Master thesis in Finance
STOCKHOLM SCHOOL OF ECONOMICS

The Effect of Congestion Charge and Fuel Arbitrage on Air Quality in Stockholm

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Abstract

In August 2007, the congestion charge is launched in Stockholm after a seven-month trial period in 2006. This paper applies empirical methods to estimate the effects of the implementation of congestion charge on the air quality in Stockholm. I find that the trial and permanent congestion tax have reduced the emissions of major air pollutants. I also find evidences that the time-varying congestion pricing decreased the air pollutions in peak hours, and suggestive signs of peak spreading onto non-peak hours. In addition, I show that the fuel switching behavior by FFV (Flexible Fuel Vehicle) motorists might have mixed effects on different air pollutant emissions.

Key words: *Air quality, Congestion charge, Fuel sales, Green cars, Stockholm*
Supervisor: Cristian Huse
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Discussants: To be determined

Acknowledgement: I would like to specially thank my supervisor Cristian Huse for giving me so much great advice and guidance, and for being patient and supportive. I also thank my family and my friends for their love and support. I dedicate this paper to my mom to whom I owe the world.

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1. Introduction

In many cities air pollution is reaching levels that would threaten people's health. More than 2 million people die every year from breathing in air pollutants present in indoor and outdoor air environment according to WHO estimate. Particulate matters (PM10 or PM2.5) for example, can penetrate into the lungs and enter the bloodstream, thus may cause heart disease, lung cancer, asthma, and acute lower respiratory infections. (WHO, 2011) In January 2013, Beijing and some other cities in China encountered an outburst of one of the worst periods of air quality in recent history, with smoggy weathers and air pollution levels that would be referred as “hazardous” by WHO. The ground-based sensors at the U.S. Embassy in Beijing reported PM2.5 concentration of 291 micrograms per cubic meter of air, way above the WHO air quality guidelines of below 25 micrograms per cubic meter as an annual average. (WHO, 2005)

Sweden, though ranked as the 25th cleanest country in the world in a WHO study in 2011, also has some work to do to fully meet WHO standards for air quality. For example, some of the most populated municipalities in Sweden suffer from above-standard concentrations of Nitrogen Dioxides and PM10. (EPA) Since a major source of the air pollutions is the road traffic - along with energy production, industry and shipping (EPA) - the Swedish government has carried out a number of policies over the years to improve the road traffic and air quality accordingly, among which include promoting clean fuel vehicles with the Green car rebate, or improving the congestion conditions with congestion tax in Stockholm and lately in Gothenburg.

The objective of my study is then to analyze the effect of these public policies on the air quality in Stockholm area, and hopefully to extract the lessons that can be learnt and applied in other regions of the world, to provide some guidance for future policy design and air quality improvement endeavor.

In my study, I focus mainly on the congestion charge in Stockholm, which was implemented permanently from 1st August 2007, after a trial period in the first seven months in 2006. I analyze the effects of the trial and permanent charge separately with a major focus on the latter. Also, how the pricing of congestion charge affects air quality is important for the future policy making, and I test the hypothesis that the time-varying pricing scheme of the congestion charge has a reducing effect on the air pollutions in peak hours.

In addition, an important consequence of congestion charge and some other incentivizing policies (e.g. Green Car Rebate), is a large fleet of alternative fuel cars in Stockholm, since they were exempt from the congestion charge up until mid 2012. (Eliasson et al., 2010) The majority of the fleet is the FFV (Flexible Fuel Vehicle) because of its allowance of seamless switch between alternative fuels, i.e. ethanol, and traditional fuel gasoline. However the drastic price drop in gasoline fuel due to the economic downturn in 2008, has led to fuel switching behaviors by most of the FFV motorists, who arbitraged between the fuels and went for the cheaper, and the ethanol fuel sales (E85) plummeted by 73% during the time. (Huse, 2012) So in the last session of my study, I also investigate the impact of such fuel switching behavior on the air quality, and provide some empirical evidence on the consequences of promoting alternative fuel vehicles.

To estimate the effects of congestion charge, I use two specifications, including the simple OLS and regression discontinuity design (RDD). I find that both the trial and permanent congestion tax are effectively reducing the emissions of air pollutants from road traffic, after controlling for meteorological conditions and other time-varying fixed effects. I use both the parametric (polynomial time trend regression) and non-parametric methods (local linear regression) in the RDD context, and find the results to be robust in the various specifications.

I use the difference-in-differences approach to test the impact of time-varying congestion pricing on air pollutant concentrations in different hours of the day, with two years of data around the implementation of permanent congestion tax. I find that the pricing has an overall negative effect on the air pollution in peak hours, and some pollutants also show a sign of substitution effect from the peak onto the off-peak (non-pricing) hours.

I also find mixed effects of fuel arbitrage on different types of air pollutants, by exploring the correlation between the air pollution and ethanol fuel sales, with an OLS regression controlled for fixed effects. I believe the diversity in results is mainly related to the effect of ethanol fuel on the emissions of each pollutant, as well as the physical features of the pollutants.

My thesis is organized like this: Section 2 introduces some institutional and theoretical background for my analyses; Section 3 reviews a number of relevant literatures on the subject; Section 4 describes my data; Section 5 explains the methodology I use for research on different sub-topics; Section 6 shows the results; Section 7 discusses some shortcomings or pitfalls in the model or data; Section 8 concludes and offers suggestions for future studies.

2. Background

2.1. Congestion Charge in Stockholm

The Stockholm congestion charge, also referred to as the congestion tax in Stockholm (*Trängselskatt i Stockholm*), was implemented on a permanent basis on 1 August 2007, following a trial of a 7 month period from 3 January to 31 July 2006. It's a congestion tax levied on certain Swedish-registered vehicles for passages in and out of Stockholm inner city, from Monday to Friday between 06:30 and 18:29, excluding public holidays and the day before, and the month of July. The tax is intended to improve traffic flow in Stockholm inner city, and contribute to improvement of the environment.

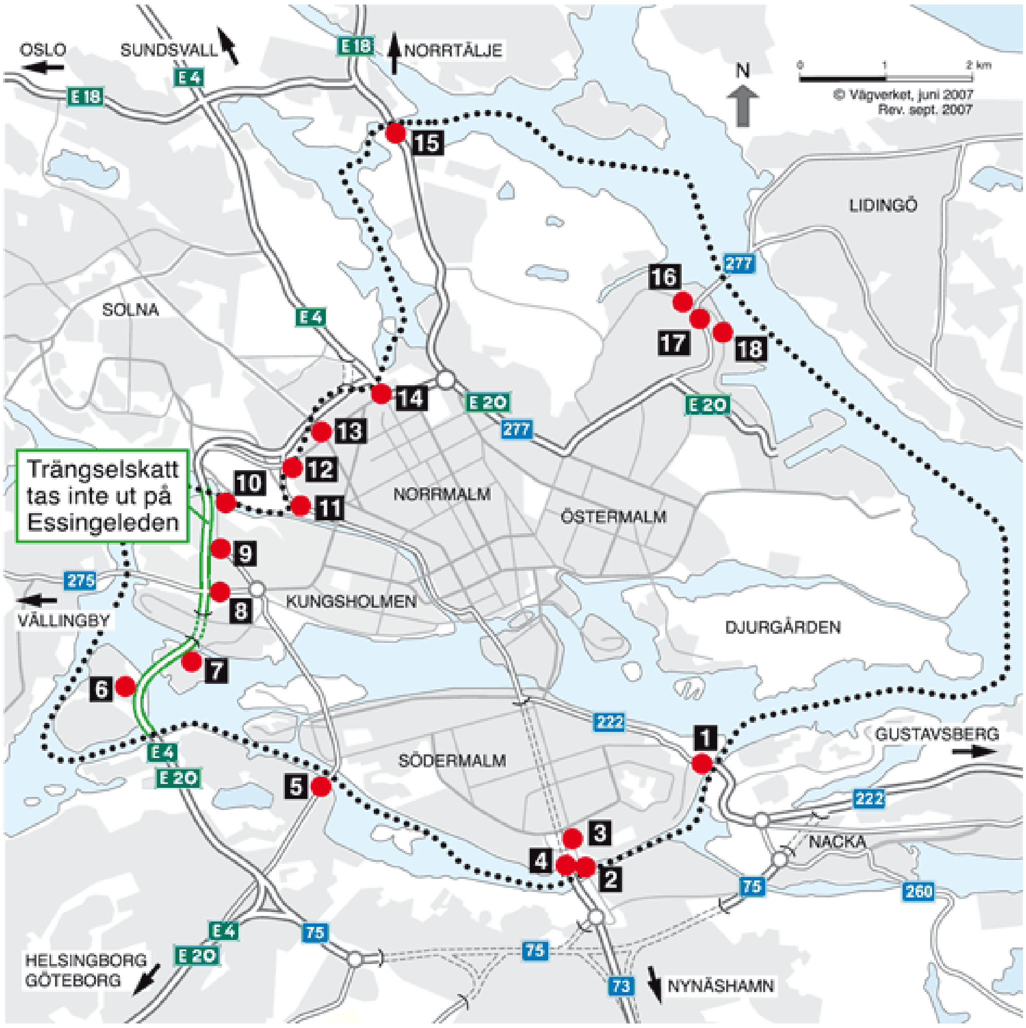
2.1.1. The control points / toll stations (cordons)

There are 18 electronic control points (cordons) surrounding the entrance to the Stockholm inner city. The toll stations have cameras that automatically record passages into and out of the inner city during the time period that the congestion tax is imposed. All the 18 control points are exhibited in Table 1 and Figure 1.

Table 1: Congestion charge control points

1.	Danvikstull	7.	Lilla Essingen	13.	Solnabron
2.	Skansbron	8.	Trafikplats Fredhäll / Drottningholmsvägen	14.	Norrtull
3.	Skanstullsbron	9.	Trafikplats Lindhagensgatan	15.	Roslagsvägen
4.	Johanneshovsbron	10.	Ekelundsbron	16.	Gasverksvägen
5.	Liljeholmsbron	11.	Klarastrandsleden	17.	Lidingövägen
6.	Stora Essingen	12.	Trafikplats Karlberg / Tomtebodavägen	18.	Norra Hamnvägen

Figure 1: Map of congestion charge control points (cordons)



2.1.2. Congestion tax pricing

Table 2: Congestion tax pricing scheme

Time	Amounts
6:30 to 6:59	10 kr
7:00 to 7:29	15 kr
7:30 to 8:29	20 kr
8:30 to 8:59	15 kr
09:00 to 15:29	10 kr
15:30 to 15:59	15 kr
16:00 to 17:29	20 kr
17:30 to 17:59	15 kr
18:00 to 18:29	10 kr
18:30 to 6:29	0

The amount of the tax for each passage into or out of Stockholm inner city ranges from 10 to 20kr, depending on the time of the passage. The maximum amount of tax paid per vehicle per day is 60 kr. Table 2 shows the congestion pricing for different hours of a day.

2.1.3. Exemptions from the congestion charge

But the congestion tax does not apply to everyone. Certain types of vehicles are exempt from the congestion charge: emergency service vehicles, buses with a total weight of 14 tons, Diplomatic-registered vehicles, Motorcycles, foreign-registered vehicles, military vehicles, cars with parking permits for disabled. Location-wise, the tax does not apply to the passage on Essingeleden, nor the traffic from and to the Lidingö island through the Stockholm inner city within a 30 minute window time.

Green cars Up to 31 July 2012, the green cars were exempt from the congestion charge as well. The exemption was valid for green cars registered before 1 January 2009. Since August 1 2012, all green cars are subject to congestion tax. The "green cars" here that were exempt refer to cars that are equipped with technology to run a) wholly or partly on electricity or gas other than LPG (Liquefied Petroleum Gas), or b) with a fuel mixture consisting primarily of ethanol, in other words, alternative fuel vehicles.

2.1.4. Tax payment

At the end of each month, the vehicle owners receive a payment slip, where the total tax decisions for the previous month's passages appear. The amount must be paid by the end of the next month. If the tax is not paid on time, a surcharge of 500 kr will be imposed. The tax amount cannot be paid at the control stations.

2.2. Swedish Green Car Rebate

Another public policy relevant to my study is the Swedish green car rebate, since it's one of the main drives for green car sales and the use of ethanol fuels. Here I provide a brief introduction. The Swedish government began to introduce the green car rebate program in April 2007, in order to promote the green car consumption and clean vehicle concept. Every natural person who buys a green car receives a rebate of 10,000 kr, which is paid out to the consumer six month after the purchase. The "green car" subjected to the rebate is defined slightly differently from the green car that were exempt from the congestion tax in Stockholm. It can be either an alternative fuel car, which runs on alternative fuels such as ethanol, gas or electricity, and consumes no more than gasoline-equivalent of 0.92 l/10km or 9.7 m3/10 km (gas-fueled), or 37 kWh/100km (electricity cars); or a conventional green car, which runs on fossil fuels such as gasoline and diesel, and emit no more than 120g CO_2/km. And the program ended at the end of June 2009.

