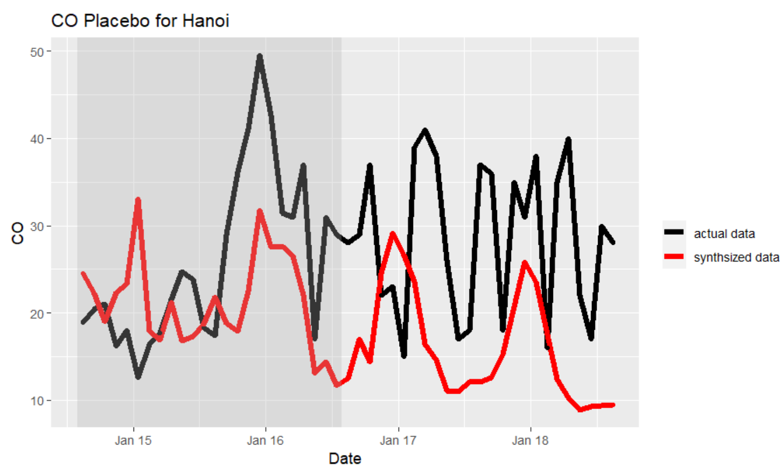
Figure 4.19: Bangkok CO Placebo Study



Source: Thailand Statistical Agency

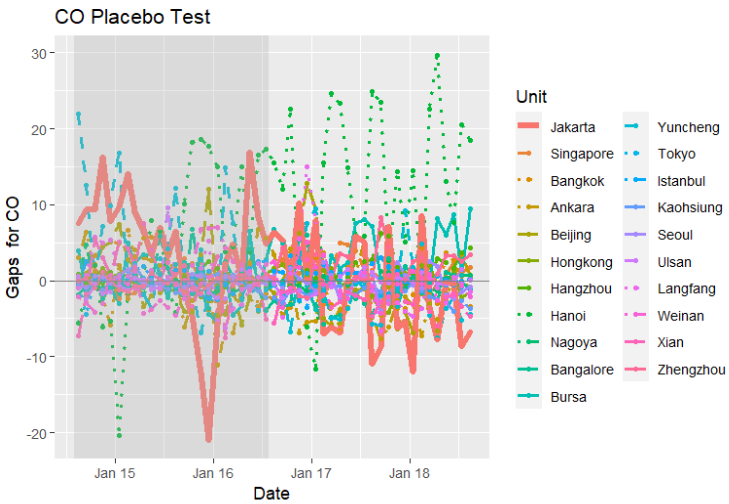
For Hanoi, it appears that the weighted combination of the donor cities managed to reproduce similar movements, although at different magnitudes. In other words, the trends appear similar although the accuracy of reproduction is low at certain time points. In the post-treatment period, consistently higher values of actual data than synthetic Hanoi suggest a negative treatment effect. This is unfortunate, as it suggests that the model may not always reproduce zero treatment effects for placebo units. Thus, a relatively poor match between actual and synthetic Jakarta in Figure 4.9 can be explained by two things. One is the fact that Hanoi too has a poor match in the placebo study. This is exacerbated by the second reason, namely the large weighting (72.31%) placed by the model in Hanoi for synthetic Jakarta.

