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How costly are driving restrictions? Contingent valuation evidence from Beijing

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ABSTRACT

A common policy response to severe air pollution and traffic congestion in developing-country megacities is to ban the driving of vehicles with license plates ending in certain numbers on certain days. We use the contingent valuation method to estimate the costs to drivers of Beijing's driving restrictions program, one of the world's largest. Our study generates three main findings. First, costs are substantial: RMB 356 to 709 (US $54 to $107) per driver per year, which represents 0.5 to 1 percent of annual income, and RMB 1.6 billion to 3.3 billion (US $247 million to $493 million) per year for all drivers. Second, comparison of our cost estimates with estimates of the benefits of Beijing's program from other studies suggests that the benefits exceed the costs. Finally, the costs per driver are significantly smaller than the costs (estimated using the same methods) of Mexico City's program, which by most accounts has had zero benefits. These findings provide some of the strongest evidence to date that driving restrictions programs can, given certain conditions, have net benefits. They also suggest that relatively high program costs are not a necessary condition for significant program benefits—in fact, the opposite may be true.

1. Introduction

The world's vehicle stock is projected to more than double between 2010 and 2030, mostly because of rapid growth in China, India and other developing countries (Sperling and Gordon, 2009). Although rapid motorization in the Global South has generated benefits, it also has had serious environmental consequences, particularly in urban areas. It has become a leading cause of air pollution, traffic congestion, and greenhouse gas emissions (Timilsina and Dulal, 2008; Pachauri and Reisinger, 2007).

An increasingly popular policy response is to ban the driving of vehicles with license plates ending in certain numbers on certain days. Typically, each car is banned one weekday per week and one Saturday per month. Three decades ago, city planners in Buenos Aires initiated the first large-scale driving restrictions program based on license plate numbers (De Grange and Troncoso, 2011). Since then, this approach has been replicated in many other developing-country megacities, including Beijing, Bogotá, Changchun, Chengdou, Delhi, La Paz, Mexico City, Medellin, Quito, São Paulo, Santiago, San José, and Tegucigalpa. Tens of millions of people now live in urban areas with driving restrictions based on license plate numbers.

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Emerging evidence on the benefits of these programs is decidedly mixed.[1] Studies of programs in Mexico City and Bogotá find that they either have had no significant effects on air pollution and congestion or have actually exacerbated these problems because drivers have adapted by shifting trips to unrestricted hours and purchasing additional cars, often old and dirty ones (Bonilla, 2019; Davis, 2008; Eskeland and Feyziouglu, 1997; Gallego et al., 2013; Zhang et al., 2017). But studies of programs in Beijing, Quito, and Santiago find some evidence for long-term benefits (Carillo et al., 2016; De Grange and Troncoso, 2011; Lu, 2016; Sun et al., 2014; Viard and Fu, 2015).

Given the mixed evidence on the *benefits* of driving restrictions programs, it is important to generate the second type of data policymakers need to decide whether to retain, replicate, and refine these programs: reliable estimates of the *costs* that these programs impose on drivers. The seemingly most straightforward strategy for estimating these costs would be to use an averting-expenditures approach—that is, to tally the pecuniary costs that households pay to adapt to driving restrictions, including costs associated with using public transportation and buying additional vehicles. But this approach has three significant drawbacks. First, it would do a poor job of estimating difficult-to-measure nonpecuniary costs—including inconvenience costs and the opportunity costs of lost time—that may well dominate pecuniary costs. For example, taking public transportation one day a week instead of driving might cause significant inconvenience and require an individual to spend several additional hours commuting and rearranging trips. An averting-expenditure approach would neglect such inconvenience costs and could provide only a coarse estimate of the opportunity costs of lost time (unless detailed household-level survey data on time allocation were collected).

Second, an averting-expenditures approach would be problematic if the strategies that households use to adapt to driving restrictions are complex, subtle, and therefore difficult to price. Anecdotal evidence suggests this is often the case, particularly when driving restrictions programs have intricate rules. For example, in Mexico City, program rules were changed to exempt relatively new vehicles in 1996. As a result, turnover of used vehicles has accelerated since 1996. An averting-expenditures approach would require estimating this acceleration and tallying its additional cost. On its face, this would be a challenging task.

Finally, an averting-expenditures approach would generate biased results if such expenditures had significant benefits independent of driving restrictions. For example, a household's purchase of an additional vehicle enables its members to drive more often than they otherwise would. This ancillary benefit would need to be valued and subtracted from the cost of the additional vehicle, an inherently difficult enterprise.

Following Blackman et al. (2018a), we use a contingent valuation (CV) method to estimate the social costs of driving restrictions in Beijing. Typically used to value nonmarket environmental and health-related goods such as clean air, scenic beauty, and avoided illness (e.g., Carson et al., 2003; Krupnick et al., 2002), a CV survey describes a policy intervention that would generate a marginal increase in the good—for example, a program to improve surface water quality—and asks a representative sample of respondents questions about their willingness to pay (WTP) for that intervention. Survey responses are then used to calculate total WTP for the intervention. We adapt this method to measuring the costs of Beijing's driving restrictions by developing a CV survey that describes a permit program that would exempt individuals from driving restrictions, and we administer it to a representative sample of drivers. We use their responses to calculate the total WTP for avoiding restrictions, which is a measure of the cost of the restrictions. As discussed at the end of Section 4, our approach estimates the annual costs that driving restrictions imposed on drivers in 2016 net of any costs incurred before 2016, including the costs of past adaptation measures related to, for example, moving closer to public transportation. To shed light on the policy implications of our cost estimates, we compare them with estimates of the benefits of Beijing's driving restrictions program (from Viard and Fu, 2015) and with estimates of the costs of Mexico City's program (from Blackman et al., 2018a).

Our study makes three main contributions. To our knowledge, it is the first to develop a rigorous estimate of the costs of Beijing's driving restrictions program, one of the world's largest in terms of the number of vehicles affected. Relatedly, it contributes to the emerging literature (cited above) that sheds light on the conditions and contexts under which driving restrictions are likely to have net benefits. And finally, to our knowledge, it is only study other than Blackman et al. (2018a) to focus directly on using stated preference methods to isolate and estimate the private costs of an existing environmental regulation.[2]

The remainder of the paper is organized as follows. The second section presents background on Beijing's driving restrictions program and briefly reviews studies of its benefits. The third section presents our analytical framework. The fourth section describes our CV instrument and its administration. The fifth section presents our results, and the sixth section discusses them. The last section considers the implications of our study for both further research and transportation policy.

[1] For a review, see Blackman et al. (2018b).

[2] As discussed in Blackman et al. (2018a), other papers have used stated preference methods to estimate the cost of hypothetical regulatory programs (Cropper et al., 2014), the public benefits of unspecified infrastructure investments that will reduce regulatory costs (e.g., Cooper et al., 2011; Hensher et al., 2006), and WTP to improve future provision of some type of public service (e.g., Howe and Smith, 1994; Koss and Khawaja, 2001). However, to our knowledge, Blackman et al. (2018a) is the only one to focus directly on using stated preference methods to isolate and estimate the private costs of an existing environmental regulation.

2. Beijing's driving restrictions program

This section first discusses the rules and implementation of Beijing's driving restrictions program, and then briefly summarizes published quasi-experimental evaluations.

2.1. Rules and implementation

Vehicle ownership in Beijing has exploded in the past two decades (Wang et al., 2014). Partly as a result, the city suffers from both severe traffic congestion and air pollution. To combat these problems, city officials have implemented a number of policies, including supply-side measures such as investments in roads and public transportation, and demand-side measures such as increased parking fees and fuel taxes, reduced public transportation fares, a lottery to restrict registration of new vehicles, and driving restrictions.

Aside from a brief four-day trial in August 2007, the first application of driving restrictions in Beijing was from July to August 2008, just before and during the Olympic Games. Vehicles could be driven only every other day, depending on the last digit of their license plates: those with plates ending in odd numbers were prohibited on odd-numbered days, and those with plates ending in even numbers were prohibited on even-numbered days. Restrictions covered cars, trucks, vans, and sport utility vehicles; only emergency vehicles (police, army, fire, ambulance), buses, taxis, postal vehicles, and embassy cars were exempted. Restrictions were in effect for all but 3 h of the day (midnight to 3 a.m.) throughout metropolitan Beijing. Drivers who failed to comply with the restrictions were fined RMB 100 per day (2008 US $14.40) and were required to return to their place of origin.

Since that two-month initiative, driving restrictions have undergone several modifications (Wang et al., 2014). On August 28, 2008, driving restrictions were limited to the area inside and including the fifth ring road.[3] On September 20, 2008, program rules were relaxed further: vehicles were restricted one day a week between 6 a.m. and 9 p.m. in the area inside but excluding the fifth ring road. The restricted day was rotated each month (so, for example, a car with a license plate ending in 5 might be prohibited on Mondays in May and on Tuesdays in June). Beginning April 5, 2009, the restrictions applied only from 7 a.m. to 8 p.m., and the rotation period was extended to 13 weeks. Finally, on January 9, 2011, the program rules were changed to allow drivers who violated the restrictions to be fined more than once per day, and the fines were increased.

