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Evaluating public policies with high frequency data: Evidence for driving restrictions in Mexico City Revisited*

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Abstract

The evaluation of public policies is on the heart of the efficient management of public resources. As complex as it generally is, any reform should be assessed on its ability to achieve its preconceived goals. This research paper attempts to show the importance of the design of a public policy's empirical evaluation, considering the susceptibility that its conclusions might have to changes in the approach to the data. The work of Davis (2008), which finds that a driving restrictions program had no impact on air quality in Mexico City, is revisited showing that reasonable changes in the methodology used can dramatically alter its conclusions. Additionally, evidence is presented that shows the success of the restrictions program in reducing air pollution by 12 to 18% during the first months of its implementation followed by a gradual increase in pollutants concentration, consistent with more limited opportunities for adaptation to the policy in the short-run. Finally, an alternative and robust framework is proposed to carry out the policy evaluation confirming the reduction of pollution right after the program's implementation.

*This working paper belongs to an extension of previous work in my thesis.

†e-mail: chsalas@uc.cl. I would like to thank Gonzalo Edwards, José Miguel Sánchez and Gert Wagner, members of my Dissertation Committee during the second semester of 2009. I would also like to thank Francisco Gallego and Juan Pablo Montero for numerous and essential comments as well as rich guidance throughout the development of this document, with a special mention to Juan Pablo who inspired a research in this topic. Finally, I would like to thank Hector Jorquera from the Department of Chemical Engineering of Pontificia Universidad Católica de Chile for crucial aid on aspects related to the behavior of air pollutants, and Borja Larraín from the Business School of the same university for helpful comments on various issues.

"Reason only perceives that which it produces after its own design."

Immanuel Kant
The Critique of Pure Reason
Preface to the second edition

1 Introduction

The evaluation of public policies is on the heart of the efficient management of public resources. As complex as it generally is, any reform should be able to be assessed on its ability to achieve its preconceived goals. Among many obstacles one could encounter on such undertaking, the ones that usually stand out are the correct identification of the specific objectives of the program, the sufficient understanding of the problem in order to carry out an informed search, and the availability of data and appropriate methodology to perform the research. In other words, in the design of the empirical quest one should be able to answer the questions what to look for in the data, where or when to look, and how to look. Establishing these issues accurately is of utmost importance to accomplish a valid evaluation of a policy, because it is what we ask the data what we are going to get from it, or continuing the quote of Immanuel Kant:

> *"Reason must approach nature with the view, indeed, of receiving information from it, not, however, in the character of a pupil, who listens to all that his master chooses to tell him, but in that of a judge, who compels the witnesses to reply to those questions which he himself thinks fit to propose."*

In this paper, I will show just how important planning the interrogation to our witness is, that is to show how important it is to properly answer the three previous questions in order to design a valid empirical search of the data. In order to accomplish this objective, I will make use of the empirical work done by Davis (2008), where he evaluated the impact of a driving restriction program on air pollution in Mexico City. Davis sets out to answer how the driving restriction program called *Hoy No Circula* (HNC) affected the concentration of air pollutants in the capital city of Mexico. It is well known that Mexico City, like other big industrial cities, had always had an air quality problem and, according to Collins and Scott (1993), Mexico had not been successful in resolving this issue. Record levels of airborne pollutants led this city's government to implement the HNC on November 20, 1989. This program consisted in banning every vehicle, except taxis, buses, ambulances, fire trucks and police cars, from driving one day of the week, from 5am to 10pm, based on the last digit of its license plate.

Using hourly series on concentration of five air pollutants, Davis presents evidence that the HNC had no significant impact on air quality. The main empirical strategy is based on a Regression Discontinuity Design (RD), which in this case basically consists of controlling time varying phenomena in an OLS estimation by adding a time trend polynomial of a predetermined length. In spite of the correct functioning of the program[1], evidence of intertemporal substitution, driving vehicles during hours of the day and days of the week when restrictions are not in place, and of greater utilization of new and used vehicles would explain the lack of improvement in air conditions. In a critic to this driving restriction program, Eskeland and Feyzioglu (1997) interpret this behavior as rational decisions made by households and firms, where cars effectively represent “driving permits” and buying such permits allows an individual to increase his driving. Question is then raised as to the feasibility of observing such purchases or adaptive behavior right after the start of the program so as to observe an immediate null impact of the program.

As Davis points out, the HNC is considered the central component of the environmental policy followed by Mexico City’s authorities although alternative strategies were and have been in discussion. A correct evaluation of the effect of HNC on air pollution, and any other strategy on the table, is of crucial importance when evaluating these alternatives. Even more so and as discussed by Eskeland and Feyzioglu (1997), in the spirit of dying down an externality these policies inherently introduce inefficiency in the normal, and supposedly efficient, functioning of the natural system it is acting on as well as inequality in the burden among the users affected, for the restriction is more easily accommodated by some than by others. If this externality is not at least partially corrected, the inefficiency created might not be justified. In fact, Eskeland and Feyzioglu (1997) argue that this ban generated high welfare costs to Mexico City’s population and did not deliver the intended benefits of reduced driving. Whichever the case, a proper evaluation of the impact of such program and its results should be of enough validity, thoroughness and robustness if it is to influence the policy decision of the authority.

Throughout this essay I will attempt to show the importance of, in the words of Kant, proposing the right questions for our witness to answer. I will do so by first demonstrating that small changes on the methodology used by Davis can bring about completely different conclusions to the problem originally proposed, second by showing that choosing wisely where to look might reveal aspects of the answer of enormous economic interest and third by illustrating that choosing differently how to look the data might help overcome the problems here to be exposed Davis’ results bear. In particular, I find that varying the time window and the length of the time trend polynomial of the RD specification changes the sign and significance of the impact of the HNC greatly. On the other hand, following the hypothesis that the program should have had a maximum impact at the beginning of its implementation, for the opportunities of adaptation of vehicle users are limited in the short-run, I allow for heterogeneity on the impact of HNC during the first year finding a negative and significant impact on pollutant concentration at the beginning, followed by a gradual increase converging to the long run result of statistically zero impact. Finally, I propose two alternative empirical approaches consisting of non-parametric and semi-parametric estimations that avoid the use of a time-trend polynomial and whose results are robust to the election of the time window. Results under this framework confirm the reduction of the main airborne pollutant right

[1]Eskeland and Feyzioglu (1997), Davis (2008) and many journalist sources consistently affirm that the driving restriction program’s heavy fines and high police control provoked a near universal compliance.

after the implementation of the HNC.

I should make clear that my objective is not to directly criticize Davis' work, a novel and serious attempt to evaluate an important public policy in a Developing Country. I intend only to establish a warning sign on the methodology used, that is, on the questions we are compelling our data to answer, even in the presence of great quality data such as this high frequency series, when evaluating public reforms and, in the means of this, shaping scientific and public opinion of such reforms.

In the next section I describe the data that was used in Davis (2008) and that will be used here as well. In section 3 I revisit the most important results from Davis (2008) and the methodology used to obtain these. In section 4, the evidence of a heterogeneous impact of HNC during its first year of implementation is presented. Section 5 proposes two alternative empirical approaches robust to changes in the specification. Section 6 concludes this document. On the body of this essay, I will only lay out the most important tables and figures so as to avoid unnecessary distractions. Every other relevant information and result will be placed in the appendix at the end of this document.

2 The Data

Concentration of Pollutants in the air is measured by the atmospheric monitoring network of Mexico City, belonging to the Department of Environment and Natural Resources of the Government of Mexico. This network consists of four subsystems, one of which reports hourly measures of ozone (ground-level), nitrogen dioxide, nitrogen oxides, sulfur dioxide, carbon monoxide and total suspended particulate matter smaller than 10 and 2.5 micrometers; another subsystem reports hourly measures of temperature, real humidity, wind speed and wind direction. During the time the HNC was implemented, this network reported all weather variables but only the first five pollutants. Davis (2008) uses this same data base.

The empirical analysis from Davis (2008) and this dissertation will focus on the period 1986-1993, that is, 4 years before and after the HNC. During this period, the network measured concentration of pollutants with a number of monitoring stations varying according to the pollutant. The number of stations that report uninterrupted data along the 8-year window are 15 stations for carbon monoxide and sulfur dioxide, 9 stations for ozone, and 5 stations for nitrogen dioxide and nitrogen oxides. On the other hand, 10 stations measured the four weather variables along this time window. On the following analysis, as Davis (2008) does too, only these monitoring stations will be used to prevent any bias caused by the entrance or removal of a specific station. Table 1 summarizes the weather variables and the concentration of pollutants during the period of study [2].

Having a complete understanding of what every pollutant stands for is crucial to interpret any result. Davis (2008) uses an emissions inventory from 2004 to establish the importance of vehicle emissions as a source of each pollutant. Fortunately, the Department of Environment and Natural Resources publishes in its web page the emissions inventory of several states,

[2]Table 20 in the appendix is a copy of the Summary Statistics that Davis (2008) reports in his paper, confirming that we are dealing with almost the exact information.

Table 1: Summary Statistics: 1986-1993

	Observations	Mean	Standard Deviation	Minimum	Maximum
Carbon Monoxide	690,559	4.76	2.26	.100	50.0
Nitrogen Dioxide	235,860	.041	.021	.001	.460
Ozone	412,409	.046	.038	.001	.500
Nitrogen Oxides	227,421	.073	.043	.001	.590
Sulfur Dioxide	641,439	.045	.022	.001	.846
Temperature	511,037	16.0	4.75	.100	49.2
Real Humidity	437,408	49.9	20.7	.050	102.4
Wind Speed	453,221	4.43	2.39	.010	95.1
Wind Direction	498,381	211.1	75.8	.000	420.0

Pollutant levels are reported in parts per million, Temperature in celsius degrees, Humidity in percentage (0 to 100), Wind Speed in kilometers per hour and Wind Direction in azimut degrees.

including the Federal District, for years 1994, 1996, 1998, 2000, 2002 and 2004. Besides, a study by Lezama (1997) uses an emissions inventory that includes year 1989.[3] According to the inventory from 1989, vehicle emissions are responsible for 96.7% of carbon monoxide, 75.4% of nitrogen oxides, 21.8% of sulfur dioxides and 52.5% of hydrocarbon compounds (precursor to ozone). A summary of the share that different sectors have on the emission of different pollutants, for several years, is presented in Table 8 in the Appendix. Comparing the inventories one could notice a change in the responsibility of transportation emissions and private vehicle emissions specially in sulfur dioxide and nitrogen oxides, responsibility which reveals to be less back in 1989. What is clear throughout the years is the importance of transportation and private vehicle emissions on carbon monoxide concentration, accounting for almost 100% the former and on average 50% the latter of the total concentration of this pollutant in the air. Is for this reason that many of the results to be shown in the following sections will concentrate on this pollutant.

Finally, the use of time series data requires to check for the usual properties belonging to this type of data base. Tables 12 to 16 in the appendix report results for Dickey-Fuller tests which show no sign of a unit root in any of the monitoring stations' series used, confirming that these are stationary. Such series have been tested for different processes they might follow finding that hourly series of carbon monoxide, ozone, nitrogen oxides and nitrogen dioxide follow an autoregressive process of order two to five, and sulfur dioxide follows a first order to a ninth order autoregressive process. Daily series all follow mainly an autoregressive process of first order, except for ozone which follows second to fifth order autoregressive process. All these results are reported in Table 19 in the appendix. These results are important and should be taken into account when estimating using these time series data

[3]Lezama (1997) presents a summary of the emissions for 1989 and 1994. Comparing the measures for 1994 with the same measures presented by the government of Mexico for the same year reveal their equivalency. This brings forth, at least tentatively, the validity of the measures for 1989.

base.

3 The HNC's Incompetence Revisited

As discussed in the previous sections, Davis (2008) main objective is to determine if mean air pollution decreased or not after the implementation of the HNC. In this section I will briefly review Davis' methodology and results to show thereafter that some of these conclusions do not necessarily hold under different equally plausible specifications.

3.1 Davis (2008) Results

The general estimation form that Davis uses is the one laid out in equation 1. In this equation, the dependent variable y_t is the average, across the available monitoring stations, of their hourly measures of concentration level of every pollutant. HNC_t is a binary variable equal to one after November 20, 1989, and the γ coefficients accompany the polynomial time trend. Finally, x_t is a vector of covariates that includes weather variables and indicator variables for month of the year, day of the week, hour of the day, and the interaction between weekends and hour of the day.

$$y_t = \beta_0 + \beta_1 HNC_t + \beta_2 x_t + \gamma_1 t + \gamma_2 t^2 + ... + \gamma_7 t^7 + u_t \tag{1}$$

In the main specification, y_t is the log of the average hourly air pollution so β_1 is the percentage effect of HNC on air pollution. Using the biggest symmetrical window available, 1986-1993, the estimation of such specification renders a difference not statistically significant[4] in the mean air pollution before and after the program[5]. These results are shown in Table 2, and are robust to eighth and ninth order time-trend polynomial. Results in this table belong to my own estimation using this methodology and the data base before described. Table 21 in the appendix reports the estimation results shown in Davis' paper. As can be seen, even though the summary statistics show almost no difference in the data base used, results differ slightly from the ones Davis (2008) reported. This difference is not sufficiently relevant to invalidate this paper's results mainly for two reasons: first, conclusions from statistical inference in both estimations are equivalent; second, the data base used in this document is the only one relevant to assess the HNC's impact on air pollution[6], which validates the empirical exercises that will hereafter be carried out.

[4]If not indicated otherwise, 95% confidence level is used all along. An asterisk (*) will be placed on coefficients that are significant to this level of confidence.

[5]Because of the use of a single time-trend polynomial for the whole sample, this difference is between the mean air pollution for the years before and the mean air pollution for the years after. I what follows, this difference will be treated as the average long-run impact of the program, and not the local impact of it as Davis (2008) seems to treat it.

[6]Even more so, Davis claims that the data base he used is this one, and every change he did to it, reported in his paper, was done to my data base. Additionally, every indication to carry out the estimation exactly as he did were taken in account. For this reason, I expected no differences between his results and mine, yet some difference persists.

Table 2: Effect of HNC: Regression Discontinuity

	CO	NO_2	O_3	NO_x	SO_2
Seventh-order polynomial	-.062	-.116	-.102	-.106	.190
	(.089)	(.105)	(.105)	(.100)	(.109)
Eighth-order polynomial	-.066	-.155	-.079	-.142	.169
	(.088)	(.102)	(.100)	(.101)	(.102)
Ninth-order polynomial	-.075	-.117	.015	-.045	.182
	(.089)	(.118)	(.102)	(.123)	(.121)

This table reports estimations of the HNC impact on pollutant concentration in logs. The estimates reported correspond to 15 separate regressions. Robust standard errors in parenthesis.

Using a similar specification, Davis tests alternative hypothesis such as changes in mean air pollution during different times of the day and days of the week, changes in the pollutant concentration's daily maximum, and changes in the number of times the concentration of every pollutant exceeded a threshold stablished by the World Health Organization as a healthy maximum. This additional evidence shows no signs of reduction in air pollution levels in these different dimensions. For example, RD evidence showed that pollution daily maximums were not affected by the program either, yet using an OLS specification indicated weak evidence of intertemporal substitution towards driving during weekends; the latter estimation, however, is susceptible to the criticism that motivated the RD methodology in the first place. All this evidence drives us to the conclusion that the HNC program did not achieve its goal of reducing the levels of air pollution.

Robustness exercises will be carried out in order to challenge the conclusions reached by Davis (2008). Before this is done, there's two main criticisms that one could formulate on this baseline specification: one concerning the weather variables and a second concerning the methodology to correct non-spherical residual errors. Davis includes three weather variables: temperature, humidity and wind speed. Weather variables wind direction and precipitation, both potencially relevant, are neglected by the author, even though the first one is reported in the same database used to extract the first three variables[7]. On the other hand, Davis' approach to correct the presence of auto-correlated residual errors is to generate 5-week clusters along the series to control for intra-cluster autocorrelation, even though the natural way of estimating a time series that shows dynamic behavior with auto-correlated residuals is through lagging the dependent variable according to the AR process it follows and controlling for residual autocorrelation through a Newey-West correction[8]. In practice, adding the two

[7]Omission of these variables could bias the HNC coefficient if the behavior of such variables are both correlated with pollution and with the period in which acts the HNC program (that is, for example, years before the HNC were in average more/less rainy than years after).

