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Abstract Ground-level ozone remains a serious problem in the United States. Because ozone non-attainment is a summer problem, episodic rather than continuous controls of ozone precursors are possible. We evaluate the costs and emissions reductions of a program that requires people to buy permits to drive on high-ozone days. We estimate the demand function for permits based on a survey of 1,300 households in the Washington, DC, metropolitan area. Assuming that all vehicle owners comply with the scheme, the permit program would reduce nitrogen oxides (NO_x) by 42 tons per Code Red day at a permit price of \$75. Allowing for non-compliance by 15 % of respondents reduces the effectiveness of the scheme to 33 tons of NO_x per day. The cost per ozone season of achieving these reductions is approximately \$9 million (2008 USD). Although year-round measures, such as the Tier II emissions standards, might be preferred on benefit-cost grounds, an episodic permit system might be considered as an interim measure before the Tier II emissions standards are fully reflected in the vehicle fleet.

Keywords Ground-level ozone · Episodic pollution control schemes · Mobile sources · Oxides of nitrogen (NO_x) · Cost per ton of NO_x removed

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1 Introduction

In spite of the progress that has been made in reducing air pollution in the United States, many areas of the country remain in non-attainment of the ground-level ozone standard. In 2010 322 of the 675 counties that monitored ozone were in violation of the standard. Violations will only increase if the ozone standard is tightened, as has been proposed by the Obama Administration.[1] Reducing ozone requires reducing oxides of nitrogen (NO_x) and volatile organic chemicals (VOCs), which combine to form ozone in the presence of sunlight. Federal regulations to reduce ozone precursors include NO_x controls on power plants and controls on motor vehicles to reduce both NO_x and VOCs. Because ozone is a seasonal problem (the peak ozone season lasts from May to October), some controls are also seasonal. For example, the NO_x Budget Trading Program and its successors are designed to reduce NO_x emissions in the summer months.[2] Requirements to sell reformulated gasoline are similarly designed to reduce VOC emissions in the summer months (Auffhammer and Kellogg 2009).

This paper takes seasonal controls one step further—suggesting the use of episodic controls of ozone precursors. Because the ozone standard is likely to be exceeded on hot, sunny days during the summer, it may be cheaper to reduce ozone precursors at times when they are likely to cause ozone peaks, rather than controlling them uniformly throughout the ozone season. Martin et al. (2007) propose that this could be done for power plants through a NO_x trading scheme. We examine a similar permit scheme for motor vehicles.

One form that episodic controls might take is to reduce driving on summer days when ozone levels are predicted to be high. Motor vehicles are estimated to account for 56 % of NO_x and 45 % of VOC emissions nationwide (U.S. EPA 2003). In addition, the environmental-engineering literature suggests that controls on mobile sources could be more effective than controls on stationary sources for certain areas. Episodic automobile emissions—control programs do exist in some areas. Previous research, however, has documented these programs' lack of success in keeping vehicles off the road on high-ozone days because the programs are all implemented on a voluntary basis.

The purpose of this study is to examine the cost-effectiveness of an episodic control scheme that would require people to purchase a permit in order to drive on a high-ozone day. On-road vehicles failing to display the permit would be subject to a fine. Such a scheme is expected to be more effective than voluntary schemes because it incorporates an incentive for people to restrict driving on high-ozone days. It also might be cheaper than schemes requiring installation of additional capital equipment on vehicles or power plants.

Due to the nature of ozone transport, the success of the scheme we are suggesting would likely require that it be implemented regionally, in multiple cities. The fact that ozone plumes travel hundreds of kilometers has made ozone control a regional issue; hence any form of episodic control would require regional coordination. It would also require the ability to forecast meteorological conditions conducive to ozone formation, and the impact of reductions in precursors in various locations on ozone formation (Mauzerall et al. 2005).

We view our study as a pilot that tests the cost of restrictions on driving in one metropolitan area—Washington, DC.[3] To measure the cost of this driving scheme we estimate the permit

[1] "E.P.A. Seeks Stricter Rules to Curb Smog". *New York Times*. January 8, 2010.

[2] See http://www.epa.gov/airmarkets/progsregs/nox/index.html.

[3] Between 2001 and 2009 the ozone standard was violated in Washington, DC an average of 16.7 days per year.

demand curve based on a survey of more than 1,300 Washington-area commuters. The survey asked each respondent whether he would purchase a permit to drive on high-ozone days, for each vehicle owned, at a stated price. The permit price was varied among respondents to trace out the demand curve for permits. We use the responses to this question to determine the cost associated with a given emissions-reduction requirement, forecast what types of vehicles will be taken off the road, and assess the cost-effectiveness of the scheme (i.e., the cost per ton of emissions reduced).

We find that, at a permit price of $75 per ozone season, 48 % of cars would be covered by permits; at a permit price of $150, 40 % of cars would be covered. Allowing for stated non-compliance we estimate that, at a permit price of $75, approximately 1 million cars would not be driven on a high-ozone day. This would reduce NOx emissions by approximately 33 tons per day. It would also yield benefits in terms of reduced congestion and, possibly, fewer road traffic accidents.

How does our scheme compare to the cost of conventional controls of ozone precursors? Fowlie et al. (2008) estimate a marginal cost per ton of NOx removed of $900 under the Tier II Emissions Standards. This is the cost of NOx emissions reductions that sum to one ton over the course of a year, implying that it would cost 365 × $900 = $328,500 to reduce NOx emissions by one ton *every* day of the year. To reduce NOx emissions by 33 tons every day would cost 33 × 365 × $900 = $10,840,500. Reducing NOx emissions by 33 tons per day on high ozone days via conventional controls is thus close to the cost of the episodic program ($9,000,000). The Tier II standards would, of course, reduce emissions by 33 tons every day, thus yielding much greater benefits than the episodic control program. We are not suggesting abandoning the Tier II emissions standards. It will, however, take time before these standards are fully reflected in the vehicle fleet. In the interim, episodic controls may be worth considering as a means of meeting the ozone standard. A serious consideration of the program would require dealing with implementation and enforcement issues, which are discussed below.

The remainder of the paper is organized as follows. Section 2 describes the nature of ozone regulations in the United States, briefly reviews the literature on episodic pollution controls, and describes our general approach. Section 3 describes our study design and sampling frame. We describe the characteristics of our sample households and the vehicles they own in Sect. 4, which also presents raw data on permit demand. In Sect. 5, we present econometric estimates of permit demand and calculate the cost and effectiveness of the program. Section 6 concludes.

2 Regulatory Context and Literature Review

2.1 Ozone Formation and Control

Colorless and odorless, ground-level ozone is a key component of urban smog and has deleterious effects on human health (U.S. EPA 2003). It can cause severe damage to lung tissue, reduce lung function, and sensitize lungs to other irritants. Individuals who engage in outdoor physical activity (such as children) or persons who have preexisting respiratory diseases are at greater risk from exposure to ozone. In addition to the adverse effects on human health, ozone reduces agricultural and commercial forest yields and increases tree and plant susceptibility to disease, pests, and other environmental stresses.

Ozone is formed when nitrogen oxides (NO_x) interact with reactive volatile compounds (VOCs) in the presence of sunlight and under certain atmospheric conditions. NO_x are by-products of combustion, and their primary sources are power plants and vehicles (cars and trucks). Important sources of VOCs are industrial plants and vehicles. According to U.S. EPA's National Air Quality and Emissions Trends reports, many major U.S. cities, and certainly most of the East coast, are NO_x-limited: In these areas, reducing NO_x will decrease ozone formation to an extent that depends on sunlight, temperature, and other conditions.[4]

Ozone is one of six air pollutants for which the U.S. EPA sets National Ambient Air Quality Standards. EPA first introduced an ambient ozone standard in 1979 by setting a daily maximum 1-h average ozone level. Studies later found that adverse health effects occur at levels lower than the 1979 standard and that exposure times longer than 1 h are also of concern. In July 1997, EPA proposed replacing the 1-h primary ozone standard with a new 8-h standard to better protect the public from ozone. Attainment of the standard requires the 3-year average of the annual 4th-highest daily maximum 8-h concentrations be less than or equal to the standard. The 8-h standard was set at 0.08 ppm in 1997 and revised to 0.075 in 2008. The EPA is currently considering whether this standard should be further tightened.

To battle the urban ozone problem, federal and state governments have adopted a variety of strategies, such as reducing NO_x emissions from power plants and industrial combustion sources; requiring the use of cleaner fuels, including reformulated gasoline; improving transit systems; and implementing vehicle inspection programs. Historically, policymakers have relied on both regulatory approaches (e.g., the Tier II emissions standards) and cap-and-trade programs for attaining reductions in NO_x emissions in the Eastern states. Despite these efforts, many regions—particularly major cities—still fail to meet the ozone standard. One explanation lies in the dramatic increase in the number of cars on the road and the miles they travel.

2.2 Episodic Pollution Controls

The episodic nature of ozone formation, its rapid dissipation (once formed, ozone lasts only 2–3 days) and the definition of the ozone standard favor control measures that focus on high ozone days. Economists have demonstrated that in theory, abating pollution only when pollution episodes are forecast is more economically efficient than undertaking continuous abatement (e.g., Teller 1967; Krupnick 1988). Despite these results and the seasonal nature of many current ozone policies, relatively few studies have empirically examined the effectiveness and cost-effectiveness of episodic programs. Krupnick and Farrell (1996) argue in favor of episodic controls, combined with ozone forecasts in advance of high-ozone events. Martin et al. (2007) focus on electricity generating plants and the cap-and-trade system in the Northeast, and show that with ozone forecasts and sufficient dispatch flexibility in the system, it is possible for power plants to reduce NOx emissions at the time when such emissions are most needed (during high ozone events) and without compromising service (high ozone events are usually on hot summer days, when the demand for electricity is extremely high).