2.2. Evaluations[4]

Evaluating Beijing's one-day-a-week driving restrictions program presents particular challenges because several other policies aimed at improving the city's air quality were implemented concurrently. In addition, the program was preceded by an every-other-day policy. Three published quasi-experimental papers have attempted to overcome these challenges. All have found that the program has had significant benefits.

Sun et al. (2014) focus on the one-day-a-week program's effects on average traffic speed and inhalable particulate matter (PM). They use day-level data along with a difference-in-difference approach (based on a plausibly exogenous scarcity of license plates ending in the number 4 due to cultural aversion to that number) that, in principle, enables them to disentangle the effects of driving restrictions from concurrent policies. They conclude that driving restrictions increased average citywide traffic speeds but did not have an appreciable effect on concentrations of inhalable particulate matter.

Viard and Fu (2015) examine the one-day-a-week program's effects on an air quality index and on television viewership, a proxy for labor supply. To isolate and identify the program's effects on air quality, they exploit both temporal variation in the policy and spatial variation in its effects (related to proximity to roads). They find that the program reduced air pollution by about one-fifth and increased television viewership 9 to 17 percent for workers with "discretionary work time." They hypothesize that the program has been more effective than the well-known program in Mexico City because purchasing additional vehicles to circumvent driving restrictions is more costly in Beijing, vehicles in Beijing are newer and cleaner, and public transportation in Beijing is cheaper and of higher quality.

Finally, Lu (2016) examines the effects of two changes in the rules of Beijing's one-day-a-week program after it was first implemented in September 2008: the April 2009 reduction in the number of hours per day during which driving is restricted and the January 2011 increase in the maximum fine for violations. Using index data for daily air pollution along with a regression discontinuity design, he finds that the 2009 weakening of the policy led to increases in pollution and the 2011 strengthening led to reductions.

3. Analytical framework

A challenge in estimating the costs to drivers of Beijing's driving restrictions program is that the program may generate both costs and benefits. The costs arise from limitations on drivers' choice sets, which cause them to adjust how much and when they drive, the travel modes they choose, and the number of vehicles they own. Potential benefits arise from reductions

[3] One of eight major highways encircling Beijing, the fifth ring road is roughly 10 km from the city center.

[4] This section is drawn from Blackman et al. (2018b).

in air pollution and traffic congestion (and therefore drive times). Our goal is to disentangle and measure the direct costs of the program, holding constant any benefits. To that end, we rely on a random utility framework (McFadden, 1974) and discrete choice econometrics. Since the general approach is well known and the specific application is detailed in Blackman et al. (2018a), we provide only a brief sketch here—an abbreviated version of the treatment in Blackman et al. (2018a). Assume driver *i*'s indirect utility function is given by

$$v = v(GC\ [q_i, T(Q_i)], E[T(Q_i)], M) \tag{1}$$

where v is the driver's indirect driver utility, GC is the generalized travel cost (opportunity cost of time devoted to travel, the direct pecuniary costs of travel, and nonpecuniary costs from, for example, discomfort; see Bruzelius, 1981), T is the traffic volume, E is environmental quality, M is income, q_i is an indicator variable equal to q_1 if driving restrictions apply to the driver and q_0 if they do not, and Q_i is an indicator variable equal to Q_1 if driving restrictions apply to all other drivers and Q_0 if they do not. Hence, GC depends directly on driving restrictions and indirectly on driving restrictions through their effect on the traffic volume, whereas E depends indirectly on driving restrictions through their effect on traffic volume. We aim to disentangle the cost of driving restrictions to driver i by comparing (a) her indirect utility given driving restrictions that are in force and are applied to the driver,

$$v = v(GC\ [q_1, T(Q_1)], E[T(Q_1)], M) \tag{2}$$

and (b) her indirect utility given driving restrictions that are in force but are not applied to the driver,

$$v = v(GC\ [q_0, T(Q_1)], E[T(Q_1)], M) \tag{3}$$

The case represented by Equation (3) is not directly observable, which is why we rely on a CV survey in which drivers are asked whether they would pay to participate in a permit program (described in the next section) that enables them to avoid the direct negative effect of a driving restrictions program (the direct effect that q_1 has on GC) without obtaining any potential benefits from reduced traffic volume or improved environmental quality (the indirect effects that Q_1 has on GC through T and on E through T).

A driver's WTP for a permit is implicitly given by

$$\begin{aligned} &v(GC\ [q_1, T(Q_1)], E[T(Q_1)], M) + \varepsilon_1 = \\ &\quad v(GC\ [q_0, T(Q_1)], E[T(Q_1)], M - WTP) + \varepsilon_0 \end{aligned} \tag{4}$$

where ε captures unobservables related to individual characteristics or preferences and measurement error. The parameters of the indirect utility function can be estimated given assumptions about the form of the utility function and the distribution of the error terms coupled with the fact that the bid (cost of the program) varies randomly among the respondents (Haab and McConnell, 2002).

Our CV survey uses a closed-ended, single-bounded format—that is, respondents are asked whether they would be willing to pay a randomly drawn amount, t, for a permit that exempts them from driving restrictions—which is generally preferable because of its incentive compatibility properties (Carson and Groves, 2007). The probability that she replies affirmatively is given by

$$\begin{aligned} P[yes] = P[&v(GC\ [q_0, T(Q_1)], E[T(Q_1)], M - t) \\ &- v(GC\ [q_1, T(Q_1)], E[T(Q_1)], M) + \varepsilon_0 - \varepsilon_1 > 0] \end{aligned} \tag{5}$$

We denote the difference in generalized cost as

$$\Delta GC = GC\ [q_1, T(Q_1)] - GC\ [q_0, T(Q_1)] \tag{6}$$

Assuming a linear utility function, we can write the probability statement in (5) as

$$P[yes] = P[\beta' \Delta GC - \lambda t + \varepsilon_1 - \varepsilon_0 > 0] \tag{7}$$

where β is a vector of parameters and λ is the marginal utility of money. The WTP implicitly defined above can then be calculated from the estimated parameters of the utility function.

Our approach estimates the annual costs that driving restrictions imposed on drivers in 2016. Hence, as noted above, it does not capture any costs incurred before 2016, including those related to adaptation measures that subsequently reduced costs—for example, purchasing an additional vehicle to drive on restricted days. In other words, our approach captures costs *conditional* on drivers' past adaptation investments.

4. Contingent valuation survey

This section discusses the design and administration of our contingent valuation survey.

4.1. Design

Our survey instrument was adapted from Blackman et al. (2018a). We held four focus groups with Beijing drivers (six persons per group, June 2015), administered an open-ended pilot survey (n = 50, September 2015), and conducted a closed-ended pilot (n = 220, January 2016) (Figure A1).

The final version of the instrument has an introduction and eight sections (Table A1). Here we briefly describe each section and, where appropriate, explain its rationale. Sections 1 and 2 focus on the location of the house and Section 3 is a brief introduction. Section 4 concerns the vehicles and drivers in the household, the respondent's access to public transportation, and current travel behavior. The purpose is to remind the respondent about factors affecting WTP for a driving restrictions permit and to collect data needed for the econometric analysis. Section 5 briefly lists the main features of the driving restrictions program.

Section 6 has two parts. The first describes the CV scenario: a new regulatory program that gives drivers the opportunity to purchase a driving restrictions permit. To reinforce this description, enumerators handed respondents a card summarizing it in bullet format. The description reads as follows:

> To reduce traffic pollution and congestion, the transportation regulatory authority in Beijing is studying the possibility of reducing the number of new license plates issued every year by 100,000. To make this policy more attractive, it is considering simultaneously issuing 50,000 driving restrictions permits that will enable people to drive on all days regardless of the year, make, or model of their vehicle. Regulatory authorities in Mexico City, Mexico, Santiago, Chile and other big cities that have driving restrictions programs like the one in Beijing have issued similar permits to offset the cost to drivers of reductions in the number of new vehicle registrations allowed. In Beijing, these permits will be issued in only a single year. Vehicles with a permit will display a sticker on their license plates that indicates to video cameras and police that they have permission to drive on all days of the week. Punishment for forging this sticker would be the same as for forging a license plate: 12 points, driver's license suspended, and detention of not more than 15 days, according to the PRC Road Traffic Law on State Security.
>
> To ensure that these permits for exemption from driving restrictions are allocated fairly, authorities will invite drivers of vehicles randomly selected by lottery from among the entire population of Beijing that already have license plates. These persons will have an opportunity to purchase one permit for their vehicle.

