The Marginal Cost of Traffic Congestion and Road Pricing: Evidence from a Natural Experiment in Beijing

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Preliminary and Comments Welcome

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ABSTRACT

Leveraging a natural experiment and big data, this study examines road pricing, the first-best policy to address traffic congestion in Beijing. Based on fine-scale traffic data from over 1500 monitoring stations throughout the city, this paper provides the first empirical estimate of the marginal external cost of traffic congestion (MECC) and optimal congestion charges based on the causal effect of traffic density on speed, a key input for measuring the MECC. The identification of the causal effect relies on the plausibly exogenous variation in traffic density induced by the driving restriction policy. Our analysis shows that the MECC during rush hours is about 92 cents (or $0.15) per km on average, nearly three times as much as what OLS regressions would imply and larger than estimates from transportation engineering models. The optimal congestion charges range from 5 to 38 cents per km depending on time and location. Road pricing would increase traffic speed by 10 percent within the city center and lead to a welfare gain of 1.4 billion and revenue of 40 billion Yuan per year.

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1. INTRODUCTION

Traffic congestion is ubiquitous in large cities around the world, especially in the middle-income countries and emerging markets where road infrastructure and regulations lag behind the rapid rise in vehicle ownership.[2] The first-best policy to address urban traffic congestion dates at least back to Vickery (1959 and 1963) who first proposed road pricing by recognizing traffic congestion as a classic externality. While the policy has since been continually advocated by economists, technical feasibility and political acceptability have hindered its wide adoption in practice. However, in the past 15 years, several European and U.S. cities have adopted different designs of road pricing while policy makers elsewhere including those in China are showing increasing interests in the policy and taking notes of these real-world implementations.[3]

In China, traffic congestion is one of the most pressing challenges in major urban areas, largely as a result of the unprecedented economic and social transformation during the last three decades. Since the turn of the century, the dramatic increase in vehicle ownership and urbanization overwhelms the provision of road infrastructure and public transit, leading to serious traffic congestion that affects the housing and employment decisions and the quality of life of urban residents (Zheng and Kahn 2013; Yang et al. 2016).[4] Between 2001 and 2015, Beijing experienced a 55 percent increase in population while its per capita GDP increased from about $1000 to over $8000, and vehicle stock increased from less than one million to nearly six million. Beijing has been now routinely ranked as one of the most congested cities in the world with average traffic speed often less than 24 kilometers (15 miles) during rush hours.

To deal with traffic congestion, central and local governments in China have been employing various policies such as driving restrictions and vehicle purchase restrictions, yet achieving little or no visible impact because these policies fundamentally failed to get the price right for road use. In December 2015, Beijing municipal government announced a plan to introduce road pricing in the near future while soliciting feedbacks from experts and general public. This policy follows the

[2] TomTom traffic index shows that among the top 20 large cities (population over 0.8 million) with worst traffic congestion, 17 are from middle-income or emerging countries. https://www.tomtom.com/en_us/trafficindex/list

[3] Singapore was the first in adopting road pricing in 1975. In recent years, London (2003), Stockholm (2006), Milan (2008), Gothenburg (2013), and some cities in the U.S. have adopted road pricing through high-occupancy tolls.

[4] From a country with virtually zero household vehicle ownership 20 years ago, China surpassed the U.S. in 2009 to become the world's largest automobile market, with over 22 million new passenger vehicles sold in 2015. At the same time, China has witnessed the largest human migration with the share of urban population increased from 25 percent to over 50 percent during the last two decades.

principle of the Pigouvian tax and congestion charges in accordance with the marginal external cost from traffic congestion road users impose to the other road users depending on the time and place of traveling.

One of the key components of road pricing is to estimate the marginal cost of traffic congestion (MECC) and the optimal congestion charges (Walters 1961; Keeler and Small 1977; Newberry 1988a; Parry and Small 2009). To do so, researchers typically specify traffic speed as a deterministic function of density (or flow) from the transportation engineering literature where this relationship is treated as one-way and mechanical. In reality, traffic speed and density affect each other and both are subject to idiosyncrasies, giving rise to endogeneity due to simultaneity in estimation (Small and Chu 2003).

The objective of this study is to empirically estimate MECC and optimal congestion charges in Beijing while examining the consequences of road pricing on traffic speed and social welfare. We identify a causal effect of traffic congestion on average vehicle by relying on plausibly exogenous variations in traffic density introduced by the driving restriction policy which restricts some vehicles from driving depending on the last digit of the license plate numbers. The policy follows a pre-set rotation schedule for what vehicles are not allowed to drive on a given day and it is not adjusted based on traffic conditions. At the same time, the policy affects the number of vehicles on the road due to the fact that the distribution of vehicles is not uniform based on the last digit of plate numbers. Vehicles with the license plate ending four only account for about two percent of all vehicles. When the numbers four and nine are restricted, more vehicles are on the road and congestion tends to be worse than other days.

The data comes from over 1500 traffic monitoring stations (detectors) throughout Beijing that record the real-time speed and density at a 2-minute interval for 2014 (the raw data has nearly 400 million observations). Our analysis shows that the average marginal cost of congestion during the rush hours is about 0.92 Yuan (about $0.16) per km, nearly three times as much as what OLS regressions would imply and larger than estimates from transportation engineering models. The optimal congestion charges range from 5 to 38 cents per km depending on time and location. Following the time-varying and location-specific congestion charges we estimated, road pricing would increase traffic speed by 10 percent within the city center (within the 3rd Ring Road) and lead to a welfare gain of 1.4 billion Yuan. The tax revenue from road pricing would amount to over 40 billion Yuan per year, more than twice as much as the annual total operating subsidy on public transit (subways and buses) by the Beijing municipal government.

Our study makes the following three contributions to the literature. First, to our knowledge, this is the first attempt in estimating the marginal cost of traffic congestion while addressing the endogeneity issue in average vehicle speed and traffic density (or flow) relationship. Existing studies conducted in developed countries are mostly based on engineering estimate of the speed-flow relationship rather than empirical estimates of the relationship (Lindsey and Verhoef 2007; Parry and Small 2009). While the endogeneity issue in the relationship in recognized (Small and Chu 2003), it has not been addressed due to the challenge in finding a valid instrument variable.

Second, our study provides the first empirical estimates of MECC in China based on extremely rich data in both temporal and spatial dimensions. There exist a number of studies that estimate the MECC in developed countries such as Canada and U.S. (e.g., Walter 1961; Kraus, Mohring, and Pinfold 1976; Keeler and Small 1977; Dewees 1979; Parry and Small 2009). Despite the seriousness of traffic congestion in China and its potential impacts on the quality of life in urban areas, there is a lack of rigorous empirical analysis on measuring marginal cost of traffic congestion in China.

Third, our analysis adds to the existing literature on estimating MECC by empirically estimating the speed-density relationship rather than the speed-flow relationship. The speed-flow relationship is useful for analyzing situations where traffic conditions do not change quickly, or the focus is on average traffic levels over extended period such as Vickrey (1963). However, the speed-flow curve could exhibit the "backward-bending" phenomenon due to hypercongestion.[5] In the presence of hypercongestion, the MECC can be properly and accurately explained based on the speed-density relationship while it cannot be explained by the traditional speed-flow relation. Else (1981) and Evans (1992) have argued that the speed-density relationship should be the appropriate basis in estimating MECC but in practice, researchers have ignored hypercongestion and continued to use the speed-flow relationship. However, our data shows that hypercongestion occurs frequently during the peak hours within the city center in Beijing.

The remainder of this paper is organized as follows. The next section presents theoretical

[5] This implies that two different speeds can lead to the same flow. So, there does not exist a one-to-one correspondence between speed and flow (Vickrey 1969; Arnott et al. 1991, 1993, 1994).

framework of road pricing. Section 3 reviews Beijing's transportation challenges, current policies and describes the data. Section 4 lays out the empirical strategy and Section 5 presents model estimation results and the estimates of MECC. Section 6 estimates optimal congestion charges and investigates the consequences on average vehicle speed and welfare. Section 7 concludes.

2. THEORETICAL FRAMEWORK

In this section, we introduce a stylized model to illustrate the foundations of traffic congestion and to derive the marginal external cost of traffic congestion (MECC) as model premises. The derivation provides a theoretical basis for our empirical strategy to estimate MECC using the observed data set.

2.1 The Speed-Density Relationship

The conventional approach to the economic analysis of traffic congestion centered on the relationship between the cost of using a road and the traffic volume (flow), which is derived from the speed-volume relationship.[6] This approach is widely employed to estimate marginal external cost of traffic congestion (MECC). The speed-volume relationship can be divided into two nonlinear parts. The first part shows ordinary traffic congestion with a negative speed-volume relationship, whereas the second part shows hypercongestion with a positive relationship. There is a turning point, where the speed-volume relationship switches from a negative to a positive relation. This point indicates the maximum traffic volume level or the engineering road capacity. The empirical estimation of a speed-volume relation is difficult as the relation from volume to speed is not a function and the relation is nonlinear. In particular, the estimation of the turning point from ordinary to hypercongestion is likely to be difficult. Most empirical studies consider only negative speed-volume relationships,[7] while in urban areas traffic is likely to be hypercongested frequently. Grid lock or very low traffic speeds throughout the day are common in major urban centers such as Beijing.

Walters (1961) notes that an increase in traffic demand does not always increase traffic volume. Since traffic volume is the product of traffic density and vehicle speed, the traffic volume at a very high demand for trip is lower than that is at a lower demand for trip. Instead of traffic volume,

[6] We use the terms traffic flow and traffic volume inter-changeably.

[7] For most economic analysis it is common to ignore the hypercongested portion of the speed-flow function (Newberry 1988a; Button 2010; Quinet and Vickerman 2004).

he proposes to use traffic density to study MECC because demand for trip directly depends on traffic density. In addition, he suggests that on the backward sloping part of time-volume cost curve, the marginal social cost cannot be measured based on the time-volume cost curve because the change in traffic volume is negative. Else (1981) argued that the relationship between costs and the number of vehicle on the road or traffic density is a more appropriate basis for these analyses because a decision to use a road is essentially a decision to add to a vehicle to the number of vehicles on the road. Following Else (1981), Newberry (1990), Evans (1992), Hills and Evans (1993) and Small and Chu (2003), we focus on the speed-density relationship in both theoretical and empirical analysis where hypercongestion can be directly modeled.