[8]Based on the analysis of the previous section, the hourly series of pollutants normally behave according to a AR(1) to a AR(4) process and all the daily series of pollutants, except for Ozone, according to a AR(1) process, both of them presenting residual autocorrelation significant for several weeks. On the one hand, the clusters procedure only accounts for residual autocorrelation, that is it does not account for the dynamic behavior of a AR process, yet on the other hand it still doesn't do this quite so well. The reason is simple:

missing weather variables individually or together does not change the conclusion of Davis' specification[9]. On the same track, changing the methodology of autocorrelation correction from a clustering procedure to a Newey-West correction does not affect significantly the magnitudes of standard errors, which in turn leaves the inference conclusions unchanged. Table 28 in the appendix reports these results and other alternative specifications, mainly confirming the conclusion we have reached already.

3.2 Robustness of Results

The conclusions obtained from evaluating a public policy could become a crucial input for the political authority when assessing the further financing, continuation or even termination of the policy. Transparency in the results becomes therefore an imperative element in the scientific quest. In this subsection I will show that changing the time window of evaluation and the length of the time trend polynomial of the RD specification changes the sign and significance of the impact of the HNC considerably.

3.2.1 Different Time Window

This research acts upon the idea that the effect of a treatment such as the implementation of the HNC on the air pollution of a city can be estimated by comparing pollution before and after the program's establishment, that is, using as counter-factual the past. In a discontinuous treatment such as this one, the ideal experiment would be to compare the same place and time with and without the program. This being impossible, a second best consists in looking at the exact instant of change so as to obtain the pure effect. This procedure fails essentially in assuming that the instants before and after the treatment have no relevant differences[10]. In this case, pollution at 5am and 6am may greatly differ, such as could differ pollution of a Friday and a Saturday, or a November and a December. For this approach to be right, a minimum of a two-year time window (one year before and one year after) is necessary to credibly control for any seasonal variation. Appart from this consideration, the election of a correct time window belongs to an a-priori, subjective and informed analysis. The benefit of a larger time window is that it helps mitigate any bias from a particular behavior during the observations closest to the treatment, that is, if

clusters are created for groups of five weeks in a chronological order without overlapping, causing the fifth week of every cluster to have no correlation relationship with the first week of its subsequent cluster. That is to say that if an air pollution shock appeared on the end of a five week cluster, this methodology would allow only the rest of the days left on that cluster to behave similarly between each other, leaving aside the first days of the next cluster which would in reality probably be affected by this shock still.

[9]Precipitation data was obtained from the Water National Commission. It is a daily series going from 1920 to 2007. Ten monitoring stations report regular measures from 1985 to 1993. The variable that is added to the estimations is a daily average of these ten monitoring stations. Table 27 in the appendix describes this weather variable and figure 4 plots the daily mean and median levels of precipitation along our sample.

[10]In RD language, this approach assumes that all other possible covariates change smoothly at the point of discontinuity. In Section 5, this idea is applied to the HNC's impact estimation, correctly accounting for these differences.

Table 3: Effect of HNC: Regression Discontinuity - Different Time Window

	1-1	1-2	2-1	2-2	2-3	3-2	3-3	3-4	4-3	4-4
CO	-.020	-.006	-.147*	-.078	-.113	.033	-.044	.000	-.082	-.062
	(.031)	(.046)	(.066)	(.064)	(.065)	(.070)	(.071)	(.087)	(.079)	(.089)
NO_2	-.417*	-.360*	-.585*	-.511*	-.053	-.126	-.113	-.062	-.199*	-.116
	(.160)	(.076)	(.140)	(.110)	(.130)	(.120)	(.120)	(.110)	(.100)	(.110)
O_3	-.033	-.071	.020	.013	.213	.112	.240*	-.100	.039	-.102
	(.071)	(.069)	(.075)	(.092)	(.120)	(.071)	(.120)	(.110)	(.097)	(.100)
NO_x	-.360*	-.296*	-.389*	-.417*	-.072	-.155	-.114	-.020	-.204	-.106
	(.130)	(.130)	(.150)	(.150)	(.140)	(.120)	(.120)	(.110)	(.110)	(.100)
SO_2	-.210	-.081	-.175*	-.088	.281*	.188*	.306*	.216	.161	.190
	(.110)	(.100)	(.087)	(.090)	(.140)	(.088)	(.130)	(.120)	(.094)	(.110)

This table reports estimations of the HNC impact on pollutant concentration in logs. The estimates reported correspond to 50 separate regressions. In the heading, the first number corresponds to the number of years before the HNC, the second corresponds to the number of years after it. All regressions use Regression Discontinuity with a seventh-order polynomial time trend and all regresors originally used. Robust standard errors in parenthesis. Marked with one asterisk (*) are estimates statistically significant to the 95% confidence level.

unfortunately either the year before or after, or both, were in some way affected by events not properly controled in the estimations. On the other hand, a smaller time window helps clearing up the estimation by excluding any event extraneous from the treatment in study.

In his paper, Davis uses the 8-year time window with the sole justification that is the largest symmetrical time window available because there's no measures of pollutant concentration previous to 1986. It is useful to clarify that, apart from the problems above mentioned, there's no necessary bias from using asymmetrical time windows. Davis presents results for different time windows only for the first OLS estimation, yet he fails to do so with the RD specification. Table 3 does this and shows that for certain pollutants and time windows the HNC evidences having improved or worsen air quality. In fact, 5 out of the 10 estimates presented for NO_2 are negative and significant, as are 4 for NO_x, and 1 for CO and O_3. Additionally, 1 out of 10 estimates of SO_2 is significantly negative and 3 out of 10 estimates of the same pollutant are significantly positive. Besides these, many other estimates are closed to been significant in a certain direction. The majority of the negative and significant estimates are observed when the time window is more narrow, which could lead us to think that if we were to have data only from 1988, or we were to think that arguments in favor of a smaller time window were ex-ante more convincing, the answer to what the impact the HNC had on pollution levels would have been completely different.

3.2.2 Different Polynomial Order

The RD estimation possess a highly flexible time trend polynomial in order to control for time varying factors that could be correlated with the pollution level but not necessarily controlled in the model. Davis argues that the seventh-order polynomial was selected as the baseline specification because lower-order polynomials were too restrictive. The election of

Table 4: Effect of HNC: Regression Discontinuity - Different Polynomial Order

	OLS	1	2	3	4	5	6	7	8	9
CO	.267*	.500*	.398*	.057	.040	-.160*	-.126	-.062	-.066	-.075
	(.052)	(.100)	(.080)	(.078)	(.079)	(.080)	(.075)	(.089)	(.088)	(.089)
NO_2	.047	-.002	.024	.015	-.021	-.035	-.078	-.116	-.155	-.117
	(.036)	(.064)	(.068)	(.087)	(.080)	(.099)	(.097)	(.110)	(.100)	(.120)
O_3	.260*	-.008	-.065	-.443*	-.386*	-.364*	-.264*	-.102	-.079	.016
	(.052)	(.075)	(.074)	(.082)	(.066)	(.090)	(.083)	(.100)	(.100)	(.100)
NO_x	.123*	-.008	.007	-.057	-.074	-.147	-.190*	-.106	-.142	-.045
	(.035)	(.054)	(.057)	(.074)	(.074)	(.084)	(.085)	(.100)	(.100)	(.120)
SO_2	-.107	.476*	.306*	-.056	-.012	-.187*	-.102	.190	.170	.182
	(.076)	(.130)	(.082)	(.092)	(.079)	(.094)	(.082)	(.110)	(.100)	(.120)
F		37.8	36.8	42.5	3.94	9.01	0.16	0.42	0.35	0.16
L	-22.9	-21.7	-15.0	-11.7	-11.6	-10.3	-10.1	-9.95	-9.95	-9.95
LM	61.0	64.2	30.3	13.2	12.4	9.06	10.4	12.0	12.1	9.95

This table reports estimations of the HNC impact on pollutant concentration in logs. The estimates reported correspond to 50 separate regressions. All regressions use the 8 year symmetrical time window and all the original regressors. The F term is the value of the F-statistic for the time trend polynomial of the CO estimation. The L term is the value of the Likelihood function in logs (in thousands) from the CO estimation. The LM (Lee and McCrary (2005)) term is the value of the F-statistic for the set of quarterly dummies from the CO estimation. Robust standard errors in parenthesis. Marked with one asterisk (*) are estimates statistically significant to the 95% confidence level.

this length followed a test used by Lee and McCrary (2005) in which alternative polynomial models were tested against a complete set of quarterly dummies. The idea is that under the null hypothesis that the polynomial model is correct, these dummies should not be predictive once the polynomial is included. Two traditional alternatives to compare different polynomials are the use of an F-statistic for the whole polynomial in each specification and a likelihood-ratio test for the whole models.

Table 4 shows the results of the HNC coefficient for different polynomial lengths. On the bottom of the table F-statistics for polynomials, Likelihood function values and F-statistics for the quarterly dummies when included[11] are presented. Evidence shows one more time the huge changes of the HNC coefficient among specifications. F-statistics for the polynomials show that lengths greater than fifth order make the polynomial not statistically significant. As expected, likelihood function's value grows as the polynomial's length does as well, and likelihood-ratio tests always reject the null of a shorter polynomial, suggesting every time a higher order polynomial. Finally, the F-statistic for the quarterly dummies show that for any specification these dummies are always significant, indicating that neither polynomial would be sufficient to correctly adjust the series[12].

On the one hand, this evidence points towards using a polynomial as flexible as possible,

[11] These F-statistics were obtained from ten separate regressions, different from the ones estimated to get the coefficients shown in this table.

[12] When testing through this last method higher order polynomials, only when estimation forces many of the quarterly dummies to drop out of the model the F-statistic indicates that these stop being significant.

yet on the other hand it shows that a polynomial larger than a fifth order one does not stand statistically significant. In broad strokes, these tools do not give us a clear answer about what order to choose. Nevertheless, one could speculate that weak evidence points towards the fifth-order polynomial for being the largest one still statistically significant, and also having the lowest F-statistic for the quarterly dummies. Interestingly enough, this specification results in the conclusion that 3 out of 5 pollutant's concentration decreased with the HNC, including carbon monoxide, the pollutant most linked with vehicle's emissions.

The central conclusion from these exercises is that the shape of the questions we compel the data to reply can dramatically change the answers we get in return. Using this methodology and lacking the necessary a-priori information, no one clear answer results from an evaluation of a public policy such as this one for this specification's results are highly sensitive to variations in the time-window and the method to fit the time series. For example, choosing a conservative four-year symmetrical window would answer that 2 out of 5 pollutants were reduced; choosing a reasonable six-year symmetrical window would answer that 2 out of 5 pollutants would have been increased; finally, choosing a fifth-order polynomial, to this point just as valid as the seventh-order one, would conclude that 3 out of 5 pollutants concentration would have been reduced. In such a study, authorities or other groups of interest could pick whichever estimate from the ones above to justify a certain path to follow. Correct a-priori beliefs about the right time window to use, that is, the sample to be tested, and an appropriate election of the method to fit the time series accurately and robustly are crucial to carry out a responsible research, that is, to formulate the right questions for the data to reply, and thereby come up with a truthful answer. Section 5 of this dissertation will present an alternative approach to solve this dilemma.

4 Adaptation to the HNC

In the introduction I pointed out that despite the successful implementation of the HNC program, additional evidence on greater vehicle utilization and intertemporal substitution in the driving election would explain the lack of improvement in air quality, as reported by Davis (2008). These being the reasons, it is fair to expect that part of the adaptation process to the restrictions program occurred in a gradual manner or at least with some delay. A family or firm would take some time to evaluate both the correct and permanent functioning of the program to then make the decision of buying an additional vehicle, for example. When presenting the additional evidence on car sales, Davis points exactly to this fact, although not exploring further on the phenomenon.

> *It seems more likely that there would have been an initial increase in purchases [of vehicles], followed by an additional, more gradual increase. [...] This distinction between short-run and long-run adaptation is relevant for interpreting the air quality evidence. The impact of driving restrictions on air quality is likely to be largest immediately after implementation because the opportunities for adaptation are most limited in the short run.*

In this section I will attempt to revisit the "where to look" question of the beginning of this document. Evidence will be presented that will show not only a gradual climbing in pollutant concentration associated with vehicle emissions, but a significant reduction of this concentration the months after the HNC's implementation.

4.1 Adaptation: Results

The strategy followed in this section seeks to introduce heterogeneity in the impact of the HNC during the months after its implementation, so as to reveal the existence of dynamics. Because adaptation behavior is highly associated to the purchase and greater utilization of vehicles, I will concentrate on carbon monoxide dynamics for being the pollutant by far more associated with this source of air pollution[13].

Table 5 reports the estimates of the same specification Davis uses, with a seventh-order polynomial and eight-year time window, and 12 other specifications adding to each one an indicator variable for each consecutive month after the implementation of the HNC[14]. The HNC coefficient in each specification indicates the average long-run effect of the program, and each monthly indicator variable the additional effect during that month of the HNC. That is, for example, in specification (2), the Month1 variable would indicate a -19.8% impact of HNC during that month over the 3% (not significant) impact of the program as a whole, with a net effect on the first month of -16.8%.

Results clearly show a short-run negative and significant impact of about 10 to 20% for about 4 to 5 Months, somewhat in concordance to the withdrawal of 20% the vehicles fleet and the previous hypothesis of a gradual and delayed adaptation of users.

Reduction of pollution in the first month ranges from 5% to 16% and the peak reduction is shown to ocurr on the third month with 8% to 18% reduction[15]. After the third month reduction vanishes gradually until showing no reduction around the fourth to seventh month, depending on the specification. Finally in the specifications containing the most monthly variables, a sort of overshooting is observed around the tenth and eleventh month, after which the last specification shows a return to a statistically zero reduction, in concordance to the long-run effect shown by the HNC coefficient. Although this overshooting is shown only in the last two specifications, maybe showing that adaptation should be captured in a smaller time window, there does not seem to be an a-priori reason to expect such temporal behavior of air pollution.

[13]Because of its nature, restriction on the use of vehicles, the HNC program was targeting the pollutants produced by their utilization, so it is natural to consider carbon monoxide the most accurate thermometer for the success of the program.

[14]Similar estimation, only for the twelve months case, is presented for the rest of the pollutants in Table 29 in the appendix.

[15]Collins and Scott (1993) predicted in the basis of theoretical arguments that the removal of approximately 450,000 vehicles should reduce general air pollution by 10 to 15 percent, interestingly coinciding with the findings here reported.

Table 5: Effect of HNC on CO: Adaptation results

	HNC	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HNC	-.062	-.016	.030	.127	.214	.295*	.348*	.412*	.450*	.448*	.416*	.270	.188
	(.089)	(.110)	(.130)	(.120)	(.120)	(.120)	(.120)	(.130)	(.140)	(.160)	(.190)	(.170)	(.180)
Month1		-.162*	-.198*	-.267*	-.330*	-.389*	-.428*	-.476*	-.504*	-.503*	-.479*	-.365*	-.297*
		(.071)	(.087)	(.081)	(.079)	(.079)	(.085)	(.087)	(.096)	(.120)	(.140)	(.120)	(.130)
Month2			-.155	-.229*	-.289*	-.346*	-.383*	-.428*	-.455*	-.454*	-.431*	-.324*	-.262*
			(.083)	(.076)	(.075)	(.075)	(.081)	(.084)	(.094)	(.110)	(.140)	(.110)	(.120)
Month3				-.309*	-.371*	-.423*	-.458*	-.501*	-.526*	-.525*	-.503*	-.400*	-.341*
				(.074)	(.071)	(.072)	(.079)	(.083)	(.093)	(.110)	(.130)	(.110)	(.120)
Month4					-.258*	-.314*	-.346*	-.385*	-.409*	-.408*	-.387*	-.290*	-.234*
					(.069)	(.066)	(.072)	(.075)	(.083)	(.100)	(.120)	(.100)	(.110)
Month5						-.230*	-.263*	-.299*	-.321*	-.320*	-.301*	-.210*	-.157
						(.062)	(.066)	(.069)	(.076)	(.092)	(.110)	(.091)	(.097)
Month6							-.136*	-.173*	-.193*	-.192*	-.174	-.088	-.038
							(.067)	(.066)	(.073)	(.088)	(.110)	(.086)	(.091)
Month7								-.156*	-.177*	-.176*	-.160	-.080	-.033
								(.073)	(.075)	(.087)	(.100)	(.084)	(.088)
Month8									-.087	-.086	-.071	.003	.048
									(.060)	(.077)	(.093)	(.075)	(.079)
Month9										.003	.020	.089	.130
										(.069)	(.086)	(.069)	(.074)
Month10											.064	.136*	.175*
											(.077)	(.062)	(.068)
Month11												.273*	.313*
												(.060)	(.074)
Month12													.130
													(.110)

This table reports estimations of the HNC impact on pollutant concentration in logs. The estimates reported correspond to 13 separate regressions. All regressions use the eight-year symmetrical time window, seventh-order time trend polynomial and all the original regressors. Month1, for example, indicates the value of the indicator variable corresponding to the first month after then HNC's implementation. Robust standard errors in parenthesis. Marked with asterisk are estimates statistically significant to the 95% confidence level.

