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How Costly are License Plate-Based Driving Restrictions?

Contingent Valuation Evidence from Beijing

Allen Blackman, Ping Qin and Jun Yang

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HOW COSTLY ARE LICENSE PLATE–BASED DRIVING RESTRICTIONS? CONTINGENT VALUATION EVIDENCE FROM BEIJING

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How Costly Are License Plate–Based Driving Restrictions?

Contingent Valuation Evidence from Beijing

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 significant: RMB 353 to 708 (US $53 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 $245 million to $493 million) per year for all drivers. Second, available evidence suggests that the benefits of the program are well above the costs. Finally, the costs per driver are significantly smaller than the costs of Mexico City's program (estimated using the same method), which by most accounts has had zero or negative benefits. These findings provide some of the strongest evidence to date that driving restrictions programs can 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.

Key words: contingent valuation; driving restrictions; regulatory cost

JEL classification: Q52, R48

1. INTRODUCTION

The world's vehicle stock is projected to more than double between 2000 and 2030, mostly because of growth in developing countries (Dargay et al. 2007). 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 license plate–based driving restrictions program (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 license plate-based driving restrictions.

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 2016; 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).

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

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* these programs impose on drivers. The seemingly most straightforward strategy would be to use an averting expenditures approach—that is, to tally up the pecuniary costs 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 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, which on its face would be a challenging task.

Finally, an averting expenditures approach would generate biased results if such expenditures have 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.

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 most important driving restrictions programs in the world 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. 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 research and transportation policy.

[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

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 restricted on even days. Restrictions were in effect all but three hours 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 this 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 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.

[3] Beijing is served by circular or ring roads. The higher-numbered ring roads are relatively farther out from the city center.

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 higher quality. In addition, they provide evidence that rates of compliance with Beijing's program are high.

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 5, 2009 decision to cut the number of hours per day during which driving is restricted and the January 9, 2011 decision to raise the maximum fine for violations.

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

Using daily air pollution index data 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 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

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

where v is 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 on both the direct effects of driving restrictions on an individual driver and the indirect effects of driving restrictions on traffic volume, whereas E depends only on the indirect effect of 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,

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

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

$$v = v(GC\ [q_0, T(Q_1)], E[T(Q_1)], M). \qquad (3)$$

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

$$v(GC\ [q_1, T(Q_1)], E[T(Q_1)], M) + \varepsilon_1 =$$
$$v(GC\ [q_0, T(Q_1)], E[T(Q_1)], M - WTP) + \varepsilon_0 \qquad (4)$$

where ε captures unobservables related to individual characteristics/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 accept a randomly drawn bid, *t*, for a driving restrictions permit—which is generally

preferable owing to its incentive compatibility properties (Carson and Groves 2007). The probability that she replies affirmatively is given by

$$P[yes] = P[v(GC\ [q_0, T(Q_1)], E[T(Q_1)], M - t) \\ -v(GC\ [q_1, T(Q_1)], E[T(Q_1)], M) + \varepsilon_0 - \varepsilon_1 > 0] \qquad (5)$$

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. As a result, 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 or moving closer to public transportation. In other words, our approach captures costs *conditional* on drivers' past adaptation investments.

4. CONTINGENT VALUATION SURVEY

4.1. Design

Our survey instrument was adapted from Blackman et al. (2018). To that end, 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).

The final version of the instrument has an introduction and eight sections. 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 driving restrictions permits 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 CV scenario was designed to be plausible. To that end, we cast the driving restrictions permit program as a means of compensating drivers for a decision to reduce the number of new vehicles registered each

year by 100,000, i.e., as a political quid pro quo. Focus groups and the pilot survey confirmed that this explanation was, in fact, plausible. To reinforce this point, we explained that other large cities with driving restrictions programs provide some drivers with permits that allow them to drive on restricted days.

Several features of the permit program were included to ensure that responses to the CV question would reflect the costs that driving restrictions imposed 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 noncommercial vehicles because we expected the costs of driving restrictions to be far greater to drivers of commercial vehicles. Reliably estimating commercial drivers' costs would require identifying and surveying a sufficiently large sample of such drivers.

After describing the driving restrictions permit program, 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 the driving restrictions program imposes on them. A second aim was 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 driving restrictions permit program. 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;
- in addition, it affects the days you choose to travel;
- and finally, it affects the buying and selling of vehicles.