Figure 1 depicts the *speed-density*, *speed-travel time*, *travel time-density*, and *cost-density* relationships. Panel (a) shows a speed-density relationship, where the vertical axis represents average vehicle speed (S, measured in kilometers per hour) and the horizontal axis represents traffic density (D, measured in vehicles per lane-kilometer). When many vehicles try to use the road simultaneously, the resulting high density forces them to slow down for safety reasons, thereby reducing average speed. The figure also shows the density D^m and speed S^m that correspond to maximum volume V^m. All other allowed volume levels can result from either a congested or a hypercongested speed and density. For example, a zero volume prevails when there are no vehicles on the road ($D=0$), allowing the free-speed S^f. Given a road with a fixed distance (say, one kilometer), the traffic speed-density curve can be converted to a travel time-density curve as travel time (T, measured in hours) is the reciprocal of average vehicle speed, with hours per kilometer-vehicle on the horizontal axis in Panel (b) of Figure 1. As other vehicles enter the road thereafter, traffic density (or number of vehicles on the road) increases, speed drops and average travel time for a vehicle lengthens. The basic relationship between average travel time of a vehicle and traffic density is presented as a solid line in Panel (c) and can be written as

$$\textit{Average travel time} = T(D) = 1/S(D), \tag{1}$$

where $T'(D) \geq 0$, and $T''(D) \geq 0$. Thus, the aggregate travel time for all vehicles on the road is the product of number of vehicles and average travel time for a vehicle:

$$\textit{Aggregate travel time} = D \cdot T(D). \tag{2}$$

Marginal change in aggregate travel time with respect to the traffic density then can be defined as follows, which is presented as a dashed line in Panel (c) of Figure 1.

$$\textit{Marginal aggregate travel time} = T(D) + D \cdot T'(D), \tag{3}$$

which meaning that as more and more vehicles join a traffic stream, the travel times of all drivers making trips are raised, resulting in delay to all.

Using a constant value of time as a shadow price for the representative driver, average travel time is then converted to a money basis, yielding time cost, called the average social cost *ASC* and shown in Panel (d) of Figure 1. The horizontal axis indicates traffic density, number of vehicles per lane-kilometer road, while the vertical axis specifies costs of using the road. The marginal private cost *MPC* curve is the time cost of each vehicle per kilometer ($/vehicle/lane-km) for using a road of a fixed distance. Because a road is a common property resource, every road users faces a same average social cost *ASC*, which is assumed to be equal to *MPC*. As illustrated in the figure, at low traffic density ($D \leq D^f$), road users can travel at the free-flow speed, and the MPC can be constant. After the traffic congestion develops at a lower vehicle speed that is caused by a higher traffic density, the *MPC* slopes upwards.

2.2 Road Pricing as a Pigouvian Tax

The market failure of traffic congestion is demonstrated in Figure 2. We assume identical road users using a uniform road network at a certain time of day. The inverse demand curve represents travelers' willingness-to-pay curve or the marginal private benefit (*MPB*) from a trip using a road. The travel decision is dictated by the *MPB* and the marginal private cost *MPC* from the trip. The marginal social cost curve *MSC* takes into account of the congestion cost imposed on others by the last road user. The *MSC* diverts from the *MPC* when traffic density is greater than D^f, defined as a traffic free-flow density. The difference between the *MSC* and the *MPC* is the marginal external cost of traffic congestion *MECC*.

The unregulated equilibrium occurs at the intersection of the *MPC* and the *MPB*, resulting in an equilibrium price at p^0 and at traffic density of D^0. This is an equilibrium point because each road user chooses whether or not to travel according to the *MPC* curve – being the decision curve – he or she totally ignores the resulting external congestion cost imposed on other road users. At this price, an additional road user enjoys his trip but only faces the MPC, whereas other road users have to bear an extra cost *MECC* in terms of their extra travel time on the road. Hence, there is an excess burden of congestion, defined as the net social cost of unregulated use of the road network (the shaded triangle in the figure). We thus have the optimal (p^*, D^*) at which the marginal cost curve intersects the inverse demand curve in Figure 2. In other words, D^* is the associated optimal traffic density level in the sense that the generalized cost which includes external congestion cost and other variable costs (i.e., constant operating cost of a vehicle and variable maintenance cost of a road), is equated the marginal social benefits.

Recognizing traffic congestion as an externality, road pricing or congestion charge is a Pigouvian Tax or a toll (Pigou 1920) that can be used to internalize the *MECC*. Every road user will be charged with the MECC – the additional time cost that a road user imposes on others, calculated by taking the increment in average time cost caused by the added trips and multiplied by the number of vehicles in the traffic stream. Hence, under road pricing regulation, every road user is paying the *MSC*, that is achieved by adding a tax of congestion cost, *MECC* to the *ASC*. The road pricing policy will lead to the social optimal level of traffic density D^*. Optimal congestion charge ($\boldsymbol{\tau}$) close the wedge between the marginal cost and average variable cost curves by giving incentives to road users to internalize the externalities.

The optimal congestion charges and the resulting impacts on traffic congestion and social welfare are therefore empirical questions. Our empirical target is therefore to estimate the three curves in Figure 2, the marginal benefit curve and the two cost curves for the city of Beijing.

3. BACKGROUND AND DATA

In this section, we first discuss Beijing's transportation challenges and review various policies implemented to address the congestion issues. We then present our data.

3.1 Traffic Congestion in Beijing

Major urban cities in China including Beijing have been experiencing world's worst traffic congestion due to the dramatic increase in vehicle ownership and travel demand in the past decade. As of 2014, Beijing's total vehicle number hit 5.6 millions; 4.5 millions of those vehicles are privately owned. The travel mode shares of private vehicles and taxis reached 63% while the share of public transportation was around 26% (Beijing Transportation Annual Report 2014). Beijing now is routinely ranked by numerous organizations as one of the most polluted and traffic congested cities in the world (TomTom Traffic Index 2015). According to the Beijing Transportation Annul Reports, the average speed of vehicles on arterial roads during the peak hours on workdays decreased to 23 km/h in 2014 from 60 km/h in 2001.

To address traffic congestion, central and local governments have adopted various policies including investment in public transportation, driving restrictions, and restrictions on purchases of new vehicles. Table 1 lists major transportation policies and actions. We briefly discuss both regulatory and marked based policy instruments in chronological order.

As a supply side strategy to address traffic congestion, the Beijing municipal government has been expanding urban road and subway systems extensively. The number of subway lines increased from two before 2002 to 18 with a total length of 554 km in 2016. However, the continuous road supply and infrastructure development have not been adequate to accommodate the increasing travel demand (Yang et al. 2015). Previous experiences elsewhere have shown that the supply side policy alone is unlikely to fully address traffic congestion in the long run because road expansion reduces the private cost of traveling and hence increases travel demand (Duranton and Turner 2011).

In addition to the road and subway expansion, Beijing imposed a parking certificate system in 1998 on newly purchased vehicles in eight urban districts to restrict the total number of vehicles on city roads. However, due to slow registration and administration of parking certificates, the high costs of verification, and the arbitrary collection of fees, the system was largely ineffective. In early 2004, the parking restriction system was replaced by a vehicle purchase tax of 10%, but Beijing continued to experience high rates of growth in motor vehicle purchases.

In 2005, the Beijing Transport Development Outlines (2004–2020) were issued and two major strategic plans were highlighted including enhancing public transportation and adjusting city's spatial structure and gradually implementing travel demand management. In accordance with this outline, Beijing implemented a low-cost public transportation policy in 2007 and expanded bus-only lines to increase the attractiveness of buses and the subway system. However, very few Beijing citizens changed their typical modes of transportation despite the lower fares.

Due to the limited impacts of these policy measures, the Beijing municipal government has decided to introduce more administrative means of policies, one of which is restriction of vehicle ownership and use.[8] However, road users have invented ways to circumvent restriction policy by gradually changing their behavior and response towards restriction such as entering the traffic zones prior to the restriction time, preferring to pay daily fines or by purchasing additional vehicles. Wang et al. (2014) found that the driving restriction did not significantly influence individual's choice to drive. Nevertheless, in the short term, driving restriction policies were effective in controlling vehicle trips for two years. However, traffic congestion index jumped back to the level observed prior to the implementation of license plate restriction.[9]

As a result, by the end of 2010 the Beijing municipal government has decided to implement a lottery policy to control quantity of automobile ownership.[10] After analyzing Beijing's lottery policy on vehicle growth, congestion and fuel consumption, Yang et al. (2014) highlighted significant yet short-term effect of the lottery policy on both vehicles sold and traffic congestion. According to Wang et al. (2014), neither the driving restriction nor the lottery policy reduces significantly traffic congestion and air pollution in the long run.

3.2 Road Pricing in Practice

The policies implemented by central and local governments such as driving restriction and vehicle purchase restriction had little or no visible impact on the traffic congestion because these policies fundamentally failed to get the price right for road use. Economists and transportation experts since Vickery (1959 and 1963) have continually advocated road pricing as the first-best policy to reduce traffic congestion. Singapore was the first to adopt road pricing in early 1975 and studies have shown that the policy has reduced traffic congestion (Small and Gomez-Ibanez 1997). In recent years, several cities and countries in Europe (Norway, London, Stockholm and Belgium) have adopted the policy in various forms. Studies suggest that road pricing has been effective in reducing congestion (Small and Gomez-Ibanez 1997; Olszewski and Xie 2005; Leape 2006; Anas and Lindsey 2011). Despite worsening traffic congestion in many middle-income countries and emerging markets, yet road pricing policy has not been introduced in these places. Some scholars have argued

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[8] During the Olympics in August 2008, Beijing implemented short-term driving restriction policies in which cars could be driven on the road only on certain days according to whether they had an even- or odd-numbered licensed plate.
[9] We discuss about the license plate restriction policy more in detail later.
[10] Since 2011, lotteries have been used to allocate about 20,000 licenses, with 88% to individuals, 20% to companies and the remaining 2% to operators of transportation services each month.

that the major reasons for avoiding road pricing policy were equity and political concerns (Rouwendal and Verhoef 2006; Eliasson and Mattson 2006; de Grange and Trocoso 2011).

Likely out of equity concerns, the Beijing municipal government has been using rationing policies, including driving and ownership restrictions, instead of road pricing to address congestion. With increasing discontent from residents with traffic congestion and air pollution, the Beijing municipal government announced a plan to adopt road pricing. The scheme under consideration is to be implemented within the 3rd Ring Road and vehicles except buses driving in this zone at any time will be charged 8RMB (about $1.25) each time of entry. According to Linn et al. (2016), relatively wealthier but small proportion of individuals are likely to be affected by Beijing's road pricing scheme. This proposal does not set the congestion charges based on the distance traveled. Although it should reduce the number of road users within the 3rd Ring Road, it will unlikely reduce the travel distance for those who decide to enter the charge zone. It may actually increase the distance travelled for this group of consumers because of reduced congestion in the short run and the need to stay within the 3rd Ring Road to avoid paying multiple entry fees.