The description of the program went on to make clear that a permit exempts a single vehicle for the duration of a single year, permits are not transferable among vehicles and cannot be affixed to vehicles used for public transportation, and the fee for the permit is to be paid together with the annual vehicle use tax.

The CV scenario was designed to be plausible. To that end, we mentioned other large cities with driving restrictions programs that issue similar permits, and we cast the permit program as a political quid pro quo—a means of compensating drivers for a decision to reduce the number of new vehicles registered each year by 100,000. Focus groups and the pilot survey confirmed that this explanation was, in fact, plausible.

Several features of the permit program were included to ensure that responses to the CV question would reflect the costs that driving restrictions impose on them, and not other factors. First, we limited its scope to 50,000 vehicles so that the net effect on air pollution and traffic congestion (in a city with more than 5.5 million vehicles) would be negligible. Second, we specified that the program would have a net effect of removing vehicles from the road (100,000 new registrations blocked and 50,000 permits issued) to reinforce the point that the program would not exacerbate air pollution or traffic congestion. Third, we prohibited transferring permits so that respondents' WTP would not reflect potential profits from selling them. And finally, we required drivers to pay for permits along with their annual vehicle registration fee so that the transaction costs associated with permit payments would be negligible, and WTP would not reflect them.

We limited eligibility for the permit program to vehicles that are not used as taxis or other forms of public transportation because we expected the costs of driving restrictions to be far greater to drivers of such vehicles. Reliably estimating commercial drivers' costs would require identifying and surveying a sufficiently large sample of such drivers.

After describing the program for exemptions from driving restrictions, Section 6 of the survey asks respondents whether and exactly how a permit would change their travel behavior. One aim of this set of questions was to encourage respondents to think carefully about how they would benefit from a permit—or equivalently, the cost that the program of driving restrictions imposes on them. A second aim was to generate data that could help us interpret and validate answers to the CV question.

Section 7 of the survey presents the actual CV question. The question was preceded by a reminder about the characteristics of the permit program, its potential cost savings, and a "cheap talk" script (Cummings and Taylor, 1999). The entire question reads,

> We want to know the total amount you would pay to obtain a driving restrictions permit for your vehicle if you were randomly chosen to participate in the program concerning permits for exemption from driving restrictions. Remember

that the driving restrictions permit has the following characteristics [show card]. Before you answer the next question about whether you'd be willing to pay a certain amount for a driving restrictions permit, please consider that the driving restrictions program can:

- affect the mode of transport that you use to go to work and school and to run errands and do other activities;
- affect the days you choose to travel;
- and finally, affect the buying and selling of vehicles.

Before responding, please also consider that if you spend money buying a permit for exemption from driving restrictions, you are not going to be able to spend money on other things. In other studies, we have seen that people sometimes give very high amounts in the survey because they have not carefully considered the other things they could buy with the money. Others give very small amounts because they do not think about all the benefits. It is important to us that you answer the following questions as carefully and accurately as possible.

The bid vector is discussed below. The second part of the CV section of the survey asks follow-on questions about the respondents' confidence in their responses, the reasons for those responses, and whether respondents who said no to their bid would be willing to pay a positive amount for a permit. The eighth and final section of the survey asks questions about the socioeconomic characteristics of drivers and their households.

4.2. Administration

Using enumerators trained by the authors, the China Mainland Marketing Research Company, a professional survey research firm, administered the survey face-to-face to a representative sample of 2055 drivers living in all 16 districts of the Beijing metropolitan area. The survey was administered in 2016 in four phases: (i) March (n = 105); (ii) April and May (n = 595); (iii) June and July (n = 706); and (iv) August and September (n = 649) (Figure A1).[5]

We used 2013 census data along with a three-stage cluster strategy to select a representative sample of drivers. First, we randomly selected 125 study communities (third-level administrative units) across Beijing's 16 districts. Next, we randomly selected two residential quarters (fourth-level administrative units) in each of the 125 study communities. Finally, we randomly selected eight to 10 households in each study residential quarter. We administered surveys only to households where at least one member who was the principal driver of a not-for-hire vehicle (car, truck, or van) owned by that household was present and agreed to participate. Where households owned more than one vehicle and the principal drivers of those vehicles were available, we randomly selected one driver to be interviewed. Where the originally selected household was not, for whatever reason, able to complete a survey, we selected contiguous households.

Each driver in our sample was asked whether he or she would be willing to pay a randomly assigned amount (bid) for a driving restrictions permit. The bid vector—RMB 100, 500, 800, 1,400, and 2200 (US $15.11, $75.55, $120.88, $211.54, and $332.42)—was based on results from the first pilot survey, which used an open-ended question format.

5. Results

This section discusses, in turn, the variables used in our regression analysis, summary statistics, responses to our CV question, econometric estimates of WTP derived from a variety of models, and our analysis of the determinants of WTP.

5.1. Vehicle, driver, and household characteristics

Table 1 defines the variables used in the regression analysis. *Socioeconomic level index* merits a brief discussion. It is a weighted index of eight variables related to household assets: *number of vehicles, multiple residences, property fee, floor space, rooms, bathrooms, light bulbs,* and *years schooling household head*. Ranging from 48 to 207, this index is used to assign each household to one of five socioeconomic classes.[6]

[5] The duration of the survey—March through September 2016—was mainly a function of size of the team of trained enumerators. It took seven months for China Mainland Marketing Research Company's team of 14 enumerators to conduct the required number of surveys. The number of questionnaires administered in the four survey phases varies because each phase was conducted in different districts with differing logistics. In addition, the first phase was purposely limited in scope in case it revealed further adjustments were needed (it did not).

[6] To enhance the comparability of our results with those from Blackman et al. (2018a), a similar study of Mexico's driving restrictions program (results from the two studies are compared in Section 6.3), we adapted the method for computing the socioeconomic class index used in that study, which in turn was taken from López Romo (2011). The weights assigned to values of each variable are as follows—values of the covariate are on the left-hand side of the equals sign and index points are on the right-hand side: *number of vehicles* (0=0; 1=13; 2=26; 3+=40); *multiple residences* (0=0; 1=20); *property fee* (0−999=0; 1,000−1,999=10; 2,000−2,999=20; 3,000−3,999=30; 40,000+=40); *floor space* (0−49=0; 50−99=4; 100−149=5; 150−199=16; 200+=20); *rooms* (0−1=0; 2−3=10; 4+=20); *bathrooms* (0=0; 1=10; 2+=20); *light bulbs* (0−1=0; 2−3=13; 4−5=26; 6+=40); *years schooling household head* (1−2=0; 3−4=15; 5=30; 6−7=45; 8−9=60).

Table 1
Characteristics of vehicle, driver, household (n = 2055).

Variable	Description	Statistic	Value	s.d.
VEHICLE				
Type				
automobile	0/1 = 1 if automobile	mean	0.89	0.31
pickup truck	0/1 = 1 if pickup truck	mean	0.01	0.12
other truck	0/1 = 1 if other type of truck	mean	0.09	0.29
lifetime km driven	Accumulated lifetime km (10,000 km)	mean	5.68	0.60
km driven per day	Average km driven per day (10 km)	mean	4.54	3.08
Principal use				
commute to work	0/1 = 1 if principal use commute work	mean	0.75	0.44
commute to school	0/1 = 1 if principal use commute school	mean	0.01	0.07
working (e.g., plumber)	0/1 = 1 if principal use working	mean	0.04	0.20
errands	0/1 = 1 if principal use errands	mean	0.12	0.32
entertainment	0/1 = 1 if principal use entertainment	mean	0.09	0.29
DRIVER				
male	0/1 = 1 if male	mean	0.65	0.48
age	Age driver (years)	mean	39.6	10.3
married	0/1 = 1 if married	mean	0.89	0.31
postsecondary education	0/1 = 1 if postsecondary education	mean	0.69	0.46
income	Annual income range (RMB1000)	median	65−90	n/a
HOUSEHOLD				
number vehicles	Number of vehicles	mean	1.05	0.24
walk time public transit	Walk time to public transit (minutes)	mean	7.82	3.72
commute time	Drive time to work or school (minutes)	mean	54.59	29.39
combine trips	0/1 = 1 if combine work w/nonwork trips	mean	0.33	0.47
commuters	No. members commute to work or school	mean	1.60	1.06
drivers	No. members with driving license	mean	1.96	0.66
socioecon. level index (SLI)	Weighted index of socioeconomic level	mean	3.19	0.66
SLI components				
number vehicles	Number of vehicles	mean	1.05	0.24
multiple residences	0/1 = 1 if household has > 1 residence	mean	0.74	0.44
property fee	Annual property fee (RMB)	mean	1189.89	1242.47
floor space	Floor space (m^2)	mean	80.57	26.42
rooms	No. rooms excluding bathrooms	mean	2.32	0.71
bathrooms	No. bathrooms	mean	1.06	0.32
light bulbs	No. light bulbs	mean	2.57	1.43
years schooling hh head	0/1 = 1 if hh head postsecondary edu.	mean	6.19	2.46

Summary statistics indicate that 89 percent of the vehicles in our sample were automobiles (versus trucks and vans) and 75 percent were used primarily to commute to work or school (Table 1). The average vehicle was driven 45 km per day and had accumulated 57,000 lifetime kms. Sixty-five percent of drivers were male, 89 percent were married, and 69 percent had at least some postsecondary education. The average driver was 40 years old and had an annual income between RMB 65,000 and 90,000 (US $9821 to $13,598). Finally, the average household had 1.05 vehicles, 1.6 members who commuted to work or school, and 2.0 drivers. The average walk time to the nearest subway or bus stop was just under 8 min, and the average drive time to work or school was 55 min. A third of drivers regularly combined work and nonwork trips.