Figures 6 in the appendix illustrates the adaptation results, graphing residuals from a regression including all covariates and a fitted line including HNC and adaptation variables. Figures 7 and 8 do the same exercise using a third-order polynomial time trend and a logarithmic function for the first twelve months of the program, showing a similar dynamic behavior. Both the third-order polynomial time trend and the logarithmic function are statistically significant in adjusting the dynamics of these months.

This adaptation results are highly intuitive and in general respond to the a-priori beliefs we had about the way both HNC and the adaptation behavior should show up on the data. The main conclusion reached through this exercise is that the HNC did achieve its desired objective of reducing pollution levels but failed to address the problems created by its own success as a restriction policy. Long-run impact remains insignificant yet we have convincingly observed a difference between the HNC's short-run and long-run impact on air quality.

4.2 Adaptation: Robustness

The previous results are of great economic interest and should be subject to the same robustness scrutiny as were Davis' results. This will consist of evaluating the behavior of the pollution reduction in the first months and the dynamics of adaptation in different environments. Estimation outputs for these exercises will be placed in the appendix.

Using as baseline identification the twelve dummies estimation, different time windows were tested. Table 30 in the appendix reports these estimations. Results show that adaptation coefficients hold their sign and remain significant as long as the estimation keeps at least 3 years before and after the HNC. Even though coefficients turn not significant in the rest of the cases, the signs (net from HNC) show the same dynamics as the baseline estimation. On another direction, Table 31 in the appendix reports adaptation coefficients when estimated using different polynomial orders. In this case, except for the estimation that uses a sixth-order polynomial, the dynamics stays unchanged. Net signs of the monthly coefficients, on the other hand, do not remain the same on the OLS, first, second, sixth and ninth-order polynomial. In the case of the sixth-order polynomial, this is due to the strong negative sign of the HNC's long-run effect, which probably contains the negative effect of the first months; in the rest of the cases the contrary happens, where HNC's long-run effect is strongly positive, and the first individual monthly measures are significantly negative but not negative enough to offset the long-run effect.

On a different approach, it would be interesting to see if the dynamic behavior of air pollution did not start from before the HNC's implementation or did not follow after for longer than a reasonable time. When sequentially adding indicator variables for months previous to the HNC, these are not significant until the fifth previous month is included. From this moment on, all previous indicator variables turn negative and significant. When including a full set of twelve monthly indicator variables for the previous months, eight out of the twelve variables turn out to be negative and significant yet not following a specific dynamics. In fact, when estimating a third-order polynomial for the back twelve months, such as the one estimated in Figure 7 for the twelve months after the HNC, it does not turn out to be significant[16]. To be able to compare the indicator variables before and after the HNC, a new estimation is made using the HNC indicator variable allong with the two sets of twelve monthly indicator variables for before and for after the implementation of the program, although now the HNC indicator variable takes the value of 1 only in the last three years of the sample, instead of the last four as before, so as to make these two sets of dummies comparable[17]. Table 32 in the appendix reports this estimation. The first months coefficients are -52%, -54% and -66%, and the coefficients for the three previous months are -38% -22% -32%; all after and previous coefficients are significant but the coefficient of the second previous month. A Wald test rejects the hypothesis that the effect on the first month after and last month before the HNC are equal with a confidence of 97%. In a different estimation where the year before was controlled by a single indicator variable, the same test rejects the hypothesis that the first months' coefficients are equal to the coefficient of the year before with a 96% confidence. In this last case, the coefficients for the first months were -30%, -29% and -38% and all significant, and the coefficient for the last year was -14% not significant. All these results show that the HNC effectively caused a reduction in carbon monoxide pollution of about 14% to 16% right after its implementation and a maximum of about 24% to 28%[18].

On the other side of the robustness check, indicator variables for the second twelve months, thirteen to twenty four, after the HNC were sequentially added to the baseline estimation showing that none of the new indicator variables turn out to be significant, rejecting any dynamic behavior passed the first year.

This evidence shows that the HNC program did achieve a reduction in the concentration of carbon monoxide, the pollutant with highest association to vehicle's employment, in the first months of its implementation, as well as showing a gradual climbing of this concentration in the months that followed, both results consistent with the withdrawal of almost 20% of the vehicle's fleet during weekdays and a gradual and delayed adaption to this policy. These findings reaffirm the importance of the design of an empirical evaluation so as to thoroughly reveal the impact of the reform at study.

[16]Higher order polynomials were tested finding that only a seventh-order and a tenth-order polynomial are successful at adjusting the dynamics of the back twelve months. Nevertheless, these results do not credibly indicate an evident dynamic behavior during the twelve months previous to the HNC which was the purpose of testing such polynomials.

[17]Each monthly indicator variable now represents the average difference of this month's concentration of pollutants and that for the first first three years of the sample (the ones without a monthly indicator variable nor the HNC dummy). This procedure is done this way so as to make the effects of each of the 24 month's specific effect comparable to one another.

[18]It is necessary to clarify that even though only 20% of the vehicles fleet was pulled out of the streets, lower congestion caused by the reduction of vehicles allows for a smoother circulation which itself causes a reduction on individual emissions which makes it possible to observe reduction in carbon monoxide higher than 20%.

5 Alternative Approach: Non-Parametric Estimations

Results in section 3 made it evident that the empirical approach used by Davis (2008) lacks of robustness; on the other hand, results in section 4 showed that, contrary to Davis (2008) results, the HNC program did cause a significant reduction in air pollution during the first months of its implementation. Lacking a-priori information required to correctly design a search of this nature, sufficiently flexible and robust results are necessary to formulate an answer appropriately. This section offers an alternative approach to the questions here examined that breaks away from the choice of a time-trend polynomial and whose results are in essence less vulnerable to the time-window election.

The following subsections will explore two non-parametric tools designed to unveil the impact of the program right at the threshold, that is, to confirm if the program did indeed have an effect on air pollution right after its implementation. The search will begin by taking a look at a semi-parametric local regression methodology, to then estimate the impact at the threshold with a non-parametric regression discontinuity design methodology.

5.1 Semi-parametric Local Regression

5.1.1 Methodology

The methodology here to be used is a semi-parametric local regression methodology, a very popular framework used to fit data that allows for as much flexibility as wished and that holds the desired efficiency and consistency properties if correctly estimated. It is semi-parametric because it combines the usual parametric approach to account for natural pollution covariates and non-parametric approach to capture the time varying component. The model to be estimated will be of the form in equation 2:

$$y_t = \beta_0 + \beta_2 x_t + \lambda(t) + u \tag{2}$$

where $\lambda(t)$ is a scalar function of time to be specified in the non-parametric estimation and x_t is the usual vector of covariates. In a full parametric approach, for instance an OLS estimation such as equation 1, the $\lambda(t)$ function takes the form of a linear polynomial. The advantage of the non-parametric approach is precisely that the function need not to have an explicit form, for its value is estimated through a local weighted average fit, both rudimentary and arbitrary, but whose structure is of much greater flexibility and simplicity than the OLS approach[19].

To allow for as much flexibility as possible, the model is estimated separately before and after the implementation of the HNC allowing all covariates to impact differently pollution, as well as allowing for different time components, depending on being subject to the HNC

[19] The OLS estimation can actually be considered a special case of the non-parametric regression. In a local weighted average estimation of $y_i = m(x_i) + \epsilon_i$, the OLS estimator of $m(x_i)$ would be $\hat{m}_{OLS}(x_i) = \sum_i \left\{ \frac{1}{N} + \frac{(x_0 - \bar{x})(x_i - \bar{x})}{\sum_j (x_j - \bar{x})^2} \right\} y_i$, where x_0 is the point at which the estimation is carried out and $\bar{x}$ is the sample average of x. The term in brackets represents the weights with which the y_i values are averaged; in a Kernel Regression, the weights employed are kernel functions.

or not. Throughout this exercise, the objective will be to seek the existence of a difference between the fitted time-series before and after the HNC's implementation so as to infer an impact of this program on air pollution.

Two methods will be carried out. The first one uses a Kernel Regression, performing the estimation in two steps: first, it clears away the effects of the covariates through an OLS regression leaving the residual series; then, the residual series is regressed on time through a Kernel Local Weighted Regression using as weights kernel function Epanechnikov, the standard and best behaved weighting function, with an optimal bandwidth of $N^{0.2}$, N being the size of the sample, which minimizes the mean integrated squared error of the estimation of the density of $\lambda(t)$.[20] The second method estimates equation 2 with a partially linear model, where the linear component is estimated with ordinary least squares and the non-linear component with locally weighted scatterplot smoothing (Lowess estimator), which is a variant of a local polynomial estimation that uses a tricubic kernel[21].

5.1.2 Results

The discussion of results will be mainly based on the estimations for carbon monoxide as it is the pollutant with the most association to vehicle emissions. All estimations are made separately for before and after the HNC, using four different time windows for carbon monoxide and using only the largest time window for the other four pollutants.

Results of the Kernel Regression for carbon monoxide are shown in figure 1, where the fitted value of the residuals of this pollutant is graphed, for four different time windows[22].

For this methodology, the fitted line of both the before and the after HNC estimation is extended for a period of one bandwidth (approximately 10 days in this case), in the form of a prediction, to produce an overlap between the two series of a total of 2 bandwidths so as to credibly compare the boundary points of each series. Results indicate that concentration of carbon monoxide was effectively reduced at the moment of the implementation by an amount of 12% to 20%, very stable throughout the use of different time windows and consistent with some of our previous parametric results. This reduction should be interpreted as the pure effect of the shock suffered by air pollution to the HNC treatment whose size corresponds to the immediate reduction, that is, the effect right after the implementation of the program. Unfortunately, this methodology does not allow us to unmistakably interpret the dynamic

[20]Kernel Function Epanechnikov: $\frac{3}{4}(1 - z^2) \times \mathbf{1}(|z| < 1)$, where $\mathbf{1}(|z| < 1)$ is an indicator function that takes the value of 1 if the condition in parenthesis is satisfied. This settings for the estimation are not only the best behaved of this sort, but they are the standard ones, which makes its choice desirable as to reduce the arbitrariness of the method.

[21]Tricubic Kernel: $\frac{70}{81}(1-|z|^3)^3 \times \mathbf{1}(|z| < 1)$, where $\mathbf{1}(|z| < 1)$ is an indicator function that takes the value of 1 if the condition in parenthesis is satisfied. This methodology has several advantages: it estimates both the linear and non-linear components all together, it uses a variable bandwidth, is robust against outliers and it minimizes boundary problems, very important in our present quest. The main disadvantage, also source of its advantages, is its complexity, one derived from a far more arbitrary and less standard setting than the first method.

[22]Figure 9 in the appendix plots the residuals for carbon monoxide using the four time windows, and figure 10 does the same for pollutants NO_2, O_3, NO_x and SO_2.

Table 6: Effect of HNC on CO: Semi-Parametric Summary Results

	4-4	3-3	2-2	1-1
Kernel Weighted Local Regression	-20.0%	-16.6%	-18.3%	-12.0%
Partially Linear Model (OLS and LOWESS)	0.0%	0.0%	-19.7%	-64.5%

This table summarizes the results obtained in this section for carbon monoxide. Each column represents a different time window of estimation, where the first number correspond to the years before the HNC implementation and the second number the years after it; that is, all time windows estimated are symmetrical. The first row shows results for a two-step Kernel Regressions, where residuals from an OLS regression of carbon monoxide in logs on weather covariates and fixed effects is fitted through a Kernel-Weighted Local Regression. The second row reports results for a Partially Linear Model where the linear component is estimated through an OLS regression and the non-linear component through a locally weighted scatterplot smoothing. Results are percentage change in carbon monoxide concentration; when "0.0%" is reported that means a statistical cero, that is, the change in pollution was not statistically significantly different from cero. This in turn means that all the other changes are statistically significant. 95% confidence level is used all along.

behavior after the discontinuity point without further manipulation of the data, for the time trend due to factors not controlled in the model (such as technology change and omitted shocks) is mixed up with behavioral responses to the program.

Results for the Partially Linear Model, our second method of estimation, for carbon monoxide are shown in figure 2, where both the carbon monoxide series, in logs, and the fitted value of the model are graphed using the four different time windows: panel A uses the eight-year symmetrical time-window, panel B the six-year one, panel C the four-year window, and panel D the two-year symmetrical window. Since the non-linear estimation is done with a methodology robust to boundary issues[23], fitted values will not overlap this time. Results show no evidence of a reduction in the concentration of carbon monoxide when regressions use a four-year or a three-year time window, although when using a two-year and a one-year window this method estimates a significant -19.7% and -64.5%.

Results for both methods of estimation are summarized in table 6. Estimations in this section support Kernel Regression as a more suitable method of estimation for this policy evaluation since its conclusions remain very stable when changing time-window.

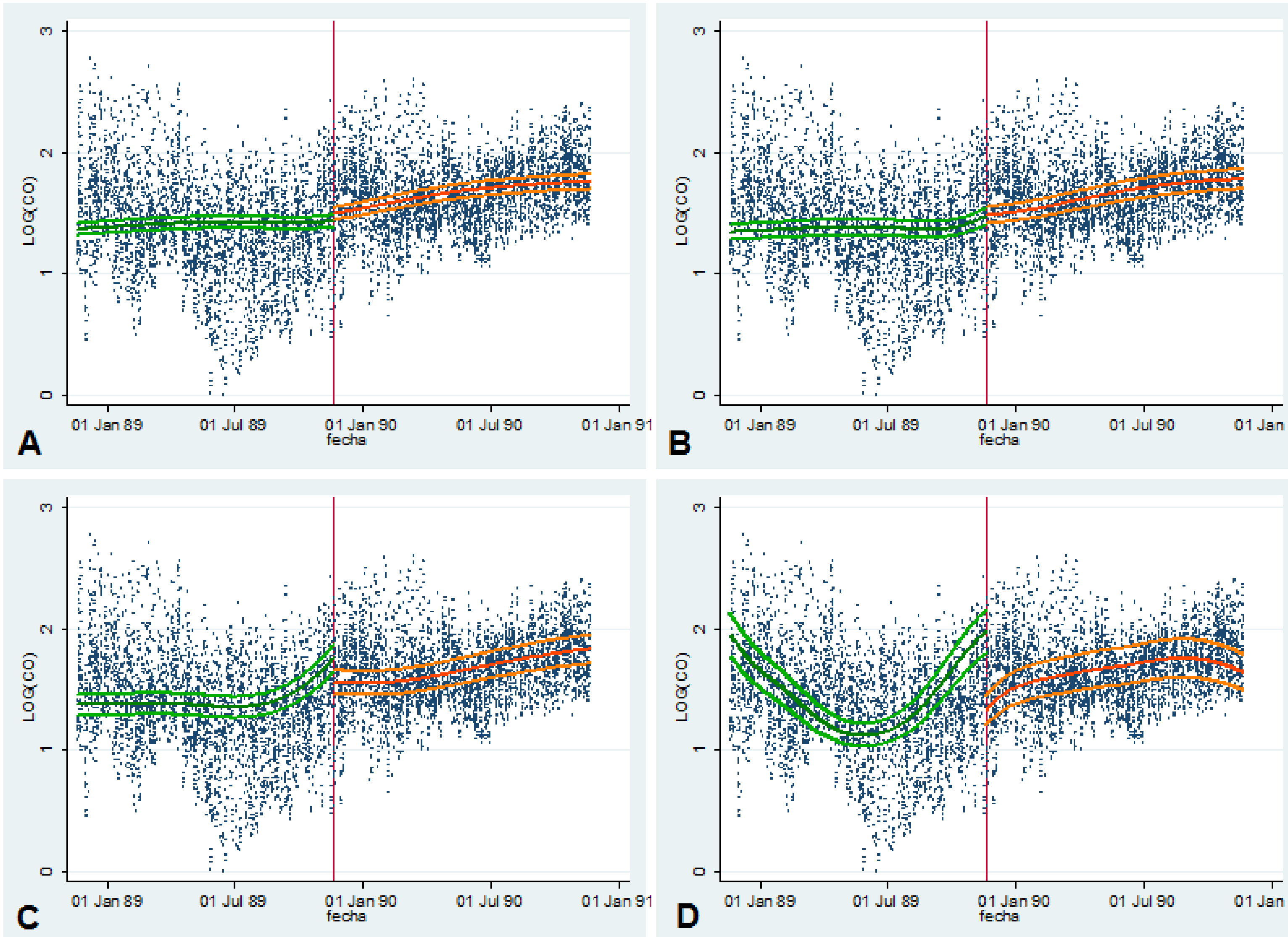
Although the Partially Linear Model tends to behave in a similar way to Kernel Regression as time window reduces, it suffers the same instability the Regression Discontinuity suffered and its conclusions are very volatile, unlike the Kernel Regression methodology. Having said this, Kernel Regressions reveal a reduction in carbon monoxide due to the HNC program, probably consistent with the withdrawal of cars during week days, as well as the increase in sulfur dioxide and no change in nitrogen dioxide, nitrogen oxides and ozone, results consistent with conclusions reached in previous sections.

