Impact of the Adoption of EV on Beijing Air Quality

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Abstract

Air quality in Beijing has been questioned for years since 2008 Olympic Game. Recently, government implemented multiple measures to address this issue. Plate registration restriction was announced in the 2010 and in 2014, there was a major change to the policy to promote electric vehicles. Electric vehicle buyers did not have to join the same lottery pool as other buyers after that. The impact of an electric vehicle on the air quality depends on reginal generation mix and Beijing is highly relied on fire power plants. This paper will empirically analyze the impact of this adoption policy by examining the relationship between air quality after 2014 and lottery results. The outcome shows that there is little effect from the policy but power plants exhibit significant impact on the air quality.

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I. Introduction

Beijing now is having serious problem of controlling its air quality. According to the historical Air Quality Index (AQI), from 2009 to 2014, only handful of days' air quality can be categorized as "good" or "moderate". In a research conducted by World Health Organization, Beijing is categorized as one of the ten dirtiest capitals (WHO, 2011). As one of the main pollutants, $PM_{2.5}$ has been proved to be hazardous by several scholars. Kaiser found that $PM_{2.5}$ is more likely to lodge in the lungs (Kaiser, 2001). It could also penetrate doors, thus altering the home environment, which makes $PM_{2.5}$ a possible cause for increasing cardiac and respiratory mortality (Ostro, 2004). As car emission contributes 17.1% of total annual $PM_{2.5}$ concentration (Yu et al, 2013), it is important to take measures to limit vehicle exhaust.

The direct impact of a vehicle to the environment is through its emission. Multiple literatures in the past has shown that car emission could be hazardous if not been regulated. In the case of Beijing, as previous paragraph said, car emission contributed 17.1% of total annual $PM_{2.5}$ concentration. To make things worse, Yu et al, also found that 12.7% of that is also related to vehicles on the road. Road dust that contains "tire/brake wear debris and road abrasion contaminate soils with metals" (Yu et al, 2012). Combining the direct and indirect impacts of a vehicle to the environment, car along is roughly responsible for 30% of total annual $PM_{2.5}$ concentration.

To deal with such problem, several methods were used since 2008. Driving restriction in Beijing and "Ten cities and Thousand Vehicles" were initiated in 2008 and 2009. The goal of those policies were to decrease car emission and substitute conventional vehicles (CV) with electric vehicles (EV). In 2011, register restrictions were implemented for purchasing conventional vehicles and electric vehicles.

Air pollution in Beijing was still a major problem after all those efforts. Scholars began to think about the social dead weight loss that previous regulations caused. Li (2014) compared Beijing's quota system with Shanghai's auction system. Both systems set an annual quota but have different impacts on social welfare. His estimation shows that at least $2.5 billion of revenue is lost due to the lottery system in 2012 (Li, 2014).

New changes were introduced to the lottery system in 2014. EV and CV buyers were separated into different pools. This change greatly promote EV sales but some scholars argued that EV is not suitable for dealing with air pollution in Beijing. Cai et al conducted a research that focus on Beijing's taxi fleet. The changing from CV to EV can reduce photochemical oxidants but acidification risk for human health will be higher (Cai et al, 2017). The limitation for this research is that it only consider the power plants located inside Beijing, which are much cleaner than other power plants. The amount of electricity that needed for charging EV would have to be supplied by power plants in surrounding areas (Cai et al, 2017). Because the geographic feature of Beijing, the pollutants from producing the electricity can be carried by the wind and concentrate in Beijing and surrounding areas.

Huo et al examined the environmental implication of EV. He claimed that the environmental impact of EV depends heavily on the generation mix of that region. With coal-power plants generating high proportion of the electricity in Beijing, EV can potentially increase sulfur dioxide and nitrogen oxide emission compared to CV (Huo et al, 2010).

In my research, I would like to focus on the fine particles concentration after 2014. A change of registration restriction was implemented in 2014. CV buyer and EV buyer do not share a common lottery pool any more. Due to this change, buying CV was harder than buying an EV afterward. Data from Beijing Traffic Management Bureau (BTMB) shows that the chance to get a permit for CV is 0.001% today and that for EV is 42% today (2016). A substitute effect was created after 2014 and as the chance of buying CV decreases to today's level and income per capita increased, effect of EV on air quality will be more and more significant.

My methodology includes finding connection between EV permits newly added to the existing car fleets and monthly average $PM_{2.5}$ concentration after 2014. I separately controlled for rush hour and non-rush hour, winter and non-winter to estimate the effect of EV in different situation. The time period I chose is from January 2014 to December 2016. In this period, Beijing Municipal government conducted new registration restriction to promote EV sales and as a result, we can have almost exact number of newly purchased EV during this period.

Regression results show insignificant relationship between $PM_{2.5}$ concentration level and EV permits and a positive relationship between electricity outputs in Beijing with pollution concentration level.

The rest part of the paper is organized as follows. Section 2-5 summarize the policy background, literature review, data and the model respectively. Section 6 presents the main results from using monthly data and daily data. Section 7 summarizes the main finding of this paper.

II. Policy Background

In the past 15 years, rapid growth in China's GDP changed people's life greatly. China now is one of the biggest automobile market in the world. Traffic congestion and air pollution became more and more serious as data shown that Beijing had increased its vehicle fleet from 1 million in early 2000s to over 5 million in 2013. To counter those effects, driving restriction and registration restriction were implemented before and after the 2008 Olympic Game.