5.2. Expected effects of permits for exemption from driving restrictions

Most interviewees indicated that given a driving restrictions permit, they would make significant changes to their travel behavior and achieve significant cost savings. These responses imply that Beijing's driving restrictions program entails significant costs. Fifty-three percent of respondents said that if they had a permit, they would change the mode of transport used to commute to work or school on their restricted day, 42 percent said they would change the time at which they commuted, 38 percent said they would change the vehicle they used to commute, and 21 percent said they would make other kinds of changes related to commuting (Table 2). Nineteen percent of respondents said these changes would reduce out-of-pocket expenses, on average by RMB 98 (US $14.81) per week, and 55 percent said they would save time spent on travel, on average 90 min per week. Finally, 58 percent of respondents said that a permit would reduce the level of inconvenience associated with commuting.

Similar percentages of respondents said that given a driving restrictions permit, they would make significant changes to their nonwork and nonschool travel. Forty-five percent said they would change the mode of transport used for such travel, 49 percent said they would change the days on which they traveled, 47 percent said they would change the times during which they traveled, and 37 percent said they would make other kinds of changes (Table 2). Twenty-one percent of respondents said these changes would reduce out-of-pocket expenses, on average by RMB 97 (US $14.66) per week, and 41 percent said they would save time spent on travel, on average 117 min per week. On average, respondents indicated that given a driving restrictions permit, they would take one additional trip per week.

Table 2
Responses to survey questions, "Would a driving restrictions permit have the following effects … ?".

Type of effects	Statistic	Value	No. obs.
… on work/school travel?[a]			
Change mode of transport used on restricted day	percentage	53.2	1633
Change time of commute	percentage	42.4	1633
Change vehicle use to commute	percentage	38.3	1633
Change commute in some other way	percentage	20.9	1633
Save money on commuting	percentage	18.8	1633
How much (RMB/week)[b]	mean	98.0	307
Save time on commuting	percentage	54.6	1633
How much (minutes/week)[b]	mean	90.0	891
Eliminate inconveniences associated with commute	percentage	57.6	1633
… on nonwork/nonschool travel?[c]			
Change mode of transport used on restricted day	percentage	44.7	2055
Change days on which make trips	percentage	48.6	2055
Change time of trips	percentage	47.1	2055
Change trips in some other way	percentage	36.5	2055
Number of additional trips	mean	0.9	2055
Save money on nonwork/nonschool travel	percentage	20.9	2055
How much (RMB/week)[b]	mean	97.1	429
Save time on nonwork/nonschool travel	percentage	41.3	2055
How much (minutes/week)[b]	mean	117.3	849
… on vehicle ownership?[c]			
Sell second vehicle in household	percentage	2.3	2055
Change plans to buy or sell vehicle in another way	percentage	6.3	2052

[a] Survey questions asked only of 1633 respondents who said they use their vehicle for work/school travel. Each row represents a separate independent question, so respondents could answer yes to multiple questions.
[b] Survey questions asked only of respondents who gave a nonzero response to question in previous row.
[c] Survey questions asked of all 2055 respondents.

Only small percentages of respondents said that a permit for exemption from driving restrictions would cause them to buy or sell their vehicles (Table 2). Two percent said they would sell a second vehicle, and six percent said they would change their plans to buy or sell a vehicle in some other way.

5.3. *Contingent valuation question*

Responses to the contingent valuation question indicate that interviewees both understood it and found it plausible. The percentage of yes responses is strictly decreasing in the level of the bid: 68 percent of respondents said they would be willing to pay the lowest amount (RMB 100), and only 12 percent said they would be willing to pay the highest amount (RMB 2200) (Table 3). Of the 698 respondents who said yes to their bid, 77 percent said they were sure of their response, 20 percent said they were more or less sure, and only 3 percent said they did not believe the CV question was realistic and gave a response just "to say something" (Table 4).

Of the 1357 respondents who said no to their bid, 18 percent said they gave a response just "to say something." The remainder of these respondents gave reasons that one would expect, including that they could not afford the permit (9 percent), the cost exceeded the benefits (73 percent), they did not want to contribute to air pollution and congestion (47 percent), and they were not confident in government administration of the program (14 percent) (Table 4). Seventeen percent of interviewees who rejected their bid said in response to a follow-up question that they would be willing to pay a positive amount for a driving restrictions permit, on average RMB 378 (US $57) (Table 4).

Table 3
Responses to bids; number of respondents (row percentage); n = 2055.

Bid (RMB)	No	Yes	Total
100	134	284	418
	(32.1)	(67.9)	(100.0)
500	253	160	413
	(61.3)	(38.7)	(100.0)
800	286	125	411
	(69.6)	(30.4)	(100.0)
1400	324	80	404
	(80.2)	(19.8)	(100.0)
2200	360	49	409
	(88.0)	(12.0)	(100.0)
Total	1357	698	2055
	(66.0)	(34.0)	(100.0)

Table 4
Interviewees' responses to follow-on questions after contingent valuation question.

Follow-on question	Statistic	Value	No. obs.
How sure are you of your "yes" response?[a]			
I am sure	percentage	77.1	698
I am more or less sure	percentage	19.6	698
The truth is that I gave a response only to say something, but I do not believe the permit program is realistic	percentage	3.3	698
What is the reason for your "no" response?[b]			
I cannot afford it	percentage	9.4	1357
Cost of permit exceeds benefits	percentage	73.0	1357
I don't want to contribute to air pollution and traffic congestion	percentage	47.2	1357
Not confident in government administration of program	percentage	13.9	1357
Not a realistic question, so I just gave an answer	percentage	18.2	1357
Would you be willing to pay a positive amount for a permit?[b]			
Positive willingness to pay	percentage	17.4	1357
How much (RMB)[c]	mean	377.5	232

[a] Survey questions asked only of 698 respondents who said yes to their bid; respondents could select only one option.
[b] Survey questions asked only of 1357 respondents who said no to their bid; respondents could select more than one reason.
[c] Survey questions asked only of 236 respondents who said no to their bid but also said they would be willing to pay a positive amount for a permit.

5.4. Willingness to pay

A variety of approaches can be used to model WTP derived from Equation (7), depending on assumptions made about (i) the underlying decision process respondents use to determine their WTP and (ii) observed zero WTPs. Regarding the first assumption, the main considerations are whether respondents make separate decisions about whether their WTP is positive and about the magnitude of WTP, and if so, how these two decisions are related to each another. The first decision is typically referred to as the "participation" decision and the second as the "level decision." Regarding zero WTPs, the main issue is whether all observed zero WTPs are true zeros representing corner solutions to a budget-constrained utility maximization problem or whether some zeros potentially reflect protest or scenario rejection responses.

The assumptions that result in the simplest approach are that respondents use the same process for both the participation and level decisions and that all zero WTPs are true zeros. Given these assumptions, Equation (7) can be estimated as a single "unconditional" equation using the entire sample of respondents, including those with positive WTP and zero WTP.

A second approach is to assume that respondents make separate, independent participation and level decisions and that stated zero WTPs are true zeros. These assumptions imply a two-part model (Cragg, 1971) wherein a participation equation is fitted using the full sample and a separate "conditional" level equation is fitted using the sample consisting only of respondents who have decided to participate—that is, those with positive WTPs (e.g., Carlsson and Johansson-Stenman, 1999; Hammitt and Zhou, 2006). Mean and median WTP derived from the conditional level equation are then multiplied by the proportion of positive WTPs to compute unconditional mean and median WTP for the full sample.

A third approach is to assume that respondents make separate but interdependent participation and level decisions and that some zeros may not be true zeros. These assumptions imply a selection model (Heckman, 1979) wherein the participation and level equations are estimated either sequentially via a two-step model or simultaneously via maximum likelihood using the full sample (Yoo et al., 2010; Yu and Abler, 2010). In general, the aim—and the potential benefit—of a selection model is to control for a censored dependent variable. Applied to CV, the goal is to control for cases where respondents report zero WTP but actually have positive WTP, which could result from protest and scenario-rejection responses. However, this model requires an exclusion restriction that is challenging to meet.