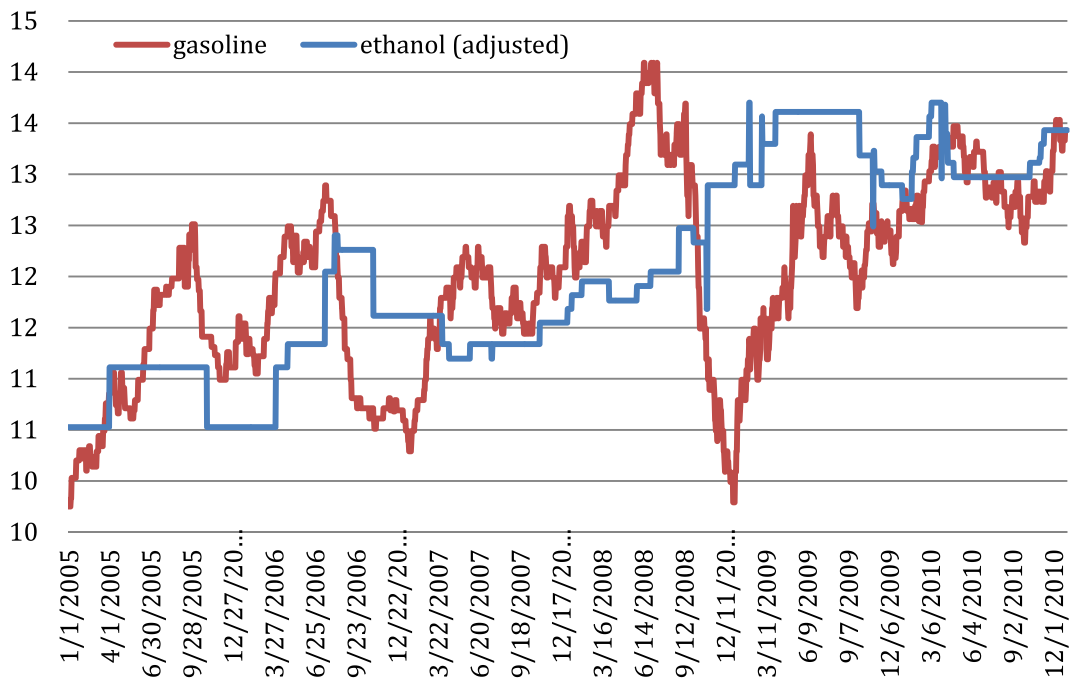
2.3. Fuel prices, fuel sales and fuel arbitrage

2.3.1. Gasoline vs. ethanol adjusted prices

In the winter of 2008, oil prices dropped drastically and fell to almost history low in 24 months in December, mainly due to the recession that spread over the global economy, and the weak consumption around the world. Meanwhile ethanol price remained stable, thus during the time gasoline became even cheaper than ethanol after adjusted for its energy content. This is illustrated in Figure 2.

The ethanol fuel used in vehicles, E85, consists of 85% of ethanol and 15% of gasoline, where the latter is used as a lubricant to facilitate the engine to start. On average, a car that runs on E85 consumes about 30% more fuel per distance traveled, since the energy content of E85 is nearly 30% lower than conventional gasoline. This leads to a price parity of $p_e \cong 0.7\, p_g$ (Huse, 2012), and I apply this adjustment in my calculation for the price premium of gasoline over ethanol, as well as the adjusted sales of ethanol. Note that in winter times, the proportion of gasoline is increased from 15% to 25% (thus E75), since it is harder to start the car with a fuel with higher ethanol content in colder climate. The increased gasoline content in winter is also important to minimize exhaust emissions, which increase at cold start and low temperatures. (Statoil)

Figure 2: Gasoline (#95) price & adjusted ethanol (E85) price, source: Statoil

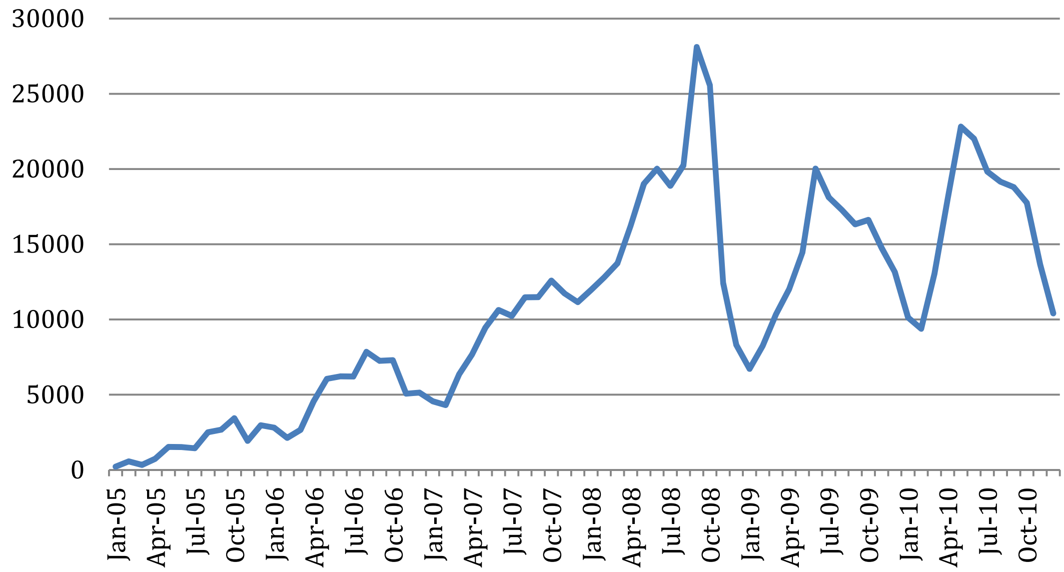


2.3.2. Fuel arbitrage and environmental impact

With the incentivizing policies such as the green car rebate and the congestion charge in Stockholm with exemptions for green cars, the sales of green cars have largely increased, and the consumers were especially embracing the alternative fuel cars (Huse, 2012). In the Stockholm area, it is even more the case since the consumers were encouraged to purchase the alternative fuel cars by both the congestion tax exemption and the rebate scheme.

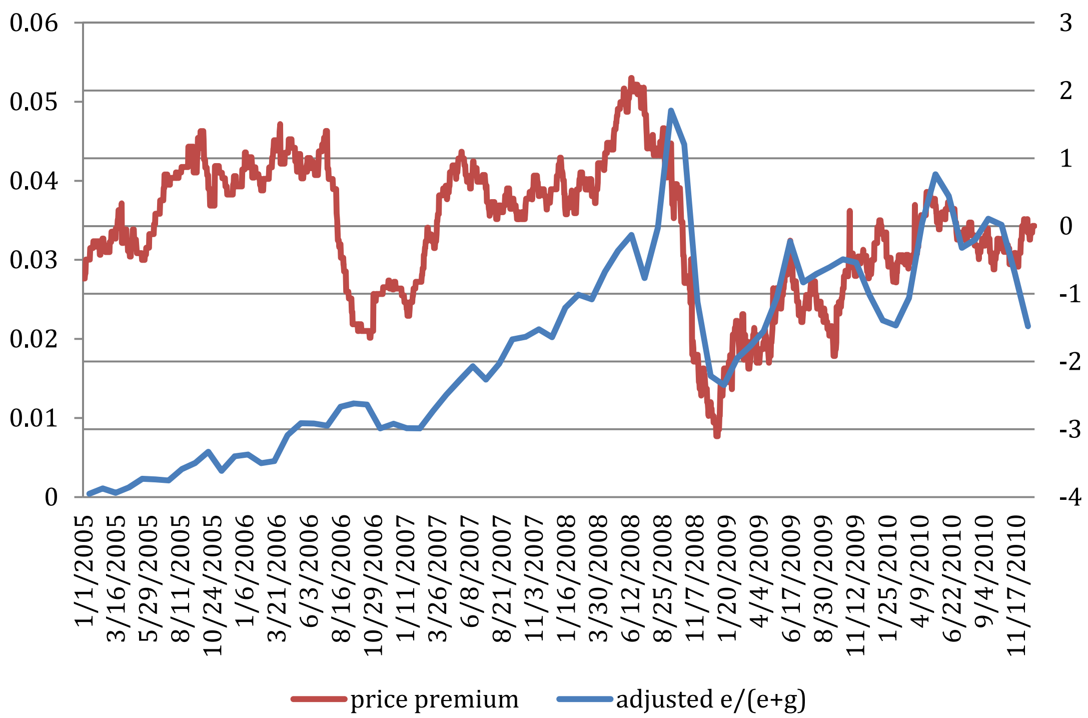
Among the alternative fuels, ethanol (E85) is the dominant fuel in Sweden. And the leading alternative green cars are FFVs (Flexible-fuel vehicles), cars that can run either on ethanol or gasoline or combination of both. With the seamless switch between the two fuels, it allows the FFV owners a possibility to arbitrage across fuels. As a matter of fact, most FFV motorists do so and buy the cheapest fuel, and the ethanol monthly sales volume dropped by 73 percent after the shock of oil price drop. (Huse, 2012) This is illustrated in Figure 3.

Figure 3: Monthly delivered volume of E85 (m3), source: SPBI



If to compare the price premium movement of gasoline over adjusted ethanol price, with the shares of energy-adjusted ethanol sales among the total sales of gasoline and ethanol, we can observe a lagged reaction pattern, implying that the motorists response to the price changes with a certain amount of time lag.

Figure 4: Gasoline-ethanol price premium and adjusted ethanol sales shares



It is generally acknowledged that ethanol is superior to gasoline in terms of CO_2 emissions, and ethanol life-cycle CO_2 emissions are about 55% lower than that of using gasoline (Swedish Consumer Agency, 2011). However ethanol might have a more complicated mix of effects on other local air pollutants, such as NOx, CO, and Particulate Matters (PM10, PM2.5). In my paper, I also take a closer look at how the air quality is affected by the fuel arbitrage behaviors by Stockholm FFV motorists.

2.4. Air quality in Stockholm

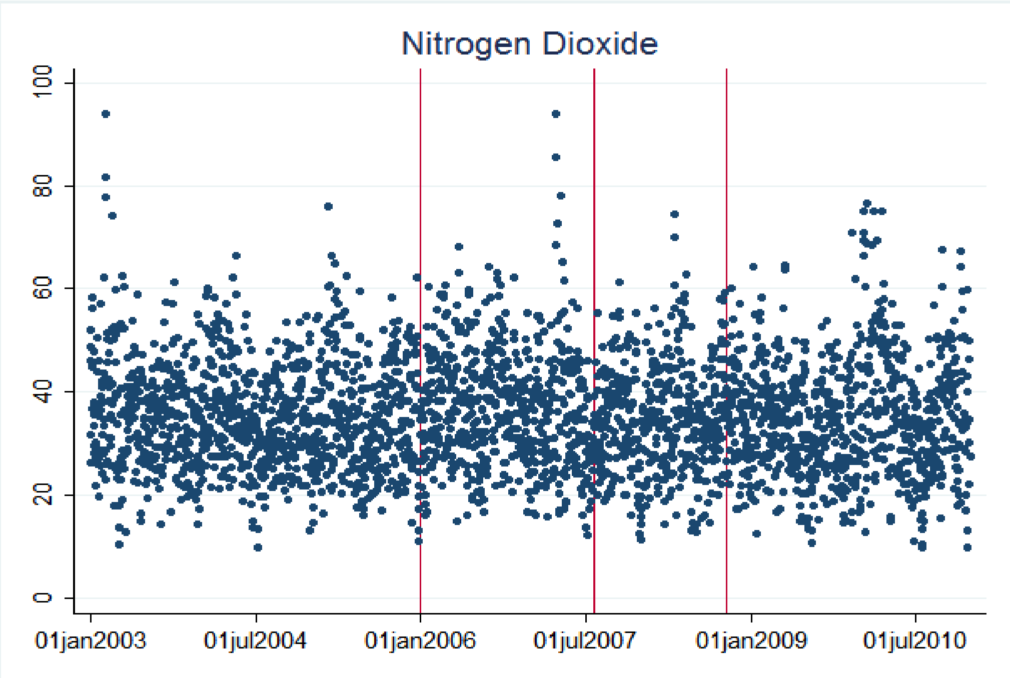
Air pollution in Stockholm comes from various types of emission sources, mostly road traffic, but also energy generation and maritime traffic. Pollution concentrations are also affected by emissions in other parts of Sweden and in other countries. Different meteorological conditions, i.e. the weather, would decide how fast air pollutants are dispersed. (SLB, 2010) The local air pollutant concentrations are influenced by a large number of factors, thus it's difficult to measure how much congestion charge or other environmental policies have affected air quality, and it would require good control of weather conditions, other fixed effects or unknown time-varying variables. In this paper, I focus on the local air pollutants including Nitrogen Oxides (NO2, NOx), Carbon Monoxide (CO), Ozone (O3), and Particulate Matters (PM10, PM2.5). These pollutants are defined as criteria air pollutants by the EPA in United States, since they are considered harmful to human health, and to the environment. (EPA) Air quality monitoring and measurement in Stockholm is conducted in 9 measuring stations in the inner city and 3 outside the inner city but within Stockholm län. The detailed summary of the air pollutants' features and the measuring stations are presented in Appendix.