Lutter (1999) examines the issue of cost-effectiveness of permanent v. intermittent controls, noting that the cost of reducing precursor emissions through conventional measures is very high, when correctly calculated. For example, if the cost of reducing one ton of NO_x over the course of a year through year-round control measures is $2,000, this is equivalent

[4] Other areas are VOC-limited, i.e., characterized by high concentrations of NOx and relatively low concentrations of VOCs. VOC-limited areas will benefit from a disproportionate reduction in VOCs (Heuss et al. 2003).

to an annual cost of \$730,000 to reduce NO_x by one ton each day, as would be required to reduce NO_x by one ton per day during the ozone season.[5]

Local governments have implemented episodic emissions-control programs targeting mobile sources in a number of regions, including Northern and Southern California, Atlanta, and the Baltimore/Washington metropolitan areas. However, the voluntary nature of these programs raises concerns about their effectiveness. Henry and Gordon (2003) and Cummings and Walker (2000), using survey data and traffic counts data, respectively, examine whether people drive less in the Atlanta Metropolitan Area on expected high-ozone days. Neither study provides convincing evidence that the program effectively reduces driving. Jiang (2009) shows that traffic in the Baltimore area failed to decline as a result of ozone alerts. Cutter and Neidell (2009) study how people respond to high-ozone alerts in the San Francisco Bay Area. They find that "Spare the Air" announcements reduce total daily traffic by 2.5–3.5 %, with the largest effects during and just after the morning commuting periods, but have a negligible effect on subway ridership. The authors conclude that voluntary programs of this kind are unlikely to result in a large improvement in air quality.

Existing evidence demonstrating the ineffectiveness of voluntary programs suggests the need for a program that provides sufficient incentives for people to forgo driving. One possibility would be to ban driving by all or most vehicles on high ozone days. An alternate scheme used in several cities to control pollution is to ban driving by *some* vehicles every day of the year. The latter approach is used in Mexico City and Beijing, which ban driving by a portion of vehicles every day based on the last digit of the vehicle's license plate.[6] A permit scheme would, however, be more efficient, as people who value driving privileges highly will buy a permit and those who are less inconvenienced will not.

Compliance with a permit scheme—or with a driving ban—clearly depends on the level of enforcement. Davis (2008) notes that compliance with the Day without a Car program in Mexico City is "near universal" due to high levels of enforcement and large fines. Viard and Fu (2012) also report high levels of compliance in Beijing, a city with 5,000 traffic policemen and a fine that involves significant time and money costs. In both cities violators are easy to spot because driving bans are based on the vehicle's license plate number. Assuring high levels of compliance with an episodic permit scheme would require vehicles to display a permit that is easily observable and would require devoting resources to enforcement.[7] It would also require significant fines. We discuss compliance problems more thoroughly in Sect. 6.

Before an episodic scheme is considered seriously, it is, however, important to investigate its cost-effectiveness, conditional on assumptions about compliance. The total emissions reductions and the cost of reducing ozone through a permit scheme depend on the shape of the demand function for permits. At the margin, the permit price should equal the value of driving forgone. The demand function for permits thus represents the marginal value of not driving. For a given supply of permits, the cost of reducing ozone precursor emissions can be

[5] When attention is restricted to the benefits of ozone control measures, it is clear that the health and non-health benefits must be larger when measures are permanent. An important question is how much larger those benefits are relative to those made possible by episodic controls, and how expensive these additional benefits are. We discuss this issue in Sect. 6 below.

[6] The Hoy No Circula program, begun in 1989 to reduce pollution in the winter, has been in effect year-round since 1990. It bans 20 % of cars from driving each weekday (Davis 2008). The Chinese government prohibited vehicles in Beijing from driving every other day in preparation for the 2008 Olympics, but replaced this with a one-day-per-week restriction in October of 2008 (Viard and Fu 2012).

[7] As a referee pointed out, enforcement is more difficult for an episodic scheme than for a regular one. One possibility would be electronic checkpoints throughtout the area that would detect whether a car has a permit and take a picture of its license plate if it odes not.

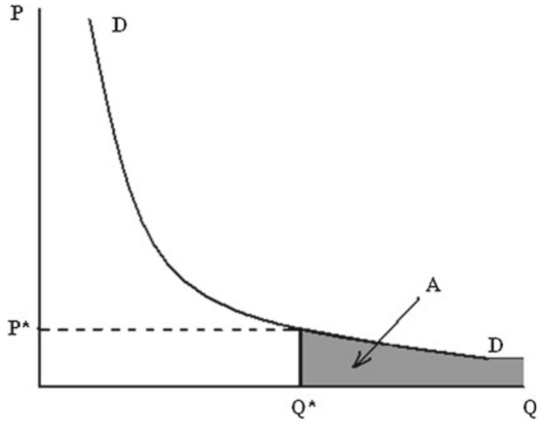

Fig. 1 Demand for permits and the total cost of the scheme. Note: the cost of a scheme in which permit price = P* and emissions = Q* is the *shaded area* A

approximately calculated as the area under the permit demand curve to the right of quantity of permits purchased (area A in Fig. 1). To determine the emissions reductions associated with this cost, one must know the characteristics and annual mileage of vehicles for which permits would be bought at that price.

In this paper, we survey residents of the Washington, DC, metro area, asking them whether they would buy permits at a given price in the presence of a no-driving scheme. The price of the permit is varied across respondents. We use the responses to these hypothetical questions to trace out the demand for permits, compute how many vehicles would stay off the road on a high-ozone day, and calculate the cost to the vehicle owner/driver.

3 Study Design

The data used to evaluate an episodic ozone control program for the Washington metropolitan area come from a survey of 1,312 area commuters conducted in January–March 2008 by Abt SRBI International. In this section, we briefly describe the questionnaire and its administration and our sampling frame.

3.1 The Questionnaire

The survey instrument collected information on household demographics, vehicle ownership and usage, and willingness to pay for a permit to drive on high ozone days. We developed the first draft of the questionnaire following the framework of the Nationwide Personal Transportation Survey, with an added section regarding local air quality and the hypothetical permit program. Thereafter, the questionnaire was subject to multiple revisions through focus groups and one-on-one in-depth interviews (see Appendix 1).

The final questionnaire consisted of five sections. The beginning section asked screening questions to identify a valid respondent: a household head (or the spouse of a household head) 18 or older who had a valid driver's license, drove at least a few days a month, and was a member of a household that owned at least one vehicle.[8] It also collected basic information

[8] Our sampling plan required an even number of men and women; hence the respondent could be either the head of household or the spouse of the head of household.

on the number of household members and number, make, and model year of vehicles the household owned.

The second section surveyed each vehicle owned by the household in detail, up to a maximum of three vehicles. For households owning more than three vehicles we asked about the three vehicles driven most often.[9] For each vehicle, we collected information on type, fuel type, mileage, miles driven within the past 12 months or since being purchased, and the primary purpose for which the vehicle is driven. Depending on the main use of the vehicle, we asked about the average number of days it was driven for this purpose each week, one-way distance driven, presence of a second passenger, and the destination to which it was driven (city or zip code). The respondent was also asked to name the household member who primarily drives the vehicle and provide information on his or her relationship to the respondent, employment situation, ability to work from home, and difficulty of substituting public transportation for driving.

The third section briefly asked about the respondent's perceptions of local air quality, his perceived impact of air pollution on household members' health, his familiarity with smog alerts (Code Red warnings), and his estimation of the number of Code Red days in 2007.[10]

The fourth section began by describing air pollution in the Washington area, its adverse effect on health, and the predictability of bad air quality days. Before describing the permit program, the interviewer stated, "One way to reduce air pollution on these days is to ban the use of personal vehicles, except in emergencies. This would reduce harmful emissions". Then, the respondent was asked how he would get around if driving were banned on a bad air-quality day. In particular, he was asked how likely he would be to work (stay) at home, take public transportation, take a taxicab, bicycle/walk, or drive anyway.

The interviewer then introduced the permit program: "Now, suppose the government were to issue a limited number of permits to allow people to drive on bad air-quality days. These permits would be for sale in April and would allow people to drive on all bad air-quality days during the summer. People found driving without a permit on a bad air-quality day would be issued a ticket. This would result in a fine and points on their driver's license. The revenues from selling permits and from fines would be used to improve public transportation in order to reduce harmful emissions. … If you bought a permit you would receive a decal to display on your windshield. The decal could not be transferred from one car to another. …" The respondent was also informed that "Although the total number of bad air-quality days that will occur is not known when the decal is purchased, we do have some information about previous years. The average number of bad air-quality days for the past five years has been 14 days per year".

A permit price was presented to the respondent, who was asked whether he would purchase a permit at this price for each vehicle owned.[11] The permit price was randomly selected from six candidate prices ranging from \$75 to \$1,000.[12] The interviewer asked people who would not buy any permits why and how likely they would be to do the following on the bad air-quality days: work (stay) at home, carpool with someone who had purchased a permit, take public transportation or a taxicab, bicycle/walk, or drive without a permit. We also asked

[9] About 7 % of households in the final sample owned more than three vehicles and were therefore affected by this rule.