3.3 Data Description

Our empirical analysis is based on two datasets. The first data set, obtained from the Beijing Transportation Research Center, contains real-time traffic volume and average vehicle speed in 2-minutes interval from over 1500 traffic monitoring stations throughout Beijing for 2014. The data is aggregated to hourly basis at the road segment level and we have 1528 road-level records representing over 12 million observations (1528×365×24) of average vehicle speed (measured in kilometer per hour) and traffic volume (measured in number of vehicles per hour) for 2014. This data has rich spatial and temporal variations. The locations of the traffic monitoring stations are shown in Figure 3. Since the dataset does not provide traffic density (measured in number of vehicles per kilometer-lane) at the road level, we generate it by comparing traffic volume per lane with average vehicle speed. Table 2 presents summary statistics of the main variables discussed here and Figure 4 plots the observations of the variables pairwise: average vehicle speed versus traffic density; average vehicle speed versus traffic volume; and traffic volume versus traffic density.

The second dataset includes hourly weather variables obtained from the ISD-Lite data set published by National Oceanic and Atmospheric Administration (NOAA). The data set contains hourly records of important weather controls for the average vehicle speed: wind speed (km/hour), visibility (km), temperature (°C), wind direction dummies – north, east, south, west, northeast, southeast, southwest, northwest, and sky coverage dummies – clear, scattered, broken, obscured, partially obscured.

4. EMPIRICAL STRATEGY

In this section, we first describe the empirical specification for the relationship between vehicle speed and traffic density, which is the basis for estimating marginal cost of traffic congestion. We then discuss our empirical strategy to deal with endogeneity of the traffic density.

4.1 Speed-Density Relationship

Following Newbery (1988a, 1988b) and Quinet and Vickerman (2004), we denote *ASC* as the average social cost of travel per vehicle. This cost is composed of monetary costs such as fuel spending and time costs and is defined as

$$ASC(T) = T \cdot o \cdot VOT = (hours) \cdot (persons/vehicle) \cdot (\$/person/hour), \quad (4)$$

where T is the average travel time of a representative to drive one kilometer, an increasing function of traffic density; o is vehicle occupancy, or average number of passengers per vehicle; VOT denotes the value of travel time for a representative driver, measured in dollars per passenger. The total social cost, $TSC(\$/km)$, is given by

$$TSC = D \cdot ASC(T) = D \cdot T \cdot o \cdot VOT, \quad (5)$$

where D is traffic density - the number of vehicles per kilometer on a lane. The marginal social cost is given by:

$$MSC = \partial TSC/\partial D = ASC(T) + D \cdot o \cdot VOT \cdot (1/S^2) \cdot (\partial S/\partial D) = ASC(T) + MECC(D), \quad (6)$$

where $MECC$ in \$/km is the marginal external cost of congestion. We expect that an increase in number of vehicle entering a road increases density, and this reduces an average speed ($\partial S/\partial D>0$). Therefore, when the impact of road congestion externalities is taken into account, the MSC will be higher than $ASC(T)$ by amount of $D \cdot o \cdot VOT \cdot (1/S^2) \cdot (\partial S/\partial D)$, the marginal external cost of congestion. If we assume that occupancy per vehicle, o, and value of travel time for a representative driver, *VOT*, are constant, then we only need to estimate the speed-density relationship in order to calculate the marginal external cost of traffic congestion, *MECC*.

We specify the following functional relationship between traffic speed and density:

$$\begin{aligned} Speed_{it} = \alpha + \beta\, Density_{it} + Weather_t\, \gamma \\ + Month_t + Hour_t + Weekday_t + Holiday_t + \\ + Road_i + Ring_i \times Month_t + Ring_i \times Hour_t + \varepsilon_{it} \end{aligned} \quad (7)$$

where $Speed_{it}$ is the average speed (measured in km/hour) of a vehicle on road i at time t; $Density_{it}$ is the average traffic density (measured in vehicles/lane-km) on on road i at time t; $Weather_t$ is a vector of hourly weather indicators including wind speed (km/hour), visibility (km), temperature (C^0), wind direction dummies - north, east, south, west, northeast, southeast, southwest, northwest, and sky coverage dummies – clear, scattered, broken, obscured, partially obscured; ε_{it} is the unobserved, time-varying, and road-specific factor.

We also include a full set of time fixed effects ($Month_t$, $Hour_t$, $Weekday_t$, and $Holiday_t$) and road-specific fixed effects ($Road_i$). The time fixed effects capture the unobserved, temporal, and common shocks associated with the traffic conditions during the month of the year, hour of the day, the day of week, holidays. Road-specific fixed effects control for road related, time-invariant, spatial factors such as road attributes that affect vehicle speed and traffic density.[11] The relationship could vary across types of vehicles (the slow wide vehicles cause more congestion than fast narrow vehicles) and across times (volume of vehicles varies by different time of the day) and across different roads. To control for possible unobserved spatial and temporal differences in traffic conditions on different times of the day and the year, we interact month fixed effect, hour-of-the day fixed effect with ring road dummies ($Ring_i$).

[11] These road attributes include qualities (grade, surface), speed limits, engineering design (e.g., oneway, twoway, number of lanes, restriction on vehicle types, bending, visibility), traffic lights, stops signs, sidewalks, bike lanes, number of intersections, and locational characteristics - street parking, pedestrian crossing, nearness to the school areas, business districts, parking areas, subway or bus stations

4.2 Identification

In the theoretical model presented above and in the transportation engineering literature, it is assumed that traffic density affects average vehicle speed and not vice versa and that the relationship is deterministic. In practice, average vehicle speed can be affected by a variety of other (human and non-human) factors that researchers do not observe as discussed above. In addition, both average vehicle speed and traffic density are realized simultaneously and affect each other. Road users decide whether they should take a trip or not based on the prevailing cost of the trip including the level of traffic congestion on the road. If a road user expects a high traffic density due to accidents, big events or road constructions, then he or she might consider to reschedule time of the trip or to optimize which route to take. This simultaneity gives rise to endogeneity in traffic density in Equation (7).

To deal with the endogeneity, we leverage the once-a-week driving restriction policy for identification by arguing that this natural experiment generates exogenous variation in traffic density which in turn affects average vehicle speed. The policy satisfies the exogeneity assumption for two reasons. First, the policy has a pre-set schedule and it rotates exogenously regardless of the traffic congestion. On any given weekday, the once-a-week driving restriction forbids vehicles with license plates ending in two different digits (1 or 6; 2 or 7; 3 or 8; 4 or 9; and 5 or 0) from driving in areas inside the 5th Ring Road, from 7:00 in the morning to 20:00 in the evening. The restricted day of the week for different numbers rotates every 13 weeks.[12] Table 3 shows the policy schedule and the rotation of the restricted digits on each weekday over time. Hence, this driving restriction policy can be argued to be exogenous to the unobserved, time-varying, and road-specific shocks. In addition, an ending digit is also expected to be distributed evenly among the days of the week because the policy rotates the assignment of restricted numbers to weekdays every 13 weeks.

[12] On October 11 2008, the Beijing municipal government announced the implementation of a half-year trial of the driving restriction until April 10 2009. During the trial period, the restricted day of the week for different numbers rotated every four weeks. The driving restriction was in force within (and including) the 5th Ring Road, from 6:00 in the morning to 21:00 in the evening. When this half-year trial ended, the government started a new round of the driving restriction lasting one year. This time, the restricted day of the week changed every 13 weeks, and the restriction area was narrowed to inside (and excluding) the 5th Ring Road and from 7:00 to 20:00. The third round of the driving restriction began immediately after the previous round on April 11 2010. Since then, there have been no changes in the policy, and the restriction remains in force. Also, the penalty for violating the regulation has changed over time. Initially, drivers who violated the restriction were stopped and fined 100 yuan (around $16.3) for the day. Since there would be no extra penalty if the violator was caught more than once in a day, some people were willing to risk being caught and pay for the daily fine. To improve enforcement, since 2011, the government has changed this daily penalty to a 100 yuan every three hours.

Second, the distribution of the last digit of license plate number is determined by the culture. Since number four is homonymous with death, Chinese people avoid having the number in many aspects of the daily life such as door, mobile, floor, and license plate numbers. So, there are fewer licenses with four as the last digit, accounts for only one to three percent of vehicles while around 12 to 13 percent of vehicles with the license plates ending with eight or six, which are traditionally considered lucky numbers. Table 4 shows the percentage of vehicles with license plates ending in each digit. Given that there are fewer vehicles with license plate numbers ending in the digit four, the once-a-week driving restriction policy in Beijing unintentionally allows more vehicles on the road during days on which plate numbers ending in four are restricted. This policy hence induces plausibly an exogenous variation in traffic density that is not correlated with the unobserved, time-varying, and road-specific shocks to average vehicle speed.

For these reasons, we argue that the policy affects average vehicle speed only through traffic density. The first step of the IV strategy specifies traffic density as a function of the policy variables (IVs) and other controls.

$$
\begin{aligned}
Density_{it} &= Tail49_t + Tail49_t \times Ring_i + Tail49_t \times Hour_t + \\
&+ Weather_t\,\sigma + Month_t + Hour_t + Weekday_t + Holiday_t + \\
&+ Road_i + Ring_i \times Month_t + Ring_i \times Hour_t + \xi_{it} \qquad (8)
\end{aligned}
$$

where the first three terms are excluded instrumental variables; $Tail49_t$ is a dummy variable indicating if the digits four or nine restricted based on the schedule of the driving restriction policy. Our data shows that the traffic density is denser during the days on which plate numbers ending with four or nine are restricted (Figure 5). However, the driving restriction policy does not vary during a weekday and it is force in roads inside the 5^{th} Ring Road during hours from 7:00 to 20:00. To introduce temporal variations during a weekday and spatial variations within the city of Beijing, we interact the dummy $Tail49_t$ with hourly dummies and ring road dummies. These interaction terms capture disproportional effects of the driving restricting policy on the traffic density at different time of the day and across different roads within the city.

Figure 5 illustrates the temporal and spatial effects of restricting vehicles with the plate numbers ending in four or nine on the traffic density and average vehicle speed. Panel (a) of Figure

5 suggests that the traffic density is higher when the plate numbers ending with four or nine are restricted and magnitude of the effects vary over different times of the day and across ring roads. The magnitude of the effect on traffic density of roads located inside the 3rd or 2nd Ring Roads increases during the morning and evening peak hours while the effect is marginal during non-restricted hours or when roads are located outside the 4th Rind Road. These results confirm that the restricting vehicles with the plate numbers ending in four or nine to drive inside the 5th Ring Road has a positive impact on the number of vehicles on the roads and hence traffic density. On the other hand, during the days on which the plate numbers ending with four or nine are restricted, traffic congestion is expected to be worse as shown in Panel (b) of Figure 5.