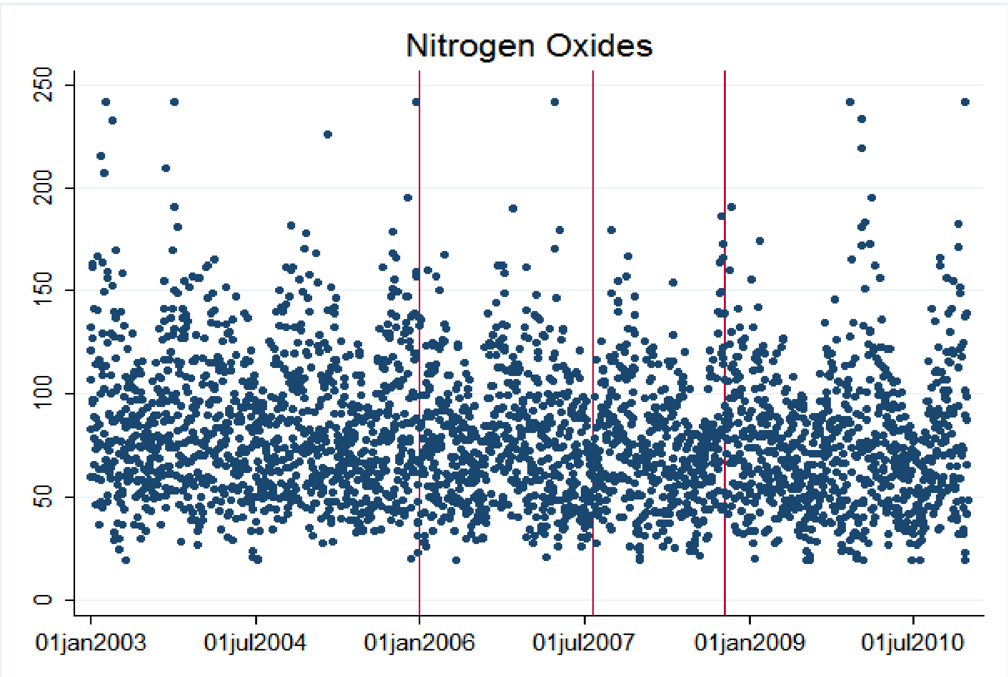
Figure 5 shows average daily air pollution levels in Stockholm inner city during the period 2003-2010. Average daily pollution levels are constructed by averaging all hours of the day and all the measuring stations in the inner city. The three straight lines label respectively 1 Jan 2006 (start of Congestion tax trial), 1 Aug 2007 (start of permanent congestion tax), and 13 Oct 2008 (the first time in two years when the gasoline-ethanol-adjusted price premium became negative).

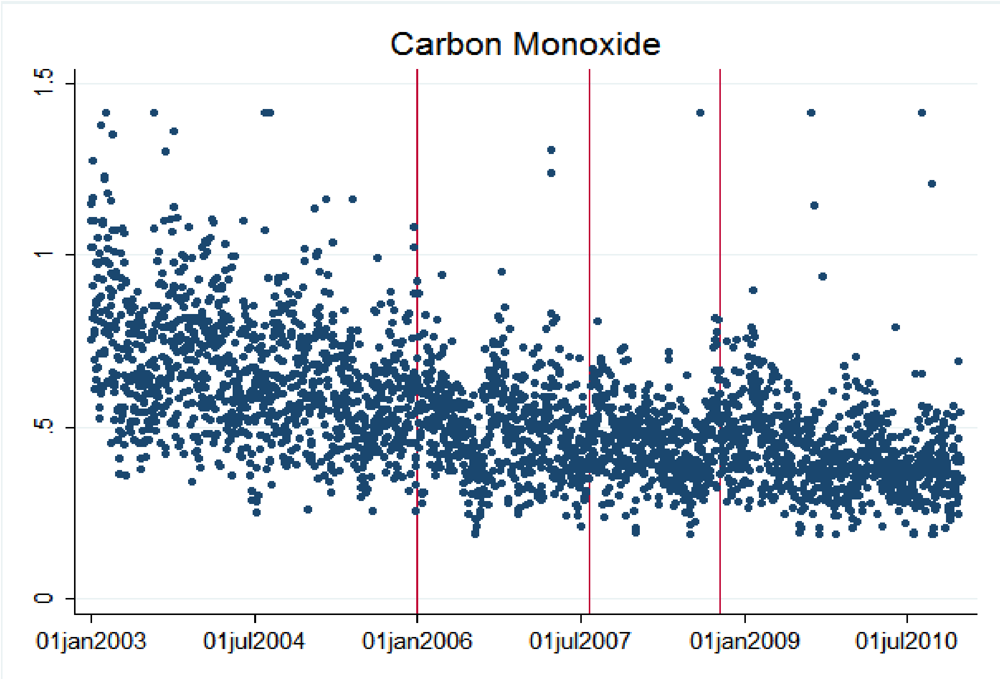
We can observe from the graphs that Carbon Monoxide and PM2.5 have obvious and significant drops after the launch of congestion charges, while Ozone and PM10 show seasonally changing patterns, and the others have limited evidence of dropping or increasing. This might give us a hint of what's going on with the air quality in those periods, but also bear in mind that the weather conditions play a very important role in the formation and concentration of air pollutants

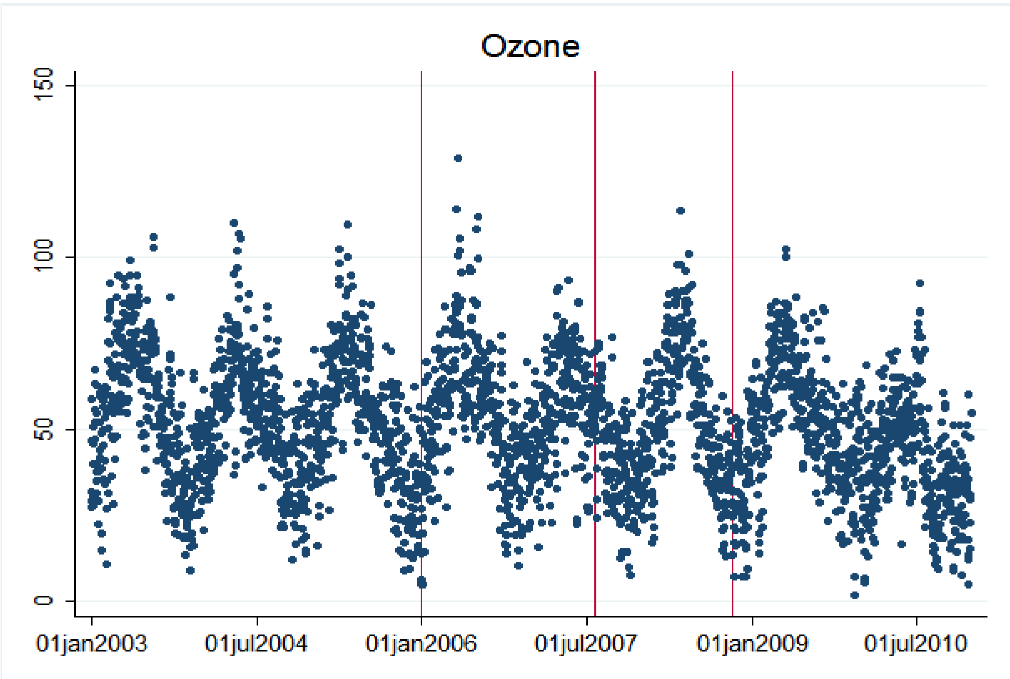
(Davis, 2008), for example, the wind speed is closely related to how fast the pollutants dissipate, or the PM10 level depend heavily on the dampness of road surface (SLB, 2009), thus precipitation is involved, and Ozone formation requires a lot of warmth and sunlight, etc. Therefore we need more complex empirical model to control for the meteorological variations and reveal the real impact of the congestion charge or fuel sales drop on the air pollution level.

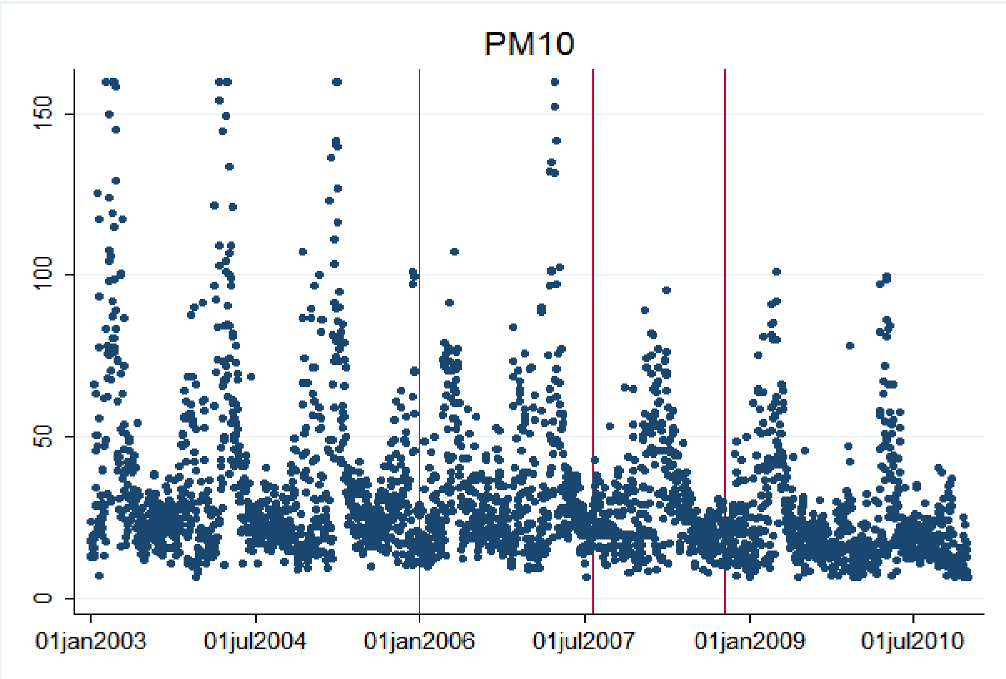
Figure 5: Daily concentration of air pollutants in Stockholm

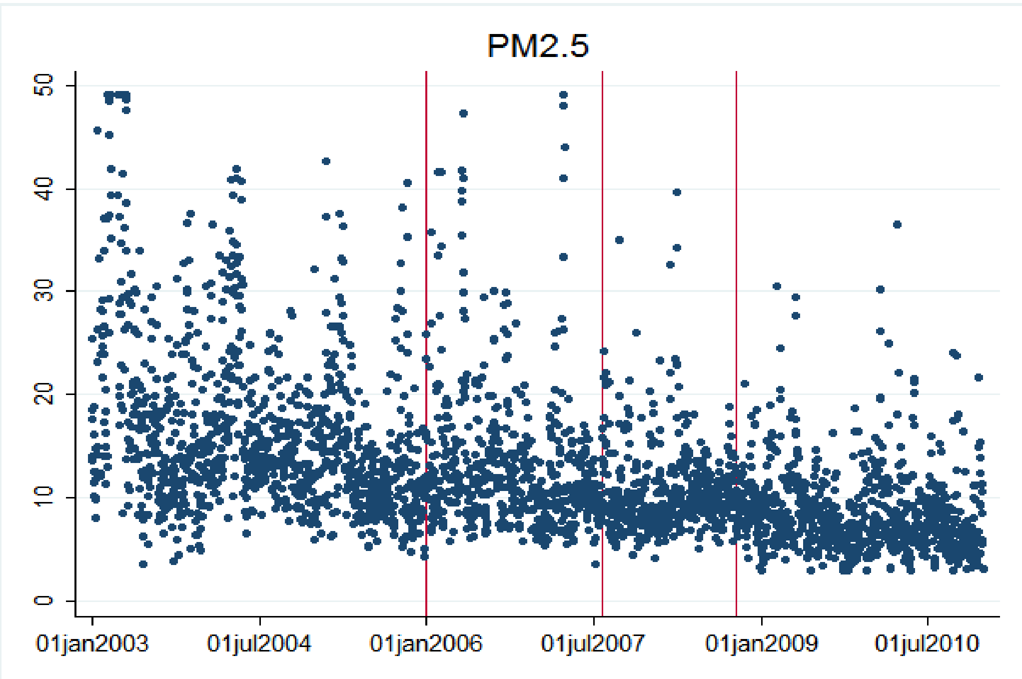





Carbon Monoxide
1.5
1
.5
0
01jan2003
01jul2004
01jan2006
01jul2007
01jan2009
01jul2010


Ozone
150
100
50
0
01jan2003
01jul2004
01jan2006
01jul2007
01jan2009
01jul2010





3. Literature Review

Many studies have been carried out on the congestion charge in Stockholm ever since the trial launch period.

SLB issued a report on the congestion tax trial in 2006, and they compare the estimated mean air pollutions before and after the trial, and note that the interim goal of the trial has been achieved, for that the emissions of nitrogen oxides and particulate matters along with other pollutants from the road traffic were reduced. (SLB, 2006) They also acknowledge the importance of the meteorological conditions when performing analysis on air quality in the short term, though no such control is included in their study. In another report from SLB on the permanent congestion tax, (SLB, 2009) similar results as the trial are presented, and evidence also shows a larger share of alternative fuel vehicles in the traffic volume, mainly thanks to the exemption of such vehicles from the tax, and surveys even show that the exemption is the single most important drive behind the increase in alternative fuel vehicles sales in Stockholm. (BEST, 2009) Another interesting finding by Hultkrantz & Liu (2012) suggests that the effect of congestion charge on the traffic volume is reducing over time, especially when more alternative fuel cars were exempt, and the congestion charge rates became deductible from income tax. They use a numerical simulation model, and conclude that it's crucial for sustaining the effectiveness of congestion charge to abolish the exemption for green cars.

These studies examine the effects of congestion charge on air quality, and conclude positively with its effectiveness. But my paper uses more extended and high-frequency data including the air quality measurements and weather conditions, and applies empirical analysis with various statistical models to control for meteorological conditions as well as some other fixed effects. I believe my work is a good complement to the previous non-empirical analyses on this subject, and strengthens the reliability and validity of findings.