[10] Code Red days are days that are forecast to be high-ozone days.The hypothetical permit scheme would require a vehicle to have a permit in order to be driven on a Code Red day.

[11] An actual permit scheme would be more acceptable if it allowed permits to be transferred from one vehicle to another. We imposed this restriction to more easily measure the emissions reductions associated with the program.

[12] See Table 7 for the exact amounts.

Table 1 Survey households and households owning vehicles in the 2000 Census by Washington metropolitan area jurisdiction

District/county/city	Survey		Regional % of households with vehicle(s) in 2000 Census
	Frequency	(%)	
District of Columbia	143	10.90	10.57
Calvert County, MD	21	1.60	1.65
Charles County, MD	32	2.44	2.66
Frederick County, MD	49	3.73	4.48
Montgomery County, MD	260	19.82	20.16
Prince George's County, MD	234	17.84	17.25
Arlington County, VA	70	5.34	5.09
Fairfax County, VA	313	23.86	22.63
Loudoun County, VA	56	4.27	3.92
Prince William County, VA	82	6.25	6.13
Alexandria City, VA	0	0.00	3.70
Fairfax City, VA	50	3.81	0.52
Falls Church City, VA	1	0.08	0.28
Manassas City, VA	1	0.08	0.75
Manassas Park City, VA	0	0	0.21
Total	1, 312	100	100

how likely the driver of one vehicle not covered by the permit would be to choose each of these options on bad air-quality days.

The last section collected information about household demographic and housing characteristics, income, residence location, as well as the proximity of household to various public transportation facilities.

3.2 Survey Administration and Sampling Frame

Abt SRBI conducted pretests and implemented the survey (see Appendix 1) via telephone. The survey began on January 29, 2008, and finished on March 9, 2008, with 1,203 completed households.[13] Since 109 of the second round of 180 pretests (see Appendix 1) shared the same survey instrument as the final survey, we pooled them with the final survey sample to enlarge the sample size to 1,312 usable interviews.

To better capture the geographical distribution of vehicle ownership in the survey, we designed a simple sampling framework in combination with random-digit dialing. Using 2000 Census micro data,[14] we calculated the share of each county-level jurisdiction within the survey region in terms of number of households owning at least one vehicle. The survey sample was required to mimic this distribution. Table 1 reports the distribution of the pooled sample across jurisdictions and the corresponding shares obtained from the 2000 Census.

[13] The response rate, defined as completes plus screen-outs divided by all eligible phone numbers called, and the cooperation rate, defined as completes plus screen-outs divided by eligible households excluding non-contact and unknown households, are 0.159 and 0.331, respectively.

[14] This is the latest data set available that allows us to do the calculation. It is plausible to think that the distribution has not changed dramatically since 2000.

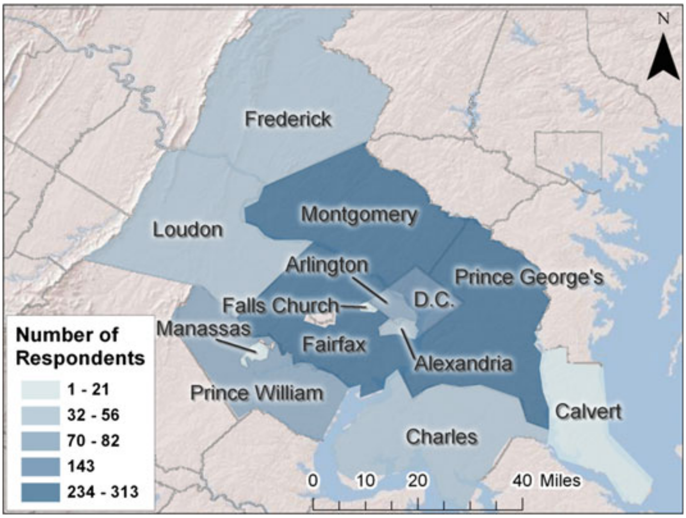

Fig. 2 Locations of survey respondents by county

It shows that implementation of the sampling framework was quite successful. The biggest gap occurred in Fairfax County, VA, where about 16 households were oversampled. Figure 2 maps the locations of these respondents.

4 Household and Vehicle Data

4.1 Characteristics of Sample Households and Their Vehicles

Table 2 describes the characteristics of our 1,312 survey respondents. The target population was heads of household over 18 years old who drive to work and own at least one vehicle. Respondents ranged in age from 18 to 91, with an average age of 49. Fifty-three percent of respondents were female. Sixty-five percent of respondents were white, 20 % black, and 6 % Hispanic.[15]

The economic and educational status of respondents reflects the fact that Washington, DC is an affluent metropolitan area. Eighty-one percent of respondents owned their own homes. Respondents were highly educated: 65 % had a bachelor's degree or better, and 32 % had a graduate degree. Twenty-one percent of respondents refused to disclose their household income. Of those who did report this information, 63 % had household incomes of $80,000 or higher and 26 % had incomes of $150,000 or higher. Thirty-eight percent of households owned one vehicle, 41 % two vehicles, 14 % three vehicles, and 7 % four or more vehicles. Vehicle ownership by our households matches closely data from the 2006 American Community Survey.

Tables 3 and 4 describe the characteristics of vehicles owned by the households in our sample. Sixty-one percent of the vehicles owned by households are cars; 37 % are SUVs or other light-duty trucks. Twenty-seven percent of vehicles are model year 2005 or more recent; 61 % are 2001 or more recent. Average annual miles driven (11,900 per year) correspond

[15] The questionnaire was administered in Spanish as well as English.

Table 2 Descriptive statistics of survey respondents

Variable	Number	Proportion (%)			
Gender ($n = 1{,}312$)					
Women	701	53.4			
Men	611	46.6			
Race or ethnicity ($n = 1{,}312$)					
White	847	64.6			
Black	368	20.4			
Asian, Native Hawaiian or Pacific Islander	56	4.1			
Hispanic	78	5.9			
Highest level of education ($n = 1{,}291$)					
High school or less	151	11.7			
Some college	190	14.7			
Associate's degree	117	9.1			
Bachelor's degree	326	25.3			
Some graduate school	89	6.9			
Graduate degree	418	32.4			
Household annual income ($n = 1{,}042$)					
<20 k	25	2.4			
20–40 k	86	8.3			
40–60 k	147	14.1			
60–80 k	131	12.6			
80–100 k	152	14.6			
100–150 k	226	21.7			
150–200 k	135	13.0			
>200 k	140	13.4			
Variable	Number	Mean	SD	Min.	Max.
Respondent age	1, 240	49	14.7	18	91
Household size (number of people)	1, 285	2.65	1.52	1	11
Number of children age 7–17	1, 286	0.48	0.88	0	5
Number of children age 6 and under	1, 286	0.28	0.64	0	4
Number of employed persons	1, 268	1.55	0.86	0	5
Number of drivers	1, 289	1.95	0.80	0	5
Number of vehicles	1, 312	1.95	1.02	1	10
Estimated code Red days per year	894	11.7	12.7	1	100

SD standard deviation

closely to the national average. More than half of the vehicles (54 %) are used primarily for commuting to work, 22 % primarily for running errands, 5 % to go to school, and 5 % to drive to public transportation. Table 4 describes the joint distribution of miles driven and vintage. On average, newer cars are driven more miles than older cars.

Table 5 describes the VOC and NO_x emissions of the vehicles in our sample. Vehicle emissions of the common air pollutants (in grams per mile) depend, among other factors, on the type of vehicle (car, truck, motorcycle), fuel used (gasoline or diesel), and model year. We have matched emissions factors (grams/mile) for NO_x, VOCs, carbon monoxide,

Table 3 Descriptive statistics of the vehicles

Description of variable	Number	Mean	SD	Minimum	Maximum
Vehicle model year	2,207	2001	5.2	1953	2008
Odometer reading (in 10,000 miles)	2,052	7.48	7.20	0.0001	98
Miles driven in last 12 months (in 10,000 miles)	1,970	1.19	1.25	0.0001	12
Average days per week car driven for primary purpose	2,173	4.52	1.54	1	7
Description of variable	**Number**	**Proportion (%)**			
Purpose for which vehicle is primarily driven					
To work	2,233	54.1			
To public transportation	2,233	4.5			
To school	2,233	4.6			
For work (plumber, carpenter, etc.)	2,233	2.8			
For errands	2,233	22.7			
For recreation	2,233	6.4			
Vehicle type					
Cars	2,233	61.0			
SUVs, trucks, and vans	2,233	36.9			

Table 4 Mileage by model year, number of observations (percentage of all vehicles)

Annual mileage	Vehicle model year					
	Before 1986	1986–1993	1994–2000	2001–2004	2005–2008	All years
<5,000	13(0.7)	57(2.9)	211 (10.8)	158 (8.1)	109 (5.6)	548 (28.0)
5,001–10,000	5(0.3)	35(1.8)	192 (9.8)	217 (11.1)	160 (8.2)	609 (31.2)
10,001–15,000	2(0.1)	15(0.8)	115 (5.9)	172 (8.8)	122 (6.2)	426 (21.8)
>15,000	3(0.2)	9(0.5)	96 (4.9)	123 (6.3)	141 (7.2)	372 (19.0)
Any mileage	23(1.2)	116(5.9)	614 (31.4)	670 (34.3)	532 (27.2)	1,955[a] (100.0)