On December 23rd, 2010, Beijing government implemented the registration restriction. The first-time buyers must win a non-transferable permit from the lottery before heading to car dealers. Those who want to receive a car as a gift, buy a used car or transfer non-Beijing plate also need to win the same lottery. Winner must finish the purchase or other process within three months after receive the permit. The quota was set at 240,000 per year and reduced to 150,000 after 2013.

The chance to win a lottery was initially 9.3% and dropped to 1% after two years. Nowadays, this number has further dropped to 0.001%. Despite suggestions about distributing permits on first come first serve bases, people who have entered the lottery pool for a long time have the similar winning rate as those who just join this. Various newspapers predict that averagely it will take 11 to 24 months to win a permit.

On the other hand, EV buyers entered a separate lottery pool after January, 2014. CV and EV buyers faced different winning rate after the change. The rate were 100% at the beginning and dropped to 42% in 2016. The decrease in the winning rate is due to the increasing amount of new EV buyers and some existing buyer that remain in the lottery pool. With two lottery pools for EV and CV, the municipal government didn't change the annual total amount of permits, meaning the winning rate for CV will drop even further.

The people joined the lottery pool nowadays has expended to nearly three million for CV and two hundred thousand for EV. The total amount of permits has dropped from a hundred and fifty thousand to a hundred thousand. All the reduction is coming from CV permits. The distribution of permits is changed from distributing throughout the year to be located in one lottery. This makes those who do not win a permit must wait for at least a year.

Besides encouraging people to buy EV instead of CV, Government also put forward policies to get rid of old cars on the road. For example, Government subsided car scrappage for vehicles that are over 6 years. Each owner according to its car's condition and fuel consumption can receive up to 20,000 Yuan. With all efforts combined, each year could reduce 300,000 CV on the road. In 2016, 340,000 CV were scrapped in the first 10 months.

III. Literature Review

Beijing and China's official air quality index didn't include $PM_{2.5}$ until 2013 (Zhang et al, 2016). Most air quality data are even confidential (Ghanem & Zhang, 2013). Ghanem and Zhang (2013) found 55% of cities reported suspicious report by applying discontinuity test. With such difficulties in using and trusting official data, scholars use their own air quality measurement or estimate the $PM_{2.5}$ concentration from various data sets.

Wang et al. (2009) uses their own data and compared that with the official air quality index. They set up the sampling site at Peking University and collected sixty-three sets of $PM_{2.5}$ and PM_{10} concentration data between July and October, 2008. Comparing with official air quality index, they found significant correlation between their $PM_{2.5}$ and Beijing's PM_{10} concentrations. A concerning finding from this comparison is that PKU's PM_{10} concentration is 1.3 times higher than official data. Although sampling difference could be an explanation (Yao et al 2009), the accuracy of official report was questioned by scholars. This finding motivated me not to only rely on official air quality index as data source for this research. Wand et al. (2009) also found that wind, humidity and other weather condition can affect $PM_{2.5}$ concentration by up to 40%. In my model, to exclude this exogenous effect, data during winter time is separated from other periods.

Chen et al. (2013) used both official air pollution index (API) and daily 10km aerosol optical depth (AOD) data between 2000 and 2009. AOD data can be converted to PM_{10} estimates and it can capture up to 70% of the PM_{10} variation. Chen et al. (2013) utilized API and AOD data in Beijing and other 39 cities in order to compare city fixed effect. The benchmark was set at one year before the preparation for Olympic and three periods were used to detected treatment effect. Chen et al. (2013) added several economic development indicators. GDP growth rate, GDP per capita, total industrial production and several other indicators were included in the model. This part gave me suggestions on all the control variables I used in the model to determine the EV's effect on Beijing's air quality. Besides the estimation results, Chen et al (2013) tested for the potential manipulation on API data that Andrews (2008) questioned about. The result from plotting the kernel density of API for all 40 cities showed that Beijing has little evidence in manipulating API data and other cities have abnormal bump. This result was proved by Ghanem & Zhang's (2013) latter research and it also proved that Beijing's API data can be seen as a trustworthy data source to estimate $PM_{2.5}$ concentration.

Many scholars also showed that missing $PM_{2.5}$ data can be estimated by using $PM_{2.5}$ and PM_{10} relationship (Li, 2002). Maraziotis (2008) used empirical analysis to prove a high correlation, which can be up to 0.98, between PM_{10} and $PM_{2.5}$. Inspired by those works, Wang et al (2013) developed the Single Point Areal (SPA) estimation to estimate Beijing's $PM_{2.5}$

concentration using official PM_{10} concentration and U.S. Embassy's $PM_{2.5}$ concentration data. They collected official PM_{10} data from 18 observation stations and daily $PM_{2.5}$ data from May 10, 2010 to December 6, 2011. The SPA technique is transforming the point $PM_{2.5}$ data to an areal average $PM_{2.5}$ concentration. The accuracy of this expansion is proved by Wang et al (2013) by using both the empirical fact that $PM_{2.5}$ and PM_{10} concentrations are highly correlated and a validation study using existing data. Main results show that U.S. Embassy's data have almost the same trend as citywide $PM_{2.5}$ concentration on both daily and monthly perspective. The winter time during January and March have lowest concentration level. This is partially because of the windy days. Embassy's data is clearly higher than the estimated concentration level. One possible reason could be that the embassy is located at the city center near the main road. The observation sites are scattered across Beijing. The Highest population density and traffic volume are found around the embassy. Those results have a great impact on my data source choosing and regressions design. Since U.S. Embassy data exhibits same pattern of areal average $PM_{2.5}$ concentration, I could rely on embassy's data since official data is hard to get (Zhang et al, 2015) and some key information are sometimes confidential (Ghanem & Zhang, 2013).