For that reason, among others, we highlight results from the unconditional and conditional models and report results from a selection model in the Appendix.[7] As discussed below, results from the selection model are quite similar to those from the single-equation unconditional and two-part conditional models. The unconditional model (Model 1) includes the untransformed bid as an explanatory variable and uses the full sample of 2055 respondents. The conditional model (Model 2)

[7] Although it is technically possible to meet the exclusion restriction by dropping from the level equation some covariates (e.g., those that are not significant), ideally, there should be a theoretical basis for including these dropped covariates in the participation equation but not the level equation. Such a basis is unclear. Absent exclusion restrictions, two-part models are adequate (Belotti et al., 2015). Several other factors argue in favor of a two-part model. First, statistical tests do not support choosing a selection model to analyze our data. A commonly used means of choosing between a two-part model and a selection model is to test whether the coefficient of the inverse Mills ratio in a two-step Heckman selection model is statistically significant (Duan et al., 1984). To that end, we use a two-step Heckman model with a linear probability model for the level equation. The coefficient of the Mills ratio is not statistically significant ($p = 0.61$). Second, a critique of selection models is that the results of the level equation are sensitive to specification of participation equation (Carlsson and Johansson-Stenman, 1999; Leung and Yu, 1996), an issue that is evident in our data. For example, when we include in the participation equation and the level equation only those covariates that are statistically significant in the two-part model (more covariates are significant in the participation equation than in the level equation, so the exclusion restriction is, technically, still met) (Table A2, Model A2), the qualitative results of the level equation are not the same as in the case where all available covariates are included in the participation equation (Table A2, Model A1). Finally, a two-part model is simpler than a selection model, and better established in the CV literature—Yoo et al. (2010) claims to be the first application of a selection model to a CV study.

Table 5
Estimates of probit regression coefficients and mean and median willingness to pay (WTP) derived from coefficients; dependent variable = 1 if response to contingent valuation question was yes, and 0 otherwise (s.e.); 2016 RMB.

	Model 1 Unconditional[a]		Model 2 Conditional[b]	
	A Univariate[c]	B Multivariate[d]	A Univariate[c]	B Multivariate[d]
Coefficient				
α (intercept)	0.626***	0.557	2.338***	1.019*
	(0.081)	(1.649)	(0.158)	(0.569)
λ_1(bid/100)	−0.176***	−0.460*		
	(0.020)	(0.275)		
λ_2 (ln[bid/100])			−0.851***	−0.896***
			(0.067)	(0.072)
WTP				
Mean unconditional[e,f]	355.527***	382.902***	1412.124***	1277.066***
	(26.145)	(28.213)	(229.336)	(196.968)
Median unconditional[e,f]	355.527***	382.902***	708.452***	685.109***
	(26.145)	(28.213)	(51.861)	(50.939)
Mean conditional[e]			3106.975***	2809.820***
			(504.588)	(433.373)
Median conditional[e]			1558.745***	1507.386***
			(114.106)	(112.076)
No. observations	2055	2055	934	934

***p<1%, **p<5%, *p<1%.
[a] Sample includes all respondents; estimates from heteroscedastic model.
[b] Conditional on respondent's having WTP >0; sample includes only such respondents; estimates from homoscedastic model.
[c] Sole independent variable is the bid.
[d] Independent variables are *bid* or *ln(bid)* and household, driver, and vehicle characteristics, specifically: *automobile, ln(lifetime km driven), km driven per day, commute, male, age, married, postsecondary education, income, number vehicles, walk time public transit, commute time, combine trips, commuters, drivers,* and *socioeconomic class*.
[e] For the unconditional models, all of which include the untransformed bid as a regressor, the estimated mean and median WTP are $-\beta'\overline{X}/\lambda_1$ where β is a vector of all regression coefficients except the bid, $\overline{X}$ is a vector of the sample means of those regressors, and λ_1 is the coefficient of the bid. For the conditional models, all of which include the logarithm of the bid as a regressor, estimated median WTP is $\exp(-\beta'\overline{X}/\lambda_2)$ and estimated mean WTP is $\exp\left(-\beta'\overline{X}/\lambda_2\right)\exp\left(\frac{1}{2*(\lambda_2)^2}\right)$ where λ_2 is the coefficient of the logarithm of the bid.
[f] For conditional models (Model 2A and 2B), unconditional WTP is derived by multiplying conditional WTP by the fraction of respondents with a positive WTP (0.45).

includes the logarithm of the bid, thereby restricting WTP to be positive (Haab and McConnell, 2002), and uses a subsample of all 934 respondents with a positive WTP—the 598 respondents who accepted their bid plus the 236 respondents who rejected their bid but said in response to a follow-up question that they would be willing to pay a positive amount for a permit (Table 4). For robustness, we report results from two different specifications of each model. A univariate specification (Model A) includes the bid as the only independent variable, and a multivariate specification (Model B) adds the vehicle, driver, and household variables listed in Table 1. We fit all four models as probits and use the delta method to calculate standard errors of WTP estimates.[8,9]

Heteroscedasticity arising from, among other factors, differential disturbances across randomly administered bids is a common concern in CV analysis (Halvorsen and Swlensminde, 1998; Yoo et al., 2010). We test each of our four WTP models for heteroscedasticity using a likelihood ratio test of a probit model with heteroscedastic errors (Harvey, 1976) against a conventional probit model with homoscedastic errors. The test rejects the null hypothesis of homoscedastic errors only for the two unconditional models (Models 1A and 1B). For these two models, we report results from a specification that allows for heteroscedastic errors (Harvey, 1976). Having estimated average annual WTP for a driving restrictions permit, we then estimate total annual WTP for all drivers of private vehicles in the Beijing metropolitan area.

5.4.1. Unconditional models

For both unconditional models, the coefficient of *bid* is negative and statistically significant, indicating that, as expected, the probability of accepting a bid is negatively correlated with its level. For the univariate model (Model 1A), estimated mean

[8] Specifically, we use Stata 14.0's nonlinear combinations of estimators ('nlcom') command to generate WTP point estimates and standard errors.
[9] For the unconditional models, all of which include the untransformed bid as a regressor, the estimated mean and median WTP are $-\beta'\overline{X}/\lambda_1$ where β is a vector of all regression coefficients except the bid, $\overline{X}$ is a vector of the sample means of those regressors, and λ_1 is the coefficient of the bid. For the conditional models, all of which include the logarithm of the bid as a regressor, estimated median WTP is $\exp(-\beta'\overline{X}/\lambda_2)$ and estimated mean WTP is $\exp\left(-\beta'\overline{X}/\lambda_2\right)\exp\left(\frac{1}{2*(\lambda_2)^2}\right)$ where λ_2 is the coefficient of the logarithm of the bid.

Table 6
Explaining positive willingness to pay (WTP) (Model 3, marginal effects) and WTP; (Model 2B, marginal median WTPs[a]); homoscedastic models (s.e.); 2016 RMB.

Variable	Model	
	3	2B
Dependent variable →	Prob (WTP>0)	Prob (Yes)
ln(bid/100)		−0.896***
		(0.072)
intercept		1.019*
		(0.569)
Vehicle characteristics		
automobile	−0.014	637.927**
	(0.037)	(288.398)
ln(lifetime km driven)	0.005	66.601
	(0.011)	(87.516)
km driven per day	0.002	−42.751
	(0.004)	(35.890)
commute	0.014	−79.623
	(0.028)	(242.631)
Driver characteristics		
male	0.010	236.236
	(0.025)	(198.450)
age	−0.004***	−8.8742
	(0.001)	(10.188)
married	0.047	18.6263
	(0.033)	(248.144)
postsecondary education	−0.080***	−324.098
	(0.028)	(233.133)
income	0.039***	79.304*
	(0.006)	(48.518)
Household characteristics		
number vehicles	−0.0643	525.202
	(0.050)	(396.019)
walk time public transit	0.002	16.883
	(0.003)	(24.639)
commute time	−0.001	2.663
	(0.000)	(4.229)
combine trips	0.058**	−264.731
	(0.024)	(191.279)
commuters	−0.025**	139.287
	(0.011)	(90.4879)
drivers	0.005	−143.855
	(0.018)	(149.154)
socioeconomic class	0.044**	422.500***
	(0.019)	(157.523)
No. observations	2055	934
Pseudo R2	0.0341	0.2820

***p<1%, **p<5%.
[a] Marginal median WTPs (the effects of a unit change in the covariate on median WTP), except *ln(bid/100)* and *intercept*.

and median unconditional WTP is RMB 356 (US $54) per year, and for the multivariate model (Model 1B) it is RMB 383 (US $58) per year (Table 5). Estimates of unconditional WTP using a sample restricted to drivers of automobiles (n = 1836 versus 2055) are similar (Table A3).