[23] Issues produced from estimating boundary points one-sidedly, unlike the symmetrically two-sided estimation of the rest of the sample.

Figure 1: Kernel-Weighted Local Regression: Smoothed values for CO: Different Time Windows

This figure shows four graphs where each plots the smoothed values of the Kernel-Weighted Local Regression of carbon monoxide's residuals on time. The y-axis is the residual value and the x-axis is time. Residuals are obtained from an OLS regression of concentration of carbon monoxide in logs on weather covariates humidity, temperature and wind speed, and fixed effects for hour of the day, day of the week, month of the year and the interaction between hour of the day and weekend. The regression uses kernel function Epanechnikov as weights with a bandwidth of $N^{0.2}$, N being the size of the sample. A red vertical line indicates the start of the HNC program. Confidence Intervals to the 95% confidence level are plotted along with the fitted line.

Figure 2: Partially Linear Model: Smoothed values for CO: Different Time Windows



This figure shows four graphs where each plots the series of carbon monoxide in logs and the smoothed values of the Partially Linear Model, using the locally weighted scatterplot smoothing (Lowess) methodology for the non-linear function of time, for carbon monoxide employing four different time-windows. Graph A uses a four-year time window, graph B uses a three-year time window, graph C uses a two-year time window and graph D uses a one-year time window. A red vertical line marks the start of the HNC program. Confidence Intervals to the 95% confidence level are plotted along with the fitted line.

5.2 Non-parametric Regression Discontinuity Design

5.2.1 Methodology

A different approach to estimating the impact at the threshold is the use of a full non-parametric Regression Discontinuity Design (RDD). The idea behind Regression Discontinuity estimation is to find the average treatment effect of a policy when such treatment's assignment is determined by the value of an observed covariate lying on either side of a threshold, that is, when assignment behaves discontinuously around such threshold. To properly estimate the impact of the policy, only observations located very closed to the threshold are considered in order to avoid contamination from strange factors, thus calling such impact the local treatment effect.

To properly pursue this task in this setting, the RDD estimator proposed by Imbens and Kalyanaraman (2009) has been chosen, for it provides with a well-defined, fully local, non-parametric estimator with optimal bandwidth. The estimand (τ_{RD}) is the difference between two local linear regressions on either side of the threshold, both evaluated at boundary points. Local non-parametric methods are attractive in this setting because they provide us with consistent estimation of regressions functions and enjoy desirable bias properties when estimating such regressions at the boundary.

More explicitely, the RDD estimator is

$$\tau_{RD} = \hat{\mu}_{+} - \hat{\mu}_{-} \tag{3}$$

where

$$\hat{\mu}_{-} = lim_{x \to c^{-}} E[Y_i(0)|X_i = x] = \hat{\alpha}_{-}(c) \tag{4}$$

and

$$\hat{\mu}_{+} = lim_{x \to c^{+}} E[Y_i(1)|X_i = x] = \hat{\alpha}_{+}(c) \tag{5}$$

where c in the threshold, Y_i is the dependent variable of interest, X_i is the forcing variable (covariate assigning the treatment), "1" indicates if the observation was treated and $\hat{\alpha}_{-}(x)$ and $\hat{\alpha}_{+}(x)$ are computed as

$$(\hat{\alpha}_{-}(x), \hat{\beta}_{-}(x)) = argmin_{\alpha,\beta} \sum \mathbf{1}_{X_i<x} \cdot (Y_i - \alpha - \beta\,(X_i - x))^2 \cdot K\left(\frac{X_i - x}{h}\right) \tag{6}$$

and

$$(\hat{\alpha}_{+}(x), \hat{\beta}_{+}(x)) = argmin_{\alpha,\beta} \sum \mathbf{1}_{X_i>x} \cdot (Y_i - \alpha - \beta\,(X_i - x))^2 \cdot K\left(\frac{X_i - x}{h}\right) \tag{7}$$

where $\mathbf{1}_{con}$ is an indicator function taking the value of 1 if condition con is satisfied, and K is a kernel function that weights the elements of the sum according to a bandwidth h.

Table 7: Effect of HNC on Different Pollutants

	CO	NO_x	NO_2	O_3	SO_2
Monthly Mean	-0.12	-0.04	-0.28	-0.13	-0.11
	(0.06)	(0.04)	(0.05)	(0.07)	(0.05)
Monthly Median	-0.18	0.05	-0.32	-0.09	-0.10
	(0.05)	(0.02)	(0.05)	(0.08)	(0.05)

This table presents results from the estimation of a Non-Parametric Regression Discontinuity Design estimator, for different pollutants. Monthly mean results take as observations for the estimation the average of the concentration of each pollutant for each month; the monthly median results take as observations for the estimation the median of the concentration of each pollutant for each month. Discontinuity is assumed happening in November 20, 1989, the day of implementation of the HNC.

Optimal bandwidth h^* is chosen so as to minimize an approximation of the mean squared error[24].

5.2.2 Results

Observations are taken at a monthly basis, that is, observations in this estimation are averages and medians of every month before and after the start of the HNC program, so RDD results should be interpreted in a monthly manner. Pollutants are taken in logs, covariates other than the forcing variable are usual weather variables temperature, real humidity and wind speed and fixed effects for hour of the day, day of the week, month of the year and interaction between hour of the day and weekend.

Results on different pollutants for both monthly averages and medians are presented in table 7. These findings confirm a negative local impact of the program of about 12 to 18% on carbon monoxide, coherent with the withdrawal of nearly 20% of vehicles during the week. For the rest of the pollutants, only nitrogen dioxide show a relevant decrease of about 30%, consistent with its strong association with vehicle's emissions and a more volatile behavior[25].

Both methodologies present remarkably coherent results, between them and among different specifications. This property shown by these methodologies makes these results more reliable than the ones obtained in Davis (2008), for neither scarcity of data nor deliberate manipulation of estimations would alter its conclusions. In other words, lack of necessary a-priori information required to design the empirical evaluation does not alter the conclusions

[24]The optimal bandwidth calculated by Imbens and Kalyanaraman (2009) is $h_{opt} = argmin_h AMSE(h)$ where $AMSE$ is the Mean Squared Error Approximation; the optimal bandwidth is then $h_{opt} = C_K \left(\frac{\frac{\sigma_+^2(c)}{f_+(c)} + \frac{\sigma_-^2(c)}{f_-(c)}}{\left(m_+^{(2)}(c) - m_-^{(2)}(c)\right)^2} \right)^{1/5} \cdot N^{-1/5}$, where C_K is a constant, $\sigma^2(x)$ is the conditional variance function of Y_i, $f(.)$ is the marginal distribution of the forcing variable X_i, and $m(x) = E[Y_i|X_i = x]$.

[25]As it has been the rule in this paper, impact of the HNC program on pollutants different than carbon monoxide will not be discussed in detail mainly because of lack of knowledge regarding the potentially erratic behavior of such chemical components and its mixed association with different sources of pollution.

reached through these non-parametric methodologies, a property that in cases such as this one makes them both desirable and reliable.

6 Conclusion

This paper has attempted to show the importance of the design of a public policy's evaluation. The empirical work of Davis (2008) has served as an instrument to outline the natural dilemmas one could encounter when addressing data to formulate questions we are seeking answers from. I have argued that the main obstacle to bear consists of providing correct answers to three questions: what to look for, where to look and how to look.

Answering the questions of "what to look for" and "where to look" seem of a trivial kind. Nevertheless, a little closer look at where we are looking reveals part of what we were missing in the first place. Failing to account for the heterogeneity of the program's impact, specially at the beginning of its implementation, has been shown to be a major overlook for the distinction of a short-run and a long-run component of the impact is crucial for the interpretation of the data. On the other hand, simple modifications on the answer to the "how to look" question revealed important differences on this study's conclusion, which in turn motivated alternative empirical approaches to generate such conclusions. One of the main decisions in the "how" of the design of an evaluation is the election of the sample to be tested, in this case the time-window. Such election should follow an a-priori criterion, concerning both the large sample properties desired and the hope to exclude any additional shock that affects the results as well. In the absence of such criterion, one must be able to test the results on the different samples to check for robustness and one should hopefully be able to explore a methodology immune to this election.

The results of this study suggest three major conclusions. First, changes in the use of different time windows to estimate the effect of the HNC and changes in the length of the time trend polynomial which controls for time varying factors reveal dramatic changes in the conclusions obtained from the approach taken by Davis (2008). For equally valid time windows and polynomial orders, estimations show that the sign of the HNC coefficient can be significantly positive or negative according to the circumstances. For example, choosing a six-year symmetrical time window, instead of an eight-year window, would show that 2 out of 5 pollutants were in the long-run increased by the HNC, and choosing a fifth-order polynomial time trend would conclude that 3 out of 5 pollutants were reduced. Second, novel evidence has been presented that supports the idea that adaptation to the program's restrictions by households and firms was of a delayed and gradual manner, allowing the HNC to reduce air pollution during the first months on about 5 to 18%. Third, a semi-parametric regression that allows for the time component to be estimated through a non-parametric method and a non-parametric regression discontinuity design are, to the extent of this research, most desirable when carrying out the evaluation of a public policy for it avoids the unstable behavior of time-trend polynomials and shows great robustness to (or no impact from) changes in the time-window of estimation. Such approach supports the previous findings revealing a carbon monoxide reduction of about 12 to 20% at the beginning of the program.

The main contribution this paper attempts to make is to warn about the way empirical analysis is used when evaluating public reforms, such as the driving restriction program implemented in Mexico City, and to shed light on a literature that could be of special interest in these sorts of quests. Careful and informed planning must be an essential component of the design of an empirical evaluation, for the shape that take the different questions we compel the data to reply might alter considerably the answers we get in return. In the presence of different degrees of data availability or insufficient information on the ex-ante assumptions needed to design the evaluation, robust methodology should be used when providing the desired conclusions. Because of the importance these conclusions might have, great care and transparency have to characterize both scientific work in the evaluation of public policy and political work when incorporating these evaluations in the decision making process.

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A Emissions Inventory Mexico City

Table 8: Emissions Inventory: 1989-2004 (% of total emission of CO by sector)

Sector	1989	1994	1996	1998	2000	2002	2004
Industry and Energy	2.30	0.40	0.50	0.52	0.53	0.35	0.36
Services	0.00	0.04	0.02	1.47	0.31	0.39	0.43
Vegetation and Natural Sources	0.90	0.00	NA	NA	NA	0.00	0.00
Transportation	96.7	99.6	99.3	98.0	99.2	99.3	99.2
Private Vehicle and Pick up	45.0	47.4	44.0	60.9	46.8	49.0	55.6
Taxi and small public transp	23.9*	28.2	11.0	8.59	13.9	13.8	10.5
Microbuses and Buses	NA	12.2	10.0	12.77	9.57	9.46	9.35
Charge Transports	27.0	11.7	35.0	13.2	27.5	25.4	18.3

Source: Inventary of emissions published by the Department of Environment and Natural Resources and Lezama (1997). *This value includes taxi, small transportation and buses. NA: Data Not Available.

Table 9: Emissions Inventory: 1989, 1994, 2004 (% of total emission by sector)

	SO_2			NO_x			HC		
Sector	1989	1994	2004	1989	1994	2004	1989	1994	2004
Industry and Energy	67.5	57.0	49.4	21.9	24.5	11.0	12.6	3.25	NA
Services	10.7	16.0	0.62	2.20	4.20	6.48	0.00	38.8	NA
Vegetation and N.S.	0.10	0.00	0.00	0.50	0.00	0.35	34.9	3.79	NA
Transportation	21.8	27.0	50.0	75.4	71.3	82.2	52.5	54.1	NA
Private Vehicle	1.73	13.3	28.1	23.7	24.8	36.8	24.7	24.8	NA
Taxi and P.T.	0.81	10.0	11.1	11.0	23.6	19.6	3.1	22.2	NA
Charge Transports	10.2	0.67	6.56	24.3	10.2	19.4	13.1	4.70	NA
Other Transports	6.47	2.02	4.17	11.8	7.58	6.53	1.22	2.22	NA

Source: Lezama (1997). HC: Hydrocarbon compounds. NA: Data Not Available.

B Monitoring Stations

In the following sections of the appendix, I numerate the monitoring stations with a letter. Table 10 describes each monitoring station used in this study and show which letter was assigned to it according to the pollutant. It is clear that some monitoring stations measured only one or few pollutants, in fact only 5 monitoring stations measured all five pollutants.

Table 10: Monitoring Stations

Station	Delegation	Zone	Station letter by pollutant				
			CO	NO_2	O_3	NO_x	SO_2
LAG	Cuauhtémoc	Center	A				
TLA	Tlalnepantla	Northwest	B	A	C	A	J
XAL	Ecatepec de Morelos	Northeast	C	B	D	B	K
MER	Venustiano Carranza	Center	D	C	E	C	L
PED	Álvaro Obregón	Southwest	E	D	F	D	M
CES	Iztapalapa	Southeast	F	E	G	E	N
PLA	Álvaro Obregón	Southwest	G		H		
UIZ	Iztapalapa	Southeast	H				
ARA	Gustavo Madero	Northeast	I				
NET	Nezahualcóyotl	Northeast	J				
IMP	Gustavo Madero	Northwest	K				
BJU	Benito Juárez	Center	L				
TAX	Coyoacán	Southeast	M				
MIN	Cuauhtémoc	Center	N				
CUI	Azcapotzalco	Northwest	O				
VAL	Gustavo Madero	Northwest					A
SUR	Coyoacán	Southwest					B
TAC	Miguel Hidalgo	Northwest					C
EAC	Naucalpan	Northwest					D
LLA	Ecatepec de Morelos	Northeast					E
LPR	Tlalnepantla	Northeast					F
LVI	Gustavo Madero	Northeast					G
SAG	Ecatepec de Morelos	Northeast			A		H
AZC	Azcapotzalco	Northwest			B		I
HAN	Venustiano Carranza	Center			I		O

C Unit root tests

The series of concentration of pollutants of every monitoring station that has been used has been test for the existence of unit root. This is an important issue for in the presence of unit root the econometrics for estimating with such a series would be different.

The tables below present the coefficient estimated and t statistics when running a Dickey-Fuller (D-F) test for each monitoring station. Dickey-Fuller test was run in three different ways: (1) with just the dependent variable lagged, (2) including a constant term, and (3) including a constant term and a time trend term. Critical values for each test have been obtained from a 10.000 replications Motecarlo simulation and are displayed in table 11. According to these results, there's no evidence of the existence of unit root in any of the monitoring stations. Since all coefficients are significant to the 95% confidence level, I do not include asteriks to indicate this significancy.

$$\begin{array}{ll} (1) & y_t = \rho y_{t-1} + e_t \\ (2) & y_t = \alpha + \rho y_{t-1} + e_t \\ (3) & y_t = \alpha + \beta t + \rho y_{t-1} + e_t \end{array}$$

Table 11: Critical Values for D-F Test

Percentile	(1)	(2)	(3)
90.0%	-1.6242	-2.5727	-3.1213
95.0%	-1.9281	-2.8610	-3.4112
97.5%	-2.2148	-3.1018	-3.6679
99.0%	-2.5672	-3.4456	-3.9764
99.5%	-2.8142	-3.6375	-4.2259

Replications: 10.000. $N = 2442$.