5. ESTIMATION RESULTS

We first present the OLS and the IV results for Equation (7) and the estimates of marginal external cost of traffic congestion.

5.1 Regression Results for the Speed-Density Relationship

Table 5 presents the results of Equation (7) for five different specifications where we add more control variables successively. All model specifications are estimated on the full sample using the ordinary least square (OLS) estimation. Standard errors were clustered on at the road segment level. The first column includes only traffic density as an explanatory variable. Column (2) includes a set of weather variables including wind speed, visibility, temperature, wind direction dummies and sky coverage dummies. Column (3) adds the time fixed effects to control for time-varying common unobservables across the road segments during the month of the year, hour of the day, the day of week, and holidays. Column (4) further adds the ring road fixed effects and their interactions with time fixed effects (month fixed effects and hour-of-the-day fixed effects) to control for possible unobserved spatial and temporal differences in traffic conditions at different times of the day and the year across different ring roads. Column (5) adds more-detailed spatial controls by adding road segment fixed effects to control for road segment related, time-invariant, spatial factors such as road attributes and locational characteristics.

In line with many empirical findings in the literature, the results suggest that average vehicle speed is significantly associated with traffic density as well as with the control variables. The results are robust to the model specifications. The discussion focuses on coefficients the traffic density – the key variable of interest. The coefficients of the other variables are all intuitively signed and are consistent with the traffic congestion literature. The coefficient estimates on traffic density are all negative and statistically significant. For the first three specifications, the coefficient estimates on traffic density are very similar, ranging from -0.452 to -0.473. The estimates became -0.373 in Column (4) after the ring road fixed effects and their interaction with the hour and month fixed effects are included. This suggests that the ring road fixed effects at different times of the day and months of the year control for unobserved ring-road-specific determinants which could be negatively correlated with traffic density. In Column (5) when the road segment fixed effects are included, the coefficient estimate further increases to -0.313. The last two columns suggest the importance of controlling for time-invariant spatial factors such as road attributes and locational characteristics that could affect both average vehicle speed and traffic density.

Before discussing the IV results, we first present an evidence how the driving restriction policy affects traffic density, the relevance assumption for the validity of the IV. Figure 6 illustrates the effect of restricting vehicles with the plate numbers ending in four or nine on the traffic density. It shows that when the plate numbers ending with four or nine are restricted, the traffic density (or number of vehicles per lane-km) on the roads located inside the 3rd Ring Road is higher by around 1.5 vehicles and the magnitude of the effects decreases as roads are located on outer ring roads such as between the 3rd and the 4th Ring Roads; between the 4th and the 5th Ring Roads; and outside the 5th Ring Road. Also, the effect is much stronger during the morning peak hours (6:00 to 9:00) and evening peak hours (17:00 to 19:00) while the effect is marginal (negative in some cases) during non-restricted hours or when roads are located outside the 5th Rind Road.

Table 6 presents the first-stage results for the five specifications corresponding to those in Table 5 where different sets of fixed effects are included. The IVs include the policy variable and its interactions with the ring-road-specific and time-of-day fixed effects. The policy variable is a dummy variable indicating if the digits four or nine restricted on a given day. The variable itself has a positive and statistically significant effect on traffic density, consistent with the fact that vehicles with the last digit being four or nine account for a small share of vehicle fleet relative to other combinations. Therefore, there are more vehicles on the road when vehicles with the license plates ending in four or nine are restricted from driving. The coefficient estimates on the interactions terms tend to be statistically significant, suggesting that the effects of the driving restricting policy on traffic density vary across different ring roads and over time. For all the specifications, the joint F-statistics on the excluded instruments are above 40. The driving restriction policy therefore provides exogenous variations in traffic density that we can leverage to identify a causal effect of traffic density on average vehicle speed.

Table 7 presents the estimates from the IV regressions for Equation (7) and the five specifications corresponds to the OLS specifications in Table 5. Comparing the OLS results in Table 5, the coefficients estimates in Table 7 are fairly similar except for those on traffic density. The coefficient estimates on traffic density from the IV regressions are negative and statistically significant and negative, ranging from -0.806 to -1.053, much larger than the estimates from the OLS regressions.

Specification (5) in Table 7 shows that a unit increase in traffic density (or having an additional vehicle per km) would result in one-unit decrease in the average vehicle speed (i.e., average vehicle speed drops by 1 km/h), three times as large (in magnitude) as the effect from the OLS regression. The comparison suggests that the OLS results are biased toward zero. The bias could be due to unobservables (such as big events or road construction) that reduces traffic density but also reduces speed, attenuating the impacts of traffic density on average vehicle speed

5.2 Marginal External Cost of Congestion

As defined in Equation (6), the marginal external cost of traffic congestion, $MECC_{it}$ (measured in Yuan per kilometer) is:

$$MECC_{it} = \partial ASC(Time)/\partial Time \cdot \partial Time/\partial Speed \cdot \partial Speed/\partial Density \cdot Density_{it}$$

$$= \cdot o \cdot VOT \cdot (Average\ travel\ time_{it}) \cdot (Elasticity_{it}), \quad (9)$$

where $Elasticity_{it}$ is elasticity of average vehicle speed with respect to traffic density on road i at time t:

$$Elasticity_{it} = -\ \partial Speed/\partial Density \cdot Density_{it}\ /\ Speed_{it} = -\ \hat{\beta} \cdot Density_{it}\ /\ Speed_{it}$$

To calculate MECC, we use the parameter estimate on traffic density, $\hat{\beta} = 1.017$, from the 2SLS regression. Vehicle occupancy, $o = 1.34$, and average value of time, $VOT = 31.49$ Yuan per hour ($3.5 per hour). The average number of passengers per vehicle (o) is assumed to 1.34

(persons/vehicle) based on the Beijing Household Travel Survey 2010. The value of time (*VOT*) is assumed to be 50 percent of market wage in Beijing, which is 54.34 Yuan per hour ($7.8 per hour) based on the monthly market wage of 8694 Yuan per month.[13]

Figure 7 depicts the MECC estimates based on Equation (9). Intuitively, the MECC increases nonlinearly as traffic density or the number of vehicles on the road increases. The MECC is estimated to be 1 Yuan per km when traffic density is around 40 vehicles per km-lane (predicted average speed is 38 km/h) while it is around 4 Yuan per km when traffic density is about 60 vehicles per km-lane (predicted average speed is 18 km/h). Since traffic conditions vary over time and space, the MECC varies accordingly. Figure 8 illustrates the temporal and spatial pattern of the MECC in Beijing. Based on the estimate from the 2SLS regression, the average marginal external cost of congestion per extra car-kilometer is 0.12 Yuan.[14] It is about 0.92 Yuan ($0.13) when average vehicle speed and traffic density on a road located inside the 2nd Ring Road during the evening peak hours are 29 vehicles/lane-km and 47.7 km/h respectively. This is nearly three times as much as what the estimate from the OLS regression would imply (0.38 Yuan or $0.05).

Our estimates are based on our data sample which covers freeway and expressway but not the secondary roads. According to 2015 Beijing Transportation Annul Report, the average speed of vehicles on arterial roads during the peak hours on workdays was 23 km/h in 2014, which implies that means the average traffic density is around 53 vehicles per km-lane. The MECC during the peak hours is about 4.18 Yuan ($0.60) per km under this traffic condition. [15]

6. ROAD PRICING AND IMPACTS

Consider a case of a single road and a single time period. A measure of aggregate net welfare in this setting is social surplus, W_{it}, dened as total benefit, B_{it}, minus total cost, C_{it}.

$$\max W_{it} = B_{it} - C_{it} = \int P(v)\, dv - V_{it} \cdot ASC(V_{it}), \qquad (10)$$

[13] The literature often suggests a rule of thumb for the value of time: half of the market wage for automobile travel in Canada, France, the United Kingdom, and the United States (Small and Verhoef 2007; Parry and Small 2009).
[14] The estimate is based on the expected average travel speed and the all-day average of traffic density of the sample.
[15] Our data shows a higher average speed than that from 2015 Beijing Transportation Annual Report for several reasons. First, the average speed from the report is based on the GPS data from a large number of taxis. Taxis stops more frequently to pick up and drop passengers. Second, the traffic monitoring stations that our data is from tend to be road segments that are less congested. The real speed on the road is likely between what is reported from Beijing Transportation Annual Report and our estimates.

where $P(V_{it})$ is the inverse demand function for travel and V_{it} is traffic volume on road i at time t.[16] $ASC(V_{it})$ is the average social cost function, which is constant for a specific road at a given time. Maximizing W_{it} with respect to V_{it} yields the optimal pricing rule:

$$P(V_{it}^*) = MSC(V_{it}^*) = ASC(V_{it}^*) + MECC(V_{it}^*). \tag{11}$$

Equivalently, the optimal congestion charge ($\boldsymbol{\tau}^*_{it}$) or Pigouvian tax is:

$$\boldsymbol{\tau}^*_{it} = MSC(V_{it}^*) - ASC(V_{it}^*) = MECC(V_{it}^*). \tag{12}$$

Figure 10 illustrates this conventional diagram of optimal road pricing. Without the congestion charge, the equilibrium occurs at the intersection of the inverse demand curve and the average social cost curve, ASC; the equilibrium traffic volume is V_{it}^0 and the corresponding travel cost is p_{it}^0. According to the optimal road pricing rule, the optimal traffic volume, V_{it}^*, occurs at the intersection of the demand curve and the marginal social cost curve, MSC, and it can be achieved by imposing the optimal congestion charge $\boldsymbol{\tau}^*_{it}$ shown in the figure. The average cost falls from is p_{it}^0 to is p_{it}^1, but with the congestion charge of $\boldsymbol{\tau}^*_{it}$, the price (travel cost) increases from p_{it}^1 to $p^*_{it} = p_{it}^1 + \boldsymbol{\tau}_{it}^*$. The gain in social surplus is shown by the shaded area, which gives the difference between social cost saved (the area below the MSC) and benefit forgone (the area below the inverse demand curve) when reducing traffic volume from V_{it}^0 *to* V_{it}^*.

For welfare analysis, therefore, we need the ASC and the MSC as functions of traffic volume,[17] and the inverse demand for travel, $P(V_{it})$. Assume travel demand as follows

$$V_{it} = A_{it} P_t^{-\eta}, \tag{13}$$

where V_{it} is average traffic volume on road i time t (or vehicle-kilometers traveled, VKT, measured in vehicles-km/h); P_t is travel cost; A_{it} is a demand shifter; and $-\boldsymbol{\eta}$ is a long-run elasticity of traffic volume with respect to travel cost. There is a large empirical literature on the overall responsiveness of traffic volume to travel cost, usually measured by fuel cost.