More specifically, a higher concentration level recorded by the embassy shows that its location is more exposed to traffic effects. Because Beijing's EV fleet is relatively smaller than its CV fleet but no driving restriction is set for EV, different location will experience the effect in various magnitude. In the area with high traffic volume, EV's effect can be more obvious. The result also inspired me to treat winter time separately. In their result, windy days are an important factor that lower winter $PM_{2.5}$ concentration. By controlling such months, the effect of EV will be more accurate.

IV. Data

The data for this research was acquired from different sources: The $PM_{2.5}$ data recorded and published by U.S. Embassy (U.S Embassy 2018), traffic volume data recorded by BTMB and provided by Ruimin Li (2016) and monthly lottery results of CV and EV published by BTMB. Income and power generation data are published by both Beijing Statistical Yearbook and China Statistical Yearbook. Table 1 and Table 2 give the summary statistics. Fig 2 shows EV and CV lottery result in every month since 2012.

$PM_{2.5}$ Data:

The $PM_{2.5}$ data records the hourly concentration level of $PM_{2.5}$ near U.S. Embassy from January 1st, 2014 to December 31st, 2016. Totally, 26,304 observations. Fig 1 shows the location of the Embassy and the distance between it and 3rd Ring road. Due to the aging of the detector and other technical issues, 26,063 observations are valid. The range is from 0 to 782 in $\mu g/m^3$. WHO suggested daily average level should below $50\mu g/m^3$ and China's standard for a healthy air quality is below $75\mu g/m^3$. According to the U.S. Embassy data, in the study period, 41% of days exceed local standard.

It is reasonable to use U.S. Embassy data instead of Beijing's official air quality index (AQI). First the AQI data is a general index that takes multiple pollutants into account. The most urgent problem nowadays is the extreme high concentration of $PM_{2.5}$ and policies are aimed to address this issue. AQI is an indicator but cannot directly reflect $PM_{2.5}$ concentration change. The second issue is that AQI tells the overall air quality of Beijing instead of that in downtown area. The detectors are scatter in Beijing gathering pollutant data from both downtown and suburban area. With a much higher traffic intensity in downtown, the AQI index cannot accurately reflect the $PM_{2.5}$ concentration change in the study area.

Using U.S. Embassy data can address both issues. The detector which records $PM_{2.5}$ concentration level hourly is located at the downtown area near the 3rd Ring road. The data can directly reflect the daily change in $PM_{2.5}$ and due to the close proximity to the main roads, air quality there is heavily affected by the traffic. Its location is also very representative. The Central Business District (CBD) and multiple residential areas surround the embassy. The pollutant in those area share the same meteorological condition as that near the U.S. Embassy. High population density around it means that vast amount of people are exposed to the pollutant concentration that is very close to U.S. Embassy's data. Thus, study on this data set can provide information of EV's effect on the air quality that impact millions of people's health.

Meteorological Data:

The daily meteorological data is obtained from China Meteorological Data Service Center (CMDC). It obtained daily wind speed, humidity, temperature and rain amount data from January 1st, 2014 to December 31st, 2016 in Beijing metropolitan area. 1,095 observations were recorded during that period ranging from 2.44 to 47.4 mph for wind speed, 8.17 to 95.17 Fahrenheit for temperature, 4.79% to 93.58% for humidity and 0 to 111.4 mm for rain amount. From previous literatures, meteorological features can greatly influence $PM_{2.5}$ concentrations, and other factors like local temperature and humidity are also important factors. Such data is usually less attractive to public but it's important to control for those exogenous effects. Due to the access level issue, only wind speed, humidity, temperature and rain amount data are available.

Those data will be very important to estimate daily $PM_{2.5}$ concentration level along with the traffic volume data. In the monthly scale, due to taking the average level will omit variations in those data, adding those factors may not very well control for the exogenous effects.

Lottery Result Data:

Monthly lottery result data is published by BTMB. The data contains EV and CV lottery result separately. The data set includes results from January 2014 to December 2016, totally 36 periods and ranging from 2214 to 17150 for EV and 13598 to 20196 for CV. Because the current registration policy in Beijing requires buyer to win the permit in a lottery, so I can get the exact number of how many permits were distributed in that giving month. Literature has shown that more than 88% of lottery winner purchased vehicles within the required period after the implementation of this policy in 2012 (Yang et al, 2014). People who failed to purchase at the beginning were not anticipating such quick win. With a much longer waiting time and low winning rate, Permit holder are less likely to let his or her permit expire. Thus, this lottery result can be used as a good indicator to estimate newly purchased vehicles within this period.

Supplementary Data:

Beijing metropolitan area residents' seasonal disposable income, monthly electricity generation amount for both Beijing and Hebei (very close Beijing), and hourly traffic volume on 3rd Ring road (a main road near U.S. Embassy) are collected as supplementary data.