C.1 Dickey-Fuller for CO

Table 12: D-F Test for CO: Coefficient and t-statistic (1)

	Monitoring Stations								
	A	B	C	D	E	F	G	H	I
(1)	0.728	0.713	0.719	0.730	0.714	0.721	0.739	0.719	0.729
	-19.57	-20.16	-19.87	-19.35	-20.14	-19.83	-19.03	-19.82	-19.52
(2)	0.272	0.248	0.252	0.282	0.239	0.234	0.270	0.241	0.258
	-37.34	-38.24	-38.05	-36.68	-38.67	-38.78	-37.26	-38.36	-37.86
(3)	0.268	0.246	0.250	0.280	0.236	0.233	0.269	0.240	0.257
	-37.48	-38.29	-38.09	-36.75	-38.77	-38.84	-37.28	-38.39	-37.93

Table 13: D-F Test for CO: Coefficient and t-statistic (2)

	Monitoring Stations					
	J	K	L	M	N	O
(1)	0.712	0.741	0.720	0.730	0.721	0.740
	-20.23	-18.95	-19.75	-19.51	-19.82	-18.99
(2)	0.220	0.266	0.246	0.262	0.235	0.252
	-39.43	-37.40	-38.06	-37.75	-38.76	-37.94
(3)	0.219	0.265	0.244	0.260	0.234	0.252
	-39.46	-37.43	-38.11	-37.83	-38.79	-37.95

C.2 Dickey-Fuller for NO_2

Table 14: D-F Test for NO_2: Coefficient and t-statistic

	Monitoring Stations				
	A	B	C	D	E
(1)	0.713	0.711	0.713	0.717	0.716
	-20.17	-20.27	-20.18	-20.03	-20.05
(2)	0.236	0.220	0.241	0.227	0.250
	-38.77	-39.46	-38.59	-39.20	-38.20
(3)	0.235	0.219	0.237	0.226	0.248
	-38.82	-39.50	-38.78	-39.25	-38.25

C.3 Dickey-Fuller for O_3

Table 15: D-F Test for O_3: Coefficient and t-statistic

	Monitoring Stations								
	A	B	C	D	E	F	G	H	I
(1)	0.734	0.749	0.718	0.737	0.698	0.720	0.690	0.732	0.692
	-19.25	-18.65	-20.01	-19.19	-20.80	-19.85	-21.15	-19.41	-21.07
(2)	0.281	0.328	0.266	0.297	0.209	0.261	0.207	0.290	0.184
	-36.82	-35.07	-37.59	-36.31	-39.91	-37.71	-40.03	-36.62	-40.99
(3)	0.280	0.326	0.265	0.296	0.208	0.260	0.206	0.288	0.184
	-36.87	-35.14	-37.64	-36.35	-39.95	-37.76	-40.07	-36.69	-41.01

C.4 Dickey-Fuller for NO_x

Table 16: D-F Test for NO_x: Coefficient and t-statistic

	Monitoring Stations				
	A	B	C	D	E
(1)	0.712	0.720	0.710	0.724	0.706
	-20.27	-19.91	-20.33	-19.74	-20.52
(2)	0.248	0.256	0.221	0.277	0.247
	-38.32	-37.98	-39.43	-37.12	-38.38
(3)	0.248	0.253	0.220	0.276	0.245
	-38.33	-38.10	-39.47	-37.15	-38.43

C.5 Dickey-Fuller for SO_2

Table 17: D-F Test for SO_2: Coefficient and t-statistic (1)

	Monitoring Stations								
	A	B	C	D	E	F	G	H	I
(1)	0.730	0.737	0.728	0.730	0.740	0.731	0.711	0.730	0.731
	-19.36	-19.20	-19.54	-19.36	-18.96	-19.43	-20.26	-19.32	-19.36
(2)	0.268	0.264	0.251	0.238	0.285	0.249	0.224	0.251	0.258
	-37.26	-37.67	-38.10	-38.46	-36.62	-38.25	-39.24	-37.88	-37.76
(3)	0.265	0.263	0.250	0.237	0.284	0.248	0.223	0.249	0.256
	-37.34	-37.73	-38.16	-38.48	-36.66	-38.30	-39.30	-37.92	-37.82

Table 18: D-F Test for SO_2: Coefficient and t-statistic (2)

	Monitoring Stations					
	J	K	L	M	N	O
(1)	0.724	0.711	0.733	0.736	0.720	0.723
	-19.75	-20.25	-19.22	-19.19	-19.92	-19.75
(2)	0.248	0.238	0.271	0.279	0.265	0.277
	-38.30	-38.67	-37.09	-36.97	-37.63	-37.11
(3)	0.248	0.237	0.269	0.277	0.264	0.276
	-38.32	-38.71	-37.17	-37.05	-37.67	-37.15

D Auto-Correlation Tests

Table 19: Number of significant lags in Auto-correlogram

		Monitoring Stations															
Pollutant	Data	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Mean
CO	Daily	1	2	1	1	3	1	1	1	1	1	1	3	1	1	1	1
	Hourly	4	5	3	2	4	2	4	4	3	4	6	4	5	2	3	5
NO_2	Daily	1	1	1	1	1											1
	Hourly	3	3	3	5	3											3
O_3	Daily	3	2	3	5	4	4	2	5	3							2
	Hourly	3	4	5	3	4	4	2	4	4							3
NO_x	Daily	1	1	1	1	3											1
	Hourly	4	2	2	3	4											3
SO_2	Daily	1	1	1	1	1	4	1	2	1	1	1	1	1	1	1	4
	Hourly	6	3	3	5	3	9	2	1	3	5	2	4	3	3	2	3

Number of significant lags looking at Auto-correlogram and regressing the pollutant on its lags. “Mean” is the same exercise looking at the average of the stations measurement, which is the variable used in this dissertation.

E Davis (2008) Tables

Table 20: Davis(2008) - Summary Statistics: 1986-1993

	Observations	Mean	Standard Deviation	Minimum	Maximum
Carbon Monoxide	690,644	4.78	3.41	.100	50.0
Nitrogen Dioxide	235,860	.042	.027	.001	.460
Ozone	412,403	.046	.044	.001	.500
Nitrogen Oxides	227,421	.075	.060	.001	.590
Sulfur Dioxide	641,439	.046	.035	.001	.846
Temperature	511,037	16.0	5.00	.100	49.2
Real Humidity	437,449	48.8	22.8	.050	102.4
Wind Speed	233,439	5.91	3.89	.016	97.4

Pollutant levels are reported in parts per million.

Table 21: Davis(2008) - Effect of HNC: Regression Discontinuity

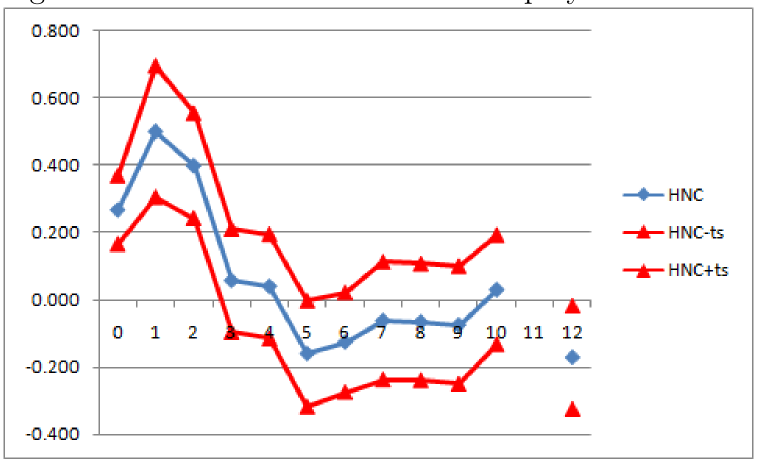
	CO	NO_2	O_3	NO_x	SO_2
Seventh-order polynomial	.048	-.020	-.042	-.029	.224
	(.100)	(.142)	(.104)	(.110)	(.109)
Eighth-order polynomial	.049	-.055	-.015	-.062	.206
	(.098)	(.142)	(.101)	(.109)	(.104)
Ninth-order polynomial	.008	-.058	.053	-.001	.207
	(.092)	(.164)	(.104)	(.135)	(.121)

This table reports estimates from 15 separate regressiones. All results use the eight-year time window and include observations from all hours of the day and all days of the week. The dependet variable is the pollution level in logs. The reported coefficients correspond to 1(HNC), an indicator variable equal to 1 after November 20, 1989. CO is carbon monoxide, NO_2 is nitrogen dioxide, O_3 is ozone, NO_x is nitrogen oxides, and SO_2 is sulfur dioxide. All estimates are from an RD specification with a time trend polynomial of a length indicated in the first column, weather covariates, and indicator variables for month of the year, day of the week, and hour of the day, as well as interactions between weekends and hour of the day. Standard errors, in parenthesis, are robust to heteroskedasticity and arbitrary correlation whithin five-week groups.

F HNC Coefficient with different Polynomial Order

HNC coefficients for different polynomial orders were estimated and plotted in figure 3. For polynomial orders eleventh, thirteenth and greater, HNC coefficient dropped out of the estimation caused by very high colinearity. The rest of the cases are graphed below.

Figure 3: HNC coef for CO: Different polynomial order



The blue line, in the middle, plots the estimate for the HNC coefficient using different time trend polynomial orders, indicated by the number in the x-axis. The red lines plot the confidence intervals to the 95% level of each estimate. The estimate using the eleventh-order polynomial does not appear because the HNC variable drops out of the estimation when regressing this specification; this same phenomenon occurs with polynomial orders larger than twelve, which is why the last estimate that is presented is this last one. Interestingly, using the fifth- and twelveth-order polynomial the HNC coefficient is negative and significant, as well as no polynomial, or first- and second-order polynomials result in a possitive estimate.

G HNC Coefficient with different Polynomial Order and Time Windows

In this section of the appendix I report the estimation of one hundred different specifications for each of the five pollutants. Each specification uses a different time window, from 4 years front and back (8 years) to 1 year front and back (2years), and a different order of the polynomial time trend, from OLS to a ninth polynomial time trend. The main objectiv of this exercise is to show once again how sensitive the HNC estimate is to changes in the specifications, now looking at every possible combination.

Tables 22 to 26, located in the next five pages, report the estimations. In this case, asterisks to indicate statistical significance will be used in the following way, with the purpose of helping the interpretation of the numerous estimates:

* One asterisk : Confidence Level of 90% ($p<0.1$)
** Two Asterisks : Confidence Level of 95% ($p<0.05$)
*** Three asterisks : Confidence Level of 99% ($p<0.01$)

Table 22: Effect of HNC on CO: Different Polynomial Order and Time Windows

	OLS	1	2	3	4	5	6	7	8	9
4-4	0.267***	0.500***	0.398***	0.057	0.040	-0.160*	-0.126*	-0.062	-0.066	-0.075
	(0.052)	(0.100)	(0.080)	(0.078)	(0.079)	(0.080)	(0.075)	(0.089)	(0.088)	(0.089)
4-3	0.391***	0.255***	0.289***	0.001	-0.032	-0.087	-0.117	-0.081	-0.081	-0.025
	(0.041)	(0.074)	(0.078)	(0.080)	(0.075)	(0.083)	(0.079)	(0.079)	(0.077)	(0.077)
3-4	0.248***	0.567***	0.263***	0.053	-0.101	-0.165**	0.010	0.003	-0.041	0.022
	(0.055)	(0.102)	(0.083)	(0.080)	(0.087)	(0.078)	(0.088)	(0.087)	(0.084)	(0.081)
3-3	0.372***	0.275***	0.215***	-0.067	-0.073	-0.071	0.002	-0.046	-0.027	-0.199***
	(0.045)	(0.084)	(0.078)	(0.077)	(0.080)	(0.089)	(0.077)	(0.070)	(0.074)	(0.066)
3-2	0.271***	0.178**	0.061	0.056	-0.087**	-0.010	-0.003	0.008	0.012	-0.005
	(0.040)	(0.072)	(0.089)	(0.054)	(0.040)	(0.050)	(0.052)	(0.047)	(0.048)	(0.044)
2-3	0.295***	0.078	0.001	0.092	-0.220**	-0.168**	-0.144**	-0.149**	-0.116*	-0.117*
	(0.041)	(0.071)	(0.063)	(0.067)	(0.087)	(0.081)	(0.064)	(0.067)	(0.063)	(0.062)
2-2	0.332***	0.157**	0.136*	-0.000	0.039	-0.099*	-0.001	-0.071	-0.083	-0.058
	(0.037)	(0.073)	(0.071)	(0.072)	(0.060)	(0.049)	(0.062)	(0.064)	(0.067)	(0.069)
2-1	0.276***	0.089	-0.073	-0.011	-0.201**	-0.172*	-0.099	-0.103	-0.105	-0.108
	(0.041)	(0.070)	(0.075)	(0.070)	(0.077)	(0.087)	(0.066)	(0.066)	(0.069)	(0.070)
1-2	0.262***	0.175**	0.109	0.047	-0.087**	0.023	0.033	0.008	0.018	-0.013
	(0.040)	(0.076)	(0.098)	(0.050)	(0.041)	(0.053)	(0.057)	(0.047)	(0.049)	(0.044)
1-1	0.201***	0.024	0.104	0.035	0.009	0.007	0.017	0.018	0.013	0.008
	(0.040)	(0.076)	(0.088)	(0.045)	(0.046)	(0.044)	(0.053)	(0.052)	(0.051)	(0.050)

This table reports estimates from 100 separate regressions, each column using a different polynomial lenght, and each row a different time window. The dependent variable is CO in logs, and specifications include weather covariates and indicator variables for month of the year, day of the week and hour of the day, as well as interactions between weekend and hour of the day. The reported coefficients correspond to the HNC estimate. Standard errors, in parenthesis, are robust to heteroskedasticity and arbitrary correlation whithin five-week groups. Confidence level indicated by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 23: Effect of HNC on NO_2: Different Polynomial Order and Time Windows

	OLS	1	2	3	4	5	6	7	8	9
4-4	0.047	-0.002	0.024	0.015	-0.021	-0.035	-0.078	-0.116	-0.155	-0.117
	(0.036)	(0.064)	(0.068)	(0.087)	(0.080)	(0.099)	(0.097)	(0.105)	(0.102)	(0.118)
4-3	0.024	0.060	0.048	-0.028	0.014	-0.105	-0.092	-0.196*	-0.160	-0.083
	(0.036)	(0.071)	(0.070)	(0.086)	(0.086)	(0.095)	(0.102)	(0.102)	(0.118)	(0.127)
3-4	0.066*	-0.036	-0.007	0.034	-0.109	-0.049	-0.070	-0.062	-0.103	-0.077
	(0.037)	(0.062)	(0.071)	(0.083)	(0.086)	(0.095)	(0.110)	(0.110)	(0.119)	(0.123)
3-3	0.044	0.018	0.017	-0.009	-0.082	-0.073	-0.085	-0.120	-0.103	-0.072
	(0.037)	(0.069)	(0.070)	(0.093)	(0.082)	(0.108)	(0.109)	(0.119)	(0.124)	(0.130)
3-2	-0.033	0.020	0.005	0.005	-0.125	-0.303***	-0.341***	-0.394***	-0.392***	-0.382***
	(0.039)	(0.071)	(0.111)	(0.110)	(0.103)	(0.068)	(0.068)	(0.071)	(0.071)	(0.066)
2-3	0.071	-0.123	-0.057	-0.110	-0.607***	-0.569***	-0.595***	-0.586***	-0.646***	-0.629***
	(0.047)	(0.087)	(0.111)	(0.113)	(0.145)	(0.139)	(0.139)	(0.137)	(0.165)	(0.158)
2-2	0.059	-0.043	-0.102	-0.078	-0.084	-0.101	-0.115	-0.517***	-0.469***	-0.406***
	(0.046)	(0.080)	(0.077)	(0.101)	(0.102)	(0.122)	(0.125)	(0.112)	(0.106)	(0.108)
2-1	0.085*	-0.184**	-0.174	-0.172	-0.564***	-0.531***	-0.537***	-0.526***	-0.582***	-0.559***
	(0.049)	(0.088)	(0.130)	(0.128)	(0.155)	(0.153)	(0.150)	(0.146)	(0.169)	(0.160)
1-2	-0.052	0.012	0.038	0.032	-0.126	-0.258***	-0.304***	-0.415***	-0.406***	-0.402***
	(0.041)	(0.075)	(0.107)	(0.108)	(0.104)	(0.072)	(0.067)	(0.075)	(0.073)	(0.071)
1-1	-0.016	-0.142	-0.130	-0.342***	-0.357***	-0.357***	-0.342***	-0.339***	-0.328***	-0.324***
	(0.045)	(0.105)	(0.105)	(0.104)	(0.105)	(0.107)	(0.086)	(0.085)	(0.092)	(0.091)