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[16] The welfare analysis is conducted in terms of traffic volume rather traffic density to be consistent with the literature and to have reliable estimate of the elasticity of travel demand.

[17] The empirical speed-density relation implies that it will be hyper-congested when density is greater than 40 vehicles per kilometer. Since we don't observe density is over 40 vehicles per kilometer on the average, there is one-to-one relation between density and volume. So, it is straightforward to convert the ASC or the MSC in terms of density into the ASC and the MSC in terms of density.

Previous studies have estimated the elasticity of traffic volume with respect to fuel prices to be between -0.1 and -0.3 (Parry 2009; Goodwin 1992, Goodwin 2004; Small and van Dender 2007; Bento et al. 2009; Knittel and Sandler 2011). We thus consider an inelastic estimate of -0.1 for the long-run traffic volume elasticity with respect to fuel cost as elasticity during the peak period and an elastic estimate of -0.3 for the long-run traffic volume elasticity with respect to fuel cost as elasticity during the off-peak period. The average of these two estimates of -0.2 is considered as the long-run VKT elasticity with respect to fuel cost for the average daily demand for travel. Following Anderson (2014), we convert these elasticities to the long-run traffic volume elasticities with respect to total travel costs (i.e., fuel cost plus time costs) of -0.44 during the peak periods, -1.32 during the off-peak periods, and -0.88 during the day.

First, given the average density on road *i* time *t*, we calculate the expected traffic volume (V_{it}^{0} in Figure 10, which is the equilibrium traffic volume without congestion charge) based on the empirical speed-density relationship. The demand shifter, denoted by A_{it}, is calculated by finding the value of A_{it} that satisfies the equilibrium without congestion charge at which $P(V_{it}^{0}) = ASC(V_{it}^{0})$. We then solve for a long-run equilibrium traffic volume, V_{it}^{*}, at which $P(V_{it}^{*}) = MSC(V_{it}^{*})$, using the demand equation in (13) with $\eta=0.44$ during the peak hours, $\eta=1.32$ during the off-peak hours, and $\eta=0.88$ during the day.

We examine four different schemes of road pricing between the hours from 6:00 to 23:00 on workdays while no congestion charges outside of this window. The first one is a basic road pricing scheme with uniform congestion charge. As illustrated in Figure 10, this congestion charge is a constant per unit of travel across different areas and over different hours. The second scheme is time-varying congestion charge but constant across locations as shown in Figure 11. For simplicity, we consider only two time periods: peak hours (the morning peak hours from 7:00 to 9:00 and evening peak hours from 17:00 to 19:00) and off-peak hours (from 6:00 to 23:00 excluding the peak hours). The third scheme is location-specific congestion charge but not time-specific (Figure 12). In this case, congestion charge will be constant throughout day-time periods but vary across different zones: zone 1 (central Beijing or inside the 3rd Ring Road), zone 2 (between the 3rd and the 5th Ring Roads), and zone 3 (outside the 5th Ring Road). The fourth road pricing scheme uses time-varying and location-specific charges (Figure 13).

Panel (a) of Table 8 reports the average MECC at the level of observed traffic density under the four different schemes before imposing the congestion charge. The average MECC across all hours from 6:00 to 23:00 throughout Beijing is estimated to be 0.14 Yuan/km. There a large heterogeneity across time and space with the a high of 0.76 Yuan/km within the 3rd Ring Road during the peak hours and a low of 0.06 Yuan/km outside the 5th Ring Road during the off-peak hours. Panel (b) presents the total external cost of congestion, the total value of lost time that drivers impose to other road users. It amounts to nearly 50 billion Yuan in Beijing in 2014, 2.34 percent of the Beijing's GDP.[18] These costs are not internalized when drivers make their trip decision.

Panel (c) of Table 8 reports optimal congestion charges for four different schemes. The optimal congestion charge is 0.11 Yuan/km under the first scheme of uniform pricing. Under the second scheme of the time varying and location-invariant) road pricing, the optimal congestion charge is 0.14 Yuan/km during the peak hours and 0.10 Yuan/km during the off-peak hours. The small difference is a reflection of small heterogeneity in MECC during the day as shown in Panel (a). The third scheme of location specific charges shows a larger range of congestion charges from 0.05 Yuan/km outside of the 5th Ring Road to 0.25 Yuan/km within the 3rd Ring Road. Taking into account the heterogeneity in congestion across both time and space, the fourth scheme of time-varying and location-specific pricing are between 0.05 Yuan/km and 0.38 Yuan/km: 0.38 Yuan/km for within the 3rd Ring Road during the peak hours and 0.05 for outside the 5th Ring Road during the off-peak hours.

Table 9 presents the implications of road pricing on traffic speed in Panel (a), social welfare in Panel (b) and revenue in Panel (c). Under the first two schemes, the speed improves by less than three percent because neither account for the large heterogeneity in congestion across space. The third scheme of location-specific road pricing has a more significant effect on speed improvement: the average speed in the central Beijing (within the 3rd Ring Road) is predicted to rise by 10 percent. The fourth scheme achieves roughly the same results as the third scheme: it would increase the average speed by 0.4-10.6 percent in charging zones and during the charging period. The predicted impacts of road pricing on congestion are at the lower end of the estimates from the road pricing policies in several cities (Singapore, London, Milan, and Stockholm) where it has been shown that road pricing improves speed by 10-30 percent (Anas and Lindsey 2011). Given that the traffic speed

[18] Beijing's GDP in 2014 was 2.133 trillion Yuan ($343.4 billion).

in our data is higher than those reported by the 2015 Beijing Transportation Report as we discussed above, our estimates of both optimal congestion charges and their impacts speed could serve as a lower bound of the optimal congestion charges and their potential impacts of road pricing.

Panel (b) suggests that the total welfare gain ranges from 0.6 billion Yuan under the uniform scheme to 1.4 billion under the location-specific and time-varying scheme. It is interesting to note that the third and fourth schemes that take into account heterogeneity across have much larger welfare gains than the first two schemes. The improvement from the first to the second scheme and that from the third to the fourth scheme by adding time-varying component are small. These comparisons are consistent with the fact that the heterogeneity in traffic congestion is small across hours but large across locations.

In addition to the large gain in social welfare, road pricing would also generate substantial revenue for Beijing municipal government. Panel (c) shows that while there are large differences in social welfare impacts across different road pricing schemes, all the schemes would generate similar revenue of around 41 billion. The revenue could be used to cover the fixed and operating costs of the road pricing scheme and/or to improve the public transit system.[19] The improvement in public transit system would provide better alternatives for road users and help to address the distributional/equity concerns that often come with road pricing.

7. CONCLUSION

This study combines a fundamental economic principle with big data to investigate the first-best policy to address urban traffic congestion. Leveraging a natural experiment, it provides the first empirical estimates of the marginal external cost of traffic congestion (MECC) and optimal congestion charges in Beijing. The analysis presents two important departures from the literature. First, we focus on the traffic speed and density relationship instead of the commonly used speed and flow relationship in order to address the issue of hypercongestion observed in our data. Second, we are the first to address the endogeneity issue due to simultaneity in this literature to quantify MECC. The driving restriction in Beijing provides plausibly exogenous variation in traffic density for the causal identification.

[19] In 2014, the total operating subsidy on the public transit system was 15.3 billion Yuan in Beijing, accounting for over four percent of the total government spending. The total capital investment on transportation in Beijing was 88.6 billion Yuan including 43 billion on subway construction.

Our analysis shows that the average marginal cost of congestion is nearly 0.12 Yuan/km on average (across road segments and time), nearly three times as much as what OLS regressions would imply. There is a large heterogeneity in MECC across space and time: it ranges from 0.92 Yuan/km within the 2nd Ring Road during the evening peak hours to 0.06 Yuan/km outside the 5th Ring Road during the off-peak hours. Based on these estimates, we then estimate the optimal congestion charges for different schemes from uniform to time-varying and location-specific road pricing. The analysis suggests that the optimal charges should be 0.38 Yuan/km within the 3rd Ring Road during peak hours and 0.05 Yuan/km for outside the 5th Ring Road during the off-peak hours. This scheme of road pricing would lead to a ten percent increase in traffic speed within the 3rd ring road during peak hours and an increase of social welfare by 1.4 billion Yuan per year. The total charges would amount to 40 billion Yuan per year to cover the capital and operating costs of the system.

We conclude with some caveats and thoughts for future research. First, our analysis represents an initial key step toward using road pricing to address urban congestion in Beijing. The optimal congestion charges are based on the road conditions in 2014 and should be adjusted based on how the policy affect the congestion level and hence the MECC across time and space. Second, the optimal congestion charges in our analysis are based on the marginal cost function estimated from the data and the travel demand function calibrated based on previous studies. The travel demand function is an important piece in the analysis. The estimation of this function while presents its own identification challenges, warrants future research. Third, automobile usage leads to multiple externalities including traffic congestion, local air pollution, traffic accidents and carbon emissions (Parry et al. 2007). Road pricing, although not the theoretical first-best policy for other externalities, would generate the auxiliary benefit from reducing these externalities. Recent research has pointed to traffic as a significant source of local air pollution, another pressing challenge that also significantly affects the quality of life in urban China.