Figure 4.20: Hanoi CO Placebo Study



Source: Vietnam Statistical Agency

Figure 4.21: Full Donor Pool CO Placebo Test

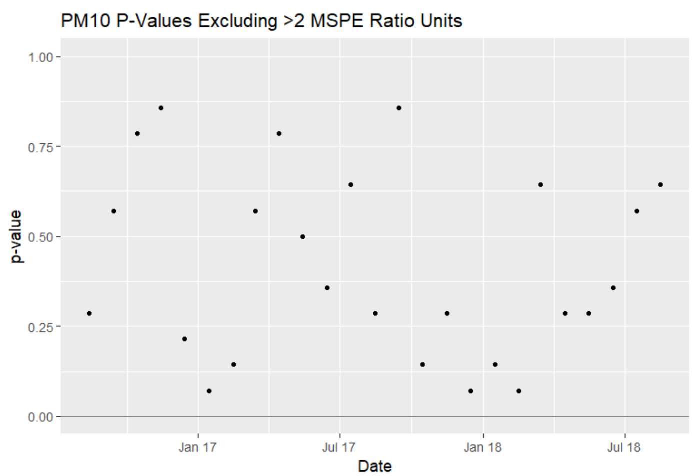


Source: Government Statistical Agency

Next, let us examine the CO placebo study results for all cities in the donor pool. Consider Figure 4.21, which shows gaps (Y_1 - Y_1*) between actual and synthetic Jakarta's CO levels. The gaps for Jakarta are shown by the thick red line, which appears to be a significant outlier compared to other cities. We can observe that the left and right charts appear identical, indicating that none of the placebo units have an MSPE ratio that is twice as bad as the treated unit. In other words, there are less cities with a high pre-period prediction error in the case of CO compared to PM10.

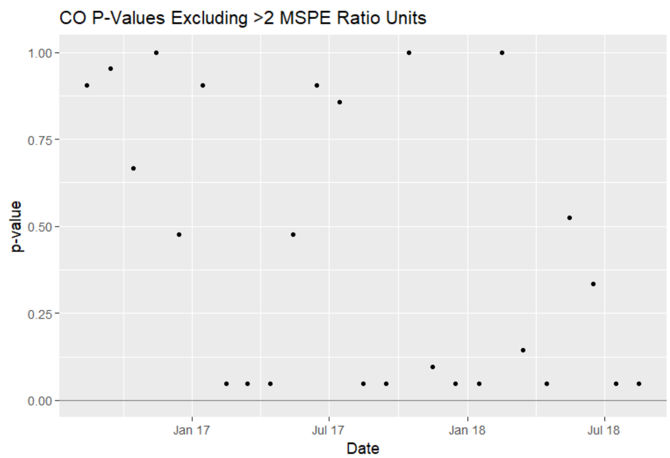
Now let us consider the p-values for each period of the previously discussed placebo tests. Consider Figure 4.22 and 4.23, which shows the p-values for each month in the post-treatment period for PM10 and CO respectively. As shown by the chart, there is a higher degree of consistency of significance for CO, with 10 observations having an identical p-value of 0.0476. The remaining 15 observations for CO, however, have a p-value greater than 0.05 and are thus statistically insignificant at the 5% level. This tells us that for those 10 periods, 4.76% of the placebo units (i.e., donor pool cities) have an estimated placebo treatment effect at least as large as the treatment unit (i.e., Jakarta). For PM10, only 3 out of 25 observations are statistically significant, all of which are significant at the 1% level with a p-value of 0.07. In other words, around 7% of placebo units have an estimated placebo treatment effect equal or greater than the treatment unit.

Figure 4.22: Full Donor Pool PM10 P-Values



Source: Government Statistical Agency

Figure 4.23: Full Donor Pool CO P-Values



Source: Government Statistical Agency

4.4 Market-Risk Event Study Results

The first step of the Event Study methodology is to estimate (alpha) and (beta) parameters using historical data. As a reminder, we are designating the estimation window to be a period of 254 trading days, starting from 300 trading days prior to the event and stopping 46 trading days prior. The estimated alpha and beta magnitudes will then be used to extrapolate the counterfactual stock return, i.e., assuming that the return would have been equal to the stock market's returns. Consider Table 4.7, which shows the estimated alpha and beta figures for the seven automotive stocks during the 254-trading day period between February 17th, 2015, to May 11th, 2016.

Table 4.7: Alpha and Beta Estimation

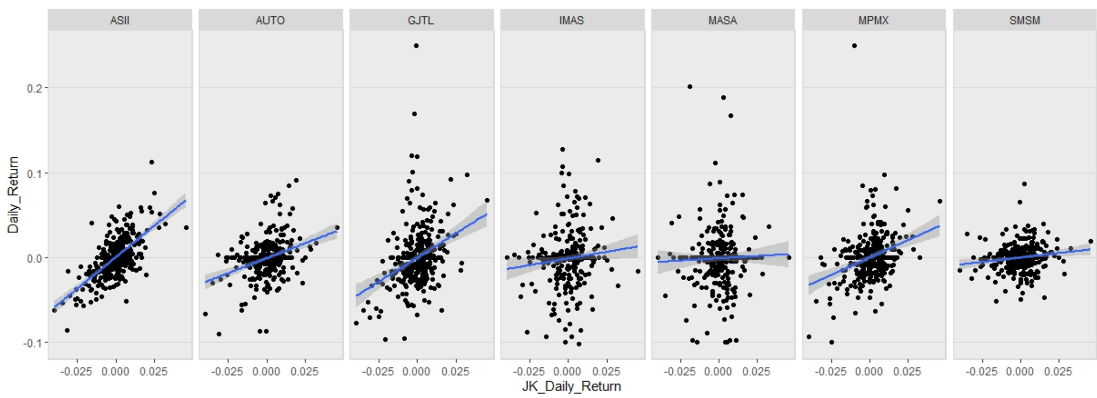
Stock	Alpha	Beta
ASII	0.0004	1.5057
AUTO	-0.0017	0.6662
GJTL	-0.0011	1.2395
IMAS	-0.0020	0.2582
MASA	-0.0014	0.1038
MPMX	-0.0010	0.9568
SMSM	-0.0001	0.2240