5.4.2. Conditional models

For both conditional models, the coefficient of the logarithm of *bid* is negative and statistically significant, indicating that here, too, the probability of accepting a bid is negatively correlated with its level. Estimates of conditional WTP are, as expected, higher than estimates of unconditional WTP. For the univariate conditional model (Model 2A), estimated mean WTP is RMB 3107 (US $469) per year, and estimated median WTP is RMB 1559 (US $236) per year. For the multivariate model (Model 2B), estimated mean WTP is RMB 2810 (US $425) per year, and estimated median WTP is RMB 1507 (US $228) per year. Unconditional WTP estimates derived from these conditional estimates are closer to WTPs from the unconditional model (Model 1). For the univariate model (Model 2A), mean derived unconditional WTP is RMB 1412 (US $213) per year, and median derived WTP is RMB 709 (US $107) per year. For the multivariate model (Model 2B), mean derived unconditional WTP is RMB 1277 (US $193) per year, and median derived WTP is RMB 685 (US $104) per year. Estimates of conditional and derived unconditional WTP using a sample restricted to drivers of automobiles (n = 1836 versus 2055) are similar (Table A3).

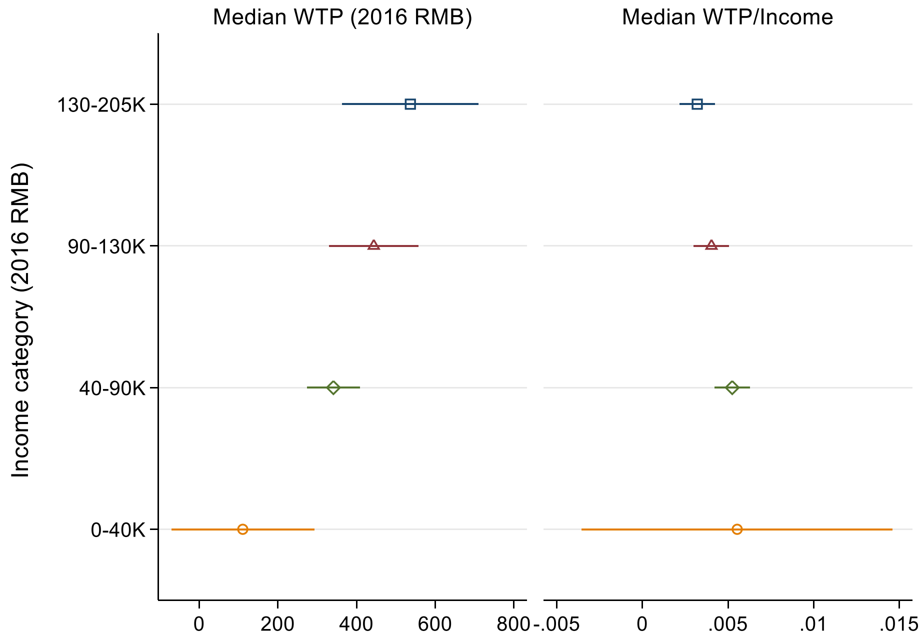

Fig. 1. Median willingness to pay (WTP) (left panel) and median WTP/income (right panel), by income category (2016 RMB). Symbols are point estimates and horizontal lines are 95 percent confidence intervals. Median WTP estimates are from heteroscedastic univariate unconditional model (Model 1A).

5.4.3. Total annual WTP

We calculate total annual WTP for all drivers in Beijing as follows. We multiply estimated median unconditional annual WTP by 4.606 million, the number of private vehicles in the city in 2016, the year our survey was administered (Beijing Transport Institute, 2017). We use median rather than mean unconditional WTP, to be conservative. To generate a range of estimates, we use the minimum and maximum median unconditional WTP estimates from the two models discussed above: RMB 356 (Model 1A) and RMB 709 (Model 2B). Hence, our estimate of total annual costs is RMB 1.6 billion to 3.3 billion (US $247 million to $493 million) per year.

5.5. Determinants of willingness to pay

To identify the determinants of WTP, we report results from both the participation and the level equations of a two-part (conditional) model. The participation equation aims to explain the determinants of positive WTP (Table 6, Model 3). It uses the full sample of 2055 respondents. The dependent variable is a dichotomous dummy that equals one if the respondent had a positive WTP. As noted above, such respondents include both the 598 respondents who said yes to their bid and the 236 who said no but indicated in response to a follow-up question that they would be willing to pay a positive amount. The model includes as regressors the vehicle, driver, and household characteristics listed in Table 1, but not the bid itself (because the likelihood of being asked the follow-up question that determines whether WTP is positive is a function of the level of the bid). We estimate the model as a probit and report marginal effects. A likelihood ratio test rejects the null of homoscedastic errors. Therefore, we report estimates from a model with heteroscedastic errors.

The level equation aims to explain the determinants of stated WTP (Table 6, Model 2B). It uses the subsample of 934 respondents with a positive WTP. The dependent variable is a dichotomous dummy variable that equals one if the respondent is willing to pay the randomly assigned amount. Regressors include the natural log of the bid (to restrict WTP to be positive; see Haab and McConnell, 2002) and the vehicle, driver, and household characteristics listed in Table 1. Hence, this model is identical to the multivariate conditional model used to estimate mean and median WTP (Table 3, Model 2B). We estimate this equation as a probit, and for each covariate other than the natural log of the bid, we report marginal median WTP, which for binary regressors is the difference in median WTP when the regressor equals one versus zero.

For the participation equation, we find that driver and household characteristics help explain positive WTP, but vehicle characteristics do not (Table 6, Model 3). Respondents with a positive WTP tend to be younger, not have postsecondary education, have higher income, combine work and nonwork trips, live in households with fewer commuters, and have a higher socioeconomic status. Marginal effects indicate that among the statistically significant continuous regressors, the most important are *income* and *socioeconomic class*, and among the binary dummy variables, the most important is *postsecondary education*. Here, too, estimates using a sample restricted to drivers of automobiles generates similar results (Table A4).

For the level equation, we find that vehicle, household, and driver characteristics explain stated WTP (Table 6, Model 4). Among respondents with a positive WTP, those who said yes to their bid tended to drive cars (versus trucks or vans), have

Table 7
Net benefits of Beijing's driving restrictions program using upper- and lower-bound estimates of benefits from Viard and Fu (2015) and costs from present study; billions 2016 RMB (billions 2016 USD).

		Costs[a] (present study)	
		Lower-bound 1.6 (0.3)	Upper-bound 3.3 (0.5)
Benefits[b] Viard and Fu (2015)	Lower-bound 3.4 (0.5)	1.7 (0.3)	0.1 (0.0)
	Upper-bound 4.6 (0.7)	2.9 (0.4)	1.3 (0.2)

[a] See Section 5.4.3.
[b] 2007 values adjusted for inflation.

higher incomes, and live in households with a higher socioeconomic status. Again, estimates using a sample restricted only to drivers of automobiles generates similar results (Table A4).

5.6. Distributional effects

In considering the distributional effects of Beijing's driving restrictions program, it is important to note that poor adults who cannot afford to own vehicles—and who were therefore excluded from our survey sample—by definition do not incur direct costs from the program. In that sense, the program has a progressive effect: richer people bear a disproportionate share of the costs. But what if we restrict our attention to the vehicle drivers who constitute our sample? For this group, one might expect driving restrictions to have a regressive effect, since poor drivers likely are less able to afford adaptive measures like purchasing additional vehicles and using taxis.

To test that hypothesis, we calculate median WTP as a percentage of annual income by income category. For simplicity, we use estimates derived from our univariate unconditional model (Fig. 1). Although not all significantly different from one another, point estimates of median WTP are monotonically increasing in income, ranging from 111 RMB for the lowest income category to 537 for the highest. These results comport with our finding that marginal median WTP for income derived from our multivariate conditional model (Model 2B) is positive. However, the distributional effect of driving restrictions depends on WTP as a percentage of income. Point estimates of that statistic are monotonically declining in income, ranging from 0.6 percent for the lowest income class to 0.3 for the highest. These results at least suggest that driving restrictions are, in fact, regressive.

6. Discussion

Here we discuss how our cost estimates compare with Beijing incomes and economic output (gross domestic product, GDP), how they compare with other researchers' estimates of the benefits and costs of the city's driving restrictions program, and how they compare with the costs of Mexico City's driving restrictions program.

6.1. Magnitude relative to Beijing incomes and GDP

Our preferred (median unconditional) average and total WTP estimates—RMB 356 to 709 (US $54 to $107) per driver per year and RMB 1.6 billion to 3.3 billion (US $247 million to $493 million) for all drivers per year—are significant relative to Beijing incomes and GDP. Median annual income of all drivers in our sample is RMB 77,500. Therefore, WTP per driver per year ranges from 0.46 to 0.91 percent of annual income. Beijing's GDP in 2016 was RMB 2.49 trillion (US $0.36 trillion). Therefore, total WTP for all drivers ranges from 0.07 to 0.14 percent of GDP.