This table reports estimates from 100 separate regressions, each column using a different polynomial lenght, and each row a different time window. The dependent variable is NO_2 in logs, and specifications include weather covariates and indicator variables for month of the year, day of the week and hour of the day, as well as interactions between weekend and hour of the day. The reported coefficients correspond to the HNC estimate. Standard errors, in parenthesis, are robust to heteroskedasticity and arbitrary correlation whithin five-week groups. Confidence level indicated by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 24: Effect of HNC on O_3: Different Polynomial Order and Time Windows

	OLS	1	2	3	4	5	6	7	8	9
4-4	0.260***	-0.008	-0.065	-0.443***	-0.386***	-0.364***	-0.264***	-0.102	-0.079	0.015
	(0.052)	(0.075)	(0.074)	(0.082)	(0.066)	(0.090)	(0.083)	(0.105)	(0.100)	(0.102)
4-3	0.302***	-0.215***	-0.225***	-0.349***	-0.425***	-0.145*	-0.142	0.036	0.284**	0.193**
	(0.059)	(0.061)	(0.063)	(0.080)	(0.090)	(0.083)	(0.108)	(0.098)	(0.108)	(0.094)
3-4	0.205***	0.021	-0.174**	-0.469***	-0.277***	-0.362***	-0.105	-0.099	0.013	-0.005
	(0.051)	(0.082)	(0.073)	(0.078)	(0.064)	(0.088)	(0.104)	(0.109)	(0.106)	(0.100)
3-3	0.247***	-0.252***	-0.253***	-0.388***	-0.272***	-0.109	-0.048	0.246**	0.181**	0.129
	(0.058)	(0.065)	(0.059)	(0.098)	(0.077)	(0.115)	(0.104)	(0.117)	(0.090)	(0.085)
3-2	0.082	-0.402***	0.097	0.100	0.255**	0.020	-0.018	-0.067	-0.058	-0.077
	(0.051)	(0.087)	(0.082)	(0.062)	(0.123)	(0.087)	(0.082)	(0.072)	(0.074)	(0.073)
2-3	-0.058***	0.031	0.023	0.020	0.074	0.055	0.008	0.015	0.025	0.025
	(0.021)	(0.034)	(0.039)	(0.046)	(0.092)	(0.093)	(0.075)	(0.076)	(0.084)	(0.084)
2-2	0.094*	-0.317***	-0.168***	0.069	0.056	0.273***	0.149	0.010	0.036	0.049
	(0.050)	(0.091)	(0.062)	(0.061)	(0.053)	(0.099)	(0.090)	(0.091)	(0.099)	(0.099)
2-1	-0.058**	0.059*	0.095*	0.080	0.051	0.056	0.022	0.023	0.029	0.036
	(0.022)	(0.032)	(0.056)	(0.059)	(0.090)	(0.090)	(0.085)	(0.083)	(0.086)	(0.089)
1-2	0.089*	-0.405***	0.051	0.096	0.256**	0.054	0.010	-0.072	-0.060	-0.087
	(0.047)	(0.086)	(0.082)	(0.060)	(0.126)	(0.092)	(0.086)	(0.069)	(0.071)	(0.073)
1-1	-0.001	-0.063**	-0.075**	-0.092*	-0.094*	-0.094*	-0.093*	-0.092*	-0.089*	-0.082
	(0.015)	(0.028)	(0.036)	(0.048)	(0.050)	(0.050)	(0.049)	(0.049)	(0.049)	(0.049)

This table reports estimates from 100 separate regressions, each column using a different polynomial lenght, and each row a different time window. The dependent variable is O_3 in logs, and specifications include weather covariates and indicator variables for month of the year, day of the week and hour of the day, as well as interactions between weekend and hour of the day. The reported coefficients correspond to the HNC estimate. Standard errors, in parenthesis, are robust to heteroskedasticity and arbitrary correlation whithin five-week groups. Confidence level indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Table 25: Effect of HNC on NO_x: Different Polynomial Order and Time Windows

	OLS	1	2	3	4	5	6	7	8	9
4-4	0.123***	-0.008	0.007	-0.057	-0.073	-0.147*	-0.190**	-0.106	-0.142	-0.045
	(0.035)	(0.054)	(0.057)	(0.074)	(0.074)	(0.084)	(0.085)	(0.100)	(0.101)	(0.123)
4-3	0.110***	-0.007	-0.024	-0.091	-0.078	-0.193**	-0.106	-0.201*	-0.170	-0.113
	(0.036)	(0.059)	(0.060)	(0.076)	(0.075)	(0.088)	(0.095)	(0.107)	(0.123)	(0.127)
3-4	0.133***	-0.030	-0.017	-0.058	-0.214***	-0.153*	-0.029	-0.016	-0.034	-0.052
	(0.037)	(0.053)	(0.067)	(0.072)	(0.076)	(0.079)	(0.105)	(0.106)	(0.123)	(0.126)
3-3	0.119***	-0.051	-0.039	-0.121	-0.191***	-0.040	-0.061	-0.124	-0.121	-0.101
	(0.038)	(0.058)	(0.063)	(0.079)	(0.069)	(0.103)	(0.106)	(0.124)	(0.125)	(0.130)
3-2	-0.046	-0.045	-0.023	-0.021	-0.096	-0.175	-0.206	-0.323**	-0.326**	-0.321**
	(0.040)	(0.068)	(0.121)	(0.123)	(0.140)	(0.156)	(0.159)	(0.133)	(0.126)	(0.122)
2-3	0.080**	-0.175**	-0.097	-0.146	-0.425***	-0.403***	-0.392**	-0.392**	-0.463***	-0.501***
	(0.037)	(0.070)	(0.086)	(0.100)	(0.146)	(0.146)	(0.148)	(0.147)	(0.151)	(0.179)
2-2	0.078*	-0.108	-0.167**	-0.076	-0.093	-0.115	-0.146	-0.426***	-0.412***	-0.364**
	(0.042)	(0.069)	(0.063)	(0.098)	(0.097)	(0.127)	(0.145)	(0.147)	(0.131)	(0.152)
2-1	0.087**	-0.240***	-0.194*	-0.198*	-0.388**	-0.376**	-0.366**	-0.360**	-0.389**	-0.398**
	(0.038)	(0.070)	(0.105)	(0.105)	(0.147)	(0.150)	(0.152)	(0.152)	(0.158)	(0.163)
1-2	-0.056	-0.049	-0.005	0.014	-0.091	-0.162	-0.194	-0.322**	-0.329**	-0.289**
	(0.039)	(0.069)	(0.116)	(0.123)	(0.143)	(0.155)	(0.159)	(0.140)	(0.132)	(0.131)
1-1	-0.023	-0.157	-0.162	-0.266**	-0.268*	-0.268*	-0.279**	-0.279**	-0.278**	-0.251*
	(0.040)	(0.138)	(0.135)	(0.126)	(0.132)	(0.132)	(0.128)	(0.129)	(0.130)	(0.141)

This table reports estimates from 100 separate regressions, each column using a different polynomial lenght, and each row a different time window. The dependent variable is NO_x in logs, and specifications include weather covariates and indicator variables for month of the year, day of the week and hour of the day, as well as interactions between weekend and hour of the day. The reported coefficients correspond to the HNC estimate. Standard errors, in parenthesis, are robust to heteroskedasticity and arbitrary correlation whithin five-week groups. Confidence level indicated by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 26: Effect of HNC on SO_2: Different Polynomial Order and Time Windows

	OLS	1	2	3	4	5	6	7	8	9
4-4	-0.107	0.476***	0.306***	-0.056	-0.012	-0.187*	-0.102	0.190*	0.170	0.182
	(0.076)	(0.126)	(0.082)	(0.092)	(0.079)	(0.094)	(0.082)	(0.109)	(0.102)	(0.121)
4-3	0.120***	0.058	0.113*	0.019	-0.049	0.017	0.038	0.162*	0.324**	0.280**
	(0.041)	(0.071)	(0.064)	(0.078)	(0.076)	(0.081)	(0.095)	(0.094)	(0.130)	(0.121)
3-4	-0.135*	0.622***	0.207**	-0.095	-0.073	-0.180**	0.185*	0.217*	0.176	0.175
	(0.075)	(0.121)	(0.087)	(0.091)	(0.085)	(0.088)	(0.108)	(0.116)	(0.116)	(0.111)
3-3	0.090**	0.156**	0.097	-0.063	-0.014	0.091	0.150	0.302**	0.256**	0.134
	(0.041)	(0.071)	(0.065)	(0.084)	(0.076)	(0.107)	(0.100)	(0.132)	(0.113)	(0.115)
3-2	0.130***	0.015	0.347***	0.350***	0.165**	0.071	0.033	-0.067	-0.051	-0.084
	(0.040)	(0.077)	(0.119)	(0.114)	(0.079)	(0.089)	(0.088)	(0.099)	(0.095)	(0.097)
2-3	0.100**	0.190**	0.234***	0.217**	-0.199**	-0.129	-0.186*	-0.177*	-0.093	-0.056
	(0.041)	(0.075)	(0.084)	(0.089)	(0.080)	(0.081)	(0.097)	(0.093)	(0.073)	(0.069)
2-2	0.122***	0.031	0.081	0.282***	0.262***	0.226**	0.298**	-0.073	-0.012	-0.032
	(0.030)	(0.076)	(0.069)	(0.088)	(0.085)	(0.091)	(0.117)	(0.088)	(0.086)	(0.086)
2-1	0.123***	0.141*	0.120	0.134	-0.197**	-0.120*	-0.059	-0.058	-0.069	-0.062
	(0.039)	(0.072)	(0.096)	(0.090)	(0.082)	(0.066)	(0.053)	(0.053)	(0.050)	(0.050)
1-2	0.119***	0.010	0.339***	0.368***	0.163**	0.114	0.076	-0.069	-0.051	-0.078
	(0.039)	(0.075)	(0.115)	(0.114)	(0.076)	(0.092)	(0.090)	(0.099)	(0.097)	(0.094)
1-1	0.126**	0.092	0.125	-0.051	-0.110**	-0.115**	-0.119**	-0.117**	-0.091*	-0.039
	(0.044)	(0.086)	(0.106)	(0.054)	(0.052)	(0.055)	(0.056)	(0.055)	(0.052)	(0.053)

This table reports estimates from 100 separate regressions, each column using a different polynomial lenght, and each row a different time window. The dependent variable is SO_2 in logs, and specifications include weather covariates and indicator variables for month of the year, day of the week and hour of the day, as well as interactions between weekend and hour of the day. The reported coefficients correspond to the HNC estimate. Standard errors, in parenthesis, are robust to heteroskedasticity and arbitrary correlation whithin five-week groups. Confidence level indicated by: *** p<0.01, ** p<0.05, * p<0.1.

H Precipitation Data

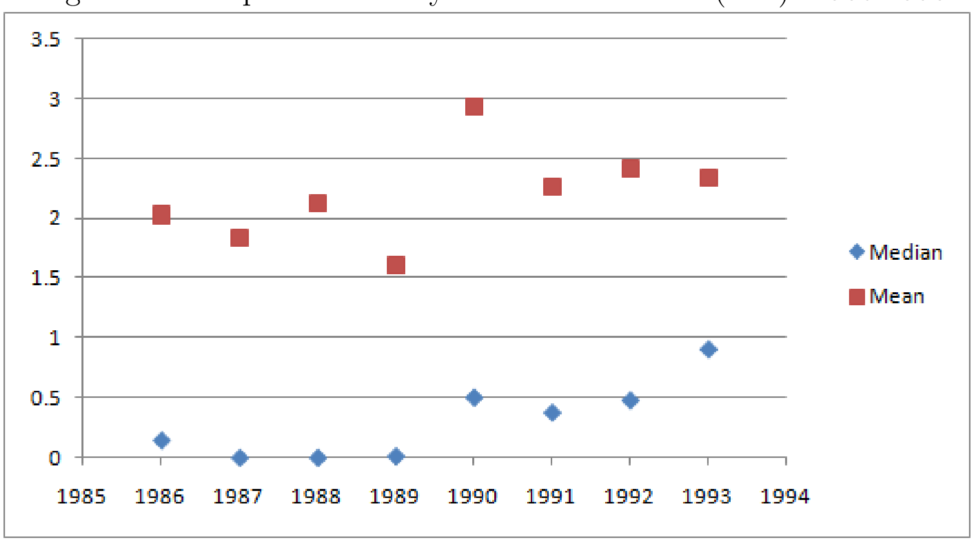
Precipitation data was obtained from the Water National Commission (Comisión Nacional del Agua: www.conagua.gob.mx). It is a daily series going from 1920 to 2007. Ten monitoring stations report regular measures from 1985 to 1993. The variable that is added to the estimations is a daily average of this ten monitoring stations. Table 27 summarizes the main statistics of these 10 monitoring stations in the years of our study, and figure 4 plots the mean and median of the average of these 10 monitoring stations along the sample.

Table 27: Precipitation Summary Statistics: 1986-1993

	Observations	Mean	Standard Deviation	Minimum	Maximum
Precipitation	24,935	2.19	4.08	.000	136.2
Precipitation: Before HNC	12,003	1.95	4.12	.000	93.0
Precipitation: After HNC	12,932	2.43	4.04	.000	136.2

Precipitation is measured in milimeters.

Figure 4: Precipitation: Daily Mean and Median (mm): 1986-1993



Interesting to notice is that both mean and median precipitation levels are higher after the HNC's implementation, allowing us to think that omitting this variable from the estimation would bias the estimators if precipitation was actually correlated with air pollution. Standard econometric theory would predict the following expression for the expected value of the estimator which omitts precipitation[26]:

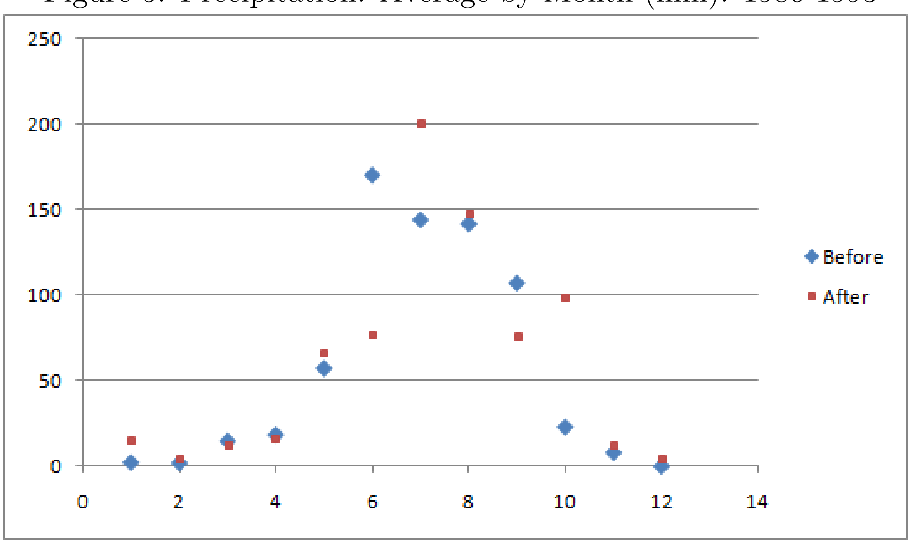
[26] The math is done supposing only two regresors, and a constant, and expressing these in deviations from the mean. It's a simplification but it serves its purpose of showing the sign of the bias.

$$E(\hat{\beta}_{HNC}) = \beta_{HNC} + \beta_{Prec}\frac{Cov(HNC, Prec)}{Var(HNC)}$$

If we assume a negative relation between precipitation and air pollution ($\beta_{Prec} < 0$), and based on these findings we discover that the HNC era was one with more precipitation ($Cov(HNC, Prec) > 0$), we would expect a negative bias on Davis' estimator $\hat{\beta}_{HNC}$, that is, underestimating the impact of the HNC on air pollution. Nevertheless, when estimating some alternative specifications in Table 28, it is shown that adding precipitation does almost nothing to the estimator, if anything slightly reducing it. In any case, a weather covariate such as precipitation should always be included in this type of estimations.