Before responding, please also consider that if you spend money paying for a driving restrictions permit, 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 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 2,055

drivers living in all 16 districts of the Beijing metropolitan area. The survey was administered in four phases: (i) March 2016 (n = 105); (ii) April and May (n = 595); (iii) June and July (n = 706); and (iv) August and September (n = 649).

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) in each of 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 in 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. In cases where households owned more than one vehicle and where the principal drivers of more than one vehicle were available for an interview, we randomly selected one driver to be interviewed. In cases where originally selected households were 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 2,200 (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

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 *postsecondary education household head*. Ranging from 48 to 207, this index is used to assign each household to one of five socioeconomic classes.

[Insert Table 1 here]

Summary statistics indicate that 89 percent of the vehicles in our sample were automobiles (versus trucks and vans) and 76 percent were primarily used to commute to work or school (Table 1). The average vehicle was driven 45 km per day and had accumulated 57,000 lifetime km. 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 $9,821 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 eight minutes, and the average drive time to work or school was 55 minutes. A third of drivers regularly combined work and nonwork trips.

5.2. Expected effects of driving restrictions permits

Most interviewees indicated that, given a driving restrictions permit, they would make significant changes to their travel behavior, which would result in 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 3). Nineteen percent of respondents said these changes would reduce out-of-pocket expenses, on average RMB 98 (US $14.81) per week, and 55 percent said they would save time spent on travel, on average 90 minutes per week. Finally, 58 percent of respondents said that a permit would reduce the inconvenience associated with commuting.

[Insert Table 2 here]

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 3). Twenty-one percent of respondents said these changes would reduce out-of-pocket expenses, on average RMB 97 (US $14.66) per week, and 41 percent said they would save time spent on travel, on average 117 minutes per week.

[Insert Table 3 here]

Only small percentages of respondents said that a driving restrictions permit would cause them to buy or sell their vehicles (Table 4). Two percent said they would sell a second vehicle, and 6.3 percent said they would change their plans to buy or sell a vehicle in some other way.

[Insert Table 4 here]

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 accepted the lowest bid (RMB 100), and only 12 percent accepted the highest bid (RMB 2,200) (Table 5). 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 6). Of the 1,357 respondents who said no to their bid, only 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 7). 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 8).

[Insert Tables 5–8 here]

5.4. Willingness to pay

We use responses to the closed-ended CV question to estimate average annual WTP for a driving restrictions permit. For robustness, we use two econometric models. Model 1 includes the bid as the only independent variable, whereas Model 2 adds the vehicle, driver, and household variables listed in Table 1.

For each model, we estimate an unconditional variant (Model A) and a conditional variant (Model B). The unconditional variants include the full sample of 2,055 respondents, but the conditional variants include only those 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 something for a permit (Table 8). For the unconditional variants, we use the untransformed bid as an explanatory variable. For the conditional variant, we use the logarithm of the bid, thereby restricting WTP to be positive (Haab and McConnell 2002).[5] For the conditional models, we derive unconditional WTP by multiplying conditional WTP by the fraction of respondents with a positive WTP (0.45). We fit all four of our models as

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

probits and use the delta method to calculate standard errors of WTP estimates.[6] 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. Univariate models

In all of our univariate (and multivariate) models, the coefficient of the bid or logarithm of the bid variable is negative and statistically significant, indicating that, as expected, the probability of accepting a bid is negatively correlated with its level. In the unconditional univariate model (Model 1A), estimated mean and median unconditional WTP is RMB 353 (US $53) per year (Table 9). In the conditional univariate model (Model 1B), WTP estimates are, as expected, significantly higher: mean conditional WTP is RMB 3,107 (US $469) per year and median conditional WTP is RMB 1,559 (US $236). Unconditional WTP estimates derived from these conditional estimates are closer to WTPs from the unconditional model (Model 1): mean derived unconditional WTP is RMB 1,412 (US $213) per year and median derived WTP is RMB 709 (US $107) per year.

[Insert Table 9 here]

5.4.2. Multivariate models

In the unconditional multivariate model (Model 2A), estimated mean and median unconditional WTP is RMB 386 (US $58) per year. In the conditional multivariate model (Model 2B), WTP estimates are, again, significantly higher: mean conditional WTP is RMB 2,819 (US $426) per year and median conditional WTP is RMB 1,509 (US $228). Mean derived unconditional WTP is RMB 1,281 (US $194) per year and median derived WTP is RMB 686 (US $104) per year.