[a] 283 observations were excluded because data on annual mileage or model year were missing (11 observations were missing both values)

Table 5 Estimated annual volatile organic compound (VOC) and nitrogen oxide (NO_x) emissions by vehicle model year

Model year	VOCs (kilograms, n = 1,860)			NO_x (kilograms, n = 1,860)		
	Mean	SD	Frequency	Mean	SD	Frequency
Before 1986	N/A			N/A		
1986–1993	47.7	67.7	113	20.6	28.0	113
1994–2000	19.0	27.5	602	16.5	18.8	602
2001–2004	5.3	5.5	651	7.5	7.5	651
2005–2008	2.9	2.9	494	2.7	2.9	494

Table 6 Permits purchased by price

Permit price ($)	75	100	150	300	500	1,000
Number of vehicles	384	361	376	389	348	375
Number of permits purchased	183	159	151	129	84	60
Percent vehicles covered by permits	47.66	44.04	40.16	33.16	24.14	16.00

and particulate matter from Mobile 6 (Davisdon 2009) to the vehicles in our dataset based on these criteria. Emissions factors are estimates for the year 2010 and cover model years 1986–2008. Multiplying each vehicle's emissions by miles driven provides an estimate of total emissions per vehicle per year. Although miles driven are higher for more recent model years, these cars are also cleaner. As a result, the average grams of pollutant emitted per year increases with vehicle vintage. For example, the average VOCs emitted by vehicles in the 1986–1993 vintage category are 16 times the emissions of vehicles in the 2005–2008 vintage category.

4.2 Scenario Acceptance and Raw Data on Permit Purchases

Table 6 presents raw data on permit purchases, as a function of permit price. Only 5 out of 1,312 respondents refused to answer the permit-demand question, while 48 were uncertain whether they would purchase a permit. We have coded both "Don't Know" and "Refused" as not buying a permit. The percent of cars for which a permit is purchased declines monotonically as a function of permit price: 48 % of vehicles are covered by a permit at a price of $75, falling to 16 % at a price of $1,000.

We asked respondents who stated they would not purchase a permit why they would not and found that 14.4 % of households objected to the permit scheme on principle. Four percent of respondents objected to the government interfering with their right to drive; 2 % objected to the program as another form of taxation. Some respondents believed that the program favored the rich (about 2 %), while 2 % believed that it was inappropriate to sell the right to drive. We also asked respondents what they would do on a Code Red day if they did not have a permit. Approximately 15 % of respondents said they would be "very likely" or "somewhat likely" to drive anyway. We term these individuals non-compliant.[16]

Who are people who would not comply with the permit scheme? Table 12 in Appendix 2 presents estimates of a probit model to explain non-compliant respondents. Briefly, (stated) non-compliance is more likely among those respondents who live far away from public transportation and among persons with less than a graduate degree or some graduate education (the omitted education category). The latter effect is more pronounced for respondents some college than for college graduates, which may reflect less flexibility in the respondent's work schedule. Income, race, and ethnicity do not matter, and even the price of a permit is only weakly associated with (stated) non-compliance.

In the next section we first estimate permit demand based on all respondents, including non-compliers. These results are used to evaluate the cost-effectiveness of the scheme assuming full compliance. (In this scenario the non-compliant buy no permits and are assumed to stay off the road on high-ozone days.) We then estimate permit demand, eliminating people who say they would not comply with the permit scheme. If the permit scheme does not apply to those respondents who would not buy a permit and continue driving without a permit (15 %

[16] Only 40 % of people who made verbal statements about the program said they would drive without a permit. We believe that the latter statement is the appropriate measure of non-compliance.

of the total respondents, or 16 % of the vehicles covered by our survey), then it would be possible to attain emissions reductions only from the remainder of the vehicle fleet (84 % of the vehicles).

5 Econometric Estimates of Permit Demand

5.1 Econometric Model

We posit that an individual will buy a permit for vehicle j at the stated price if the utility of driving that vehicle on a Code Red day is greater that the utility of not driving it, even though the permit costs money. Formally, the individual will buy the permit for vehicle j if

$$U(\text{driving}, y - P) > U(\text{not driving}, y), \tag{1}$$

where y is income and P permit price. This is equivalent to stating that the individual buys the permit if his or her willingness to pay for it is greater than the price of the permit. The probability of purchasing a permit for vehicle j is thus:

$$\Pr(Permit_{ij}) = \Pr(WTP^*_{ij} > P_{ij}), \tag{2}$$

where i denotes the individual and WTP* is the unobserved willingness to pay for a permit.

We further assume that $WTP^*_{ij} = \exp(\mathbf{x}_i \boldsymbol{\beta} + \mathbf{z}_{ij} \boldsymbol{\gamma}) \cdot \exp(\varepsilon_{ij})$, where $\mathbf{x}$ is a vector of individual or household characteristics, $\mathbf{z}$ is a vector of vehicle characteristics, and ε is an econometric error term, implying that

$$\Pr(Permit_{ij}) = \Pr(\mathbf{x}_i \boldsymbol{\beta} + \mathbf{z}_{ij} \boldsymbol{\gamma} + \varepsilon_{ij} > \ln P_{ij}). \tag{3}$$

We assume that the marginal distribution of ε is a zero-mean normal. However, we wish to allow for the possibility that unobserved factors within a household affect all permit purchase decisions for that household. In other words, $\varepsilon_{ij} = \nu_i + \eta_{ij}$, where ν is a normally distributed zero-mean variate and η is an independently and identically distributed error with mean zero and variance one. Both ν and η are uncorrelated with $\mathbf{x}$ and $\mathbf{z}$; ν and η are also independent of one another. It follows from these assumptions that the ε is correlated across the vehicles within a household (the correlation coefficient being $Var(\nu)/(1 + Var(\nu))$ but independent across households. This results in a random-effects probit model.

5.2 The Effect of Permit Price on Demand

Table 7 presents the results of random-effects probit regressions where we suppress $\mathbf{x}$ and $\mathbf{z}$, and the only regressor is the log of the permit price. Panels A–D differ only in that specific observations were excluded from the sample as indicated to check the robustness of the results.

Comparison of panel A with B implies that it is reasonable to treat a failure to answer the permit question as a "no", whereas panels C and D imply that the estimated coefficients are very stable to excluding vehicles for which we do not know the mileage or the model year. As shown in the table, the coefficient on the log of the permit price is always negative and significant, as expected, and the estimates for the different runs are extremely close to one another.[17]

[17] The samples used in runs A–D include all of the individuals who said that they would continue to drive even in the presence of a ban. We examine these effect of excluding their responses to the hypothetical permit questions in Sect. 5.5.

Table 7 Random-effects probit models of permit purchase: basic model

Variable	Sample description							
	A Entire sample, treating "Don't Know" and "Refused" as "No"		B Drop "Don't Know" and "Refused"		C Further drop observations with unknown vintage or mileage		D Treat "Don't Know" and "Refused" as "No," drop observa tions with unknown vintage or mileage	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	1.8183	0.236	1.8503	0.236	1.9032	0.249	1.8737	0.248
Log (permit price)	−0.4254	0.044	−0.4224	0.044	−0.4288	0.047	−0.4308	0.047
Number	2,233	–	2,153	–	1,895	–	1,955	–
Log (L)	−1,353.29	–	−1,322.65	–	−1,170.14	–	−1,194.1	–

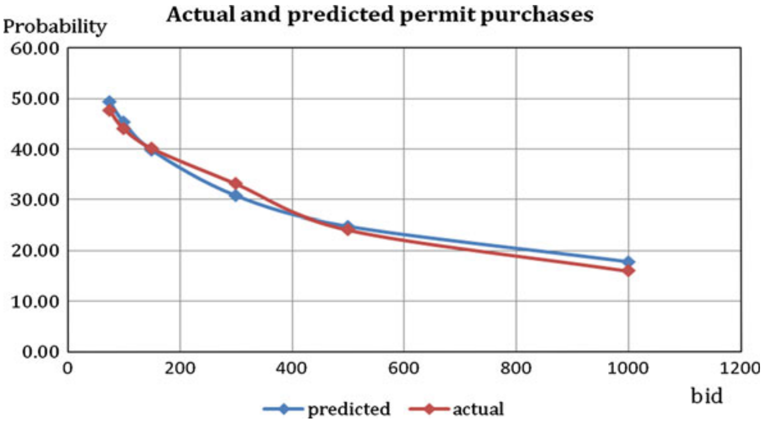

Fig. 3 Actual and predicted probability of purchasing a permit

As shown in Fig. 3, which is based on run A, the model does a very good job of predicting the actual relative frequencies of the purchases at any given permit price. Figure 3 also confirms that it is appropriate to enter the log of the permit price (as opposed to the price) in the probit model.[18]

5.3 The Impact of Vehicle and Household Characteristics on Permit Demand

Economic theory suggests that the higher the cost of not driving a vehicle, the greater the chance that the respondent will buy a permit at the stated price. Individuals should be more likely to buy permits for vehicles that they drive more frequently, account for a larger share of the miles driven by the household, and are used primarily for commuting or as part of someone's job, or when there are few or no public transportation alternatives. We also believe that individuals with heavy family demands, and especially those with small children, will

[18] If price is entered linearly, the model predicts that at the price of \$1, permits would be bought for only 46.90 % of the vehicles. Predicted probabilities of purchasing the permits are flatter with respect to price than their counterparts from the log price model.

find it more difficult to substitute an alternative mode of transportation for driving and will therefore be more likely to purchase a permit.