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Tables

Table 1: Congestion Alleviation Policies in Beijing

Policies	Year	Actions
Investment policy	1986-2010	Road expansion
	2007-2011	Railway, subway expansion
Parking restriction policy	1998-2002	Parking certificate
		Parking fee increase in selected areas
Public transportation policy	2007	Low-cost fare and subsidy for bus and subway
		Increase in bus-only lanes
Market based policies	2009-2011	Vehicle purchase tax 10%
		Taxi fuel surcharge for trips over 3kms (1-2RMB)
		Gasoline price adjustments
Environmental policies	2008	Temporary shutdowns of factories and construction sites
		Revised commercial and light-duty vehicle emission standards
Driving restriction policy	2008	Restriction by odd-even license plate numbers
		One-day-a week at certain period of time
Ownership restriction policy	2011	Private car license Lottery

Table 2: Summary Statistics

Main variables	N	Mean	S.D.	Min	Max
Traffic variables					
Speed (km/h)	12147416	67.30	14.47	0.41	165.70
Volume (cars/h)	12147416	1666	1476	1.00	125700
Density (cars/km/lane)	12147416	9.70	10.94	0.06	467.74
Weather controls					
Temperature (C)	12147416	13.52	11.52	-12.78	42.22
Wind speed (km/h)	12063653	9.21	7.42	0.00	72.00
Visibility (km)	12147416	10.55	7.84	0.00	30.08

Note: The unit of observation is the road-hour. There are two sets of dummies in weather controls. *Wind direction (in compass degrees)*: north, east, south, west, northeast, southeast, southwest, northwest; *Sky coverage dummies*: clear, scattered, broken, obscured, partially obscured;

Table 3: Driving Restriction Policy Schedule

Policy Period		Ending Digit of License Plate				
Starting Date	Ending Date	Mon	Tue	Wed	Thu	Fri
2008.10.11	2008.11.10	(1, 6)	(2, 7)	(3, 8)	(4, 9)	(5, 0)
2008.11.11	2008.12.7	(5, 0)	(1, 6)	(2, 7)	(3, 8)	(4, 9)
2008.12.8	2009.1.4	(4, 9)	(5, 0)	(1, 6)	(2, 7)	(3, 8)
2009.1.5	2009.2.1	(3, 8)	(4, 9)	(5, 0)	(1, 6)	(2, 7)
2009.2.2	2009.3.1	(2, 7)	(3, 8)	(4, 9)	(5, 0)	(1, 6)
2009.3.2	2009.4.10	(1, 6)	(2, 7)	(3, 8)	(4, 9)	(5, 0)
2009.4.11	2009.7.10	(5, 0)	(1, 6)	(2, 7)	(3, 8)	(4, 9)
2009.7.11	2009.10.9	(4, 9)	(5, 0)	(1, 6)	(2, 7)	(3, 8)
2009.10.10	2010.1.8	(3, 8)	(4, 9)	(5, 0)	(1, 6)	(2, 7)
2010.1.9	2010.4.10	(2, 7)	(3, 8)	(4, 9)	(5, 0)	(1, 6)
2010.4.11	2010.7.10	(1, 6)	(2, 7)	(3, 8)	(4, 9)	(5, 0)
2010.7.11	2010.10.9	(5, 0)	(1, 6)	(2, 7)	(3, 8)	(4, 9)
2010.10.10	2011.1.8	(4, 9)	(5, 0)	(1, 6)	(2, 7)	(3, 8)
2011.1.9	2011.4.10	(3, 8)	(4, 9)	(5, 0)	(1, 6)	(2, 7)
2011.4.11	2011.7.9	(2, 7)	(3, 8)	(4, 9)	(5, 0)	(1, 6)
2011.7.10	2011.10.8	(1, 6)	(2, 7)	(3, 8)	(4, 9)	(5, 0)
2011.10.9	2012.1.7	(5, 0)	(1, 6)	(2, 7)	(3, 8)	(4, 9)
2012.1.8	2012.4.10	(4, 9)	(5, 0)	(1, 6)	(2, 7)	(3, 8)
2012.4.11	2012.7.10	(3, 8)	(4, 9)	(5, 0)	(1, 6)	(2, 7)
2012.7.11	2012.10.9	(2, 7)	(3, 8)	(4, 9)	(5, 0)	(1, 6)
2012.10.10	2013.1.8	(1, 6)	(2, 7)	(3, 8)	(4, 9)	(5, 0)
2013.1.9	2013.4.7	(5, 0)	(1, 6)	(2, 7)	(3, 8)	(4, 9)
2013.4.8	2013.7.6	(4, 9)	(5, 0)	(1, 6)	(2, 7)	(3, 8)
2013.7.7	2013.10.5	(3, 8)	(4, 9)	(5, 0)	(1, 6)	(2, 7)
2013.10.6	2014.1.4	(2, 7)	(3, 8)	(4, 9)	(5, 0)	(1, 6)
2014.1.5	2014.4.11	(1, 6)	(2, 7)	(3, 8)	(4, 9)	(5, 0)
2014.4.14	2014.7.12	(5, 0)	(1, 6)	(2, 7)	(3, 8)	(4, 9)
2014.7.13	2014.10.11	(4, 9)	(5, 0)	(1, 6)	(2, 7)	(3, 8)
2014.10.12	2015.1.10	(3, 8)	(4, 9)	(5, 0)	(1, 6)	(2, 7)
2015.1.11	2015.4.10	(2, 7)	(3, 8)	(4, 9)	(5, 0)	(1, 6)

Source: Beijing Transportation Research Center

Note: Each column lists the ending digit pairs of license plates that is restricted on a certain weekday over different policy periods shown in Column 1 and Column 2. The policy applies to within (and including) the fifth ring road from 7:00-20:00.

Table 4: Distribution of License Plates with Ending Digits

Ending Digit	2009	2010	2011	2012	2013	2014
1	10.0	9.9	9.9	9.9	9.9	9.8
2	10.2	9.9	9.9	9.9	9.9	9.8
3	9.9	9.7	9.6	9.6	9.6	9.7
4	2.8	2.3	2.2	1.9	1.7	1.5
5	10.4	10.4	10.5	10.6	10.7	10.7
6	11.7	12.1	12.3	12.3	12.3	12.4
7	10.1	10.1	10.2	10.3	10.4	10.4
8	12.7	13.0	12.9	12.9	12.8	12.9
9	11.6	12.1	12.2	12.3	12.2	12.3
0	10.6	10.5	10.5	10.5	10.5	10.5
(1, 6)	21.7	22.0	22.1	22.2	22.2	22.2
(2, 7)	20.3	20.1	20.0	20.1	20.3	20.2
(3, 8)	22.6	22.6	22.5	22.4	22.3	22.6
(4, 9)	14.4	14.4	14.4	14.1	13.9	13.9
(5, 0)	21.0	20.9	21.0	21.1	21.3	21.2

Source: Beijing Traffic Management Bureau, 2009-2014.

Note: Eas column shows percent of cars with license plates ending with digits of 1, 2, 3, 4, 5, 6, 7, 8, 9 and 0 for each year. The ending digits of license plates are grouped into five pairs of (1, 6), (2, 7), (3, 8), (4, 9) and (5, 0). In each panel, it sums up to 100.

Table 5: OLS Relationship between Speed and Density

	Dependent variable: Speed				
	(1)	(2)	(3)	(4)	(5)
Density (cars/km)	−0.452***	−0.456***	−0.473***	−0.373**	−0.313**
	(0.108)	(0.112)	(0.124)	(0.117)	(0.120)
Weather Xs	No	Yes	Yes	Yes	Yes
Time FEs	No	No	Yes	Yes	Yes
Ring road FE	No	No	No	Yes	No
Interactions	No	No	No	Yes	Yes
Road segment FE	No	No	No	No	Yes
N	12147519	12063756	12063756	12063756	12063756

Each column reports results from an OLS regression where the dependent variable is speed (km/h) and the key explanatory variable is traffic density (cars/km). The unit of observation is road-hour. The weather control include hourly variables: temperature (C^0), wind speed (km/h), visibility (km) and two sets of dummies for wind direction and sky coverage. The time fixed effects include day-of-week, month-of-year, hour-of-day, holiday-of-sample dummies. Rin road fixed effects include dummies for road segments (or monitoring stations) and the interactions term include the ineractions of ring road dummies with hour-of-day (Ring×Hour). Parentheses contain standard errors clustered by road segment. Significance: $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Table 6: First-Stage Results

	Dependent variable: Density				
	(1)	(2)	(3)	(4)	(5)
(4,9) restricted	5.296***	5.487***	10.199***	1.537***	1.217***
(4, 9) × Ring23	−2.307*	−2.306*	−2.320*	−0.038	0.026
(4, 9) × Ring34	−8.104***	−8.100***	−8.121***	−0.893***	−0.656***
(4, 9) × Ring45	−9.587***	−9.583***	−9.600***	−1.560***	−1.221***
(4, 9) × Ring5	−14.306***	−14.297***	−14.342***	−1.959***	−1.464***
(4, 9) × Hour	Yes	Yes	Yes	Yes	Yes
Weather Xs	No	Yes	Yes	Yes	Yes
Time FEs	No	No	Yes	Yes	Yes
Ring road FE	No	No	No	Yes	No
Interactions	No	No	No	Yes	Yes
Road segment FE	No	No	No	No	Yes
N	12147519	12063756	12063756	12063756	12063756
F	118.11	94.61	69.66	55.53	47.48

The dependent variable is traffic density. Each column reports results from an OLS regression of the dependent variable the density (cars/km) on the interactions of indicator for (4,9) with ring road and hour-of-day dummies. The unit of observation is road-hour. The weather control include hourly variables: temperature (C^0), wind speed (km/h), visibility (km) and two sets of dummies for wind direction and sky coverage. The time fixed effects include day-of-week, month-of-year, hour-of-day, holiday-of-sample dummies. Rin road fixed effects include dummies for road segments (or monitoring stations) and the interactions term include the interactions of ring road dummies with hour-of-day (Ring×Hour). Standard errors are clustered by road segment. Significance: $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$.

Table 7: IV Results

	Dependent variable: Speed				
	(1)	(2)	(3)	(4)	(5)
Density (cars/km)	−0.806***	−0.881***	−1.019***	−1.053***	−1.017***
	(0.024)	(0.028)	(0.039)	(0.039)	(0.041)
Weather Xs	No	Yes	Yes	Yes	Yes
Time FEs	No	No	Yes	Yes	Yes
Ring road FE	No	No	No	Yes	No
Interactions	No	No	No	Yes	Yes
Road segment FE	No	No	No	No	Yes
N	12147519	12063756	12063756	12063756	12063756

Each column reports results from a 2SLS regression where the dependent variable is speed (km/h) and the key explanatory variable is traffic density (cars/km). The IVs are the policy indicator for (4,9) and its interactions with ring road and hour-of-day dummies. The unit of observation is road-hour. The weather control include hourly variables: temperature (C^0), wind speed (km/h), visibility (km) and two sets of dummies for wind direction and sky coverage. The time fixed effects include day-of-week, month-of-year, hour-of-day, holiday-of-sample dummies. Rin road fixed effects include dummies for road segments (or monitoring stations) and the interactions term include the ineractions of ring road dummies with hour-of-day (Ring×Hour). Parentheses contain standard errors clustered by road segment. Significance: *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$.

Table 8: MECC, Total Congestion Cost, and Congestion Charges

(a) $MECC(V^0)$ without Road Pricing (Yuan/car/km)

		Uniform	Time-varying	
		All-Day	Peak	Off-Peak
Uniform	Beijing	0.138	0.170	0.129
Location-specific	within 3rd ring	0.498	0.759	0.440
	between 3rd & 5th	0.163	0.215	0.149
	outside 5th ring	0.060	0.066	0.058

(b) Total External Cost of Congestion (Annualized, Mil. Yuan)

		Uniform	Time-varying		
		All-Day	Peak	Off-Peak	Total
Uniform	Beijing	47316	12198	35120	47318
Location-specific	within 3rd ring	16949	4417	12560	16977
	between 3rd & 5th	21311	5695	15638	21333
	outside 5th ring	11501	2875	8625	11500
	Total	49758	12986	36823	49810

(c) Road Pricing $\tau^* = MECC(V^*)$ (Yuan/car/km)

		Uniform	Time-varying	
		All-Day	Peak	Off-Peak
Uniform	Beijing	0.110	0.144	0.097
Location-specific	within 3rd ring	0.254	0.383	0.212
	between 3rd & 5th	0.125	0.173	0.108
	outside 5th ring	0.054	0.062	0.051

Note: Panel (a) reports the average MECC (Yuan/car/km) under the four different road pricing scheme: (i) uniform for time and space, (ii) uniform for space and varying over time, (iii) location-specific and uniform for time, (iv) differentiated over time and space. Panel (b) reports the total external cost of congestion (TECC) without road pricing. Panel (c) reports the corresponding estimates of the optimal congestion charges.