Source: Yahoo Finance

The beta estimates for ASII, GJTL, and MASA are positive and greater than one, whereas the remainder of the stocks have values between zero and one. This is in line with the general view that consumer discretionary stocks such as automotive companies are cyclical, as they have a positive correlation with the market. These results suggest that ASII is the most sensitive to changes in market returns and MASA as the least responsive. Figure 4.24 shows a visualization of the regression of individual stock daily returns against JKSE daily returns, where ASII and GJTL have the most visibly steep regression line. Distributionally, ASII, AUTO, and SMSM appear to be less dispersed than the other stocks, especially compared to MASA and IMAS which appears to be most dispersed.

Using the estimated alpha and beta figures in Table 4.7, we estimated the abnormal returns for each stock in the event window, namely during the June 15th, 2016 to August 1th, 2016 period. Essentially, the abnormal return is the difference between actual returns and the predicted returns from the market-risk adjusted model, or in other words $Y_{1,POST} - Y_{0,POST} \mid D = 1$. Figure 18 below shows the estimated average abnormal return and corresponding cumulative abnormal return for all seven stocks in each day within the 41 day event period (i.e., the event day of July 20, 2016 is denoted as 0). At the event day of t = 0, the abnormal return is estimated to be -0.02%, with a cumulative abnormal return of 5.14% starting from t = -20.

Figure 4.24: Stock Beta Regression



Source: Yahoo Finance

Visually, the mean abnormal return of all seven stocks is depicted in Figure 4.25. The daily abnormal return appears to fluctuate, with a general upwards trend prior to the event and a sharp decline prior to the event. This is followed by a flatter trend in the post-event period.

Figure 4.26 shows a decomposition of the mean abnormal return into each individual stock. It appears that MPMX experienced an outlier-sized abnormal return a few days prior to the event. Generally, however, it is difficult to discern an overall trend from abnormal returns alone, given its fluctuating nature. Viewing the causal impact of the event on stock performance is better done based on the cumulative abnormal returns, as it being a stock as opposed to a flow variable means that it is less susceptible to fluctuations.

Consider Figure 20, which shows the plot of mean cumulative abnormal returns across the seven stocks, which is the main object of interest in event study research. We can observe that the seven automotive stocks experienced a run up in abnormal returns from before the event day. In t = -20, abnormal returns fluctuated around 0.0%, and began to rise in t = -10. This continues until t = 5, where abnormal returns began declining. This finding is in line with Huberman and Regev (2001) and Fama et al., (1969), which showed that the treatment stock will experience a run up in abnormal returns even prior to the event as information was made public prior to the actual implementation, which in our case happened one month prior in the June 28th - July 19th, 2016, period.

Thus, it is plausible that the market was purchasing more automotive stocks in days leading up to the first trial of the policy, bidding up prices. In other words, the market is efficient enough to incorporate this information into the price of the stocks, anticipating the potential benefits that automotive companies will experience from the policy. Consider Figure 21, which decomposes the mean cumulative abnormal returns into each individual stock.