Based on these considerations, we fit several specifications of the random-effects probit models.[19] We report specifications that include vehicle characteristics (miles driven, vintage, type of vehicle, and driving purpose) in Table 8. Specifications that check whether individual or household characteristics influence the decision to purchase a permit are displayed in Table 9. Table 8 shows that, given the price, the likelihood of buying a permit increases monotonically with the number of miles a vehicle is driven each year (conditional on knowing mileage). This effect is strong and robust across specifications.[20]

The effect of the model year is more difficult to interpret. Respondents are more likely to buy permits if their vehicles belong to any one of the four indicated vintage categories (1986–1993, 1994–2000, 2001–2004, and 2005–2008) than to the reference group (pre-1986). The point estimates of the coefficients on the dummy variables for these vintage categories are large, but statistically insignificant at the conventional levels, and suggest a non-monotonic relationship between the age of the vehicle and the probability of a permit purchase. The larger the share of the total driving within the household that is accounted for by this particular vehicle, the more likely is the respondent to purchase a permit for this vehicle. The coefficient on this variable is large (about 0.60) and strongly statistically significant, with p-values on the order of 10^{-5} or smaller.

To get a sense of the magnitude of the above effects, we created four hypothetical vehicle "profiles". Profiles 1 and 2 are vehicles driven less than 10,000 miles a year, with model years in the 1986–1993 and 1994–2000 categories, respectively. Profiles 3 and 4 are vehicles driven more than 15,000 miles a year that belong to the 2001–2004 and 2005–2008 model year categories, respectively. In each case, we assume that the vehicle accounts for 61 % of the total miles driven within the household (the sample average). Under these assumptions, if we set the permit price at $100, the predicted probability of purchasing a permit is 31.8 % for profile 1 and 42.4 % for profile 2—a large increase. At higher miles driven, and with a newer vehicle, the likelihood of purchasing the permit at the same price is 59.6 % for profile 3, and 56.3 % for profile 4.[21]

Specifications B–D show that ease of access to public transportation and the specific type of vehicle (whether it is a car, a pickup truck, a van, or a sport utility vehicle) do not have a statistically significant impact on the decision to purchase a permit. We measure the impact of public transportation in two ways. One is to ask how easy it would be for the main driver of each vehicle to use public transportation rather than drive the vehicle. For 13 % of the drivers, it would be "very easy"; for 26 %, either "very easy" or "somewhat easy". The second is to ask how far the household is from a bus stop, the Metro, or a commuter train. Approximately 70 % of households are within a mile of a bus or Metro stop. Neither variable has a statistically significant effect on permit demand, although their coefficients

19 To preserve model comparability, all models are estimated using the set of 2,233 vehicles, with indicator variables used to capture the effects of missing data.

20 In this paper, we control for miles driven using mileage category dummies because this specification is more flexible than the others we experimented with. We also tried entering exact miles driven in a linear and quadratic fashion. We found that the latter specification fit the data better than the former, but was inferior to the model with mileage category dummies.

21 Estimating marginal effects is somewhat unwieldy when so many of the independent variables are dummies. To get a sense of the marginal effects of permit price, mileage, vintage, and share of the total household mileage driven by any given vehicle, we ran a probit model that includes log price, an exact measure of annual miles driven, a dummy to denote whether this information is missing, model year on a continuous scale, and share of total miles. At the sample means, the marginal effects are, in order, −0.1288 (standard error 0.011), 0.0000521 (standard error 8.59E−7), 0.0181 (standard error 0.0339) and 0.0000404 (standard error 0.0000492).

Table 8 Random-effects probit models of permit purchase: vehicle characteristics and driving patterns (N = 2,233)

Variable	Specification A		Specification B		Specification C		Specification D	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	0.6540	0.437	0.6746	0.441	0.3730	0.470	0.0220	0.530
Log (permit price)	−0.4498	0.047	−0.4517	0.047	−0.4623	0.049	−0.4670	0.049
12-month mileage 5,001–10,000	0.2372	0.102	0.2326	0.102	0.1641	0.106	0.1769	0.107
12-month mileage 10,001–15,000	0.5076	0.112	0.4954	0.112	0.3472	0.116	0.3625	0.117
12-month mileage > 15,000	0.6769	0.120	0.6728	0.121	0.4519	0.125	0.4656	0.126
12-month mileage unknown	0.5476	0.153	0.5646	0.153	0.4606	0.160	0.4770	0.161
Model year 1986–1993	0.2257	0.396	0.2281	0.396	0.1185	0.410	0.1574	0.413
Model year 1994–2000	0.5773	0.367	0.5863	0.368	0.4538	0.380	0.4924	0.383
Model year 2001–2004	0.6829	0.370	0.6879	0.370	0.5618	0.382	0.6049	0.386
Model year 2005–2008	0.5773	0.371	0.5839	0.371	0.4635	0.383	0.5038	0.386
Model year unknown	0.3618	0.499	0.3859	0.500	0.3327	0.518	0.4018	0.524
Vehicle share of total household 12-month mileage (%)	0.5951	0.128	0.6117	0.131	0.5966	0.135	0.5841	0.136
Easy for respondent to access public transportation			−0.0824	0.086	−0.0466	0.089	−0.0540	0.090
Accessibility to public transportation unknown			−0.1322	0.150	−0.5063	0.236	−0.4827	0.238
Respondent lives within a mile of a bus or metro stop			0.0180	0.092	0.0023	0.094	0.0016	0.095
Proximity to a bus or metro stop unknown			−0.1608	0.184	−0.1364	0.189	−0.1269	0.191
Vehicle driven primarily to work					0.8072	0.165	0.7808	0.166
Vehicle driven primarily for work					1.477	0.343	1.4331	0.345
Vehicle driven primarily to school					0.5392	0.225	0.5144	0.227
Vehicle driven primarily to public transportation stop					0.3936	0.233	0.3610	0.234
Vehicle driven primarily for errands					0.2710	0.172	0.2526	0.173
Primary vehicle purpose unknown					0.0162	0.274	0.0112	0.275
Car							0.3983	0.254
Pickup							0.3266	0.283
SUV							0.3323	0.262
Van							0.2150	0.274
Log likelihood	−1,299.83		−1,298.64		−1,263.19		−1,260.87	
Wald χ^2 statistic	152.44		153.60		179.45		179.45	

Table 9 Random-effects probit models of permit purchase: sociodemographic variables (N = 2,233)

Variable	Specification A		Specification B		Specification C	
	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic
Constant	1.4356	3.78	1.60307	4.03	1.7165	7.01
Log (permit price)	−0.4319	−9.76	−0.43232	−9.72	−0.4290	−9.72
Female	0.0116	0.16	−0.00386	−0.05	0.0062	0.08
Log (household annual income)	0.0666	0.72	0.04472	0.67		
Household income unknown	0.2262	0.72	0.09643	0.3		
Has children age 0–6	0.1316	2.31	0.14327	2.53	0.1382	2.44
Number of children age 0–6 unknown	−0.68520	−1.93	−0.67701	−1.89	−0.6419	−1.78
Black	0.4142	4.34			0.3949	4.15
Asian, Hawaiian or Pacific islander	0.2215	1.18			0.2209	1.18
Race unknown	−0.1144	−0.62			−0.1192	−0.65
Hispanic	0.1893	1.17			0.1588	0.99
Hispanic ethnicity unknown	−0.3126	−0.87			−0.2543	−0.69
Highest education level						
High school			0.23091	1.77	0.1333	1.06
Some college			−0.02453	−0.21	−0.1037	−0.89
Associate's degree			0.15662	1.14	0.0646	0.46
Bachelor's degree			0.01831	0.19	0.0016	0.02
Unknown			−0.35151	−0.98	−0.3661	−1.00
Log likelihood	−1,333.70		−1,341.985		−1,332.61	
Wald χ^2statistic	122.74		107.37		123.78	

have negative signs.[22] Model D suggests that households are no more likely to buy a permit for a car, pickup truck, van, or SUV than for a recreational vehicle or motorcycle (the omitted category).

Specifications C and D, however, suggest that use patterns matter. For example, respondents are more likely to buy a permit for vehicles that are driven to work, for work (e.g., by a plumber or carpenter), or to school—all of which are presumably regarded as non-discretionary travel.

In Table 9, we report the results of specifications that examine the effect of individual and household characteristics on the likelihood of purchasing a permit. The impact of sociodemographic variables on permit demand is clearly of interest for policy purposes; however, household income and respondent education and gender have no statistically significant effect on permit purchase. Because income affects vehicle ownership and miles driven, we estimate a set of models that exclude these variables. Income in the survey was recorded in a series of intervals. We have modeled income as a series of dummy variables and also as a continuous variable equal to the midpoint of the reported interval. Models A and B report the impact of log(income) on permit demand, controlling for gender, presence of young children in the

[22] A likelihood ratio test of the null hypothesis that all four public transportation variables have zero coefficients fail to reject the null hypothesis (P value $= 0.6708$).

household, and race. Although income is positively related to permit demand, it is never significant at the conventional levels. Models B and C add respondent education to the model. Respondents with a high school education or less appear more likely to purchase permits than respondents with a graduate degree or some graduate training (the omitted category), but this, too, is not significant at the conventional levels. Respondent gender has no effect on permit demand.