In addition, my study is also related to several literatures on topics including time-varying pricing scheme, fuel arbitrage, and transport or environmental policies. First, on time-varying congestion pricing, Foreman (2013) uses the difference-in-differences approach as well as regression discontinuity to estimate the traffic effects of the congestion charge implemented on the San Francisco-Oakland Bay Bridge in US. She finds that the traffic volume and travel time are significantly reduced in peak hours due to the pricing scheme, and also evidence of substitution effects to non-peak hours or to a close-by bridge where no congestion charge is applied. Her methodology is very inspiring for my analysis on the time-varying congestion pricing design. Second, Davis's (2008) work on the effect of driving restrictions in Mexico City is one of the many economic analyses on the policy attempts that are aimed at improving congestion and air quality. In his study, Davis use regression discontinuity approach and shows that the one-day-in-a-week driving restriction carried out in 1989 in Mexico City failed to reduce air pollution and even worse resulted in more higher-emission vehicles in traffic. Finally, as for fuel arbitrage, the research by Huse (2012) on the Green Car Rebate on alternative fuel vehicle sales, discovers that most of the FFV (Flexible Fuel Vehicle) motorists tend to arbitrage across fuels and always choose the cheaper, which might lead to unexpected impact on air pollutions and sabotage the effectiveness of the policy.

4. Data description

In my study, I combine several different datasets, including the air pollutant, weather condition, fuel price and fuel sales. The details are as follows.

Air pollutant I obtain the hourly air pollutant data from 2003-2010 from the IVL Swedish Environmental Research Institute. The air pollutants I focus on include Nitrogen dioxide (NO2), Nitrogen oxide (NOx), Carbon Monoxide (CO), Ozone (O3), Particulate matters (PM10, and PM2.5). I mainly use the data that are monitored in 12 stations in Stockholm inner city, and 3 stations in the outer city but within the Stockholm län. The measuring stations have two classifications, "Traffic/street" and "Urban Background", with regard to the main emission source influencing the air quality at the station. "Traffic" stations measure emissions mainly from traffic, and "Urban background" stations usually situates at the rooftop level and represents the urban background emissions without a clear dominant source. (IVL) In my study, I mainly use data from "traffic" stations, but also include "urban background" stations as robustness checks. Note that they also report Sulfur dioxide which is also very relevant, however the data is very limited in the Stockholm city, so I have to drop it.

All pollutants are expressed in micrograms per cubic meter (μg/m3), except that carbon monoxide (CO) is stated in milligrams per cubic meter (mg/m3).

Weather I use the Meteorological weather data from SMHI (Swedish Meteorological and Hydrological Institute). The weather characteristics that are most interesting to my study include temperature, wind speed, wind direction, precipitation and humidity. The data I use are reported every three hours from 2003-2010, from 2 monitoring stations in Stockholm inner city, and 2 outside the city.

Fuel price I retrieve recommended fuel prices on a daily basis for gasoline (95#), diesel and ethanol (E85/E75[2]) from the motor fuel provider Statoil in Sweden. The ethanol prices are only available from the start of 2005. I also use actual fuel prices on a daily basis from 2007-2009 from bensinpriser as in robustness check.

Fuel sales I acquire monthly delivered volume of petroleum products and renewable fuels from SPBI (The Swedish Petroleum and Biofuels Institute), from 2005 to 2010. The fuel sales data are only available either monthly on national level, or annually on län or kommun level. I also use the latter as part of robustness checks.

Combining datasets I first match the air pollutant data with the weather characteristics from the closest stations by distance. In the inner city in Stockholm, the paired air quality and weather stations are all within a maximum of 3km of distance from each other. In the outer city area, the matched stations have distance of 7~16 km in between, due to the limited number of stations in the outskirts of Stockholm city. One challenge coming up when combining the data is that the weather data are every three hours while air quality is reported hourly, so I have to let go of some data points and make the whole dataset in every three hours. But when researching on the time-varying pricing effect, I interpolate the weather data into hourly frequency to enable the analysis. I also merge the fuel prices which remain the same within one day. As for fuel sales, which are in monthly frequency, I mainly use the shares of ethanol fuel in relative to the total motor fuel consumption.

5. Methodology

5.1. Congestion tax in Stockholm

To estimate the effect of congestion tax on air quality in Stockholm, I use the log of air pollutant concentrations (every 3 hours) as the dependent variable, and regress it on I(congestion), an indicator variable for observations after the implementation of congestion charge, either the trial or the permanent charge, and control for time varying fixed effects, as well as weather variables.

$$y_t = \alpha_0 + \beta_1 I(congestion_t) + \beta_2 x_t + \epsilon_t \tag{1}$$

[2] In cold climates, it is harder to start the car with a fuel with high ethanol content. Therefore, the proportion of gasoline is increased from about 15% to about 25% in winter. (Statoil)

The vector of covariates x_t, controls for the fixed effects for hour of the day, day of the week, week of the year, interactions between hour of the day and weekends, as well as the measuring stations. Also, x_t controls for weather variables represented by the quartics in temperature, humidity, wind speed, wind direction, and precipitation. The coefficient β_1 indicates the percentage effect of the congestion charge (trial or permanent) on air pollutant concentration.

I first estimate equation (1) using OLS for different time windows for both the trial and the permanent tax. I don't consider windows with length smaller than two years in order to better control for the seasonal patterns. When using a fairly longer window period, the estimated effects might be influenced by other time-varying factors, such as other environmental policies or incentives created by the Swedish government which might also have an impact on the air quality. Therefore, besides limiting the windows to a fairly narrow range of time, I also adopt the method of regression discontinuity design to deal with the endogeneity issue. It would consider an arbitrarily narrow time interval lying closely on either side of the cutoff or threshold, and achieve a more likely unbiased estimate of the local average treatment effect around the cutoff, since the unknown time-varying factors are likely to be similar in the narrow time window on both sides, and thus provide a good control.

I use both the parametric and non-parametric estimations for RDD, and try not to rely solely on the results from one particular method. The parametric functional form usually takes as a low-order polynomial regression, which would use a relatively global set of data points including those both close to and far away from the cutoff. As for non-parametric method, the most common form is a local linear regression, which base only on data close to the cutoff, and the choice of bandwidth would be very important therefore.

5.2. Time-varying congestion tax

The economic principle of law of demand would suggest here that the varying congestion prices during different hours in a day would have an impact on the traffic flows accordingly and thus influence the air pollutant concentrations, especially those resulting from the road traffic.

I test this hypothesis with a Difference-in-difference (DiD) model using air pollution data and interpolated hourly weather data. I use the midnight hour from 12:00 am to 1:00 am as the control group, and compare the air pollutant concentrations during each hour of the day before and after the implementation of permanent congestion charge, i.e. 1 Aug 2007. Also I control for the weather condition and its lags, fixed effects of hour of the day, day of the week, and week of year. Since the congestion tax doesn't apply for weekends, the month of July and holidays, I exclude those data points.

$$y_t = \alpha_0 + \gamma_h + \beta_1\, post_t + \beta_h\, h * post_t + \beta_3 x_t + \epsilon_t \tag{2}$$

Where $post_t$ is the same with I(permanent congestion tax), an indicator variable for observations after the implementation of permanent congestion tax, denoted differently only to avoid confusion. The coefficient β_h, which is the coefficient of the interaction of each hour of the day (1:00-23:00) with$after_t$, is the one of interest, estimating the hourly average treatment effect of the congestion tax pricing scheme. Furthermore, γ_h is the fixed effect for hours of the day from 1:00 to 23:00, and the vector of covariates x_t, controls for the fixed effects for day of the week, week of the year, and the measuring stations, as well as the weather condition and its lags[3].

I use the observations one year before and after 1 Aug 2007, and try to always use a complete week rather than partial ones. Thus the data I use start from 7 Aug 2006 (Monday) and end on 27 June 2008 (Friday). I also drop the data from 30 June 2007 to 5 Aug 2007 during the week of implementation of congestion tax, since it's not a full week.

5.3. Fuel prices, fuel sales and fuel switching

In the last part of my study, I also want to empirically analyze how air quality is influenced by the fuel arbitrage behavior among FFV motorists. In order to do so, I focus on the time window from August 2007 until end of 2010, after the permanent congestion tax is in place. Choosing this time window is because I want to rule out the effect of congestion charge as possible and study the effects of fuel switching alone. I also only look at the Stockholm area, although this behavior pattern can be shared among the FFV owners from all over Sweden, since there's a larger FFV fleet in Stockholm as mentioned in previous sessions.

I use an OLS regression setting with control for several time-varying fixed effects.

$$y_t = \alpha_0 + \beta_1 fuel_t + \beta_2\, x_t + \epsilon_t \tag{3}$$

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[3] The reason to include the lags of weather variables is to better control for the autocorrelation in the pollutant concentration, since the pollutants tend to stay and linger in the air depending on different meteorological conditions.

Where y_t can be log of air pollution, or daily or monthly average of air pollutions; and $fuel_t$ can be the adjusted sales shares of ethanol among the total sales of ethanol and gasoline, or the ethanol sales, etc. The covariates x_t again would control for weather variables (up till quartics), and fixed effects for hour of day, day of week, week of year, and the measuring stations.

6. Results

6.1. Congestion tax in Stockholm

Selected results from the different specifications including OLS and RDD based on Equation (1) are presented in this section, for the congestion charge in Stockholm, both the trial phase and the permanent implementation.

Table 3 shows OLS estimates of the congestion tax trial on different air pollutants. For each pollutants and time windows, the coefficients and p-values are reported. The estimates are collected from 18 different regressions. Since I use the log of air pollutants as the dependent variables, the coefficients would indicate a percentage effect of the tax trial. E.g. for CO, the coefficient would imply that around 19 percent decrease in the concentration is associated with the implementation of the tax trial. All coefficients are negative during all time windows, and statistically significant for almost all pollutants, except for Ozone[4]. During the time window 2004-2008, the effects are stronger than the period from 2004 until July 2006 (exactly when the tax trial ended), which makes sense since the former might have been strengthened by the later implemented permanent tax effect.

Table 3: Effect of Congestion Tax Trial on Air Pollutions – OLS

	NO2	Nox	CO	O3	PM10	PM2_5
2004-2006/7	-0.054	-0.109	-0.188	-0.014	-0.075	-0.017
(p-values)	0.000	0.000	0.000	0.481	0.001	0.392
2004-2008	-0.076	-0.153	-0.247	-0.001	-0.043	-0.148
	0.000	0.000	0.000	0.920	0.001	0.000
2003-2010	-0.096	-0.203	-0.376	0.028	-0.126	-0.327
	0.000	0.000	0.000	0.004	0.000	0.000

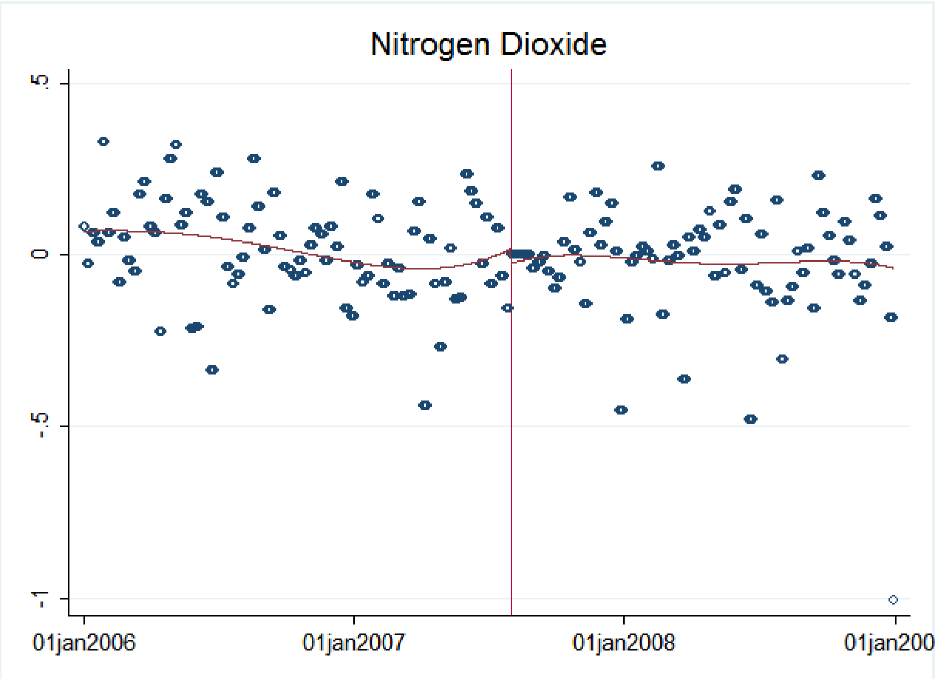
[4] The different results for Ozone might be due to several reasons. First, the Ozone data is only available from the urban background measuring stations, thus it might have limited relevance to the road traffic or the congestion tax. Second, the formation pattern for Ozone is quite different from the other pollutants, and its formation requires a lot of warmth and sunlight, thus making controlling for weather conditions especially important.