Industry as another major factor are mentioned by Chen et al (2013). To control for factories' emission, GDP growth rate are used as the indicator. In this paper, unlike the precious study, electricity generation amount data is used to control for industrial emission. One reason for this is that GDP data are annually published by government but electricity data are published monthly. Multiple literatures have shown that GDP can be a driving forces for electricity consumption (Mozumder & Marathe, 2007), so to better variate with the dependent value, I choose electricity generation data instead of GDP data.

Ruimin Li (2016) used data from Beijing Traffic Management Bureau and he kindly provided me the data set. The traffic volume is recorded by highway detectors that located at the 3rd Ring road near U.S. Embassy. It recorded total amount of vehicles in every two minutes from June to July, 2014. This data can potentially help run regression with daily $PM_{2.5}$ concentration. Since all the other variables are monthly or seasonal, there are a few factors that could affect daily average $PM_{2.5}$ concentration. Besides daily meteorological factor, traffic volume would be one of the biggest factor that could cause regional $PM_{2.5}$ concentration change.

Data Limitations

The data set here still have several limitations. We do not have a precise data about how many EV and CV are on the road every day. This is an important factor since tail emission and road dust are related to how much you drive every day. Knowing only how many new permits were added into the market let us can do only a little on testing the impact of EV.

Other supplementary data such as GDP doesn't have monthly and daily record publicly, so the model cannot include all the factors and we have to average the daily $PM_{2.5}$ level into monthly average level, although we will lose volatility during this process. All those combined together, the monthly model only have limited number of control variables and it is hard to test the impact of EV.

The daily data set is limited to two months. This is caused by the limitation in traffic volume data. There are no public accesses to the hourly or daily traffic volume in Beijing, so we cannot choose the type and period of the data we want to use. Since most control variables are constant during this two months, we cannot include most factors into the model. The current traffic data also does not tell how many EV and CV are passing by the detector every day. So it is impossible to separate the effects of EV and CV.

V. Model

Monthly Estimation Model:

To estimate the EV's effect to $PM_{2.5}$ concentration, the following model is been used:

$$PM_{2.5_t} = \beta_0 + \beta_1 EV_t + \beta_2 \frac{\sum_{t=0}^{36} EV_t}{\sum_{t=0}^{36} CV_t + EV_t} + \beta_3 spring + \beta_4 winter$$
$$+\beta_5 fall + \beta_6 powertotal + \beta_7 powertotalh + \beta_8 t + \mu_t$$

Where β_1 is the scale effect of each newly assigned EV permit. The ratio part represent the share of total new vehicle stock of EV. It reflect how hard that government is trying to promote EV number. The dummy variable winter indicate whether this month is in winter heating season. powerhtotal are the total electricity output in nearby province and powertotal is that in Beijing. To address the issue of losing volatility in averaging the daily $PM_{2.5}$ level into monthly level, I will also use average maximum and minimum value as dependent variable to test whether the policy have impact on those.

β_1 and β_2 are the effects I am testing. Although Cai et al run a Life Cycle Analysis (LCA) on EV and conclude that each EV could generate more pollutant instead of help reduce that given Beijing's generation mix (Cai et al, 2017), I still expect that their signs are both negative. The reason could be that most pollution from EV is from manufacturing and electricity generation but they are outside of Beijing, also part of those two effects are captured by the last two control variables.

Meteorological data is not used in the monthly model as we discussed is the previous section. However, the exogenous effects are still needed to be addressed. The weather condition is highly seasonal. Taking precipitation as an example, there are clear gap between winter and summer. Adding dummy variables for spring, fall and winter can both solve the seasonality of the $PM_{2.5}$ and control for the weather condition during those season.

Power generated in surrounding area may have positive effect and power generate in Beijing may have a negative effect on concentration level. This difference in signs is caused by different technology used in those two areas' power plants. Power plants in Beijing were adapting new technology to control its pollutant emission but power plants in the surrounding provinces didn't start that process.

According to the regulation policy, buyers need to purchase the vehicle within three months. The model initially lagged both EV and ratio for three months to accommodate to this policy. Soon it turns out that the lags are not statistically significant. Considering the long waiting for each buyer, a possible explanation for this situation could be that most lottery winner will purchase their car shortly after the lottery.

It is possible for this model to have omitted variable bias. From the previous literature, we know that GDP per capita could be related to the air pollution. Public GDP data is in annual term, which lack variation in this model and income per capita is in seasonal term, which will have the same problem. To control for this, I added electricity to absorb some effect from GDP growth. However, there will be still some effects that cannot be captured by this term. As for the impact from EV, there is no data of average driving mileage and other similar data. With driving restriction imposed on CV, it is hard to know the impact of new permits on traffic volume and thus on tail emission. To improve this part, it is important to know how the traffic volume of EV and CV separately.

Daily Estimation Model:

To test daily effect of EV, I am using the following model:

$$PM_{2.5_t} = \alpha_0 + \alpha_1 volume_t + \alpha_2 humid_t + \sum_{j=0}^{1} \alpha_{3-t-j} windsped_{t-j}$$
$$+\alpha_4 temp_t + \alpha_5 rain_t + \alpha_6 critical_{t-1} + \epsilon_t$$

It is important to have a daily model. In the first model, the $PM_{2.5}$ are in average level. The volatility is lost during the process. To test the effect of adopting EV more precisely, we need to run the model using daily $PM_{2.5}$ concentration which contains more volatility than the average term. This however creates other problem, all the previous data are in monthly term and the traffic volume is for only two months. Thus control variables are constant during the giving months and we cannot get a meaningful result from the model. On the other hand, weather condition are highly related to the air quality so in the daily model, using daily air quality as new control variables can help construct this model. The only daily data that is related to the vehicle is traffic volume, having that on the right-hand side with weather conditions as control variables is the first step to set up a daily estimation model.