[6] Specifically, we use Stata 14.0's nonlinear combinations of estimators ('nlcom') command to generate WTP point estimates and standard errors.

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). As noted above, we use median rather than mean unconditional WTP in order 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 353 (Model 1A) and RMB 708 (Model 1B). Hence, our estimate of total annual costs is RMB 1.6 billion to 3.3 billion (US $245 million to $493 million) per year.

5.5. Determinants of willingness to pay

To identify the determinants of WTP, we estimate two equations: one (Model 3) sheds light on the determinants of positive WTP and the other (Model 4) on the determinants of stated WTP. Note that the WTPs in our data that are zeros are not due to censoring. Rather they are real zeros. As a result, these two equations can be estimated separately or jointly as a selection model. We estimate them separately because selection models are often highly sensitive to model specification when the inverse Mills ratio is correlated with covariates in the second stage (Carlsson and Johansson-Stenman 1999; Leung and Yu 1996).

In our model of positive WTP (Model 3), the dependent variable is a binary dummy equal to one if the respondent had a positive WTP. We use the full sample of 2,055 respondents and include as regressors the vehicle, driver, and household characteristics listed in Table 1, but not the bid itself (since 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. We find that driver and household characteristics help explain positive WTP, but vehicle characteristics do not (Table 10). Respondents with a positive WTP tend to be younger, not have postsecondary education, have higher income, live in households with fewer commuters,

combine work and nonwork trips, 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*.

[Insert Table 10 here]

In our model of WTP (Model 4), the dependent variable is a binary dummy equal to one if the respondent accepted the bid. We estimate the model as a probit, use the sample of 934 respondents with a positive WTP, and include the natural log of the bid to restrict WTP to be positive (Haab and McConnell 2002). Hence, this model is the same as the multivariate conditional model of WTP (Model 2B). For each covariate, we report marginal median WTP (for binary regressors calculated as the difference in median WTP when the regressor equals one versus zero). We find that vehicle and household characteristics, but not driver characteristics, help explain WTP (Table 10). Among respondents with a positive WTP, those with higher WTP tend to drive a car (versus truck or van), drive a vehicle with fewer lifetime kms, have higher incomes, and live in households with a higher socioeconomic status.

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 353 to 708 (US $53 to $107) per driver per year and RMB 1.6 billion to 3.3 billion (US $245 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 0.45 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 program

As discussed above (Section 2), using high-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.[7] Their estimates (adjusted for inflation) range from RMB 3.38 billion to 4.58 billion (US $510 million to $690 million) per year (Table 11). 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 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 RMB 672 million per year.

[Insert Table 11 here]

[7] 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.

How do our own cost estimates compare with Viard and Fu's (2015) estimates of the benefits and costs of Beijing's driving restriction program? Before answering that question, it is important 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, Viard and Fu's (2015) estimates do shed light on the relative magnitude of our cost estimates. Depending on whether we use upper or lower bounds of Viard and Fu's benefits estimates and of our own cost estimates, benefit-cost ratios range from 1.04 to 2.82 (Table 11). In other words, depending on the estimates used, the benefits from reducing PM10 range from just about equal to the costs, to about three times the costs. 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.

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 significantly lower than for Mexico City (Table 12). Average annual WTP for Beijing is 60 to 80 percent 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 58 to 78 percent of that for Mexico City. However, city GDP for Beijing is several orders of magnitude larger than that for Mexico City. Therefore, expressed as a percentage of city GDP, total WTP for Beijing is only 2 to 3 percent of that for Mexico City.

[Insert Table 12 here]

At least three factors could explain why the costs of driving restrictions are lower in Beijing than in Mexico City. First, in Beijing, the time period and the geographic area covered by driving restrictions are smaller, making it easier to adapt to restrictions by shifting driving times and routes. In Beijing, restrictions are enforced 12 hours per day (from 7 a.m. to 8 p.m.) inside the fifth ring road. In Mexico City, they are enforced 16 hours a day (from 5 a.m. to 10 p.m., although not on Sundays) in the entire metropolitan area and surrounding states. 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 12). 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 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 significant: RMB 353 to 708 (US $53 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 $245 million to $493 million) for all drivers per year. Second, although we do not have the data needed to conduct a full-fledged benefit-cost analysis, available evidence suggests that the