6.2. Magnitude relative to benefits of Beijing's program

As discussed above (Section 2), using high spatial resolution daily data on PM10 air pollution, along with regression discontinuity methods, Viard and Fu (2015) find that Beijing's driving restrictions program reduced air pollution in the city by 20 percent. They use benefit transfer methods to generate back-of-the-envelope estimates of the annual monetary value of reductions in PM10 concentrations in 2007 RMB.[10] Their estimates (adjusted for inflation) range from 2016 RMB 3.4 billion to 4.6 billion (2016 US $0.5 billion to $0.7 billion) per year (Table 7). In addition to calculating the annual benefits of Beijing's driving restrictions program, the authors also estimate one component of annual costs. Using regression discontinuity

[10] Specifically, following Matus et al. (2012), they use concentration-response coefficients from the epidemiological literature to estimate the number of avoided cases of reduced-activity days (mean estimate of 15.3 million per year) and acute mortalities (hastened deaths resulting from current-year pollution: mean estimate of 1,114 per year). Next they value reduced-activity days using the average daily wage in Beijing and acute mortalities using a lower-bound forgone wages approach and an upper-bound value of statistical life approach.

Table 8
Comparison with Blackman et al. (2018a) estimates of costs of Mexico City's driving restrictions program (all monetary values 2016 USD).

Variable	Beijing	Mexico City	Ratio
No. vehicles (millions)	4.61[b]	4.77[c]	0.97
Median annual income[a]	11,710	7188	1.63
GDP (millions)	362,300.00	146.10	2479.81
Mean *walk time public transit*	7.82	10.05	0.78
Lower bound			
WTP	53.72	88.09	0.61
WTP/median annual income (%)	0.46	1.23	0.37
Total WTP (millions)	247.43	419.81	0.59
Total WTP/GDP city (%)	0.07	2.87	0.02
Upper bound			
WTP	107.05	133.45	0.80
WTP/median annual income (%)	0.91	1.86	0.49
Total WTP (millions)	493.05	635.99	0.78
Total WTP/GDP city (%)	0.14	4.35	0.03

[a] Among survey respondents.
[b] 2016.
[c] 2013.

methods, they find that the driving restrictions program caused television viewership, a proxy for lost work, to increase 9 to 17 percent for those workers with discretionary time. They use that estimate, along with data on daily wages and GDP, to calculate the value of work lost because of driving restrictions, arriving at a mean estimate of 2016 RMB 0.7 billion per year.

How do our own cost estimates compare with Viard and Fu's (2015) estimates of the benefits and costs of Beijing's driving restrictions program? Before answering that question, we want to make clear that—as Viard and Fu themselves note—their estimates do not capture the full range of benefits and costs needed for a formal benefit-cost analysis. They consider benefits from reductions in one air pollutant (PM10) but not from reductions in other types of pollution, traffic congestion, or traffic accidents. Moreover, they capture only the cost of lost work, not increases in general travel costs (reducing or rescheduling trips, switching modes, buying and selling vehicles, etc.).

That said, depending on whether we use upper or lower bounds of Viard and Fu's benefits estimates and our own cost estimates, net benefits range from 2016 RMB 0.1 to 2.9 billion (2016 USD $0 to $0.4 billion) (Table 7). As for cost estimates, ours are roughly five to seven times larger than Viard and Fu's—which is to be expected, since our estimates capture a much broader range of costs.[11]

6.3. *Magnitude relative to costs of Mexico city program*

As discussed in the introduction, the present study applies to Beijing the methods used in Blackman et al. (2018a) to estimate the costs of driving restrictions in Mexico City. In general, WTP for exemptions from driving restrictions in Beijing is substantially lower than in Mexico City (Table 8). Average annual WTP for Beijing is 61–80 percent of that for Mexico City. However, median annual income of respondents in Beijing was 1.6 times larger than that of respondents in Mexico City. Therefore, expressed as a percentage of annual income, WTP for Beijing was only 37 to 49 percent of that for Mexico City. Total annual WTP for Beijing is 59–78 percent of that for Mexico City. However, city GDP for Beijing is several orders of magnitude larger. Therefore, expressed as a percentage of city GDP, total WTP for Beijing is only 2 to 3 percent of that for Mexico City.

At least three factors could explain why the costs of driving restrictions are lower in Beijing than in Mexico City. All three suggest that Beijing's program is less "binding" than Mexico City's. First, in Beijing, the time period covered by driving restrictions is shorter and the geographic area is smaller, making it easier to adapt to restrictions by shifting driving times and routes. In Beijing, restrictions are enforced 12 h per day (from 7 a.m. to 8 p.m.) inside the fifth ring road. In Mexico City, they are enforced 16 h a day (from 5 a.m. to 10 p.m., although not on Sundays) in the entire metropolitan area and surrounding states. Hence, driving restrictions in Beijing may be less of a constraint on behavior. Second, residents of Beijing may have better access to high-quality public transportation that they can use on restricted days. Mean *walk time to public transit* in Beijing is about three-quarters of that in Mexico City (Table 8). Also, participants in the Beijing focus groups rarely found fault with public transportation, whereas participants in the Mexico City focus groups regularly complained about the safety, reliability, and cleanliness of public transit. Finally, it may be less costly to violate driving restrictions in Beijing than in Mexico City. Using household survey and travel diary data, Wang et al. (2014) find that 48 percent of Beijing car owners actually do

[11] Our net benefits estimates are for a single year, 2016. All other things equal, these estimates would vary across years if program costs varied across years. A reasonable hypothesis is that costs were higher in the early years of the program, when drivers likely would have incurred fixed adjustment costs, including, for example, costs of purchasing additional vehicles and moving their households to reduce commute times. If that hypothesis were true, then net benefits would be lower in the program's early years.

drive inside the fifth ring road on their restricted days. Although, to our knowledge, no comparable study has been conducted in Mexico City, the conventional wisdom is that restrictions there are strictly enforced (Davis, 2008; Gallego et al., 2013).

7. Conclusion

We have used the CV method to estimate the costs to drivers of Beijing's license plate−based driving restrictions program. Our study generates three main findings. First, the costs of the program are substantial: RMB 356 to 709 (US $54 to $107) per driver per year, which represents 0.5 to 0.9 percent of annual income and RMB 1.6 billion to 3.3 billion (US $247 million to $493 million) for all drivers per year. Second, comparison of our cost estimates with estimates of the benefits of Beijing's program from other studies suggests that the benefits are greater than the costs: the net benefits of reductions in a single air pollutant, PM10, range from 2016 RMB 0.1 to 2.9 billion (2016 USD $0 to $0.4 billion). Finally, when estimated using the same methods, the costs per driver of Beijing's program are significantly smaller than the costs of Mexico City's program.

What are the policy implications? These findings provide some of the strongest evidence to date that driving restrictions programs can, given certain conditions, have net benefits. Seminal quasi-experimental studies of Mexico City's Day Without Driving initiative, one of the world's oldest and best-known driving restrictions programs, suggests that they are apt to exacerbate air pollution and traffic congestion (Eskeland and Feyziouglu, 1997; Davis, 2008; Gallego et al., 2013). This pessimistic assessment has been reinforced both by a rigorous study of the program's costs, which found that these costs are substantial, and by quasi-experimental evidence on the Bogotá program, which concluded that at best, it had no air pollution benefits (Blackman et al., 2018a; Bonilla, 2019). More recently, however, rigorous studies have found that driving restrictions programs in Beijing, Quito, and Santiago are effective at cutting air pollution and/or traffic congestion (Carrillo et al., 2016; De Grange and Troncoso, 2011; Lu, 2016; Sun et al., 2014; Viard and Fu, 2015). The relevant question from a policy standpoint then becomes: do the benefits of these last three programs exceed the costs? Our study suggests that for Beijing at least, the answer is likely to be yes.

In addition, our study adds to the growing but still thin body of evidence that is needed to understand conditions under which driving restrictions based on license plates are likely to have net benefits. So far, we have rigorous evidence on the benefits of such programs for six cities and on the costs for two cities—not enough to allow conclusions to be confidently drawn (Blackman et al., 2018b). However, this evidence suggests hypotheses to be tested. Somewhat counterintuitively, one hypothesis is that relatively high program costs are not a necessary condition for significant program benefits—in fact, the opposite may be true. Conventional wisdom holds that as environmental regulatory stringency is ratcheted up, both benefits and costs increase. But this conventional wisdom does not appear to be borne out in the case of driving restrictions programs, at least based on evidence from Beijing and Mexico City. Mexico City's program has been more stringent than Beijing's in terms of the hours of the day and geographic area covered, and arguably in terms of enforcement as well. Evidence from CV studies indicates that, as expected, the costs of Mexico City's program have been higher than the costs of Beijing's. But evidence from quasi-experimental studies suggests that benefits have been smaller, not greater. So regulatory stringency is not necessarily positively correlated with benefits, and certainly not with net benefits. Rather, the primary determinants of both benefits and net benefits may well be mediating factors outlined in the last part of our Discussion section and in some of the recent quasi-experimental studies: access to and quality of public transportation, and the price and availability of new and used vehicles (Viard and Fu, 2015; Carillo et al., 2016).