Although using plate registration data can be better to identify the effect of EV, that kind of data is confidential to the public. There are few literatures that use traffic volume to estimate how many EVs are on the road, and considering multiple driving restriction implemented in Beijing, traffic volume that contains both EV and CV become the most reliable variables to estimate daily effect. One way to improve this estimation is to find the traffic volume data before 2014 and compare the magnitude of this two estimators. Other meteorological factors are added according to Chen et al (2013). In his model, those factors are added to better control daily concentration variation due to weather change.

Volume may have a positive sign given the relative small amount of EV compared with the existing CV fleet. Wind speed may have a quadratic relationship. As I explained earlier, breezes may lift pollutant on the ground but cannot carry that away from the city. In the monthly model, I do not think there will be a quadratic relationship between wind speed and concentration level. The average monthly wind speed has less variation and after running a jointly hypothesis test, it shows that there does not exist such quadratic relationship between concentration value and wind speed in both monthly and daily model.

However, it appears that yesterday's meteorological condition will affect today's air quality. Among all those variables, wind speed is lagged for one term to control for this effect. Other factors' lag terms are not statistically significant so they are excluded from this model.

Another difference from the monthly model is that a dummy variable critical is added into the model. This indicate whether yesterday is categorized as unhealthy. According to government's plan to bring back good air quality, once a day is categorized as unhealthy, administrative methods will be applied to local and nearby factories and other main pollutant sources. One close example is the heating shortage in Hebei province in 2018 winter. Due to the shutdown of coal fire plants and insufficient power generation from new natural gas plants, heating in Hebei was out for several days. To control for the administrative factors, adding dummy variable could be the most efficient way giving the vast amount of regulations implemented.

VI. Results

Monthly Model:

The result from running monthly model is given by Table 4. EV and ratio term have a negative effect on $PM_{2.5}$ concentration. Both terms are insignificant after introducing trend term t into the model. And the magnitude for EV term is very low compared to the ratio term. Unlike Cai et al's finding (2017), the result here support the policy of substituting CV with EV. They were looking at the total effect of EV. This include the pollution from manufacturing batteries, emission from power plants and disposal after it is broken. Most of the pollution is generated at the factories and power plants which are far from metropolitan area. However in this model, adopting EV seems have little impact on average air quality and the maximum and minimum of the pollution level. The impact of EV to Air quality is indirect. With more CV are scrapped than added each year, buying an EV instead of a CV can reduce tail emission. If more EV is on the road the effect of that should be more obvious. In the model, the scale effect cannot reflect this indirect effect since the number of permits cannot accurately reflect how many EV are on the road each day.

Another interesting finding is that there is no need to add lagged term for EV and ratio term. We know that each buyer have three months, including the current month to finish their purchase or transaction after win the lottery. In the original model, both EV and CV are lagged for two periods to reflect this regulation. After the regression, none of the lagged terms are statistically significant in 10% level. This indicate that people will purchase the vehicle shortly after they received the permit.

A possible reason for this situation is the low winning rate of previous lottery. The winning rate was less than 1% before 2014. A low waiting rate means people have to wait for long time, roughly one to two years. Although some people may save the money after joining the lottery to anticipate for this long waiting, most people are holding the money during this process. By the time they switch to the EV pool for a better chance after 2014, they have the money and the motivation to purchase new car shortly after they win.

The effect of Beijing and nearby province's power plants is different. It seems using more electricity generated from power plants outside of Beijing can reduce pollutant concentration in downtown. This difference can partially answer the question that whether using EV is shifting pollution from Beijing downtown to other areas. Since EV does not have tail emission, regional generation mix is the most important factor of its impact to the environment. According to the regression result, if Beijing is heavily rely on local power plants, EV may cause more pollution than CV. On another hand, upgrading emission abetment technology could make EV cleaner than now. Although it seems like relying on other province's electricity can help reduce pollutant in downtown, it could be very possible to be a tradeoff between the air quality in Beijing to that in other locations. It will require air quality data from regions near power plants to know whether the pollutant is truly reduced or just shifted out.

Daily Model:

The result in daily model is less persuasive. Due to the restriction of the model, it cannot provide an direct result. Although the average traffic volume is available to us, it is hard to separate the effect of EV and CV. Table 5 shows the result from running daily model. One problem from using daily model is that the traffic volume is limited between Jun and July, 2014. This restriction makes all the control variables in the Monthly Model unusable. There is little variation on the left-hand-side compared to the right-hand-side.

With only Meteorological variables as control variables, the result shows no statistical significance on traffic volume and wind speed. The dummy variable shows that the pollutant is tend to stick around since yesterday's pollution level has a significant impact on today's air quality.

To improve this model, driving mileage and plate information is essential. Those two data could help determine how many EV and CV is on the road and how intensive people are driving it. Shangjun Li gather the driving mileage data by handing out question sheet to gather such information. The other data is available to only certain scholars since it is confidential to the public.