program's benefits are well above the costs: the benefits of reductions in a single air pollutant, PM10, exceed costs by a factor of three to one. 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 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 driving restrictions programs are apt to exacerbate air pollution and traffic congestion (Eskeland and Feyziouglu 1997; Davis 2008; Gallego et al. 2013). This pessimistic conclusion has been reinforced both by a rigorous study of the program's costs, which found that these costs are quite 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 2016). 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 programs exceed the costs? Although we are not able to conduct a full-fledged benefit-cost analysis, 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 license plate based driving restrictions are likely to have net benefits. So far, we only have rigorous evidence on the benefits of driving restrictions programs in six cities and on the costs of such programs in two cities, too little to confidently draw conclusions (Blackman et al. 2018b). However, this evidence suggests hypotheses to be tested. One is that, somewhat counterintuitively, relatively high program costs are not a necessary condition for significant program benefits—in fact, the opposite may be true. Conventional wisdom holds that 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 key determinants of both benefits and net benefits may well be mediating factors discussed 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).

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Table 1. Characteristics of vehicle, driver, household (n = 2,055)

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 (‘0,000)	mean	5.68	0.60
Km driven per day	Average km driven per day	mean	45.43	30.75
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 post-sec. education	mean	0.69	0.46
Income	Annual income range (’000 RMB)	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
Socioec. 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	Floors pace (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
Postsec. edu. hh head	0/1 = 1 if hh head post-secondary edu.	mean	0.69	0.46

Table 2. Effect of driving restrictions permit on work/school travel
(n = 1,633 respondents who use
vehicle for work or school)

Would a driving restrictions permit have the following effects?	**Statistic**	**Value**	**No. obs.**
Change mode of transport used on restricted day	percentage	53.2	1,633
Change time of commute	percentage	42.4	1,633
Change vehicle use to commute	percentage	38.3	1,633
Change commute in some other way	percentage	20.9	1,633
Save money on commuting	percentage	18.8	1,633
How much (RMB/week)	mean	98.0	307
Save time on commuting	percentage	54.6	1,633
How much (minutes/week)	mean	90.0	891
Eliminate inconveniences associated with commute	mean	57.6	1,633

Table 3. Effect of driving restrictions permit on nonwork/nonschool travel (n = 2,055)

Would a driving restrictions permit have the following effects?	**Statistic**	**Value**	**No. obs.**
Change mode of transport used on restricted day	percentage	44.7	2,055
Change days on which make trips	percentage	48.6	2,055
Change time of trips	percentage	47.1	2,055
Change trips in some other way	percentage	36.5	2,055
Number of additional trips	median	1	2,055
Save money on nonwork/nonschool travel	percentage	20.9	2,055
How much (RMB/week)	mean	97.1	429
Save time on nonwork/nonschool travel	percentage	41.3	2,055
How much (minutes/week)	mean	117.3	849

Table 4. Effect of driving restrictions permit on vehicle ownership

Would a driving restrictions permit have the following effects?	**Statistic**	**Value**	**No. obs.**
Sell second vehicle in household	percentage	2.3	2,055
Change plans to buy or sell vehicle in another way	percentage	6.3	2,052

Table 5. Responses to bids; number of respondents (row percentage); n = 2,055

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)
1,400	324	80	404
	(80.2)	(19.8)	(100.0)
2,200	360	49	409
	(88.0)	(12.0)	(100.0)
Total	1,357	698	2,055
	(66.0)	(34.0)	(100.0)

Table 6. Interviewees' assessments of yes responses to their bids
(n = 698 interviewees who responded yes)

How sure are you of your response?	**Percentage yes**
I am sure	77.1
I am more or less sure	19.6
The truth is that I gave a response only to say something, but I do not believe the permit program is realistic	3.3

Table 7. Interviewees' reasons for no responses to their bids (n = 1,040)*

Reason	Percentage yes
I cannot afford it	9.4
Cost of permit exceeds benefits	73.0
I don't want to contribute to air pollution and traffic congestion	47.2
Not confident in government administration of program	13.9
Not a realistic question, so I just gave an answer	18.2

*Respondents could select more than one reason.

Table 8. Interviewees with positive willingness to pay for permit
(n = 1,357 interviewees who said no to bid)

Variable	Statistic	Value	No. obs.
Positive willingness to pay	percentage	17.4	1,357
How much (RMB)	mean	377.5	232

.

Table 9. Estimates of mean and median willingness to pay (WTP) derived from probit models; dependent variable = 1 if response to contingent valuation question was yes, and 0 otherwise (s.e.)