Table 9: Congestion Reduction, Welfare and Revenue

(a) Increase in Average Speed (%)

		Uniform	Time-varying	
		All-Day	Peak	Off-Peak
Uniform	Beijing	2.445	2.007	2.881
Location-specific	within 3rd ring	10.068	10.480	10.640
	between 3rd & 5th	3.040	2.751	3.459
	outside 5th ring	0.711	0.465	0.927

(b) Welfare Gain (Annualized, Mil. Yuan)

		Uniform	Time-varying		
		All-Day	Peak	Off-Peak	Total
Uniform	Beijing	608.1	129.1	531.7	660.7
Location-specific	within 3rd ring	931.8	259.3	722.0	981.3
	between 3rd & 5th	342.3	83.3	285.3	368.6
	outside 5th ring	42.0	6.9	41.2	48.1
	Total	1316.1	349.5	1048.5	1398.0

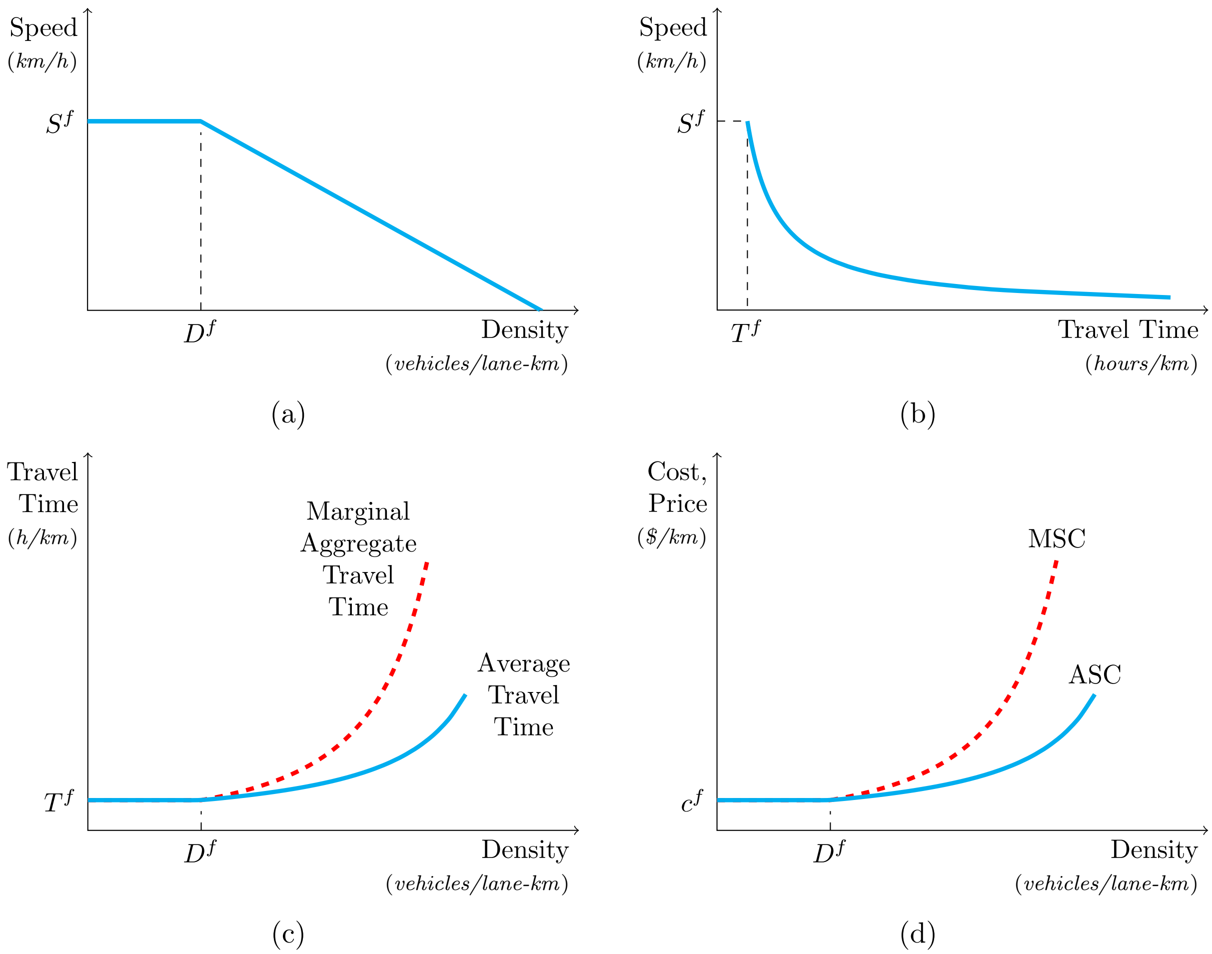
(c) Tax Revenue (Annualized, Mil. Yuan)

		Uniform	Time-varying		
		All-Day	Peak	Off-Peak	Total
Uniform	Beijing	40854.5	11025.0	29167.2	40192.1
Location-specific	within 3rd ring	12676.7	3466.1	8992.6	12458.7
	between 3rd & 5th	18096.9	5053.2	12774.4	17827.7
	outside 5th ring	10622.9	2742.7	7742.7	10485.4
	Total	41396.5	11262.0	29509.7	40771.7

Note: Panel (a) shows the predicted improvement in average travel speed under different road pricing schemes. Panel (b) reports the estimated annual welfare gain after imposing the proposed road pricing schemes in panel (b) of Table 8 under the four different road pricing scheme: (i) uniform for time and space, (ii) uniform for space and varying over time, (iii) location-specific and uniform for time, (iv) differentiated over time and space. Panel (c) reports the estimated annual tax revenue from the proposed congestion charges.

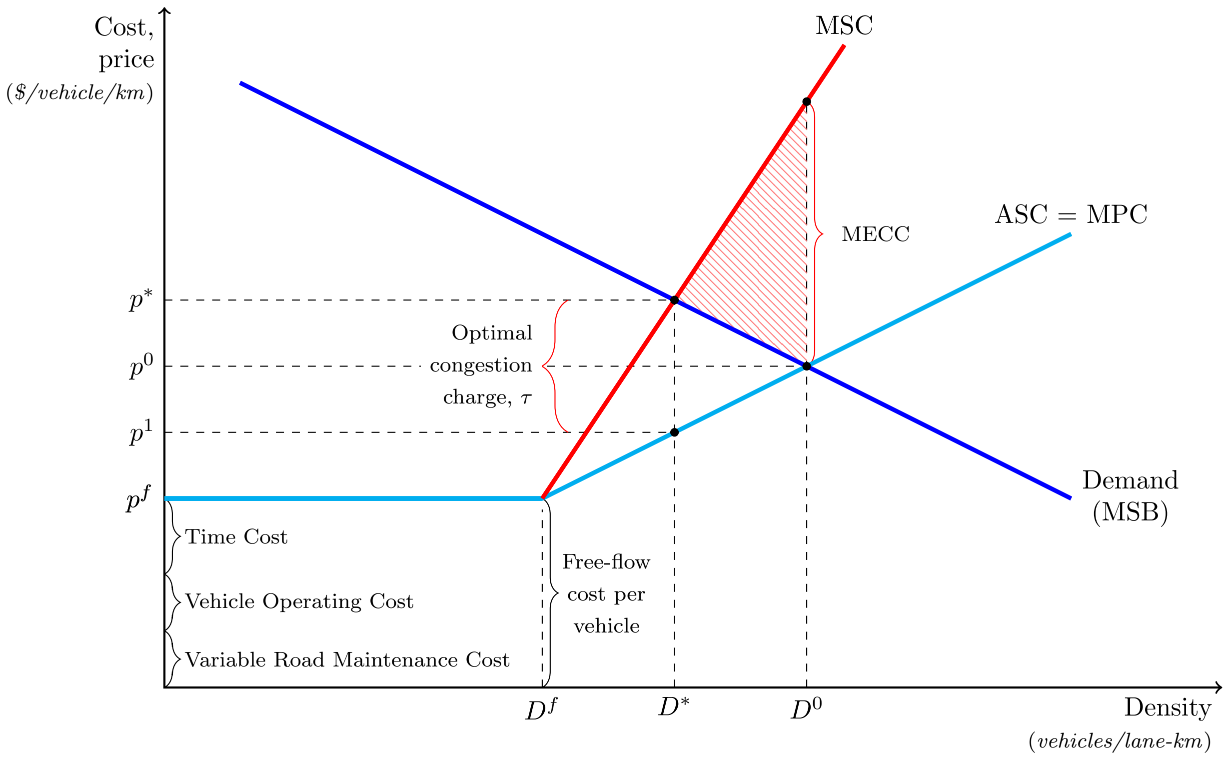
Figures

Figure 1: Speed-Density, Speed-Time, Time-Density, and Cost-Density Relationships