The only demographic variables that appear to affect permit demand are race and the presence of small children in the household. Blacks are significantly more likely to purchase a permit (holding income and education constant) than the omitted group (which is comprised of whites and 21 Native Americans) and a category comprising Asians, native Hawaiians and Pacific Islanders. We also find that among the respondents who did provide information about the composition of their household, those respondents who have small children are more likely to purchase a permit at any price.

5.4 Calculating the Cost and Effectiveness of the Permit Scheme

To predict the number of cars that will not be driven under the scheme and the resulting reduction in vehicle emissions, we need to know how permit demand varies with vehicle emissions. We focus here on NO_x emissions; however, we obtained similar results for VOC emissions. When permit demand is estimated as a function of annual NO_x emissions per vehicle and the log of permit price, annual NO_x emissions have no statistically significant effect on demand—either linearly or when interacted with permit price.[23] (This is also true for VOC emissions.) Although vehicle owners are more likely to purchase permits for cars that are newer and driven more, these cars are substantially cleaner than older cars that are driven fewer miles (see Table 5). Thus, from the perspective of predicting the reduction in vehicle emissions, we can ignore vehicle characteristics and focus on permit demand as a function of permit price alone.[24]

To predict the reduction in miles driven and the cost of the permit scheme, we must evaluate the probability of purchasing a permit, as a function of permit price, for prices below \$75—the lowest price offered in the survey.[25] Table 10 shows the predicted probability of purchasing a permit for a randomly chosen vehicle, as a function of price, using model A from Table 7. The aggregate demand for permits is the demand curve in Table 10 multiplied by the number of passenger vehicles in the metropolitan area. According to the National Capital Region Transportation Planning Board (2006), approximately 2.0 million passenger vehicles and 1.2 light-duty trucks were registered in the Washington Metropolitan Area as of June 1, 2005; hence, we treat the number of vehicles as 3.2 million.[26]

What is the cost of the episodic control scheme? Table 7 implies that free permits would cover virtually all vehicles. Raising permit price to \$75 would reduce the percent of vehicles

[23] The intercept from the random-effects probit regressions is 0.9542 (t statistic 1.76), the coefficient on log price is −0.3783 (t statistic −4.08), the coefficient on log total NOx emissions is 0.1088 (t statistic 1.62), that on a dummy denoting missing NOx information is −0.4335 (t statistic 1.91) and that on the interaction between total NOx emissions and price is −0.0062 (t statistic −0.54).

[24] As a referee pointed out, our permit scheme would be more efficient if permit prices varied with the number of miles traveled and the emissions per vehicle mile. We focus here on the scheme described to repondents, which faces all vehicles with a uniform price.

[25] Because demand is a function of log(permit price), the lowest price used is \$1.

[26] The exact numbers are 2,004,089 passenger vehicles and 1,180,563 light duty trucks (National Capital Region Transportation Planning Board 2006).

Table 10 Cost and emissions reductions associated with the episodic ozone control program (standard errors in parentheses)

Permit price ($)	Vehicles removed from road (%)	Vehicles removed from road per day (millions)	Cost of the program per high-ozone day (thousand $)	Tons of NO_x reduced per high-ozone day	Cost per ton of NO_x abated per day (thousand $)
75	43.9 (1.28)	1.40 (0.04)	863 (89)	42.2 (1.32)	20.5 (1.61)
100	47.9 (1.69)	1.53 (0.05)	1,324 (155)	46.0 (1.62)	28.8 (2.44)
150	53.5 (2.77)	1.71 (0.07)	2,318 (293)	51.4 (2.09)	45.1 (4.08)
300	62.5 (2.97)	2.00 (0.10)	5,477 (754)	60.0 (2.85)	91.3 (8.60)
500	68.5 (3.45)	2.19 (0.11)	9,661 (1337)	65.8 (3.31)	146.9 (12.34)
1,000	75.5 (3.89)	2.42 (0.12)	19,289 (2483)	72.5 (3.73)	266.0 (21.50)

NO_x nitrogen oxides

covered by approximately 44 %.[27] The lost consumer surplus associated with a permit price of $75 for each vehicle not driven is the shaded area in Fig. 1. This area, multiplied by the number of vehicles removed (0.44 × 3.2 million), is approximately $12 million per ozone season. Assuming 14 Code Red days per season, the welfare cost per Code Red day is approximately $863,000.[28]

How would this affect emissions? Multiplying the number of vehicles removed by average daily tailpipe emissions implies that a permit price of $75 per season would reduce emissions on a Code Red day by 42.2 tons of NO_x. This implies a cost per ton of NO_x abated of approximately $20,500 per Code Red day. Raising permit price above $75 would further reduce emissions but would significantly increase the cost per ton of NO_x reduced (see Table 10).

Of course, the episodic control scheme also would raise revenue. At a price of $75, the sale of permits would raise approximately $119 million in revenue. In addition to reducing NO_x, the scheme would have benefits in terms of reduced traffic congestion and reductions in other pollutants.

5.5 The Cost of the Scheme with Less than Full Compliance

The calculations presented in previous sections assume 100 % compliance, as is usual when examining the impact of proposed regulations. However, about 15 % of our respondents said that if the permit program were enacted, they would be "very" or "somewhat" likely to drive without a permit. In this section we examine program cost-effectiveness figures based on stated non-compliance. If the permit scheme does not apply to those respondents who would ignore the program and continue driving without a permit (15 % of the respondents, or 16 % of the vehicles in our survey), then it would be possible to attain emissions reductions only from the remainder of the vehicle fleet (84 % of the vehicles).[29]

[27] It should be noted that not all registered vehicles in the metropolitan area are driven every day. We account for this by calculating NO_x emissions based on the average miles driven per day. As a referee pointed out, reduced congestion resulting from the permit scheme could induce drivers to increase their miles driven.

[28] This ignores the revenue implications of the scheme and tax interaction effects. Permit revenues should equal approximately $119 million per season at a permit price of $75.

[29] We acknowledge that non-compliance with an actual permit program might exceed stated non-compliance in our survey. It would also depend on the level of enforcement undertaken. We return to this point in Sect. 6.

When we exclude from the sample those respondents who insisted that they would continue driving without a permit, the likelihood of purchasing a permit is higher at any given permit price. This is not surprising, since only 9.52 % of the "non-compliers" would buy a permit against 39 % of the "compliers". If the "non-compliers" value driving highly, taking their "no" responses at face value would understate the demand function and the cost of the driving ban scheme.

To illustrate, at \$75, the fraction of vehicles that would be covered by a permit is 47.66 % for the full sample and 54.21 % for the "compliant" sample.[30] At higher prices, the percentage of vehicles covered by a permit is about 4–6 percentage points higher in the compliant sample than in the full sample. Permits priced at \$1,000 would cover 18.03 % of the compliant respondents' vehicles, compared to 16 % for the full sample.[31] We note, for the purpose of calculating emission reductions, that excluding the non-compliant respondents leaves the average annual emissions of NO_x (and VOCs) virtually unchanged.

A random-effects probit model of the responses from the compliant owners confirms that at any given price, the likelihood of purchasing a permit is greater than for the full sample. The slope of the demand function with respect to permit price, however, is similar.[32] When we include driving patterns and characteristics of the vehicle in the random-effects probit models, the results (displayed in Appendix 2, Table 14) are, for the most part, similar to those of the models for the full sample in Table 8. The decision to purchase a permit appears to depend in virtually the same fashion on log permit price and miles driven but is somewhat less strongly associated with the model year of the vehicle. One difference between the two sets of results is the impact of vehicle type: cars and pickup trucks are more likely to be covered by a permit in the compliant sample than in the full sample.

The impacts of sociodemographic variables on permit purchase (displayed in Appendix 2, Table 13 for the non-compliant sample) are similar for the two samples: income has no statistically significant impact on permit purchase, but respondents with young children are more likely to purchase a permit. Non-whites are more likely to purchase a permit than whites (our omitted race category), other things equal. One difference between the two samples is in the effect of education. In the compliant sample, respondents whose highest level of education is a high school degree (or less) are more likely to purchase a permit relative to persons with some graduate education, and the effect is significant at the 5 % level or better in specification B, and at the 10 % in A.

Using the basic random-effects probit with no covariates, we predict the number of vehicles that would not be driven under the permit scheme (out of $3{,}200{,}000 \times 0.84 = 2{,}688{,}000$ eligible vehicles), the associated emissions reductions, cost per ton of NO_x, and cost of the total emissions reductions attained per day (Table 11).

On the basis of a cost per ton of NO_x, the two programs are virtually identical. However, less than full compliance clearly limits the emissions-reduction potential of the episodic control scheme. For example, at a permit price of \$75, only 32.8 tons of NO_x would be

[30] A referee raises the question: what would people who do not buy a permit do? The drivers of cars who said they would not buy a permit were either "very" or "somewhat" likely to work or stay at home (44 %); take public transit (29 %) or ride a bicycle (24 %). We note that the maximum roundtrip fare on the Washington Metro at the time of our survey was \$4.70 (off peak) assuming no advance ticket purchase.

[31] All of these calculations are based on a random-effects probit model with intercept equal to 1.9980 (t statistic 8.15), coefficient on log price equal to −0.4290 (t statistic −9.40). The sample contains 1876 observations and the likelihood function is −1184.01.

[32] When the full sample is used, the estimated coefficients from a random-effects probit are 1.818256 (intercept) and −0.425366 (coefficient on log bid). The compliant sample results in a larger intercept (1.997979) and a virtually identical slope (−0.4290023).