VII. Conclusion

Car emission has been causing environmental problems for a long time in Beijing. In recent years, government came up with multiple regulations to address this serious problem. To promote EV in Beijing, major policy change was introduced in 2014. In this research, the most recent regulation policy is analyzed. To find the impact of adoption EV to Beijing's air quality, monthly lottery result for EV and CV, electricity output in Beijing and nearby province and

Beijing meteorological data is used in two different model. By using U.S. Embassy record on Beijing's downtown $PM_{2.5}$ concentration level as indicator for air quality, we found that EV has insignificant effect in reducing downtown monthly average $PM_{2.5}$ concentration level.

The electricity output in Beijing is positively related to the pollution concentration level and electricity output in nearby province is negatively related to that. According to this finding, it is still possible that EV have an impact to the air quality. To further test this effect, air quality data of region near the power plants, average driving mileage and generation mix are required.

There are little findings in daily $PM_{2.5}$ concentration level due to the limitation of the data. Monthly control variables has little variation during the target period. Traffic volume data is limited to two months in 2014 and we could not separate effect of EV and CV. To improve this model, average driving mileage for EV and CV and plate information will be very helpful.

With the current result, adoption of EV hardly a solution for air pollution but it provide an alternative choice for those who do not want to wait so long in lottery. Thus, in order to address air pollution issue, current vehicle regulation policy still need to be changed. Also, it is important to upgrade the emission abatement technology in every Beijing power plant. Since Beijing is heavily relying on its electricity supply, local governments also need to keep upgrading their emission abatement methods to accommodate future increase in electricity demand.

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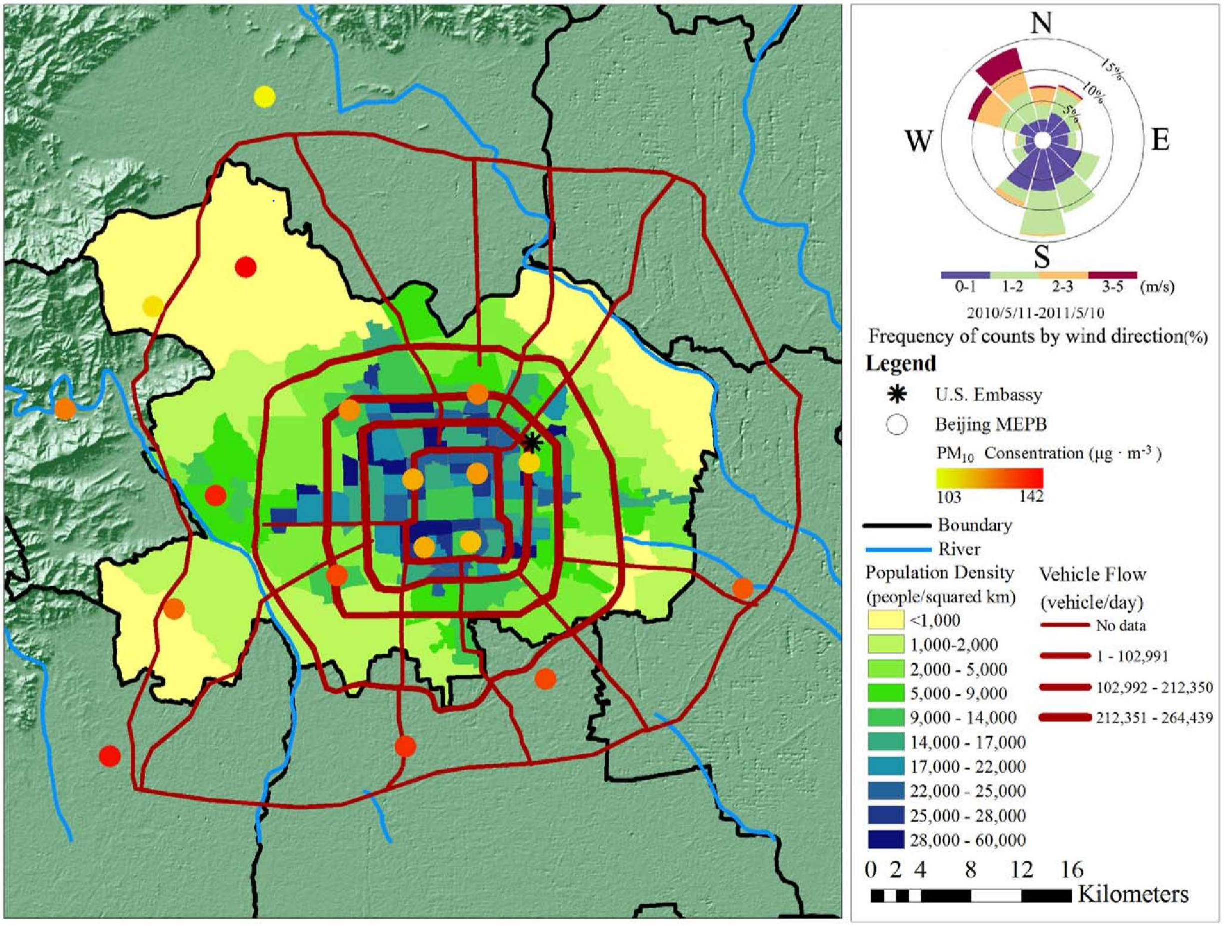