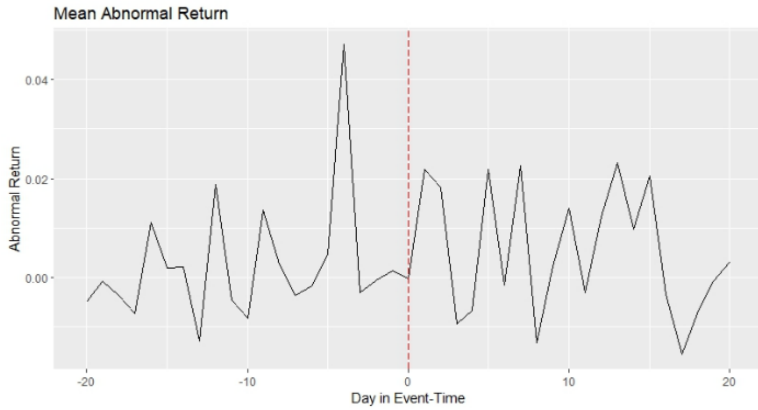
Table 4.8: Mean Abnormal and Cumulative Abnormal Return

Pre-Event			Post-Event		
Event Time	Mean AR	Mean CAR	Event Time	Mean AR	Mean CAR
-20	-0.50%	-0.50%	1	2.18%	7.32%
-19	-0.08%	-0.58%	2	1.81%	9.14%
-18	-0.37%	-0.95%	3	-0.94%	8.19%
-17	-0.72%	-1.67%	4	-0.66%	7.53%
-16	1.10%	-0.57%	5	2.18%	9.71%
-15	0.18%	-0.38%	6	-0.15%	9.56%
-14	0.22%	-0.17%	7	2.26%	11.82%
-13	-1.29%	-1.46%	8	-1.32%	10.50%
-12	1.88%	0.43%	9	0.24%	10.74%
-11	-0.45%	-0.03%	10	1.40%	12.14%
-10	-0.83%	-0.86%	11	-0.30%	11.83%
-9	1.35%	0.50%	12	1.22%	13.06%
-8	0.27%	0.76%	13	2.32%	15.38%
-7	-0.36%	0.41%	14	0.98%	16.36%
-6	-0.18%	0.23%	15	2.04%	18.40%
-5	0.46%	0.69%	16	-0.35%	18.06%
-4	4.71%	5.40%	17	-1.54%	16.51%
-3	-0.31%	5.09%	18	-0.73%	15.78%
-2	-0.05%	5.03%	19	-0.08%	15.70%
-1	0.13%	5.16%	20	0.31%	16.01%
0	-0.02%	5.14%			

Source: Yahoo Finance

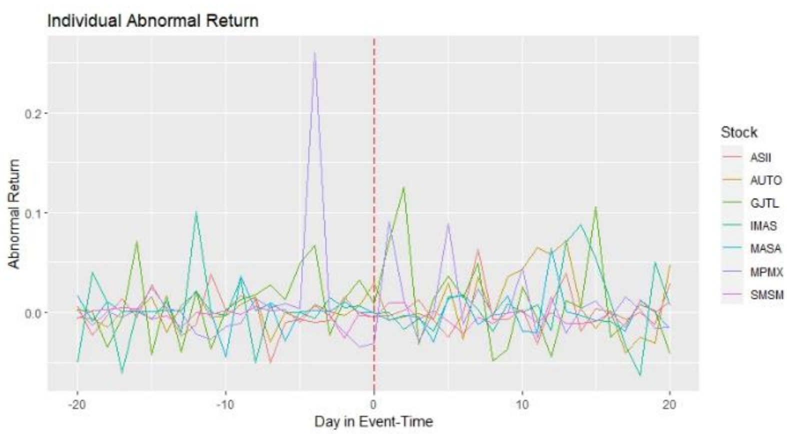
As shown by Figure 4.28, GJTL, MPMX, AUTO, and IMAS showed rapidly rising cumulative abnormal returns after the event. On the other hand, cumulative abnormal returns were relatively flat for MASA and ASII and declined steadily for SMSM. It is likely that SMSM’s business, which is highly dependent on revenues from car and radiator filters, are not affected by the policy as most individual cars should have driven the same or perhaps lower average daily mileage due to the policy.