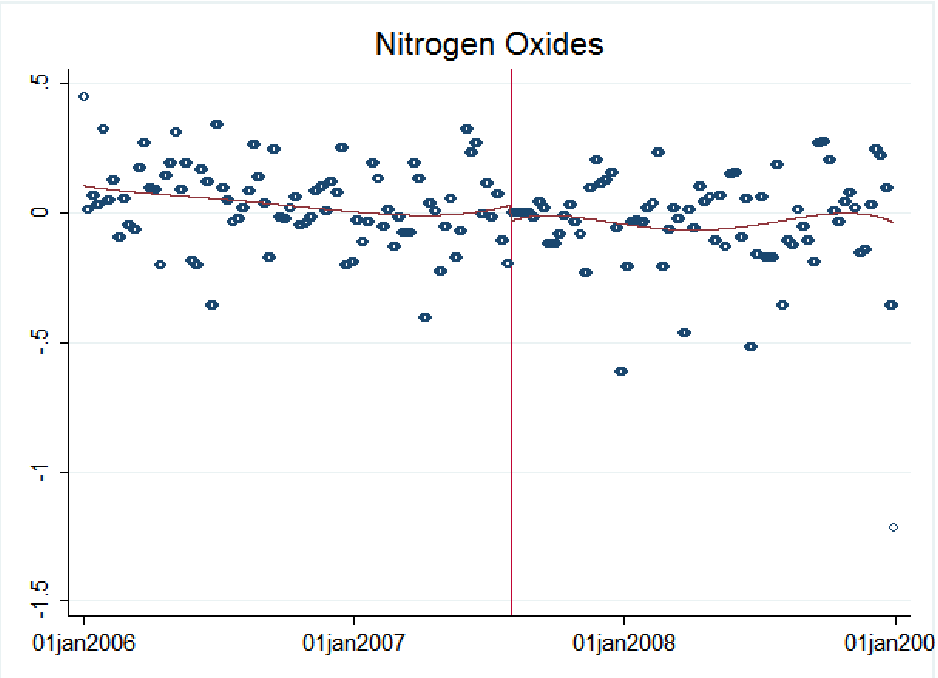
Table 4: Effect of Permanent Congestion Tax on Air Pollutions – OLS & RDD

2006-2008	NO2	Nox	CO	O3	PM10	PM2_5
OLS						
coefficients	-0.036	-0.080	-0.084	0.000	-0.037	-0.071
p-values	0.000	0.000	0.000	0.988	0.002	0.000
RDD						
3rd order	-0.124	-0.111	-0.216	-0.004	-0.265	-0.012
	0.008	0.064	0.000	0.970	0.000	0.858
4th order	-0.065	-0.209	-0.213	0.643	-0.401	-0.174
	0.302	0.010	0.002	0.570	0.000	0.053

Table 4 reports the estimates for the permanent tax within the time window of 2006-2008. Analyses for different time windows are also performed and have similar results. Estimates from OLS suggest similar results as for the tax trial, and the coefficients are all significantly negative except for Ozone, and imply a negative effect the permanent tax implementation has on the air pollutants. The RDD estimates are reported with 3^{rd} and 4^{th} order of polynomial time trends. Across the different orders of time trend specifications, the results also suggest a negative effect of the permanent tax on different pollutants (except a fairly mixed result for Ozone). With the 4^{th} order polynomial time trend, the coefficients for air pollutants range from -0.401 to -0.065. To illustrate the polynomial regression results in more details, Figure 6 plots the residuals from estimating Equation (1) without the indicator variable of I(Congestion), with a 4^{th} order polynomial time trend and the intercept of congestion tax on each sides of the cutoff.

Figure 6: mean weekly pollution level, 4^{th} order polynomial time trend


Nitrogen Dioxide
.5
0
-.5
-1
01jan2006
01jan2007
01jan2008
01jan200


Nitrogen Oxides
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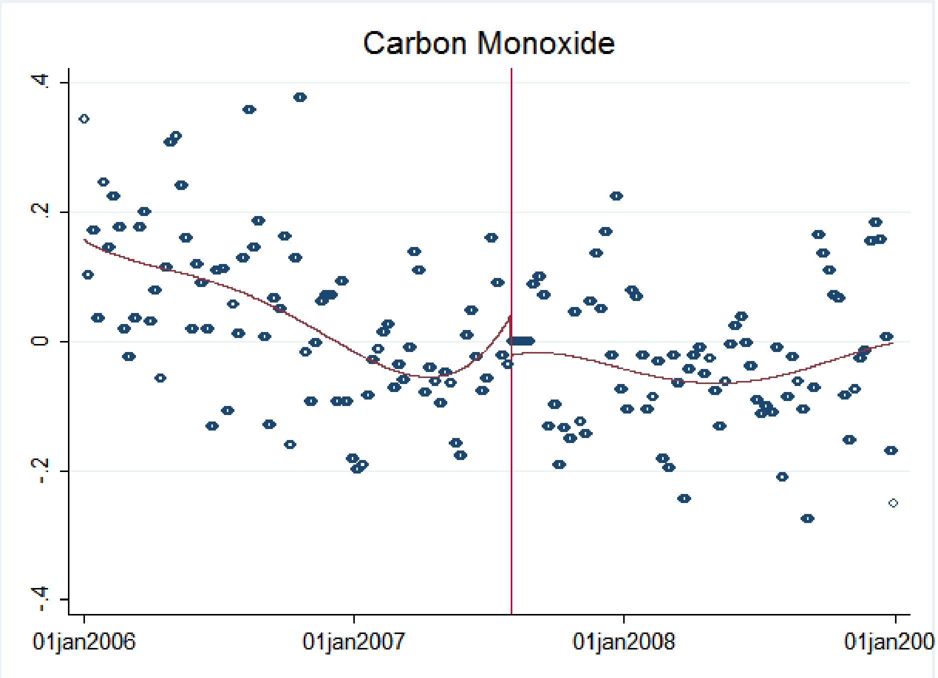
01jan200


Carbon Monoxide
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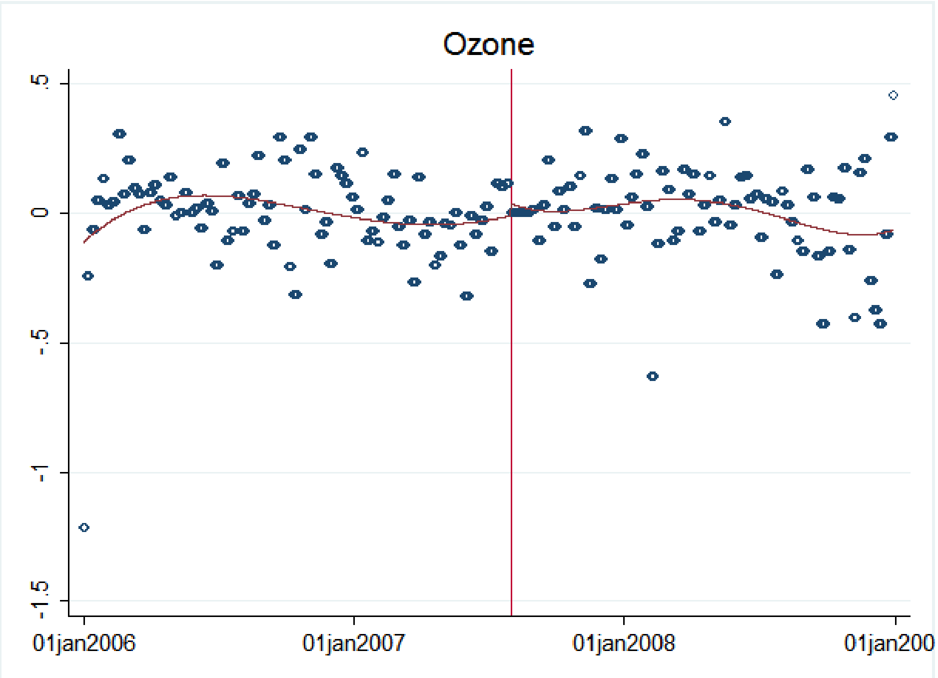
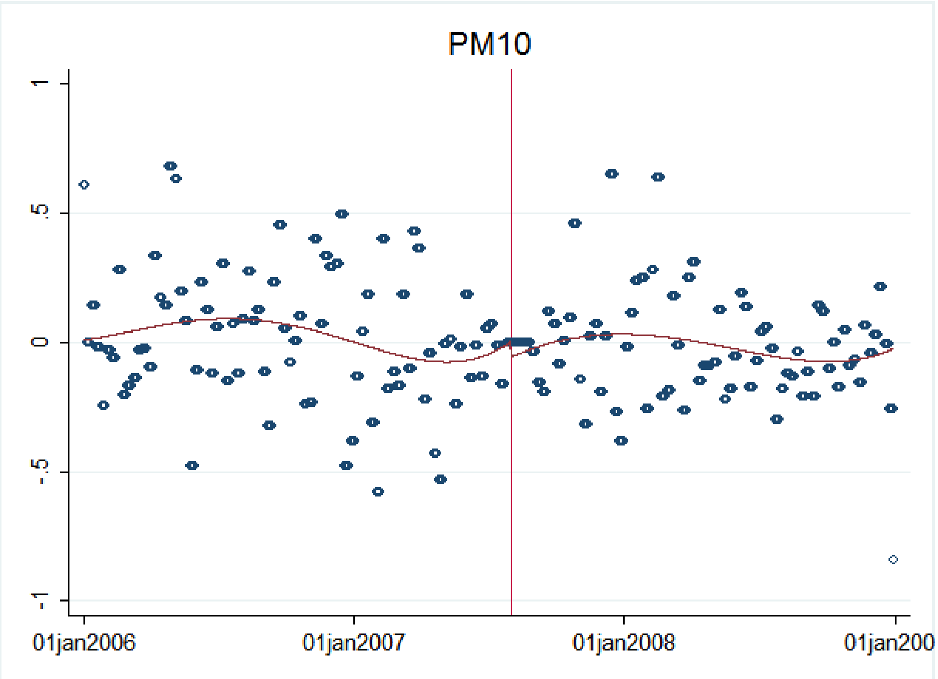
.2
0
-.2
-.4
01jan2006
01jan2007
01jan2008
01jan200


Ozone
.5
0
-.5
-1
-1.5
01jan2006
01jan2007
01jan2008
01jan200



The reported estimates from parametric RDD, i.e. with polynomial time trend setting, are quite consistent with my predictions, however when applying different orders of the polynomial time trend, I find that the results can vary a bit across different choice of the orders, e.g. when the orders go up to 7th, some of the coefficients become positive or insignificant. Also the choice of the orders of polynomial trend is quite disputed among scholars. Another drawback of using polynomial trend, as mentioned in previous sessions, is that it uses the relatively "global" set of data points rather than sticking to the "locals", and could result in possibly biased estimates. And a mix of using both the parametric and non-parametric methods for RDD is always more reliable in terms of interpreting the results.

Table 5 reports the estimates from local linear regression, the non-parametric approach in RDD context. It reports the optimal bandwidth that's selected using the Imbens and Kalyanaraman (2009) procedure, and the coefficients of interest are in the row with lwald, which is the estimated average local effect with the chosen optimal bandwidth. The other coefficients are estimates with either half (lwald50) or twice (lwald200) of the optimal bandwidth as robustness checks. The estimates with log of air pollutants as independent variables are reported as usual, and estimates with the level of air pollutants are presented as a robustness proof. Note that the choice of optimal bandwidth and resulting estimates are sensitive to scales. The coefficients across specifications are again negative, and actually even suggest a more economically significant effect for most pollutants, especially for NO2, CO, PM2.5, which are also statistically significant. The coefficients for half of the optimal bandwidth are less significant than those with optimal bandwidth, since the choice of bandwidth involves always a tradeoff between precision and bias, where the bandwidth should be wide enough to reduce noise but also narrow enough to compare observations close enough on each sides of the cutoff. (Lee, 2009)

Table 5: Effect of Congestion Tax on Air quality – Local Linear Regression

2006-2008	No2	Nox	Co	Ozone	PM10	PM2.5
log						
Optimal bandwidth	3.558	2.845	3.219	4.299	2.480	2.428
lwald	-.355*	-0.209	-.305*	-0.016	-0.276	-.448***
lwald50	-0.067	-0.207	-0.249	-0.256	-0.223	-0.339
Lwald200	0.007	-0.200	-.195*	0.097	-0.107	-.236*
level						
Optimal bandwidth	7.477	11.521	3.068	7.237	10.481	6.307
lwald	-3.270	-14.990**	-.144**	-1.910	-5.560***	-3.051***
lwald50	-9.450	2.540	-0.045	-22.060	-4.029	-6.170
Lwald200	-2.110	-1.560	-.103*	-0.097	1.093	-1.060

$P < 0.05$ *; $P < 0.01$ **; $P < 0.001$ ***

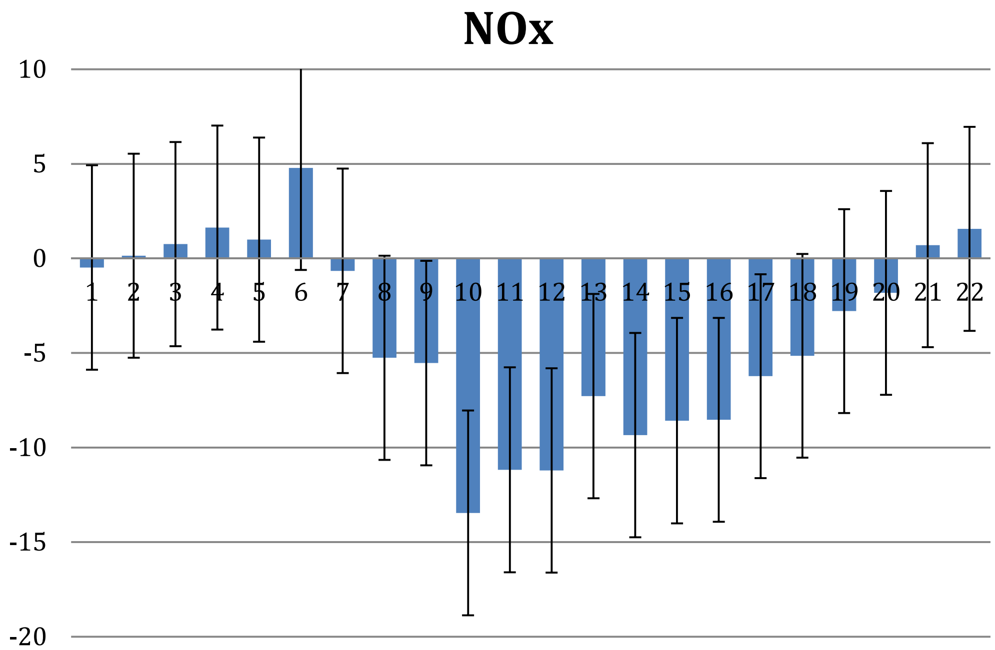
6.2. Time-varying congestion tax pricing