Fig 1 Beijing GIS Map

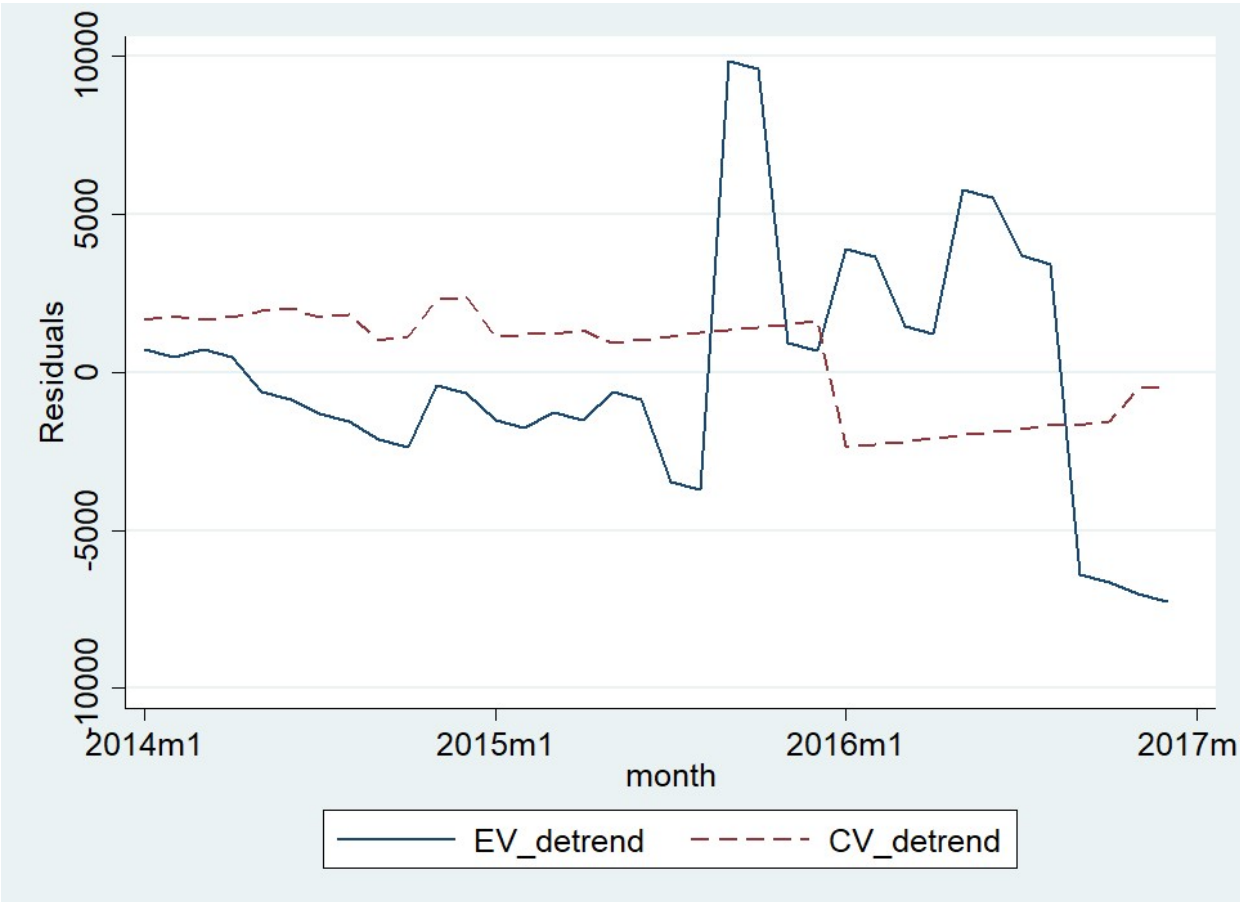

Fig.2 Detrended EV and CV Permits in Every Month

Table 1: Summary Statistics for Monthly Data

	max	min	mean	st.dv
PM2.5	161.97	38.73	77.73	32.49
Number of EV permits	9841.40	-7271.59	0.00	3975.79
Number of CV permits	2395.04	-2378.47	437.45	1609.88
Total electricity output of nearby province	2616.8	396.93	1481.34	686.37
Total electricity output of Beijing	433.7	71.34	238.56	108.59

a.The data is in monthly average value collected from Jan 2014 to Dec 2016.
b.PM2.5 is in $\mu g/m^3$; Number of EV and CV permits are in number of permits per month; Total power output is in 100 milion mkh;

Table 2: Summary Statistics for Daily Data

	max	min	mean	st.dv
PM2.5	217.5	12.52	74.06	49.41
Traffic volume	123.42	98.31	112.04	6.32
Wind speed	9.60	2.53	5.35	1.71
Temperature	91.46	73.56	83.81	4.36
Humidity	75.83	27.54	47.05	11.89
Rain amount	9.9	0	0.90	1.89

a.The data is in daily average value collected from Jan 2014 to Dec 2016. Traffic volume is collected from Jun 1st, 2014 to July 31st, 2014
b.PM2.5 is in $\mu g/m^3$; Traffic volume is in number of car per minute; wind speed, temperature, humidity and Rain amount are in mph, F°, percentage and mm/h