Declaration of competing interest

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APPENDIX

Table A1
Contingent valuation survey

Section	Description
1	Address and geographic identification
2	Information needed to locate house
3	Introduction
4	Travel behavior
4.1	Number and characteristics of vehicles
4.2	Access to public transportation
4.3	Travel to work and school
5	Description of driving restrictions program
6	Driving restrictions permit
6.1	Description of permit
6.2	Expected changes in travel for work and school
6.3	Expected changes in travel for reasons other than work and school
6.4	Expected changes in vehicle ownership
7	Contingent valuation question
7.1	Contingent valuation scenario and question
7.2	Follow-up questions
8	Respondent and household characteristics

Table A2
Comparing two-part and selection models of willingness to pay (WTP); dependent variable = 1 if response to contingent valuation question was yes, and 0 otherwise; sample includes respondents with positive WTP; homoscedastic models. (coefficients and marginal median WTPs[a]) (s.e.); 2016 RMB.

Variable	Model		
	2B	A1	A2
Type →	Two-part	Selection	Selection
Specification of WTP >0 model →	All covariates	All covariates	Only significant covariates
	Coefficients or marginal mean WTP[a]		
ln(bid/100)	−0.896***	−0.833***	−0.870***
	(0.072)	(0.1284)	(0.099)
intercept	1.019*	0.668	0.944
	(0.569)	(0.711)	(0.778)
Vehicle characteristics			
automobile	637.927**	403.488	496.297
	(288.398)	(266.533)	(343.973)
ln(lifetime km driven)	66.601		
	(87.516)		
km driven per day	−42.751		
	(35.890)		
commute	−79.623		
	(242.631)		
Driver characteristics			
male	236.236		
	(198.450)		
age	−8.8742		
	(10.188)		
married	18.6263		
	(248.144)		
postsecondary education	−324.098		
	(233.133)		
income	79.304*	58.116*	51.566
	(48.518)	(30.614)	(40.829)
Household characteristics			
number vehicles	525.202		
	(396.019)		
walk time public transit	16.883		
	(24.639)		

Table A2 (*continued*)

Variable	Model		
	2B	A1	A2
Type →	Two-part	Selection	Selection
Specification of WTP >0 model →	All covariates	All covariates	Only significant covariates
	Coefficients or marginal mean WTP[a]		
commute time	2.663		
	(4.229)		
combine trips	−264.731		
	(191.279)		
commuters	139.287		
	(90.4879)		
drivers	−143.855		
	(149.154)		
socioeconomic class	422.500***	280.566**	331.006*
	(157.523)	(141.023)	(182.199)
Rho			
atanh ρ[b]		0.420	0.218
		(0.474)	(0.527)
Mean unconditional[c]	1277.066***	936.955***	1071.292**
	(196.968)	(278.487)	(455.0292)
Median unconditional[c]	685.109***	455.538**	553.193**
	(50.939)	(208.977)	(283.919)
Mean conditional[d]	2809.820***	2061.502***	2357.073**
	(433.373)	(612.731)	(1001.162)
Median conditional[d]	1507.386***	1002.282**	1217.144**
	(112.076)	(459.794)	(624.683)
No. observations	934	2055	2055
Log likelihood	−379.083	−1746.778	−1757.622

***p<1%, **p<5%, ***p<1%.

[a] Coefficients for *ln(bid/100)* and *intercept* and marginal median WTP for remaining covariates.

[b] $\text{atanh}\rho = \frac{1}{2}\ln\left(\frac{1+\rho}{1-\rho}\right)$

[c] Unconditional WTP is derived by multiplying conditional WTP by the fraction of respondents with a positive WTP.

[d] For the conditional models (conditional on WTP > 0), estimated median WTP is $\exp(-\beta'\overline{X}/\lambda_2)$ and estimated mean WTP is $\exp\left(-\beta'\overline{X}/\lambda_2\right)\exp\left(\frac{1}{2*(\lambda_2)^2}\right)$ where λ_2 is the coefficient of the logarithm of the bid.

Table A3

Cars-only sample; estimates of probit regression coefficients and mean and median willingness to pay (WTP) derived from coefficients; dependent variable = 1 if response to contingent valuation question was yes, and 0 otherwise (s.e.); 2016 RMB

	Model A3 Unconditional[a]		Model A4 Conditional[b]	
Coefficient	A Univariate[c]	B Multivariate[d]	A Univariate[c]	B Multivariate[d]
α (intercept)	0.580***	0.390	2.331***	1.371**
	(0.085)	(1.418)	(0.168)	(0.603)
λ_1*(bid/100)*	−0.164***	−0.321		
	(0.020)	(0.206)		
λ_2 *(ln[bid/100])*			−0.828***	−0.876***
			(0.071)	(0.076)
WTP				
Mean unconditional[e,f]	354.246***	387.907***	1577.473***	1387.453***
	(29.192)	(32.981)	(299.570)	(245.6256)
Median unconditional[e,f]	354.246***	387.907***	760.208***	723.667***
	(29.192)	(32.981)	(64.0742)	(60.684)

(*continued on next page*)

Table A3 (*continued*)

	Model A3 Unconditional[a]		Model A4 Conditional[b]	
Mean conditional[e]			3470.778*** (659.117)	3052.693*** (540.429)
Median conditional[e]			1672.620*** (140.977)	1592.223*** (133.513)
No. observations	1836	1836	823	823

***p<1%, **p<5%, *p<1%.

[a] Sample includes all respondents; estimates from heteroscedastic model.

[b] Conditional on respondent's having WTP >0; sample includes only such respondents; estimates from homoscedastic model.

[c] Sole independent variable is the bid.

[d] Independent variables are *bid* or *ln(bid)* and household, driver, and vehicle characteristics, specifically: *automobile, ln(lifetime km driven), km driven per day, commute, male, age, married, postsecondary education, income, number vehicles, walk time public transit, commute time, combine trips, commuters, drivers,* and *socioeconomic class*.

[e] For the unconditional models, all of which include the untransformed bid as a regressor, the estimated mean and median WTP are $-\beta'\overline{X}/\lambda_1$ where β is a vector of all regression coefficients except the bid, $\overline{X}$ is a vector of the sample means of those regressors, and λ_1 is the coefficient of the bid. For the conditional models, all of which include the logarithm of the bid as a regressor, estimated median WTP is $\exp(-\beta'\overline{X}/\lambda_2)$ and estimated mean WTP is $\exp\left(-\beta'\overline{X}/\lambda_2\right)\exp\left(\frac{1}{2*(\lambda_2)^2}\right)$ where λ_2 is the coefficient of the logarithm of the bid.

[f] For conditional models (Model A4A and A4B), unconditional WTP is derived by multiplying conditional WTP by the fraction of respondents with a positive WTP.

Table A4

Cars-only sample: Explaining positive willingness to pay (WTP) (Model A5, marginal effects) and WTP (Model A4B, marginal median WTPs[a]); homoscedastic models (s.e.); 2016 RMB

Variable	Model A5	A4B
Dependent variable →	Prob (WTP>0)	Prob (Yes)
ln(bid/100)		−0.876*** (0.076)
intercept		1.371** (0.603)
Vehicle characteristics		
ln(lifetime km driven)	0.005 (0.012)	50.481 (106.126)
km driven per day	0.002 (0.005)	−34.233 (41.704)
commute	0.017 (0.030)	−64.293 (280.770)
Driver characteristics		
male	0.018 (0.026)	292.555 (228.557)
age	−0.004*** (0.001)	−7.193 (11.826)
married	0.051 (0.036)	−8.596 (283.174)
postsecondary education	−0.071*** (0.029)	−329.394 (266.064)
income	0.041*** (0.007)	67.749 (57.970)
Household characteristics		
number vehicles	−0.095*** (0.055)	378.517 (475.2858)
walk time public transit	0.002 (0.003)	24.157 (28.067)
commute time	−0.001 (0.001)	1.195 (4.941)
combine trips	0.064*** (0.025)	−318.952 (221.941)
commuters	−0.021* (0.012)	81.102 (102.659)
drivers		

Table A4 (*continued*)

Variable	Model	
	A5	A4B
Dependent variable →	Prob (WTP>0)	Prob (Yes)
	0.009	−133.004
	(0.019)	(168.660)
socioeconomic class	0.052***	525.900***
	(0.021)	(183.265)
No. observations	1836	823
Pseudo R2	0.0369	0.2652

***p<1%, **p<5%.

[a] Marginal median WTPs, except *ln(bid/100)* and *intercept*.

Fig. A1. Design and implementation of contingent valuation survey, June 2015–September 2016.

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