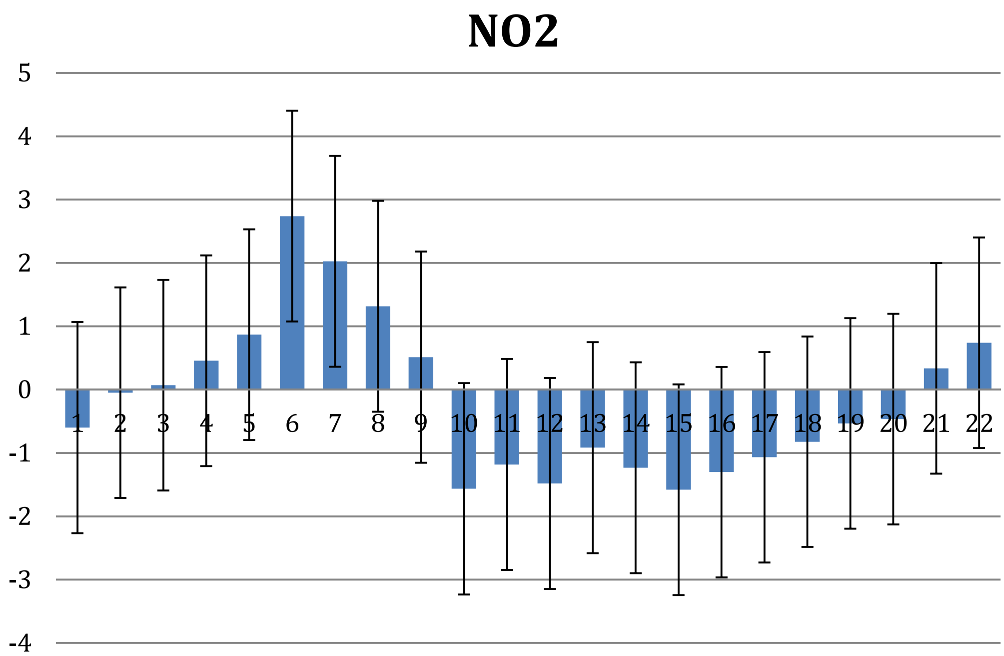
Figure 7 shows the estimates for each hour of the day from 1:00 – 23:00, showing the treatment effect of time-varying congestion tax pricing on the changes in air pollutant concentrations. To start with, the graph for PM10 reveals a very interesting result. It shows significantly negative effects during the tax charged time period (7-18[5]), and positive effects on the off-peak hours (before 6:30 and after 18:30). The negative results suggest that the congestion tax pricing is effective in reducing the air pollutant concentrations during peak hours and people might have reduced their car rides or substituted to public transportation, etc.; and the positive effect implies a possible substitution effect from the peak or tax charging hours to the off-peak or non-charging hours. For example, a person who used to drive to work from home at 6:45 a.m. before the implementation of permanent tax, and now due to the pricing, he would prefer to set out 30 minutes earlier to avoid the payment. The same logic applies for the non-charging hours in the evening.

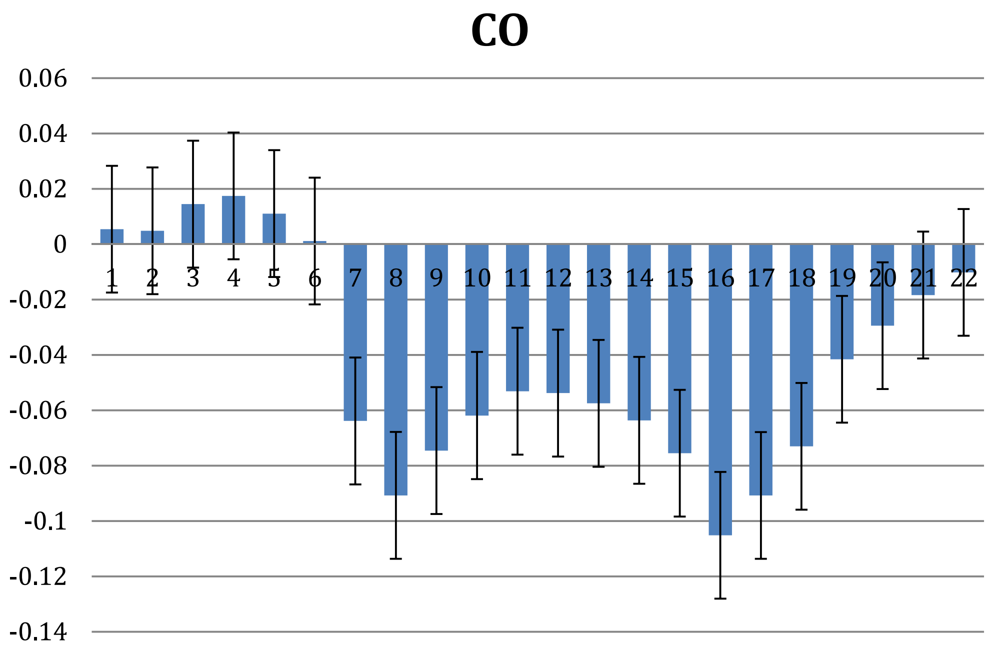
A similar pattern is also shared by the results for NOx and CO, significantly negative effects on pricing hours, and positive effects on non-pricing period especially in the mornings. However the non-pricing hours in the afternoon are also negatively influenced suggested by the results, though with a descending trend. Such patterns are also observed in results for NO2. One possible explanation is that the air pollutant might tend to linger around in the air for some time and thus create a certain lagged effect. For example, NO2 is heavier (more dense) than air, and it might stay in the air for hours and thus makes the hour effects less informative. One option is to control for the lagged weather variables and hope to eliminate the potential autocorrelation in the air pollution data, but I control for lagged weather variables (up to 3 hours) and the results stay similar, and I suppose some stronger control is needed.

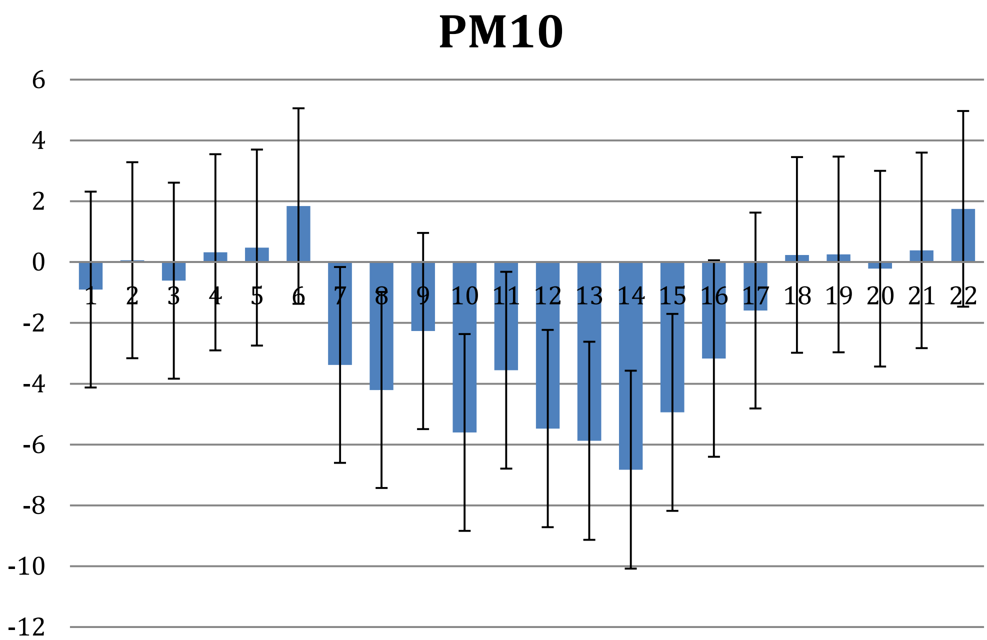
Figure 7: Effect of time-varying congestion pricing

[5] In the graphs, the hour 17 would suggest the time period from 17:00 to 18:00.


NOx
10
5
0
-5
-10
-15
-20
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22


NO2
5
4
3
2
1
0
-1
-2
-3
-4
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22


CO
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22


PM10
6
4
2
0
-2
-4
-6
-8
-10
-12
1
2
3
4
5
6
7
8
9
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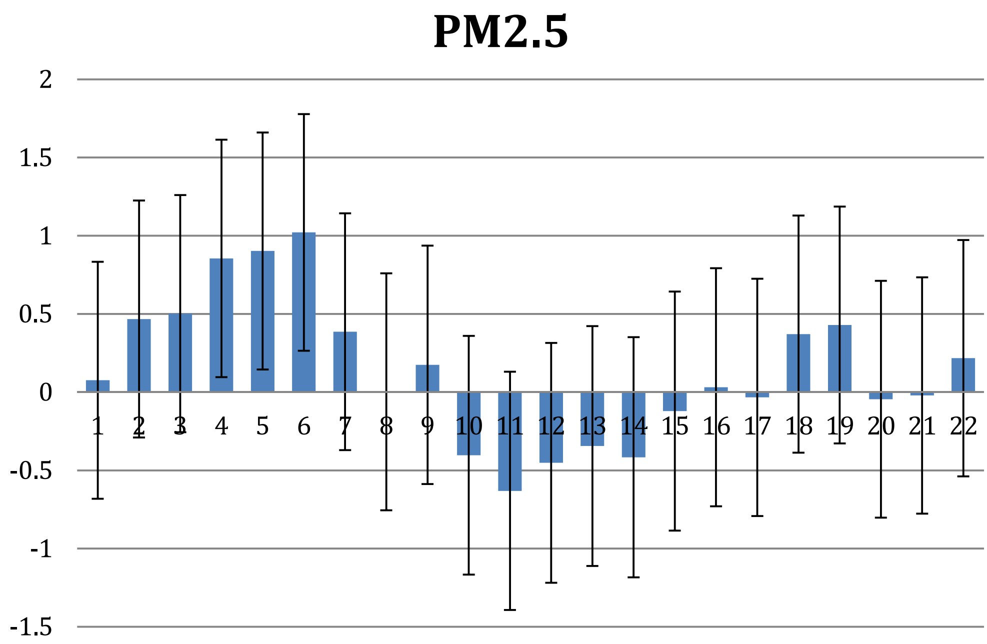
18
19
20
21
22



6.3. Fuel price, sales and fuel arbitrage

In the last part of my study, I also take a closer look at the effect of fuel arbitrage of the FFV motorists in Stockholm on air quality for the time span of 2007/08 – 2010. Table 6 shows a selected set of results from this analysis. It reports the OLS coefficient of regressing log pollutants on the adjusted ethanol shares in the total sales of ethanol and gasoline. The coefficients are significantly negative for CO and PMs, however positive for NOx. I also include the coefficients of using the daily and monthly average of pollutant concentrations as dependent variables, where the effects for CO and PMs are consistent with the previous, whereas quite mixed results for NOx. I don't include Ozone here since I only use data from the air quality monitoring stations for road traffic emissions, where there's no Ozone data recorded.

Table 6: Effect of fuel switching on air quality 2007/08 - 2010

	NO2	NOx	Co	PM10	PM2.5
Log pollution on adjusted ethanol shares					
Coef.	0.762	1.688	-1.421	-2.712	-5.138
p-value	0.195	0.047	0.050	0.003	0.000
R2	0.440	0.430	0.360	0.410	0.230
obs	16940	17007	12247	10898	10243
Daily average pollution on adjusted ethanol share					
Coef.	-0.745	-0.060	-2.622	-2.540	-4.669

p-value	0.108	0.927	0.000	0.000	0.000
Monthly average pollution on adjusted ethanol share					
Coef.	-2.173	-1.864	-1.874	-4.702	-5.682
p-value	0.000	0.000	0.000	0.000	0.000
Log pollution on ethanol sales					
Coef.	1.58E-07	2.19E-06	-9.94E-07	-3.11E-06	-1.67E-06
p-value	0.885	0.170	0.478	0.068	0.360

A possible explanation for this set of results is that ethanol fuel, though more environmentally friendly than gasoline in terms of CO2 emissions, it might have various impacts on other air pollutants such as the ones in interest here. According to BEST (2008), ethanol is theoretically expected to generate lower emissions of carbon monoxide, sulphur dioxide, volatile organic compounds (VOCs) and other unregulated pollutants in vehicle exhausts, since its oxygen content is believed to promote more complete combustion. However it may on the other hand, result in increased NOx emissions due to increased combustion temperatures from the improved availability of oxygen in the engine. (Best, 2008) Empirical studies however have diverse results for ethanol's impact on these pollutants, where most controversially they've found evidence for both increases and decreases in NOx emissions.

Another challenge here is that the ethanol sales data are only available in national level and monthly frequency, thus might cause biased results for the hourly or daily pollutions in Stockholm area. I also try to estimate the adjusted ethanol shares with price and economic variables to populate the monthly national data into daily frequency, however I struggle to find a proper estimation model with strong enough explanatory power (with big R2), since the ethanol sales is affected by various amount of factors, some of which are not easily accessible data or beyond my research scope.

7. Discussion

In the analysis of the effect of congestion charge, the estimates might be exposed to the pitfalls of adopting RDD approach, as I mentioned in previous sections. The parametric approach, i.e. polynomial regressions, might be accurate enough due to its usage of the "global" set of data, and it might also be fairly sensitive to the choice of order of polynomial time trend. The non-parametric method, i.e. the local linear regression, is more "local", however the choice of bandwidth also has to tradeoff between the accuracy and the significance of the estimates. (Lee & Lemieux, 2009) I hope the adoption of both can be a good complement and a show of proof for rather robust results.