Table 11 Cost and emissions reductions associated with the episodic ozone control program, based on compliant drivers (standard errors in parentheses)

Permit Price ($)	Vehicles removed from road (%)	Vehicles removed from road per day (millions)[a]	Cost of the program per high-ozone day (thousand $)	Tons of NO_x reduced per high-ozone day	Cost per ton of NO_x abated per day (thousand $)
75	40.7 (1.13)	1.09 (0.03)	648 (59)	32.8 (0.91)	19.7 (1.46)
100	44.9 (1.33)	1.21 (0.04)	1,021 (105)	36.2 (1.08)	28.2 (2.30)
150	50.8 (1.75)	1.37 (0.05)	1,850 (220)	41.0 (1.41)	45.2 (4.05)
300	60.6 (2.57)	1.63 (0.07)	4,606 (622)	48.9 (2.07)	94.3 (9.05)
500	67.2 (3.10)	1.81 (0.08)	8,404 (1157)	54.2 (2.50)	155.0 (16.62)
1,000	75.2 (3.60)	2.02 (0.10)	17,870 (2248)	60.6 (2.91)	294.7 (24.13)

NO_x nitrogen oxides
[a] Based on 84 % of all eligible vehicles

reduced each day, against the 42 tons achieved under a full-compliance scenario.[33] The total cost of the program for a 14-day ozone season would be $9.1 million. To compare this to the cost of year-round controls one must compute the cost of reducing NO_x by 33 tons every day via year-round controls. Fowlie et al. (2008) report the marginal cost of reducing one ton of NO_x per year, via the Tier II emissions standards, as $896. This implies that reducing one ton of NO_x every day costs = $896 × 365 = $307,000. The cost of reducing NO_x by 33 tons every day is approximately $10.8 million through these year-round controls.

The purpose of our cost comparison is to suggest that the episodic program, under the above assumptions, would yield emissions reductions at a reasonable cost, and might be considered as an interim program during the time it will take the Tier II emissions standards to be fully reflected in the vehicle fleet. The Tier II emissions standards have the advantage that they yield year-round benefits, which episodic controls do not. Indeed, the benefits of the Tier II emissions standards per ton of NO_x (and VOCs) reduced are substantial. Calculations based on Muller's APEEP model (2012) suggest that the average benefit per ton of pollutant reduced per year is $221 for NO_x and $2330 for VOCs in the Washington metropolitan area.[34] It will, however, take decades before, all cars in the passenger fleet meet the Tier II standards.

6 Conclusions

In spite of increasingly stringent controls on motor vehicles and power plants, many US metropolitan areas remain out of compliance with the ground level ozone standard. One possible method of achieving compliance would be to use episodic pollution controls. One form that these could take would be to require drivers to buy permits in order to drive on

[33] Standard errors for all key measures of the accomplishments of the program are based on the approach described in Krinsky and Robb (1986).

[34] These data were accessed at https://sites.google.com/site/nickmullershomepage/home/ap2-data. We weighted the ground-level damages per ton of NOx and VOCs in each jurisdiction by the weights in the last column of Table 1.

high ozone days. Due to the fact that may ozone travel outside of a metropolitan area, such a program would need to be implemented in several cities simultaneously.

The practical difficulties in implementing an episodic permit program should not be underestimated. Drivers in the United States have often failed to comply with programs that restrict their freedom to drive. In the Washington, DC metropolitan area, for example, it is estimated that 25 % of the vehicles in High Occupancy Vehicle (HOV) lanes are single-occupant vehicles, in spite of high fines associated with violating the HOV program.[35] The issue is one of enforcement—and enforcing an episodic control program is likely to be more difficult than enforcing a program, such as HOV restrictions, which operates on a regular basis. One possibility for enforcement would be for machines (similar to red-light cameras) to read a car's permit and take a picture of the license plate if no permit is detected. Enforcement costs could be financed out of permit revenues; however, an important question is how large enforcement costs would be.

The welfare cost of the vehicle permit program is approximated by the area under the demand curve for permits to the right of the quantity of permits issued (Fig. 1). We estimated this cost based on a survey of more than 1,300 Washington-area commuters conducted in 2008. Our calculations suggest that a permit price of $75 per season would remove approximately 44 % of cars and light-duty trucks from the roads on high-ozone days, assuming full compliance with the scheme, and 34 % of passenger vehicles, allowing for non-compliance. Focusing on the non-compliance scenario and assuming 14 high-ozone days in an average summer, the program would cost approximately $648,000 per day in lost consumer surplus and would result in approximately 32.8 fewer tons of NO_x emitted per day, at a cost of $19,700 per ton of NO_x removed per high-ozone day. The program would also raise approximately $111 million in revenue per ozone season, which could be used to defray administrative costs.[36] Raising permit price above $75 would increase the effectiveness of the scheme but would also raise the cost per ton of NO_x removed, due to the steepness of the demand curve for permits.

How does the cost of the episodic scheme compare with the cost of year-round controls? One way to compare the cost of the episodic program with the cost of year-round controls is to convert the cost of the episodic control scheme into the cost of an equivalent year-round scheme. If the cost of reducing a ton of NO_x over the course of a year were $760, it would cost $\$760 \times 365 = \$277{,}400$ to reduce a ton of NO_x every day. The cost of meeting an additional 32.8 ton reduction would be $9.1 million—the cost of the episodic program. So, the episodic control program is equivalent to a program of permanent controls costing $760 per ton of NO_x reduced per year.

We note that this cost compares favorably with the cost of reducing NO_x through year-round mobile source controls (Fowlie et al. 2008). This might lead one to conclude existing mobile source controls should be tightened: their cost per ton is approximately the same as the episodic control scheme, but they yield year-round benefits. What must be realized is that mobile source controls, such as the Tier II emissions standards, take years to fully penetrate the vehicle fleet.[37] In the interim, cities will continue to violate the ozone standard. A program such as the one we suggest could be used to achieve compliance in the short-to-medium term.

[35] The Washington Post reports HOV violation rates of 21–24 % on interstate highways in Northern Virginia in spite of the fact that a fourth violation carries with it $1,000 fine and three points on the owner's drivers license. http://www.washingtonpost.com/wp-dyn/content/story/2009/02/14/ST2009021401992.html?sid=ST2009021401992.

[36] In the full compliance scenario, 55 % of compliant vehicles would be covered by a permit at a price of $75.

[37] EPA's Regulatory Impact Analysis of the Tier II Emissions Standards assume that they will not be fully reflected in the vehicle fleet until 2030.

Concerns may arise about the possible regressivity of the episodic control scheme. The demand for permits is not significantly related to income and/or education, although non-whites appear to be more likely to purchase a permit. Finally, it should be noted that the scheme is progressive to the extent that people who do not own a car (who are likely to be poor) will benefit from air-quality improvements while bearing none of the scheme's costs.

7 Appendix 1: Development of the Survey Instrument

As a first step in designing the survey, the authors arranged four focus groups, comprising 38 Washington-metropolitan residents who drive to work, in Rockville, Maryland; and Vienna and McLean, Virginia. We hired a graduate student from the Joint Program in Survey Methodology of University of Maryland as moderator. The moderator prompted participants to talk about area traffic and their commuting experience, their perceptions of local air quality, and any thoughts about the permit program as described by the moderator. Open-ended questions solicited minimum and maximum willingness to pay for the permit. Consensus existed among the groups that traffic conditions are far from pleasant—and are worse in Northern Virginia than in Maryland. Many participants also linked local air quality (smog) to massive traffic.

While some people appreciated the episodic permit program, others gave frank concerns and opinions about the program. Members of the focus groups commonly raised questions regarding the cost-effectiveness and fairness of the program, the few alternatives available to driving, and use of program revenues. The discussions also touched on many details of program implementation and enforcement. For instance, would medical emergencies be exempted from the permit program? When people were presented with a choice between a decal attached to the windshield and an electronic chip installed in the car, they were inclined to choose the former, as the chip would result in an intruding, "Big Brother" effect. The majority of the stated amounts people would pay for a permit—which allows vehicle owners to drive on 14 days during ozone season (based on historical averages)—ranged from \$10 to \$500. Overall, the focus groups were highly informative and helpful in improving the questionnaire.

Edge Research Inc. then conducted one-on-one in-depth interviews to fine-tune the questionnaire. The firm recruited twelve participants, demographically representative Washington-metropolitan residents who commute by driving. A professional moderator from Edge Research led each participant through the entire questionnaire, making sure that the participant could easily understand and answer all questions. Each interview took between 45 and 60 min. After each interview, the moderator briefly discussed the participant's responses to and comments on the questionnaire with the authors, who observed the interview behind a one-way mirror. The questionnaire was then updated in real time. The in-depth interviews helped us adjust the structure of the survey instrument and make its language clearer and more accurate.

We initially intended to administer the survey to 1,500 households, divided into 300 pretest households and a formal sample of 1,200. Abt SRBI Inc. programmed the questionnaire into the CATI (Computer-Assisted Telephone Interviewing) system in early December 2007. A pretest of 120 households was carried out in the middle of December 2007. The authors listened to some of the interviews and decided to further adjust the survey, especially the section on vehicle use. Abt SRBI conducted the remaining 180 pretests between January 16 and January 24, 2008. No additional changes were found necessary. Our final sample thus consisted of 1,200 households plus 109 households in the second pretest who received the same design values for permit price as households in the final survey.

8 Appendix 2

See Tables 12, 13 and 14.