Figure 4.25: Plot of Mean Abnormal Returns



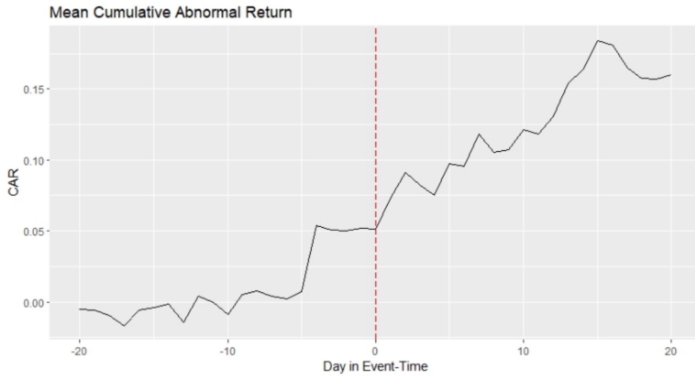
Source: Yahoo Finance

Figure 4.26: Plot of Individual Mean Abnormal Returns



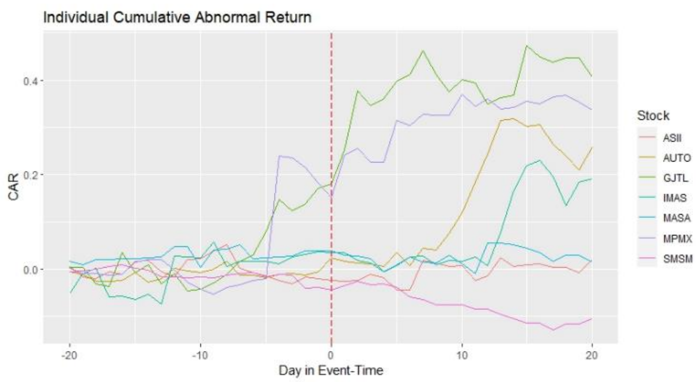
Source: Yahoo Finance

Figure 4.27: Plot of Mean Cumulative Abnormal Returns



Source: Yahoo Finance

Figure 4.28: Plot of Individual Cumulative Abnormal Returns



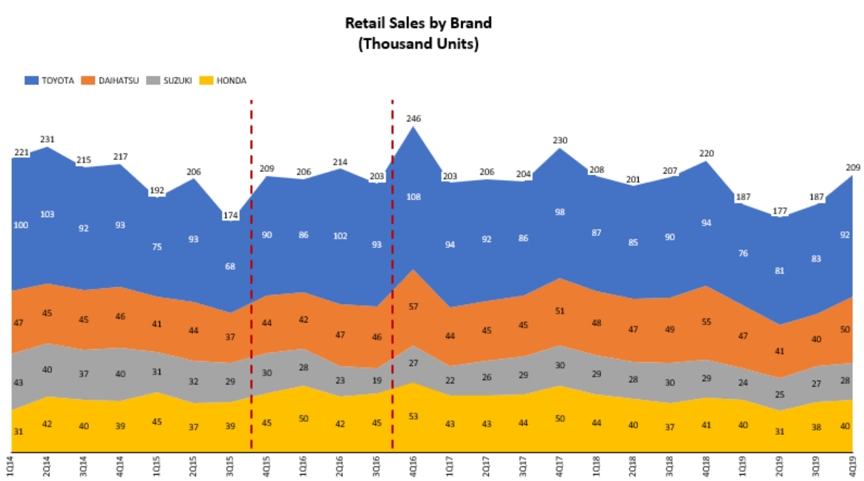
Source: Yahoo Finance

It is interesting to note that among the car manufacturer companies, IMAS showed significantly higher cumulative abnormal returns than ASII, despite the latter being the highest capitalized automotive stock and thus seek to benefit the most from the policy. One potential explanation for this is the fact that IMAS has higher-end European brands under its portfolio, as opposed to Japanese mass-market brands under

ASII. The majority of ASII sales are generated by cars and motorcycles aimed to the mass-market, which may not have the financial means to purchase an additional car in response to the OEP. On the other hand, households that purchase high-end European vehicles are more likely to compensate for the OEP by purchasing an additional vehicle.

Consider Figure 4.29, which shows retail car sales data in 2011 to 2022 from the Indonesian Automobile Sole Agent Association (Gaikindo). Note that this data reflects car sales from wholesalers to end consumers, as opposed to manufacturers to wholesalers. This is to reflect actual individual household response to the policy, as opposed to business response. From the chart we can observe two spikes in car sales within our study period. The first spike occurs in between the third and fourth quarter of 2015 during the estimation window, and the second spike occurring in between the third and fourth quarter of 2016 around the event day of t = 0.