When estimating the effect of time-varying congestion pricing, the weather variables are interpolated into hourly data from every-three-hour frequency, I do this in order that I could perform the analysis on hourly air pollutions and congestion prices in different hours. But by doing the interpolation, the control power over meteorological conditions is compromised, since the interpolated weather is not necessarily the accurate condition in the time being, and even the original every-three-hour-reported weather variables have many missing data points already.

Also, I only look at the two-year period around permanent congestion tax implementation, exactly one year before and after it. A very likely assumption would be that the results are very much associated with motorists' behavior. The one year period before the permanent tax starts from August 2006, right after the tax trial ended, thus the effects of the permanent tax might be diluted since the motorists' behavioral habits might have already been adapted to the pricing scheme from the congestion tax trial, thus making the results not as significant as it might supposedly be.

In addition, the fuel sales data of ethanol and gasoline are available only on a monthly and national level, or an annual and kommun level, thus I have to make a few assumptions when estimating the effect of fuel sales, including that the shares of ethanol sales remain constant in a month, and the sales share in Stockholm is similar to that in national level. I try to populate the fuel sales data into hourly or kommun level by estimating a regression model, however the model fails to have good enough explanatory powers so I have to drop it.

My study may also inevitably suffer from some further shortcomings of data sets. To start with, there are quite many missing data in the weather variables (about 50%), which creates a challenge for the analysis since controlling for the meteorological conditions is a crucial foundation for more reliable results. Also, the passage traffic data through the congestion tax control points is only available daily and not aggregated by fuel types, thus making it not possible if I want to test the effect of the time-varying congestion pricing on the traffic flow, which might help me further distinguish the air pollution variations impacted from the pricing alone from those which might be affected by their physical features or other unknown sources (e.g. construction in cities, etc.).

8. Conclusion

In my study, I investigated the effects of congestion charge and fuel switching on the air quality in Stockholm area. First I use various specifications, including OLS, Regression Discontinuity Design, to perform my analyses on the effect of the trial and permanent congestion charge, controlling for weather variations and other relevant fixed effects, and find that the congestion charge is effectively reducing the air pollutant concentrations, and the effect is quite significant and robust across different specifications. Then I adopt Difference-in-Differences approach to further test the impact of the time-varying congestion pricing on the air pollutions in different hours of a day, and the results show that the pricing scheme does reduce the air pollutant emissions during most of the peak hours, and even show some substitution effect from the peak to non-peak hours in some pollutants. Additionally I run several regressions with control for fixed effects to estimate the correlation between the air pollution and the drop of ethanol fuel sales, and find that with the drop of ethanol sales shares, some pollutants would increase due to a higher usage of gasoline fuels, whereas some others drop which might be related to ethanol fuel's different impact on the emission of certain pollutants.

In sum, my study further shows proof of the effectiveness of congestion charge on improving air quality in Stockholm, and provides some evidence for the validity of the time-varying pricing scheme design of congestion tax, and also presents argument that echoes with some previous literatures on the pitfall of promoting flexible fuel vehicles.

For future researches, I believe it would be very interesting to explore the relationship between the time-varying congestion pricing with the traffic flow if the data would be available or estimated properly, since the traffic flow is more directly related to the congestion tax, and is not impacted by as complicated sources as the air pollutions. It's also meaningful to future policy making to perform a cost-effectiveness or welfare analysis on the pricing scheme. Another direction could be including the considerations of substitution channels, such as public transport, taxis, and even biking, as well as the car fleet and registrations of vehicles of different fuel types or models, to further explore the possible roles these factors might be playing in the air quality improvement. Furthermore, since Gothenburg is launching the congestion charge from the start of 2013, more proof can be found from there and hopefully it would contribute reference for future public policy settings.

9. References

9.1. Literatures

Chen, Y. and Whally, A. (2012), Green Infrastructure: The Effects of Urban Rail Transit on Air Quality, *American Economic Journal: Economic Policy*, Vol. 4, No. 1, pp. 58–97.

Davis, L.W. (2008), The Effect of Driving Restrictions on Air Quality in Mexico City, *Journal of Political Economy*, Vol. 116, No.1, pp. 38-81.

Eliasson, J. et al. (2010), The Stockholm Congestion Charges – Four Years on. Effects, Acceptability and Lessons Learnt, WCTR, Working Paper.

Foreman, K. (2013), Crossing the Bridge: The Effects of Time-Varying Tolls on Curbing Congestion, UC Berkeley, Job Market Paper.

Goel, D. and Gupta, S. (2011), The Effect of Metro Rail on Air Pollution in Delhi, Delhi School of Economics. Working paper.

Hill, J. et al (2009), Climate Change and Health Costs of Air Emissions from Biofuels and Gasoline, *PNAS*, Vol. 106, No. 6, pp. 2077-2082.

Hultkrantz, L. and Liu, X. (2012), Green Cars Sterilize Congestion Charges: A Model Analysis of the Reduced Impact of Stockholm Road Tolls, *Transport Policy*, Vol. 21, pp. 110-118.

Huse, C. (2012), Fast and Furious (and Dirty): How Asymmetric Regulation May Hinder Environmental Policy, Stockholm School of Economics and IIOC, Working paper.

Huse, C. and Salvo, A. (2010), Is Arbitrage Tying the Price of Ethanol to that of Gasoline? Evidence from the Uptake of Flexible-Fuel Technology, Stockholm School of Economics, Working paper.

Imbens, G.W. & Kalyanaraman, K. (2009), Optimal Bandwidth Choice for the Regression Discontinuity Estimator, Harvard University and NBER. Working paper.

Imbens, G.W. & Lemieux, T. (2007), Regression Discontinuity Designs: A Guide to Practice, *Journal of Econometrics*.

Lee, D.S. and Lemieux, T. (2009), Regression Discontinuity Design in Economics, NBER, Working paper.

Lee, H. and Munk, T. (2008), Using Regression Discontinuity Design for Program Evaluation, *JSM*.

Lin, C. et al (2011), The Effects of Driving Restrictions on Air Quality: Evidence from Bogotá, São Paulo, Beijing, and Tianjin, University of California and AAEA. Working paper.

Salle, J.M. and Slemrod, J. (2010), Car Notches, University of Chicago and University of Michigan, Working paper.

Winther, M. et al (2012), Emission Consequences of Introducing Bio Ethanol as a Fuel for Gasoline Cars, *Atmospheric Environment*, Vol. 55, pp. 144-153.

Wolff, H. and Perry, L. (2011), Keep Your Clunker in the Suburb: Low Emission Zones and Adoption of Green Vehicles, University of Washington. Working paper.

9.2. Electronic:

Best (2008), Review of Fuel Ethanol Impacts on Local Air Quality, Retrieved on March 1, 2013 from http://www.best-europe.org/upload/BEST_documents/info_documents/Best%20reports%20etc/D9.14%20-%20Review%20of%20Ethanol%20Fuel%20Impacts%20on%20Local%20Air%20Quality_080516.pdf

Best (2009), Promoting Clean Cars, Retrieved on March 10, 2013 from http://www.best-europe.org/

SLB (2006), The Stockholm Trial: Effects on Air Quality and Health, Retrieved on February 23, 2013 from http://www.stockholmsforsoket.se/upload/Sammanfattningar/English/Effects%20on%20air%20quality%20and%20health.pdf

SLB (2009), The Effects of the Congestion Tax on Emissions and Air Quality, Retrieved on February 24, 2013 from http://slb.nu/slb/rapporter/pdf8/slb2010_006.pdf

Stockholms Stad (2009), Analysis of traffic in Stockholm, retrieved on March 15, 2013 from http://www.stockholm.se/

WHO (2005), Air Quality Guidelines – Global Update 2005, Retrieved on April 8, 2013 from http://www.who.int/phe/health_topics/outdoorair/outdoorair_aqg/en/index.html

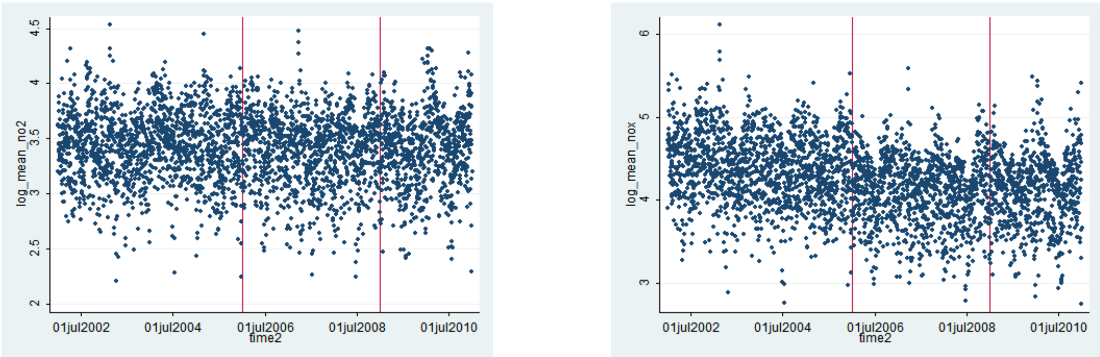
WHO (2011), Air Quality and Health, Retrieved on March 15, 2013 from http://www.who.int/mediacentre/factsheets/fs313/en/index.html

10. Appendix

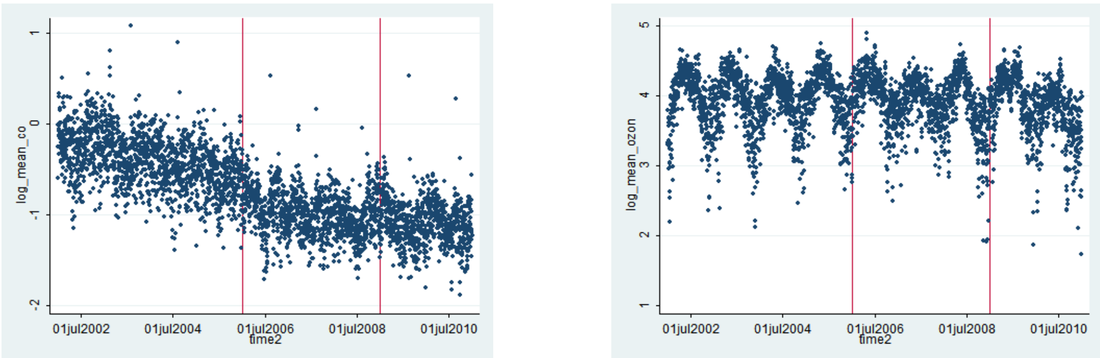
10.1. Measuring air quality in Stockholm

Figure 8 below shows the average daily pollutant concentration in Stockholm in logs, and presents similar results to the previously presented graphs in level.

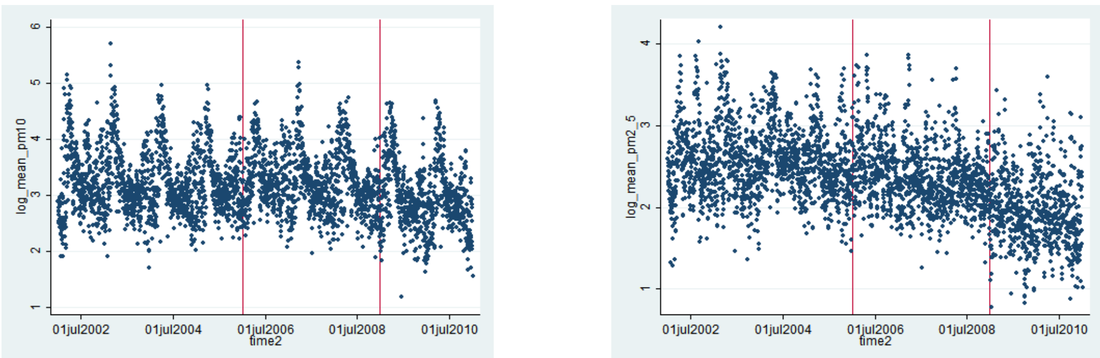
Figure 8: Average daily air pollution in Stockholm (in logs)



NO2 (left); NOx (right)



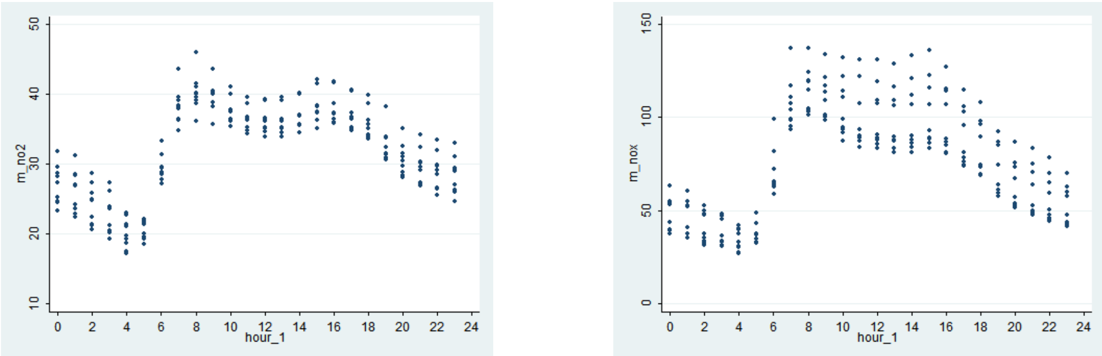
CO (left); Ozone (right)



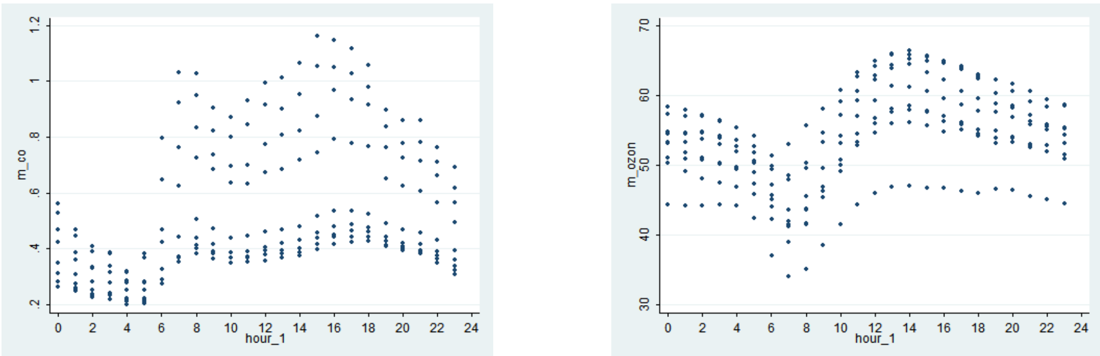
PM10 (left); PM2.5 (right)

Figure 9 below plots the air pollutions levels across different hours of the day. Each dotting line corresponds to a year from 2002-2010, by averaging hourly emissions recorded from all measuring stations. It first illustrates the peak emission periods during the morning (around 7-8), and in the afternoon around 15-16. Also, a notable observation about ozone emission, which is quite different from the others, shows that the pollutant peaks its concentration level much later than most other pollutants. This is because that the formation of ozone requires warmth and sunlight, and it does not come directly from the exhaust emissions from road traffic (Davis, 2008). In addition, the decrease in CO concentration is fairly obvious especially for the daytime hours after the implementation of congestion charge (since the year of 2006 and 2007).