Table 12 Probit models of people protesting the permit scheme: demographic characteristics (N = 1,312)

Variable	Specification A		Specification B		Specification C	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	−2.1236	0.613	−1.9577	0.623	−2.0331	0.630
Log (permit price)	0.0883	0.047	0.0935	0.047	0.0956	0.047
Log (household income)	−0.0476	0.081	−0.0503	0.082	−0.0368	0.083
Household income unknown	0.0032	0.383	0.0100	0.385	0.0792	0.389
Respondent age	0.0340	0.018	0.0348	0.018	0.0344	0.018
Square of respondent age	−0.0004	0.000	−0.0004	0.000	−0.0004	0.000
Respondent age unknown	0.7384	0.486	0.7798	0.488	0.7371	0.495
Female	−0.0884	0.088	−0.1027	0.088	−0.1076	0.0884
Black	−0.1147	0.114	−0.0846	0.115	−0.0703	0.115
Asian, Hawaiian or Pacific Islander	−0.1941	0.242	−0.1849	0.241	−0.1936	0.241
Race unknown	−0.0201	0.205	−0.0391	0.207	−0.0421	0.208
Hispanic	−0.3012	0.206	−0.2802	0.207	−0.2676	0.208
Ethnicity unknown	−0.4752	0.467	−0.5396	0.470	−0.6541	0.491
Number of vehicles owned by household	0.0841	0.043	0.0657	0.044	0.0685	0.044
Highest education level						
High school or less	0.1694	0.150	0.1631	0.150	0.1738	0.151
Some college	0.2874	0.133	0.3022	0.133	0.3084	0.133
Associate's degree	−0.0036	0.167	−0.0243	0.168	−0.0130	0.169
Bachelor's degree	−0.1254	0.113	−0.1172	0.114	−0.1255	0.114
Level of education unknown	0.3153	0.365	0.2173	0.370	0.0668	0.387
Respondent lives within a mile of a bus or metro stop			−0.2448	0.102	−0.2476	0.102
Proximity to bus or metro stop unknown			0.0810	0.192	0.0751	0.193
Has children age 0–6					0.0071	0.074
Number of children age 0–6 unknown					0.5841	0.291
Log likelihood	−534.92		−531.46		−529.53	

Table 13 Random-effects probit models of permit purchase: sociodemographic variables, protestors removed (N = 1,876)

Variable	Specification A		Specification B		Specification C	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	1.6270	0.389	1.9775	0.253	1.9276	0.252
Log (permit price)	−0.4409	0.046	−0.4335	0.046	−0.4387	0.046
Female	−0.0225	0.076	−0.0418	0.076	−0.0324	0.076
Log (household annual income)	0.0708	0.065	0.0841	1.23		
Household income unknown	0.2600	0.318	0. 2978	0.89		
Has children age 0–6	0.1360	0.059	0.1552	0.058	0.1439	0.058
Number of children age 0–6 unknown	−0.5143	0.370	−0.5299	0.369	−0.4747	0.373
Black	0.4632	0.099			0.4180	0.098
Asian, Hawaiian or Pacific Islander	0.2403	0.198			0.2401	0.198
Race unknown	−0.0475	0.186			−0.0458	0.184
Hispanic	0.1372	0.164			0.0751	0.163
Hispanic ethnicity unknown	−0.4181	0.348			−0.3580	0.355
Highest education level						
High school			0.3052	0.131	0.2482	0.131
Some college			−0.0108	0.121	−0.0542	0.121
Associate's degree			0.1864	0.141	0.1044	0.142
Bachelor's degree			−0.0411	0.093	−0.0204	0.093
Unknown			−0.4596	0.253	−0.3590	0.372
Log likelihood	−1,164.46		−1,172.54		−1,162.00	

Table 14 Random-effects probit models of permit purchase: vehicle characteristics and driving patterns, protestors removed (N = 1,876)

Variable	Specification A		Specification B		Specification C		Specification D	
	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic
Constant	0.9436	2.09	1.0092	2.21	0.7230	1.51	0.3068	0.57
Log (permit price)	−0.4604	−9.42	−0.4635	−9.44	−0.4739	−9.46	−0.478	−9.46
12-month mileage 5,001–10,000	0.2286	2.18	0.2227	2.12	0.1532	1.43	0.1664	1.53
12-month mileage 10,001–15,000	0.5342	4.64	0.5185	4.47	0.3568	3.01	0.3663	3.06
12-month mileage > 15,000	0.7825	6.27	0.7681	6.09	0.5203	4.02	0.5250	4.02
12-month mileage unknown	0.6361	3.95	0.6587	4.05	0.5660	3.37	0.5863	3.46
Model year 1986–1993	0.1852	0.45	0.1946	0.47	0.0671	0.16	0.0835	0.2
Model year 1994–2000	0.4345	1.14	0.4502	1.18	0.2867	0.73	0.3052	0.78

Table 14 continued

Variable	Specification A		Specification B		Specification C		Specification D	
	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic
Model year 2001–2004	0.5801	1.51	0.5908	1.54	0.4280	1.09	0.4484	1.13
Model year 2005–2008	0.4964	1.29	0.5084	1.32	0.3578	0.91	0.3772	0.95
Model year unknown	0.1398	0.28	0.1704	0.34	0.0690	0.13	0.1123	0.21
Vehicle share of total household 12-month mileage (%)	0.6140	4.69	0.6424	4.77	0.6390	4.61	0.6328	4.53
Easy for respondent to access public transportation			−0.0558	−0.62	−0.0262	−0.29	−0.0273	−0.3
Accessibility to public transportation unknown			−0.1164	−0.75	−0.5382	−2.28	−0.5131	−2.16
Respondent lives within a mile of a bus or metro stop			−0.0605	−0.63	−0.0746	−0.77	−0.0680	−0.69
Proximity to bus or metro stop unknown			−0.1609	−0.84	−0.1420	−0.73	−0.1302	−0.67
Vehicle driven primarily to work					0.8480	5.09	0.8275	4.95
Vehicle driven primarily for work					0.3760	1.6	0.3420	1.45
Vehicle driven primarily to school					0.5588	2.45	0.5487	2.39
Vehicle driven primarily to public transportation stop					1.6444	4.69	1.5857	4.5
Vehicle driven primarily for errands					0.2662	1.53	0.2564	1.46
Primary vehicle purpose unknown					0.1506	0.54	0.1666	0.6
Car							0.4455	1.71
Pickup							0.2770	0.98
SUV							0.4444	1.65
Van							0.5462	1.85
Log likelihood	−1,127.05		−1,126.12		−1,088.04		−1,085.29	

References

Auffhammer M, Kellogg R (2009) Clearing the air? The effects of gasoline content regulation on air quality. CSEM Working Paper 185, University of California, Berkeley

Cummings RG, Walker MB (2000) Measuring the effectiveness of voluntary emission reduction programmes. Appl Econ 32(13):1719–1726

Cutter WB, Neidell M (2009) Voluntary information programs and environmental regulation: evidence from "Spare the Air". J Environ Econ Manag 58(3):253–265

Davis L (2008) The effect of driving restrictions on air quality in Mexico City. J Political Econ 116(1):38–81

Davisdon K (2009) Personal communication between Kenneth Davidson, Economist, USEPA, and the authors. January 13, 2009

Fowlie M, Knittel CR, Wolfram C (2008) Sacred cars? Optimal regulation of stationary and non-stationary pollution sources. NBER Working Paper 14504, Cambridge, MA

Henry GT, Gordon CS (2003) Driving less for better air: impacts of a public information campaign. J Policy Anal Manag 22(1):45–63

Heuss JM, Kahlbaum DF, Wolff GT (2003) Weekday/weekend ozone differences: what can we learn from them? J Air Waste Manag Assoc 53(7):772–788

Jiang Y (2009) Do people drive less on code Red Days? Mimeo. Asian Development Bank, Manila

Krinsky I, Robb AL (1986) On approximating the statistical properties of elasticities. Rev Econ Stat 68(4):715–719

Krupnick AJ (1988) Temporal and spatial control of ambient ozone. Discussion paper QE88-05. Resources for the Future, Washington, DC

Krupnick AJ, Farrell D (1996) Six steps to a healthier ambient ozone policy. RFF Discussion Paper 96–13, Washington, DC, March

Lutter R (1999) Is EPA's ozone standard feasible? Working paper 99–6. AEI-Brookings Joint Center for Regulatory Studies, Washington, DC

Martin KC, Joskow PL, Ellerman AD (2007) Time and location differentiated NOx control in competitive electricity markets using cap-and-trade mechanisms. CEEPR Working Paper 07-004, Center for Energy and Environmental Policy Research, Massachusetts Institute of Technology, Cambridge, April

Mauzerall DL, Sultan B, Kim N, Bradford DF (2005) NOx emissions from large point sources: variability in ozone production, resulting health damages and economic costs. Atmospheric Environ 39:2851–2866

National Capital Region Transportation Planning Board (2006) The composition of vehicle fleet in the Washington metropolitan region. MWCOG, Mimeo. Washington, DC

Teller A (1967) Air pollution abatement: economic rationality and reality. Daedalus 96(4):1082–1098

U.S. EPA (Environmental Protection Agency) (2003) Ozone: good up high, bad nearby. 451/K-03-001. EPA, Washington, DC

Viard VB, Fu S (2012) The effect of Beijing's driving restrictions on pollution and economic activity. Draft, March 2012