	Model 1 Univariate[a]		**Model 2 Multivariate**[b]	
Variable	A unconditional[c]	B conditional[d]	A unconditional[c]	B conditional[d]
Intercept (α)	0.265***	2.338***	-0.446	1.010*
	(0.049)	(0.158)	(0.326)	(0.568)
Bid/1000 (λ_1)	-0.075***		-0.083***	
	(0.005)		(0.005)	
Ln (Bid/1000) (λ_2)		-0.851***		-0.894***
		(0.067)		(0.071)
WTP				
Mean unconditional[e,f]	352.523***	1412.124***	385.502***	1281.448***
	(49.961)	(229.336)	(45.183)	(212.331)
Median unconditional[e,f]	352.523***	708.452***	385.502***	685.890***
	(49.961)	(51.861)	(45.183)	(65.115)
Mean conditional[e]		3106.975***		2819.460***
		(504.588)		(467.174)
Median conditional[e]		1558.745***		1509.104***
		(114.106)		(143.266)
No. observations	2,055	934	2,055	934

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

[a]Sole independent variable is the bid.

[b]Independent variables are the bid and household, driver, and vehicle characteristics, specifically: *automobile, 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.*

[c]Sample includes all respondents.

[d]Conditional on respondent having WTP > 0; sample includes only such respondents.

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

[f]For conditional models (B variants), unconditional WTP is derived by multiplying conditional WTP by the fraction of respondents with a positive WTP (0.45).

Table 10. Explaining positive willingness to pay (WTP) (Model 3, marginal effects) and WTP (Model 4, marginal mean WTPs[a]) (s.e.)

Variable	**Model**	
	3	**4**
Dependent variable →	Prob (WTP>0)	Prob (Yes)
Ln(Bid/100)		-0.894***
		(0.071)
Constant		1.010*
		(0.568)
Vehicle characteristics		
Automobile	-0.012	673.946**
	(0.037)	(291.711)
Lifetime km driven	0.000	-0.001***
	(0.000)	(0.000)
Km driven per day	0.000	-3.985
	(0.000)	(3.589)
Commute	0.015	-80.392
	(0.028)	(244.205)
Driver characteristics		
Male	0.010	238.316
	(0.025)	(199.813)
Age	-0.004***	-8.159
	(0.001)	(10.218)
Married	0.047	19.468
	(0.0327)	(248.310)
Postsecondary education	-0.081***	-327.797
	(0.028)	(234.163)
Income	0.039***	79.410*
	(0.006)	(48.799)
Household characteristics		
Number vehicles	-0.063	531.677
	(0.049)	(397.138)
Walk time public transit	0.002	17.486
	(0.00)	(24.717)
Commute time	-0.001	2.897
	(0.005)	(4.250)
Combine trips	0.058**	-264.314
	(0.024)	(191.952)
Commuters	-0.0242**	130.470
	(0.012)	(90.183)
Drivers	0.004	-124.708
	(0.018)	(149.292)
Socioeconomic class	0.045**	426.478***
	(0.019)	(159.943)
No. observations	2,055	934
Pseudo R2	0.0341	0.282

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

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

Table 11. Comparison with Viard and Fu's (2015) estimates of benefits and costs of Beijing's driving restrictions program: Benefit/cost and cost/cost ratios

	Present study	
	Lower-bound costs	Upper-bound costs
Viard and Fu (2015)		
Lower-bound benefits	2.08	1.04
Upper-bound benefits	2.82	1.40
Costs	5.03	6.82

Present study cost estimates: 2016 RMB 1.6 billion to 3.3 billion (see Table 10); Viard and Fu (2015) benefit estimates: 2016 RMB 3.38 billion to 4.58 billion (2007 values adjusted for inflation); Viard and Fu (2015) cost estimates: 2016 RMB 0.67 billion (2007 values adjusted for inflation).

Table 12. Comparison with Blackman et al. (2018a) estimates of costs of Mexico City's driving restrictions program (all monetary values 2016 US$)

Variable	**Beijing**	**Mexico City**	**Ratio**
No. vehicles (millions)	4.61[b]	4.77[c]	0.97
Median annual income[a]	11,710	7,188	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	53.27	88.09	0.60
WTP/median annual income (%)	0.45	1.23	0.37
Total WTP (millions)	245.34	419.81	0.58
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.