Table 3: Regression Results for Monthly Model

	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled
$EV_{d}etrend$	-0.005	-0.001	0.001	0.001	0.001	0.003	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)
L1.$EV_{d}etrend$	-0.005	-0.003	0.001	0.001	0.001	-0.001	
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	
L2.$EV_{d}etrend$	0.002	0.002	0.001	0.0004	0.0004		
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		
EV/CV+EV	19.16	-4.67	-20.25	-20.25	-20.25	-28.02	1.26
	(26.88)	(27.74)	(28.05)	(28.05)	(28.05)	(27.00)	(2.37)
L1.EV/CV+EV	13.87	22.38	14.27	14.27	14.27	27.25	
	(43.95)	(43.53)	(41.52)	(41.52)	(41.52)	(25.10)	
L2.EV/CV+EV	-30.51	-16.50	4.04	4.04	4.04		
	(25.19)	(26.66)	(25.71)	(25.71)	(25.71)		
Spring		18.27	27.80	27.80	27.80	18.74	14.35
		(15.17)	(16.17)	(16.17)	(16.17)	(14.66)	(13.68)
Winter		34.29**	27.02	27.02	27.02	34.13**	30.96**
		(15.36)	(16.32)	(16.32)	(16.32)	(15.72)	(14.97)
Fall		30.89**	23.24	23.24	23.24	29.76*	22.24*
		(14.38)	(14.63)	(14.63)	(14.63)	(14.67)	(12.75)
Total electricity output of nearby province			-0.10	-0.10	-0.11	-0.13**-0.13**	
			(0.061)	(0.061)	(0.061)	(0.056)	(0.051)
Total electricity output of Beijing			0.81*	0.81*	0.81*	1.00**	0.88**
			(0.42)	(0.42)	(0.42)	(0.39)	(0.35)
trend	-2.72	-1.53	-0.80	-0.80	-0.80	-1.97	-3.33**
	(2.035)	(2.21)	(2.06)	(2.06)	(2.06)	(1.80)	(1.29)

a.PM2.5 level is measured during 6am to 20pm. Monthly result used general monthly average value of PM2.5 as dependent variable.
b.$EV_{d}etrendisthedetrendedmonthlypermitnumberforEV$; $RatioofEV/CV+EVis\sum_{0}^{36}EV_t/\sum_{0}^{36}EV_t+CV_t*100$.
c.Spring, Winter and Fall are seasonal dummies; Spring is between March and May; Winter is between December and February; Fall is between September and November.

Table 4: Sub-Group Regression Results

	Pooled	Non-Rush -Hour Only	Rush -Hour only	Max	Min
EV	-0.001	-0.001	-0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EV/CV+EV	1.261	1.287	1.224	1.380	1.327
	(2.37)	(2.39)	(2.37)	(3.10)	(1.75)
Spring	14.35	13.71	15.33	33.32*	7.513
	(13.68)	(13.75)	(13.66)	(17.85)	(10.11)
Winter	30.96**	29.96*	32.48**	64.46***	18.04**
	(14.97)	(15.05)	(14.95)	(19.53)	(11.06)
Fall	22.24*	22.34*	22.07*	27.67	14.70
	(12.75)	(12.81)	(12.73)	(16.63)	(9.42)
Total electricity output of nearby province	-0.113**	-0.113**	-0.112**	-0.130*	-0.0686*
	(0.051)	(0.051)	(0.050)	(0.066)	(0.037)
Total electricity output of Beijing	0.880**	0.874**	0.887**	1.075**	0.532*
	(0.35)	(0.35)	(0.34)	(0.46)	(0.26)
trend	-3.33**	-3.28**	-3.40**	-3.87**	-2.34**
	(1.294)	(1.300)	(1.292)	(1.688)	(0.956)

a.PM2.5 level is measured during 6am to 20pm. Monthly result used general monthly average value of PM2.5 as dependent variable; Rush Hour result used only PM2.5 during rush hour; Non-Rush result exclude the rush hour pm2.5 value. Max/Min uses average maximum/minimum pm2.5 level as dependt variable.

b.The Rush hour is between 7 to 9 AM and 5 to 7 PM every weekday.

c.$EV_detrendisthedetrendedmonthlypermitnumberforEV; EV/CV + EVisequalto\sum_0^{36} EV_t/\sum_0^{36} EV_t + CV_t * 100.$

d.Spring, Winter and Fall are seasonal dummies; Spring is between March and May; Winter is between December and February; Fall is between September and November.

Table 5: Regression Results for Daily Model

	Daily (1)	Non-Rush-Hour Only (2)	Rush-Hour only (3)
Traffic Volume	0.401	0.342	0.585
	(0.792)	(0.789)	(0.835)
Wind speed	-2.511	-2.650	-2.118
	(2.997)	(2.984)	(3.157)
Temperature	3.179**	3.200**	3.128**
	(1.400)	(1.383)	(1.464)
Humidity	2.024***	1.997***	2.110***
	(0.586)	(0.583)	(0.617)
Precipitation	1.531	1.302	2.192
	2.67)	(2.65)	(2.81)
L.unhealthy	44.76**	46.29**	40.20**
	(16.60)	(16.53)	(17.49)

a.Daily result used general daily average value of PM2.5; Rush Hour result used only PM2.5 during rush hour; Non-Rush result exclude the rush hour pm2.5 value. Rush hour is between 7 to 9 AM and 5 to 7 PM every weekday.
b.meteorological variables are in daily average amount.
c. Unhealthy is the percentage of hours with pm2.5 over $75\mu g/m^3$ on yesterday