Figure 4.29: Gaikindo Historical Sales Data



Source: Gaikindo

In the first spike, units of automobiles sold increased by 20.1% quarter-on-quarter from 174 in 3Q to 209 thousand in 4Q. The first increase prior to the closure of the 3-in-1 policy was driven largely by Toyota, with other brands experiencing softer spikes. On the other hand, the second increase around the socialization of the odd-even policy was uniformly pronounced for all brands. This spike is even more pronounced when compared to 3Q14, 3Q15, and 3Q17, 3Q18, and 3Q19, supporting the idea that the increase around the event window is irregular and not a mere seasonal effect. The fact that car sales increased around the odd-even policy supports the previous finding that automobile stocks generated abnormal returns in days leading to the policy announcement date. Thus, it is plausible that stock investors purchased shares of automobile companies in expectation of increasing sales of automobiles. Consequently, automobile companies are clear beneficiaries of the Odd-Even Policy, experiencing a temporary increase in equity value because of positive sentiment from investors.

CHAPTER 5

CONCLUSION

5.1 Conclusion

The use of road-space rationing policies as a tool to reduce pollution is widespread across many countries. In essence, the purpose of road-space rationing is to limit the number of vehicles on roads at any given time, with the hopes that individuals will shift their behavior into using other modes of transportation that results in a net reduction of pollution. In June of 2016, the Jakarta Provincial Government implemented the Odd-Even Policy as a replacement to the 3-in-1 policy. Previously, each car that travels through select streets must at least have 3 passengers for an entry permit. The Odd-Even Policy replaces this by permitting only odd plated cars to travel on odd dates, and vice versa.

This study aims to study the causal effect of the Odd-Even Policy on two outcomes, measures of pollution and automotive stock prices. First, the study employs synthetic control methodology on Jakarta's Carbon Monoxide (CO) and Particulate Matter 10 (PM10) levels to examine the causal effect on pollution. The method extrapolates data for synthetic Jakarta using a weighted average of 20 cities' CO and PM10 levels across two years before and after the policy implementation date of August 30th, 2016. From the main estimation, we found that the RMSPE-minimizing weights for PM10 in Jakarta is Singapore (17.16%), Bangalore (81.34%), and Weinan (1.47%). The model estimates an average PM10 level of 55 ppm in the absence of the Odd-

Even Policy, versus the actual average of 44.5 ppm. Thus, the OEP caused an average of 10.5 ppm reduction in PM10 concentration in the two-year period after the policy implementation. On the other hand, the RMSPE-minimizing weights for CO in Jakarta is Bangkok (27.69%) and Hanoi (72.31%). The main model estimates CO levels of 22.3 ppm in the absence of the OEP, versus average actual data of 17.1 ppm. We can thus infer that the OEP resulted in a 6.2 ppm reduction in CO levels.

As a robustness check, we conducted a placebo study to verify that the estimated causal effect did not occur by chance. Essentially, the placebo study calculates differences between synthetic and actual versions of each outcome variable for each city in the donor pool, including Jakarta. The placebo study shows that the gap between actual and synthetic Jakarta is an outlier relative to other cities in the donor pool for both CO and PM10 outcomes. This supports the finding that our results did not happen by coincidence, as gaps for non-treatment cities (i.e., cities that did not experience any change in policies that have large effects on pollution) should have been equally large as Jakarta if the OEP has a zero-treatment effect.

It should be noted however that despite the placebo study supporting the robustness of the results, the p-values are quite high in some observations. This is likely caused by the high-frequency nature of daily PM10 and CO data, given that synthetic control studies are typically used for annual data such as GDP in the case of Abadie and Gardeazabal (2003). Regardless, the nature of the synthetic control study is such that single observation p-values are rarely placed importance on, and placebo study is used in place of p-values to assess robustness.

Lastly, we conducted a market-risk event study to estimate the causal effect of the public announcement of the OEP to the prices of seven automotive stocks trading in Indonesia Stock Exchange. The method first estimates alpha and beta parameters for the seven stocks within a 254-trading day window between February 17th, 2015, and May 11th, 2016, by regressing individual returns against the JKSE return. These alpha and beta parameters are then used to estimate what each stock's return would have been in the absence of the OEP. Next, we then calculated the abnormal return by finding the difference between estimated and actual returns for each stock. We found that cumulative abnormal returns increased since t = -10, reaching 5.14% at t = 0 (i.e., the first public announcement of the OEP) on June 20th, 2016, and peaking at 17.8% at t = 15 prior to dissipating. This increase in cumulative abnormal return is driven largely by GJTL, MPMX, AUTO, and IMAS. This finding suggests that information of the OEP was priced in by automotive stocks as shown by an increase in cumulative abnormal returns. In line with past event studies, the results are indicative of information leaks prior to t = 0 and dissipating cumulative abnormal returns in the post-event window as speculators began selling their positions.