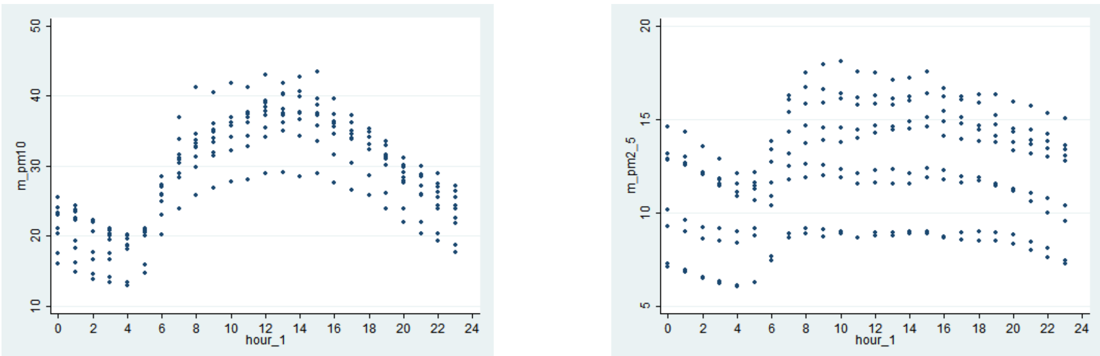
Figure 9: Average daily pattern of air pollutants in Stockholm



No2 (left) & Nox (right)



Co (left) & Ozon (right)



PM10 (left) & PM2.5 (right)

10.2. Summary of the air quality and weather monitoring stations

Table 7: Summary of air quality and weather measuring stations

Air quality monitoring station name	Kom mun code	Km to SMHI station	SMHI stations (weather)	Year	Inner / outer city	Station type
Stockholm Sveav.	180	0.12	Stockholm	2002 - 2010	Inner	TRAFIK
Stockholm Hornsg.	180	2.79	Stockholm	2002 - 2010	Inner	TRAFIK
Stockholm Torkelknutsg.	180	2.79	Stockholm	2002 - 2010	Inner	URBBAK
Stockholm Hornsg. tak	180	2.78	Stockholm	2006 -2010	Inner	URBBAK
Stockholm Hornsg. 85	180	2.78	Stockholm	2006 -2010	Inner	TRAFIK
Stockholm Sveav. tak	180	0.14	Stockholm	2006 -2010	Inner	URBBAK
Stockholm Sveav. 88	180	0.14	Stockholm	2006 -2010	Inner	TRAFIK
Lilla Essingen	180	3.53	Stockholm	2006 -2010	Inner	TRAFIK
Stockholm Norrlandsg	180	0.98	Stockholm A	2003 - 2010	Inner	TRAFIK
Sollentuna or E4 Häggvik	163	7.39	STOCKHOLM-BROMMA	2003 - 2010	Outer	TRAFIK
Botkyrka, Alby	127	7.82	Tullinge A	2005 - 2010	Outer	URBBAK
Södertälje Turingegatan	181	16.73	Tullinge A	2007 - 2010	Outer	TRAFIK

10.3. Summary of air pollutants' features

The air pollutants in focus in this paper, including Nitrogen Oxides, Ozone, Carbon Monoxide, and Particulate Matters are considered the criteria pollutants by the US EPA, Table 8 shows a brief summary of the basic features of the air pollutants.

Table 8: Summary of air pollutants

WHO	Components and	Note	Health Effect

	Guideline 2005	formation		
NO2	40 µg/m3 annual mean 200 µg/m3 1-hour mean	Mainly formed by combustion processes (heating, power generation, and engines in vehicles and ships).	Contribute to formation of Ozone and fine particulars (PM2.5)	Associated with bronchitis in asthmatic children; reduced lung function growth.
Ozone	100 µg/m3 8-hour mean	Formed by the reaction with sunlight (photochemical reaction) of nitrogen oxides (NOx) and volatile organic compounds (VOCs).	Only refer to ground-level ozone.	Cause breathing problems, trigger asthma, reduce lung function and cause lung diseases.
PM10	20 µg/m3 annual mean 50 µg/m3 24-hour mean	Sulfate, nitrates, ammonia, sodium chloride, carbon, mineral dust and water.	Particles with an aerodynamic diameter smaller than 10 µm	Associated with cardiovascular and respiratory diseases, as well as of lung cancer, premature death.
PM2.5	10 µg/m3 annual mean 25 µg/m3 24-hour mean		Particles with diameter smaller than 2.5 µm	
CO	9 ppm 8-hour mean[6]	Majority comes from mobile emissions.		Reduce oxygen delivery to the body's organs and tissues. Could cause death.

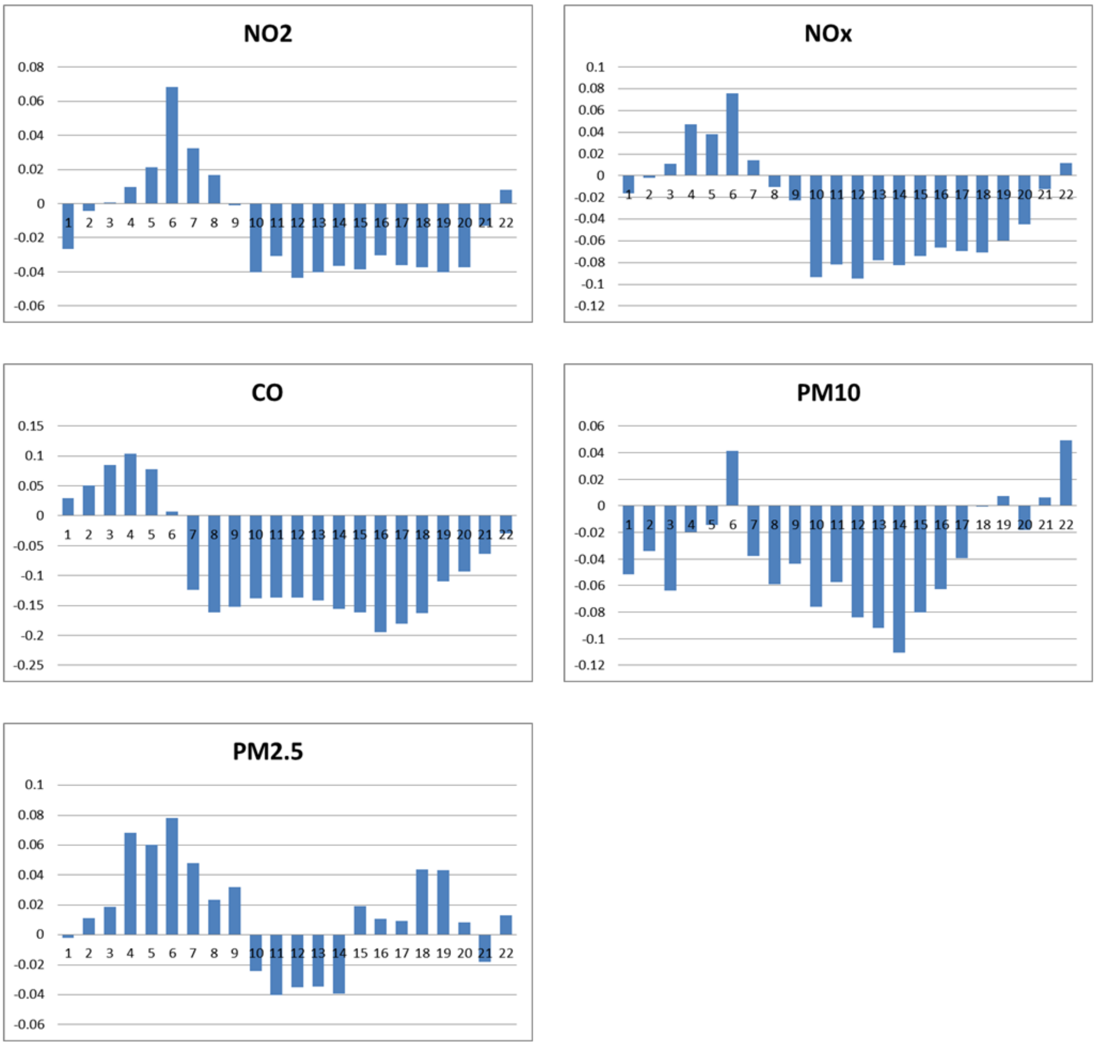
10.4. Robustness checks

10.4.1. Using logs of air pollutions

I also use logs of air pollutions as a robustness check, and the results are similar to what I present as in the main result.

[6] According to EPA US standards.

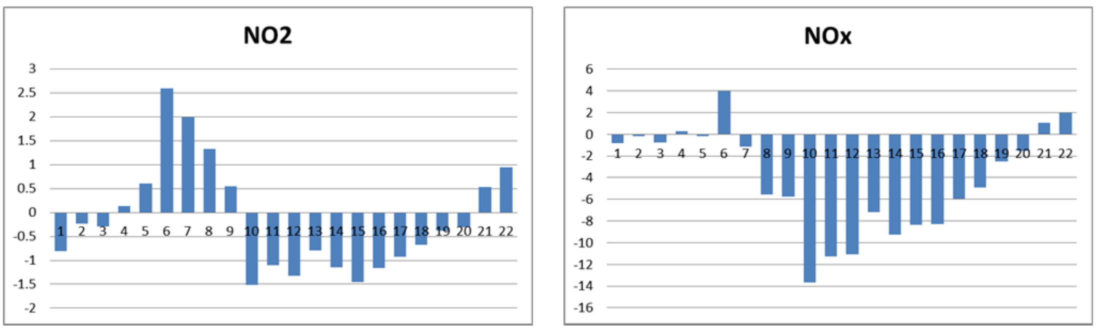
Figure 10: Effect of time-varying congestion pricing on air quality (logs)

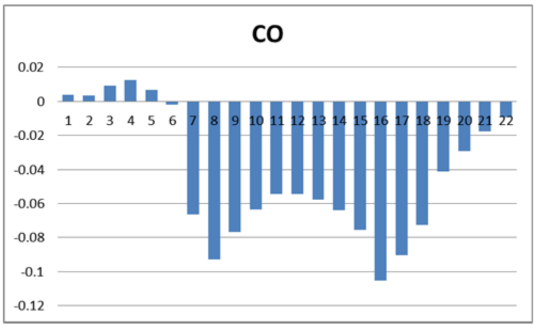


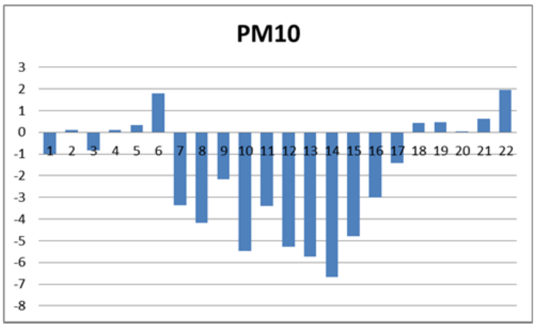
10.4.2. Results with control for lagged weather variables (up to 3 hours)

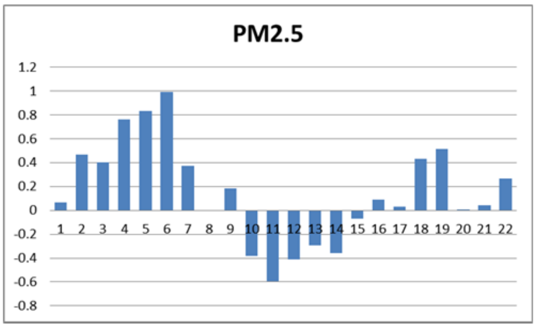
To better control for the meteorological factors, I also include controls for up to 3 hours lags of weather condition, and the results are shown in Figure 11, which present similar results.

Figure 11: Effects of time-varying congestion pricing (controlled for lagged weather)




CO
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22


PM10
3
2
1
0
-1
-2
-3
-4
-5
-6
-7
-8
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22


PM2.5
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22