Figure 5 shows the behavior of rain during an average year, both before and after the HNC. The graph plots the average of every month along each sub-sample, where the measurement of every month is the sum of the precipitation during that month. This figure mainly confirms the fact that precipitation was somewhat higher after the HNC's implementation, but it reveals a very important fact: precipitation seems to only have raised significantly during the rain season, in the middle of the year, when precipitation is already high enough to trim down concentration of pollutants. More rain during this season would not help reduce air pollution more than it was reduced already, which could be the reason for the lack of evidence reported in the alternative specifications of an underestimation of the impact of HNC.

Figure 5: Precipitation: Average by Month (mm): 1986-1993



I Alternative Specifications

Table 28: Effect of HNC: Alternative Specifications

	CO	NO_2	O_3	NO_x	SO_2
Original Coefficients	-.062	-.116	-.102	-.106	.190
	(.089)	(.105)	(.105)	(.100)	(.109)
1 hour lag**	-.017	-.023	-.011	-.027	.021
	(.011)	(.017)	(.013)	(.018)	(.014)
1 day lag***	-.039	-.048	-.046	-.055	.035
	(.025)	(.035)	(.036)	(.036)	(.031)
Wind Direction	-.050	-.112	-.092	-.099	.190
	(.090)	(.106)	(.102)	(.101)	(.109)
Precipitation	-.069	-.118	-.096	-.113	.192
	(.088)	(.104)	(.103)	(.099)	(.109)
Wind Direction and Precipitation	-.056	-.114	-.086	-.106	.192
	(.089)	(.105)	(.100)	(.099)	(.108)
No Weather Variables	.038	-.049	-.112	-.050	.241*
	(.088)	(.118)	(.098)	(.108)	(.107)
GDP per capita	-.011	-.154	-.056	-.135	.191
	(.089)	(.102)	(.099)	(.094)	(.109)
Center Stations****	-.373*	.564	-.255	.285	-.295
	(.121)	(.291)	(.156)	(.239)	(.229)
North Stations****	.427*	-.678*	.112	-.545*	.215
	(.169)	(.172)	(.177)	(.168)	(.137)
South Stations****	-.042	.158	-.110	.287	.609*
	(.112)	(.151)	(.125)	(.151)	(.153)

This tables reports alternative estimates of the HNC coefficient. **HNC long-run coefficients are -.144, -.143, -.061, -.151 and .175. ***HNC long-run coefficients are -.124, -.163, -.105, -.164 and .128. Precipitation, Wind Direction and GDP per capita estimates are the baseline original estimations when added the regressor that is indicated in each case. GDP per capita is Mexico's anual Gross Domestic Product divided by its population in each year. ****Monitoring Stations located in the center of Mexico City, where the most part of the economic and governmental activity takes place. It includes 4 stations for CO, 2 for O_3 and SO_2, and only 1 for NO_2 and NO_x. Monitoring stations located in the north are 2 stations for CO, NO_2 and NO_x, 3 stations for O_3 and 7 stations for SO_2. Monitoring Stations located in the south are 5 stations for CO, 2 for NO_2 and NO_x, and 3 for O_3 and SO_2. Standard errors in parenthesis are robust to heteroskedasticity and serial autocorrelation within 5 week-clusters. One asterisk (*) indicates coefficients significant to the 95% confidence level.

J Adaptation: Other Pollutants

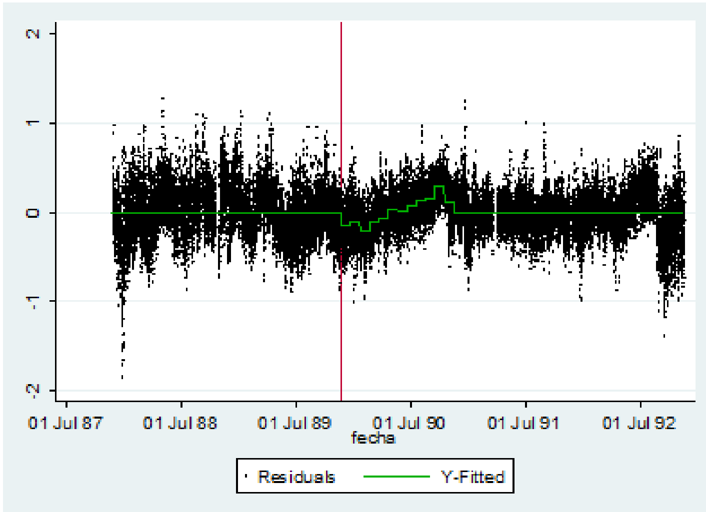
Table 29: Impact of HNC: Adaptation

	CO	NO_2	O_3	NO_x	SO_2
HNC	.181	-.398	-.662*	-.488	-.403*
	(.184)	(.221)	(.252)	(.254)	(.196)
Month1	-.295*	-.096	.471*	.090	.300
	(.131)	(.159)	(.179)	(.170)	(.165)
Month2	-.259*	.178	.495*	.305	.281
	(.121)	(.150)	(.171)	(.161)	(.165)
Month3	-.336*	.351*	.411*	.331*	.277
	(.117)	(.143)	(.166)	(.156)	(.153)
Month4	-.228*	.304*	.488*	.275	.454*
	(.107)	(.142)	(.150)	(.151)	(.141)
Month5	-.161	.235	.442*	.277*	.428*
	(.098)	(.130)	(.144)	(.133)	(.135)
Month6	-.043	.380*	.473*	.477*	.654*
	(.091)	(.118)	(.135)	(.129)	(.116)
Month7	-.021	.225*	.156	.259*	.622*
	(.088)	(.108)	(.117)	(.110)	(.111)
Month8	.038	.192	.008	.225	.572*
	(.079)	(.099)	(.119)	(.118)	(.109)
Month9	.128	.298*	.148	.251*	.586*
	(.073)	(.098)	(.104)	(.107)	(.104)
Month10	.165*	.239*	.229*	.229*	.533*
	(.070)	(.093)	(.112)	(.088)	(.102)
Month11	.310*	.105	.079	.142	.311*
	(.075)	(.085)	(.108)	(.080)	(.099)
Month12	.130	-.106	-.080	-.070	-.116
	(.102)	(.077)	(.104)	(.093)	(.096)

Robust standard errors in parenthesis. One asterisk indicates coefficients significant to the 95% confidence level.

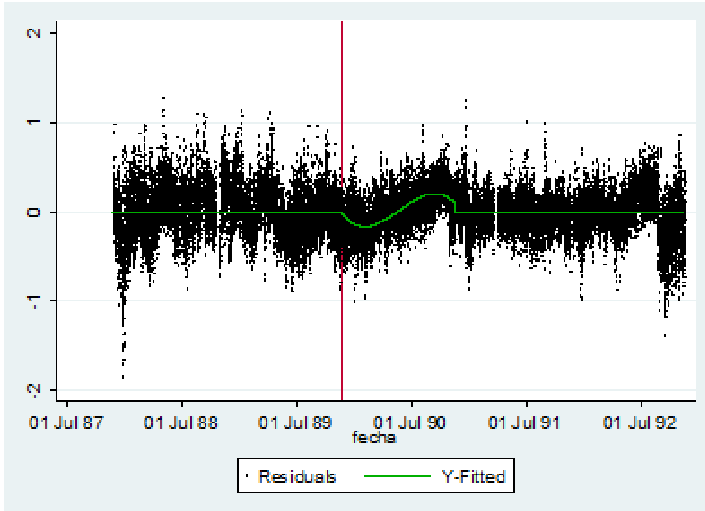
K Adaptation Graphs

Figure 6: Impact of HNC on CO: 12 month dummies



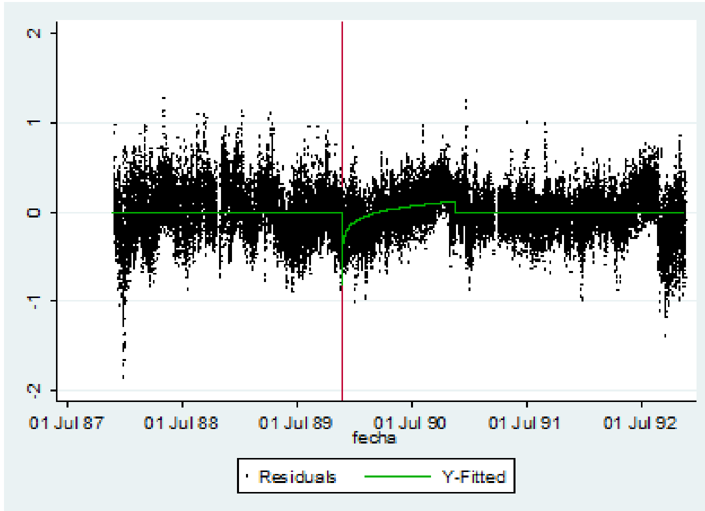
This figure graphs residuals from the carbon monoxide regression of weather covariates, fixed effects and a seventh order time-trend polynomial, and fitted line that includes the HNC coefficient, a dummy variable for the last four years of the sample, and twelve dummies for each month after the HNC's implementation, so as to capture the heterogeneity of the impact of this program on the pollution levels net from other covariates.

Figure 7: Impact of HNC on CO: Third-order polynomial



This figure graphs residuals from the carbon monoxide regression of weather covariates, fixed effects and a seventh order time-trend polynomial, and fitted line that includes the HNC coefficient, a dummy variable for the last four years of the sample, and a third-order polynomial for the first year after the HNC's implementation, so as to capture the heterogeneity of the impact of this program on the pollution levels net from other covariates.

Figure 8: Impact of HNC on CO: Logarithm Form



This figure graphs residuals from the carbon monoxide regression of weather covariates, fixed effects and a seventh order time-trend polynomial, and fitted line that includes the HNC coefficient, a dummy variable for the last four years of the sample, and a logarithmic function of time for the first year after the HNC's implementation, so as to capture the heterogeneity of the impact of this program on the pollution levels net from other covariates.

L Adaptation Robustness

Table 30: Impact of HNC on CO: Adaptation - Different Windows

	2-2	2-3	3-2	3-3	3-4	4-3	4-4
HNC	-.044	.253	-.362	.419	.489	.114	.188
	(.274)	(.364)	(.415)	(.282)	(.269)	(.236)	(.184)
Month1	-.060	-.366	.297	-.436*	-.518*	-.247	-.297*
	(.246)	(.310)	(.372)	(.204)	(.196)	(.181)	(.130)
Month2	.044	-.279	.378	-.324	-.436*	-.192	-.262*
	(.239)	(.285)	(.351)	(.188)	(.187)	(.168)	(.121)
Month3	.011	-.325	.301	-.383*	-.512*	-.262	-.341*
	(.232)	(.268)	(.335)	(.175)	(.178)	(.158)	(.117)
Month4	.012	-.267	.268	-.342*	-.408*	-.213	-.234*
	(.220)	(.245)	(.313)	(.163)	(.163)	(.149)	(.107)
Month5	.020	-.202	.250	-.276	-.316*	-.165	-.157
	(.205)	(.223)	(.290)	(.148)	(.148)	(.137)	(.097)
Month6	.161	-.051	.355	-.125	-.182	-.036	-.038
	(.201)	(.211)	(.277)	(.134)	(.133)	(.129)	(.091)
Month7	.176	-.041	.331	-.108	-.166	-.033	-.033
	(0.179)	(.197)	(.254)	(.130)	(.127)	(.124)	(.088)
Month8	.210	.017	.340	-.033	-.100	.060	.047
	(.137)	(.161)	(.208)	(.115)	(.108)	(.115)	(.079)
Month9	.232*	.082	.348*	.055	.000	.138	.130
	(.111)	(.132)	(.172)	(.104)	(.097)	(.106)	(.074)
Month10	.190*	.165	.285*	.145	.079	.198	.175*
	(0.090)	(.107)	(.142)	(.098)	(.098)	(.104)	(.068)
Month11	.241*	.301*	.356*	.318*	.234*	.358*	.313*
	(.081)	(.097)	(.129)	(.091)	(.095)	(.100)	(.074)
Month12	.055	.099	.152	.130	.068	.158	.130
	(.105)	(.121)	(.148)	(.116)	(.102)	(.126)	(.107)

This table reports estimations of the HNC impact on carbon monoxide concentration in logs. The estimates reported correspond to 7 separate regressions. All regressions use the seventh-order time trend polynomial and all the original regressors. Month1, for example, indicates the value of the indicator variable corresponding to the first month after then HNC's implementation. Robust standard errors in parenthesis. One asterisk indicates coefficients significant to the 95% confidence level.

Table 31: Impact of HNC on CO: Adaptation - Different Polynomial Order

	OLS	1	2	3	4	5	6	7	8	9
HNC	.233*	.486*	.631*	.210*	.294*	-.043	-.183	.188	.330	.671*
	(.062)	(.126)	(.070)	(.092)	(.109)	(.140)	(.139)	(.184)	(.255)	(.282)
Month1	-.153*	-.308*	-.596*	-.351*	-.445*	-.202	-.045	-.297*	-.422*	-.673*
	(.062)	(0.083)	(.048)	(.064)	(.087)	(.102)	(.108)	(.130)	(.192)	(.204)
Month2	-.128*	-.258*	-.530*	-.282*	-.375*	-.172	-.020	-.262*	-.381*	-.596*
	(.055)	(0.077)	(.050)	(.056)	(.082)	(.092)	(.099)	(.121)	(.182)	(.188)
Month3	-.162*	-.283*	-.578*	-.340*	-.440*	-.262*	-.116	-.341*	-.458*	-.652*
	(.056)	(.077)	(.052)	(.051)	(.081)	(.085)	(.093)	(.117)	(.174)	(.182)
Month4	-.055	-.173	-.477*	-.242*	-.340*	-.177	-.035	-.234*	-.348*	-.522*
	(.084)	(.091)	(.058)	(.062)	(.082)	(.084)	(.094)	(.107)	(.164)	(.172)
Month5	.027	-.095	-.396*	-.174*	-.270*	-.120	.013	-.157	-.267	-.420*
	(.094)	(.089)	(.052)	(.057)	(.074)	(.080)	(.092)	(.097)	(.152)	(.158)
Month6	.171	.047	-.253*	-.058	-.154*	-.013	.111	-.038	-.142	-.270
	(.087)	(0.082)	(.049)	(.047)	(.071)	(.079)	(.084)	(.091)	(.140)	(.146)
Month7	.190	.069	-.224*	-.053	-.146	-.015	.099	-.033	-.128	-.232
	(.103)	(0.097)	(.060)	(.055)	(.075)	(.078)	(.081)	(.088)	(.134)	(.139)
Month8	.273*	.164	-.141*	.017	-.073	.048	.158*	.047	-.041	-.119
	(.089)	(.093)	(.054)	(.046)	(.064)	(.062)	(.065)	(.079)	(.118)	(.118)
Month9	.357*	.238*	-.044	.102*	.018	.125*	.228*	.130	.053	-.004
	(.090)	(0.094)	(.055)	(.048)	(.062)	(.063)	(.061)	(.074)	(.108)	(.106)
Month10	.412*	.286*	.010	.145*	.066	.158*	.256*	.175*	.107	.067
	(.087)	(0.093)	(.056)	(.054)	(.058)	(.064)	(.061)	(.068)	(.108)	(.103)
Month11	.573*	.442*	.162*	.276*	.203*	.288*	.378*	.313*	.257*	.228*
	(.091)	(.101)	(.073)	(.075)	(.072)	(.075)	(.074)	(.074)	(.105)	(.098)
Month12	.388*	.274*	-.013	.082	.016	.090	.171	.130	.087	.071
	(.120)	(.124)	(.097)	(.103)	(.098)	(.105)	(.115)	(.107)	(.113)	(.107)

This table reports estimations of the HNC impact on carbon monoxide concentration in logs. The estimates reported correspond to 10 separate regressions. All regressions use the eight-year symmetrical time window and all the original regressors. Month1, for example, indicates the value of the indicator variable corresponding to the first month after then HNC's implementation. Robust standard errors in parenthesis. One asterisk indicates coefficients significant to the 95% confidence level.