There are several potential effects of the Odd-Even Policy to economics and business conditions. If the finding that the OEP results in a reduction of PM10 and CO holds true, road space rationing should be expanded to other areas to improve citizen health and wellbeing. Economically, this might result in lower mortality and healthcare spending, as was found in past studies that lower air pollution levels are associated with decreased hospitalization rates due to respiratory problems. In addition, the increase in purchases of automotives due to road space rationing might support the growth of the local manufacturing industry, opening more job availabilities as manufacturers seek to correspond to higher demand. However, this is a conjecture that must be verified by further research that considers the mediating variables between air pollution and increased car demand.

5.2 Limitation of Study and Recommendation

In analyzing the causal effect of the Odd-Even Policy on pollution using synthetic control, the study encounters several limitations. First, from a data source standpoint PM10 is not the most ideal indicator for pollution measurement. PM10 levels measure the concentration of particulate matter that is 10 micrometers or less in diameter. Given the large size of PM10 pollutants, particulate matter included in PM10 are coarser, and may include particles larger than vehicular exhaust pollutants such as dust. Thus, any potential treatment effect observed might be influenced by surrounding area activities that produce dust, such as construction sites or mining operations. In addition, the high-frequency nature of daily pollutant data might result in an overly noisy estimation. In the past, minimal synthetic control studies have utilized high-frequency data and used annual data instead. The author realizes this and thus the significance of the study results must be taken with higher scrutiny compared to other synthetic control studies.

Second, this study faces the issue of a limited number of verified data sources resulting in a small donor pool of 20 cities. Not all cities own and operate a particulate matter detection device, and in the case that they do, data might not be publicly accessible. Even then, the time horizon available for the data might be limited as many cities only began measuring PM10 in the past 10 years.

Third, the synthetic control study also suffers from a lack of external validity. This is because the estimated synthetic values of outcome variables are based on pollutant data that are local in nature (e.g., Bundaran HI surrounding areas only for Jakarta). The nature of air pollutants is highly variable across geographic regions, and what holds true for a particular region may not necessarily hold true for another region in the same country. Thus, the causal effect observed cannot be generalized for Indonesia as a whole, but rather only for the Bundaran HI area which is observed in the study.

In the case of the market-risk event study, there are also several limitations faced by the market-risk event study method. First, the method uses the Market-risk Model as the basis for estimating counterfactual returns of each automotive stock in the absence of the OEP. The true counterfactual may not necessarily behave in accordance with the model, as there might be idiosyncratic movements in stock prices that are not entirely captured by the market return. Further, another shortcoming of this method is that it rests on the assumption that the treatment only affects the treatment stocks (i.e., automotive sector stocks) and has no effect on the larger market. If the market is affected, then the cumulative abnormal return would be overestimated.

Despite these limitations, the value of the study is not undermined. Rather, interpretation of the results should be done with caveat. Given these limitations, future studies should consider using a more robust data source for pollutants (e.g., PM2.5). Given the high frequency nature of the data, a more generalized version of the synthetic control method, namely the Robust Synthetic Control which can select a good subset of donors and can address missing data in their estimation of synthetic data. In the case of the event study, there are a host of expected return models that account for other factors besides beta, such as the Fama-French 3 Factor Model or the Matched Firm Model.

For future studies, it is important to consider two key aspects related to the Odd-Even Policy, namely the weakness of restriction mechanisms and other compensating public responses, both of which may contribute to the relatively weak treatment effect. Regarding restriction mechanisms, punishment for violation of the Odd-Even Policy is a relatively small fine of IDR 500 thousand. Within August to December 2016 alone, there was a recorded 4861 violators of the Odd-Even Policy. This number appears small as bribery is commonplace among traffic violators in Jakarta, resulting in the omission of some violators. In addition, compensating responses may be broader than the purchase of an additional car, such as the use of ride hailing services or public transportation.

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