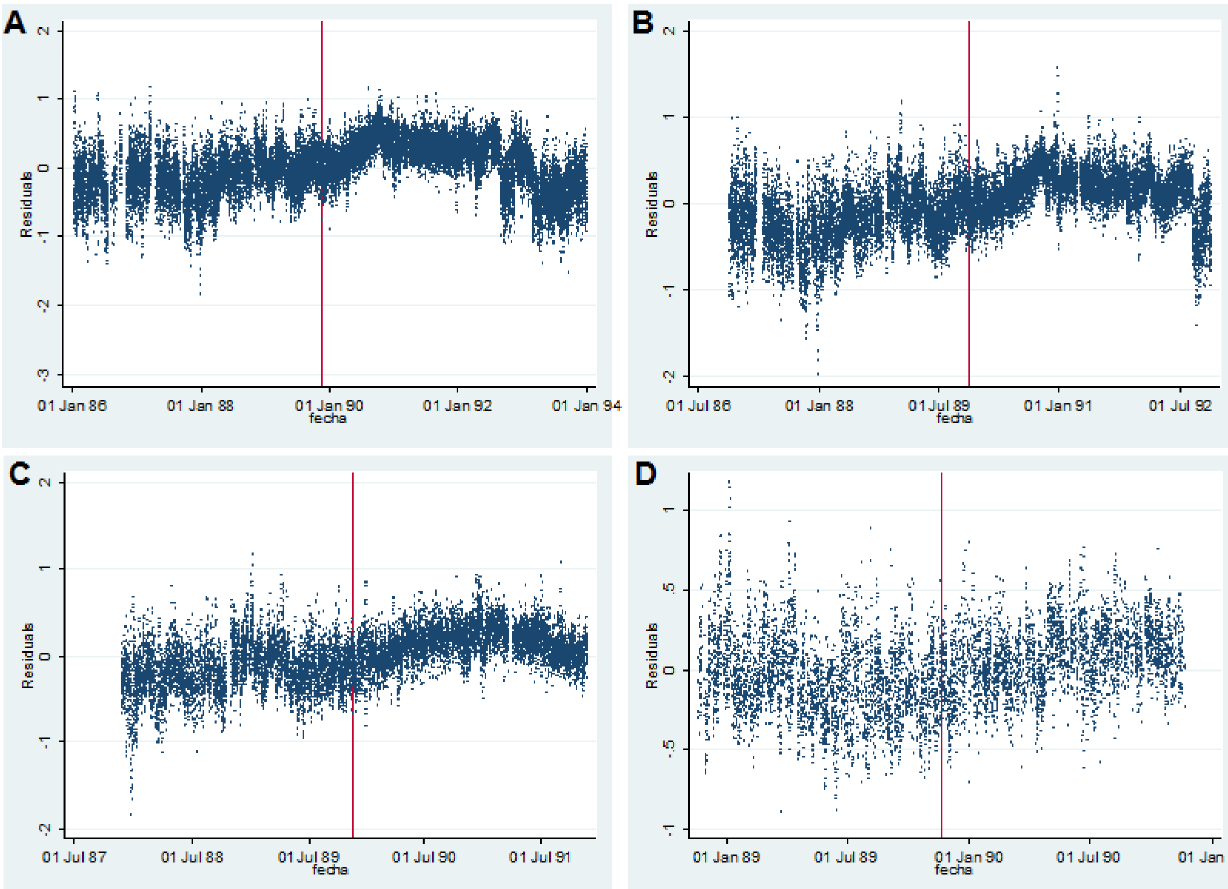
Table 32: Impact of HNC on CO

COEFFICIENT	VALUE	
HNC	-.534	
	.406	
	After	Before
Month1	-.523*	-.377*
	(.209)	(.175)
Month2	-.541*	-.223
	(.236)	(.157)
Month3	-.663*	-.318*
	(.253)	(.153)
Month4	-.560*	-.375*
	(.271)	(.144)
Month5	-.493	-.369*
	(.286)	(.134)
Month6	-.420	-.546*
	(.297)	(.125)
Month7	-.458	-.363*
	(.309)	(.116)
Month8	-.385	-.034
	(.315)	(.108)
Month9	-.308	-.116
	(.323)	(.097)
Month10	-.268	-.335*
	(.327)	(.104)
Month11	-.136	-.147
	(.331)	(.083)
Month12	-.324	-.027
	(.311)	(.074)

Robust standard errors in parenthesis. One asterisk indicates coefficients significant to the 95% confidence level. Monthly indicators front and back.

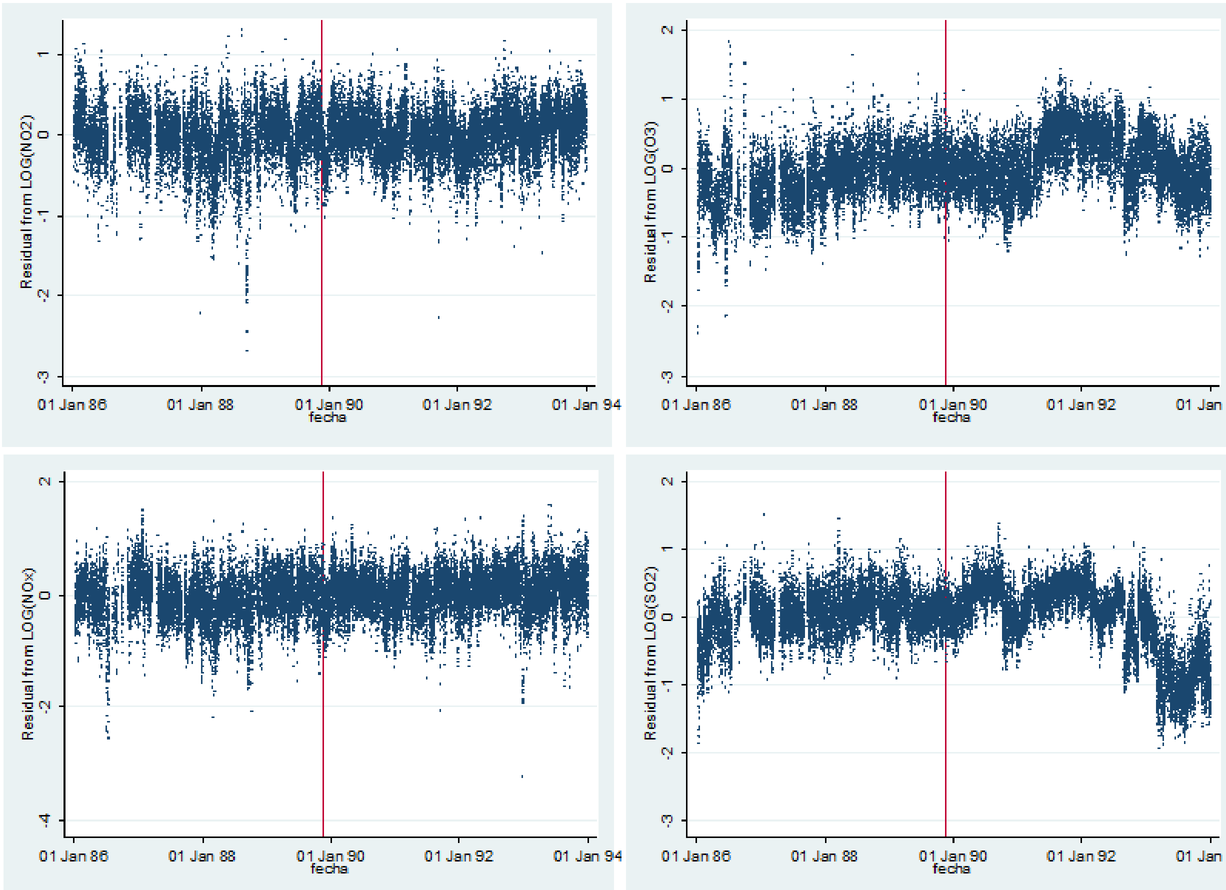
M Residuals of Pollutants

Figure 9: Residuals of CO: Different Time Windows



This figure shows four graphs where each plots the residuals of the regression of CO in logs on the baseline regresors used by Davis (2008): weather variables real humidity, temperature and wind speed, and fixed effects for hour of the day, day of the week, month of the year and the interaction between weekend and hour of the day. Graph A uses a four-year time window, graph B uses a three-year time window, graph C uses a two-year time window and graph D uses a one-year time window. A red line indicates the date of start of the HNC program.

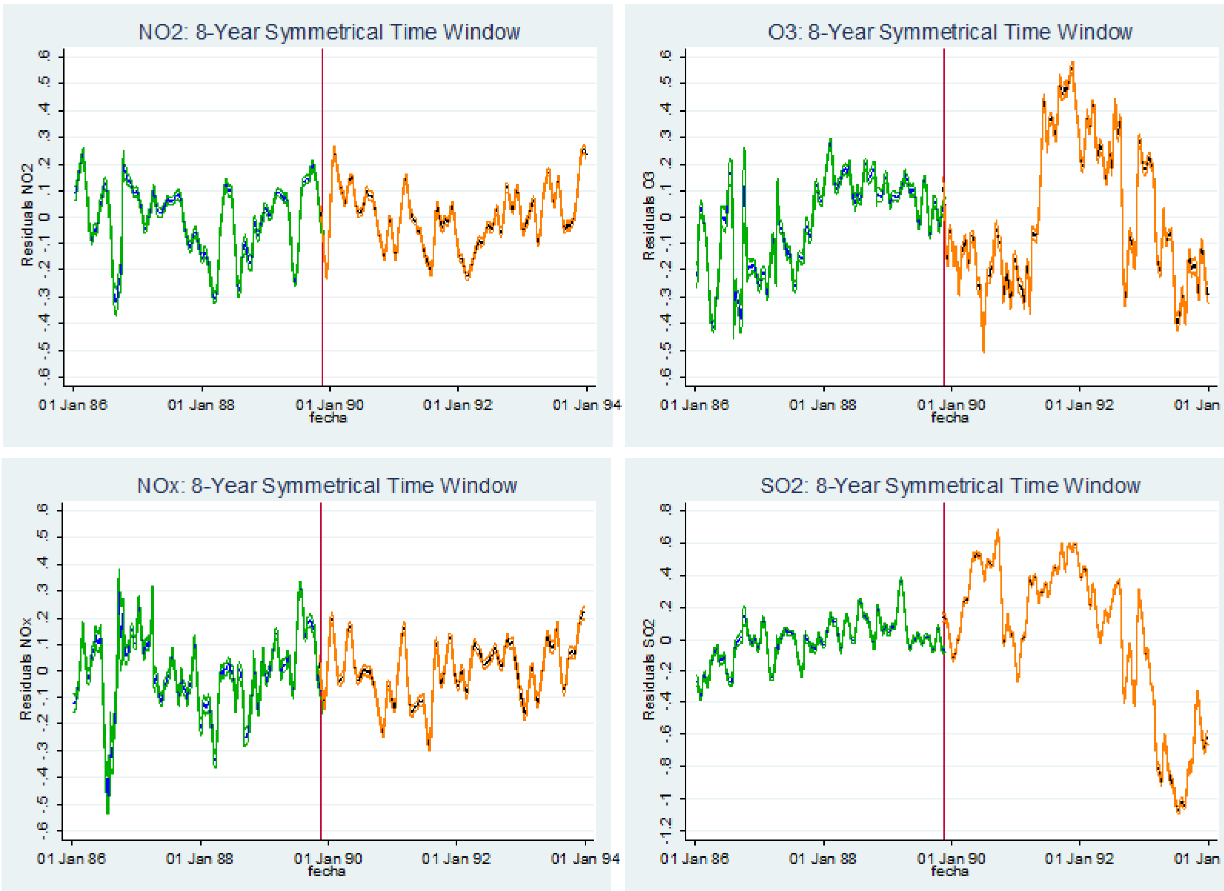
Figure 10: Residuals of NO_2, O_3, NO_x and SO_2



This figure shows four graphs where each plots the residuals of the regression of different pollutants in logs on the baseline regresors used by Davis (2008): weather variables real humidity, temperature and wind speed, and fixed effects for hour of the day, day of the week, month of the year and the interaction between weekend and hour of the day. The graphs from the top corresponds to residuals of NO_2 and O_3, and the graphs from the bottom corresponds to residuals of NO_x and SO_2, as indicated in the y-axis of each graph. A red line indicates the date of start of the HNC program.

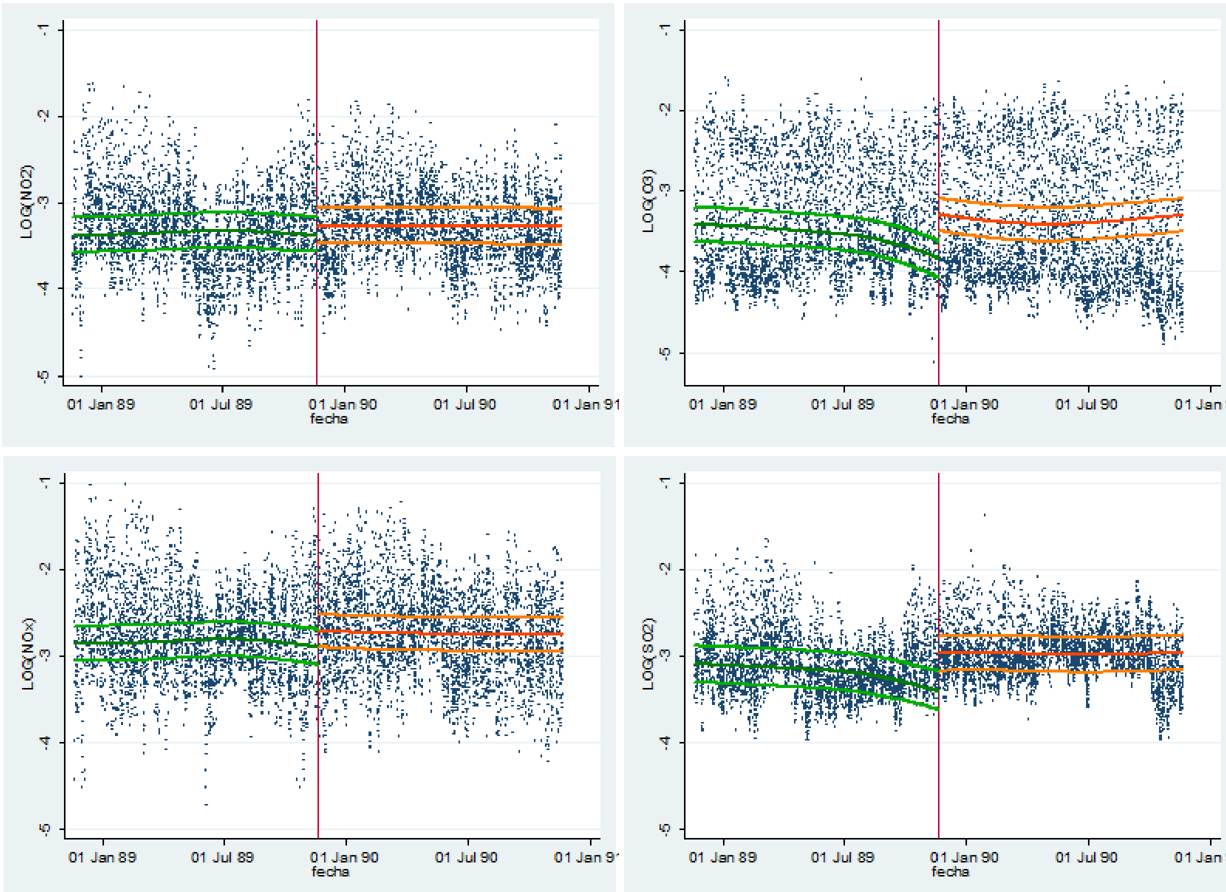
N Semi-Parametric Estimations: Other Pollutants

Figure 11: Kernel-Weighted Local Regression: Smoothed values for NO_2, O_3, NO_x, SO_2



This figure shows four graphs where each plots the smoothed values of the Kernel-Weighted Local Regression of different pollutants' residuals on time. The y-axis is the residual value and the x-axis is time. Residuals are obtained from an OLS regression of concentration of the pollutant in logs on weather covariates humidity, temperature and wind speed, and fixed effects for hour of the day, day of the week, month of the year and the interaction between hour of the day and weekend. The regression uses kernel function Epanechnikov as weights with a bandwidth of $N^{0.2}$, N being the size of the sample. A red vertical line marks the start of the HNC program. Confidence Intervals to the 95% confidence level are plotted along with the fitted line.

Figure 12: Partially Linear Model: Smoothed values for NO_2, O_3, NO_x, SO_2



This figure shows four graphs where each plots the series of each pollutant in logs and the smoothed values of the Partially Linear Model, using the locally weighted scatterplot smoothing (Lowess) methodology for the non-linear function of time, for four different pollutants. Graphs from the top correspond to NO_2 and O_3, and graphs from the bottom corresponds to NO_x and SO_2, as indicated on the y-axis of each graph. A red vertical line marks the start of the HNC program. Confidence Intervals to the 95% confidence level are plotted along with the fitted line.