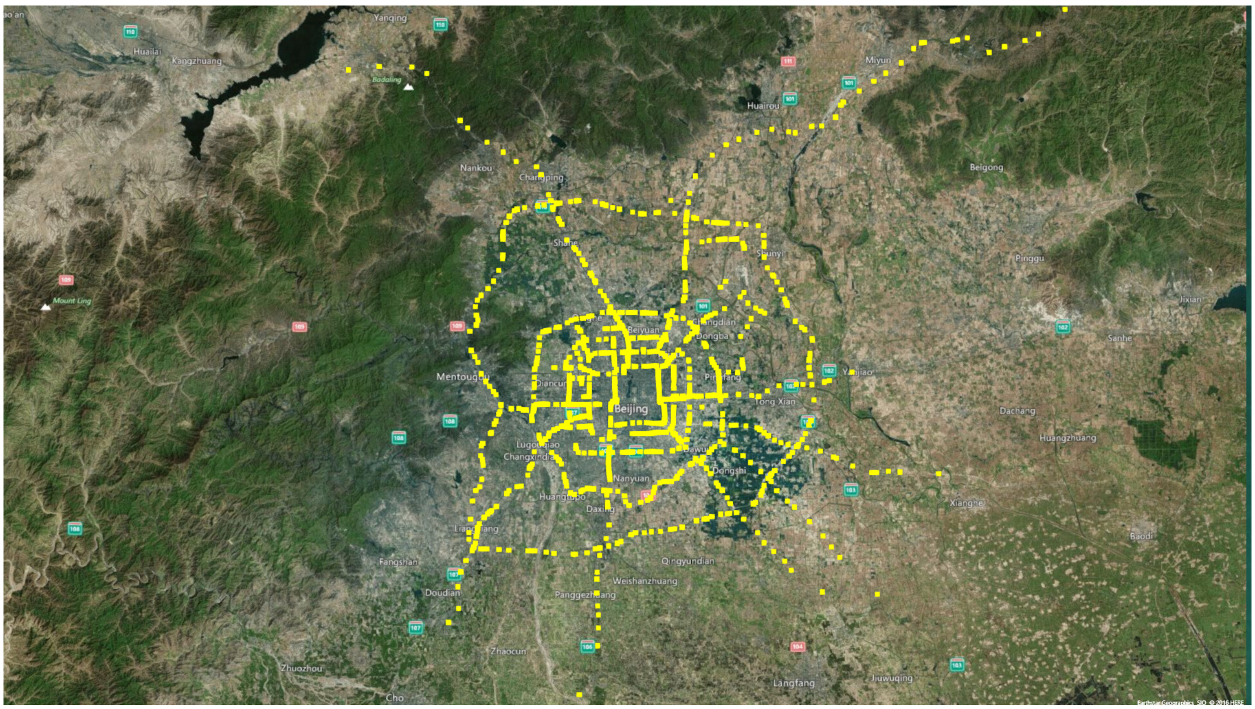
Note: Panel (a) shows the realationship between speed and density. As the density of vehicles increases, the speed at which they travel decreases. Panel (b) shows the relationship between density and travel time -the reciprocal of average vehicle speed. As the avreage travel speed drops, the average travel time increases. Panel (c) shows the relationship between average travel time and traffic density and the relationship between marginal change in aggregate travel time for all vehicles on the road and traffic density. Panel (d) shows the convertion of Panel (c) into a money basis using a constant value of time.

Figure 2: Market Failure of Traffic Congestion



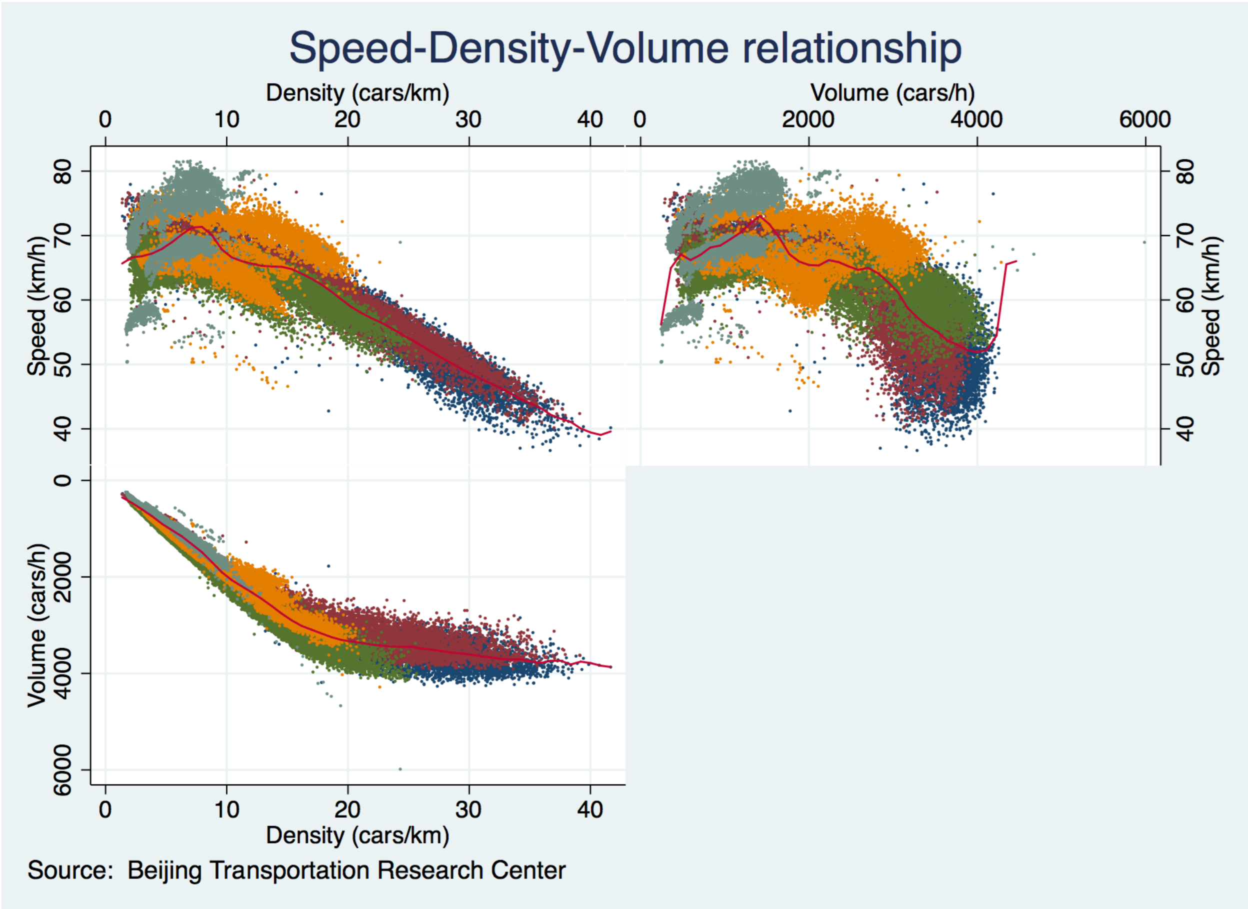
Note: The figure illustrates the market failure of traffic congestion. The MSB curve represents the inverse demand curve (willingness to pay for various quantities of trips). In the absense of any road pricing or congestion charge, equilibrium occurs at D^0 where the inverse demand curve intersects the average social cost ASC. At this point, the extra cost to society or marginal social cost MSC exceeds the benefit derived by the last road user. The same is true for all road users beyond D^*. The amount by which additional cost of these $D^0 - D^*$ road users exceeds the additional benefits is shown by the shaded area. This area represents the welfare loss from non-optimal road pricing. In order for equilibrium to occur at the optimal level of traffic density D^*, a Pigouvian tax or a toll, τ, must be imposed. This tax equals the congestion externality $MECC$, the difference between the cost the road user imposes on society (MSC) and the cost the road user bears (ASC).

Figure 3: Locations of the Road Traffic Monitoring Stations



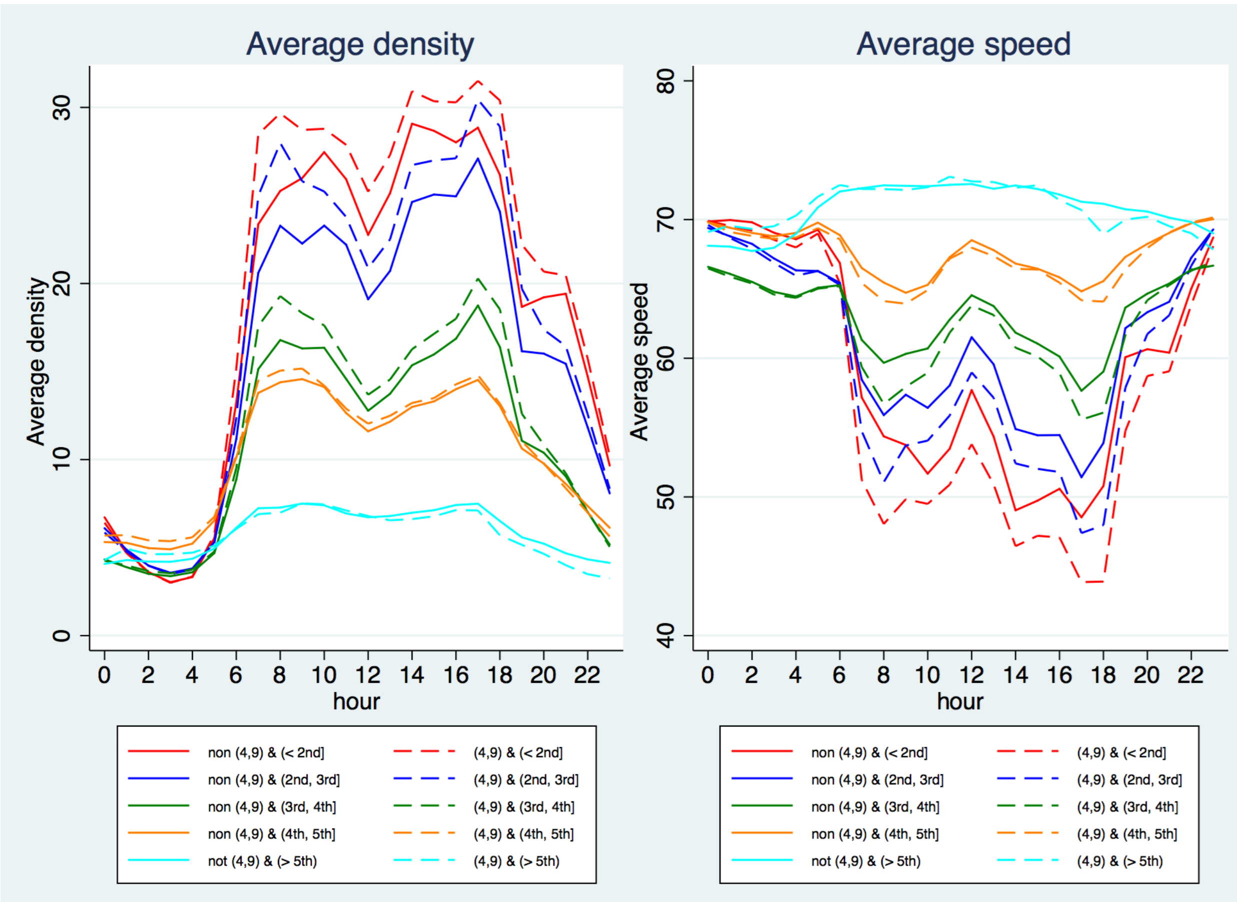
Note: Real-time traffic data (in 2 minutes interval) in Beijing was monitored by a network of over 1528 road traffic monitoring stations in 2014. The dots in the graph show the locations of the 1528 road traffic monitoring stations operated by the Beijing Transportation Research Center.

Figure 4: Speed-Density, Speed-Volume, Volume-Density Relationships



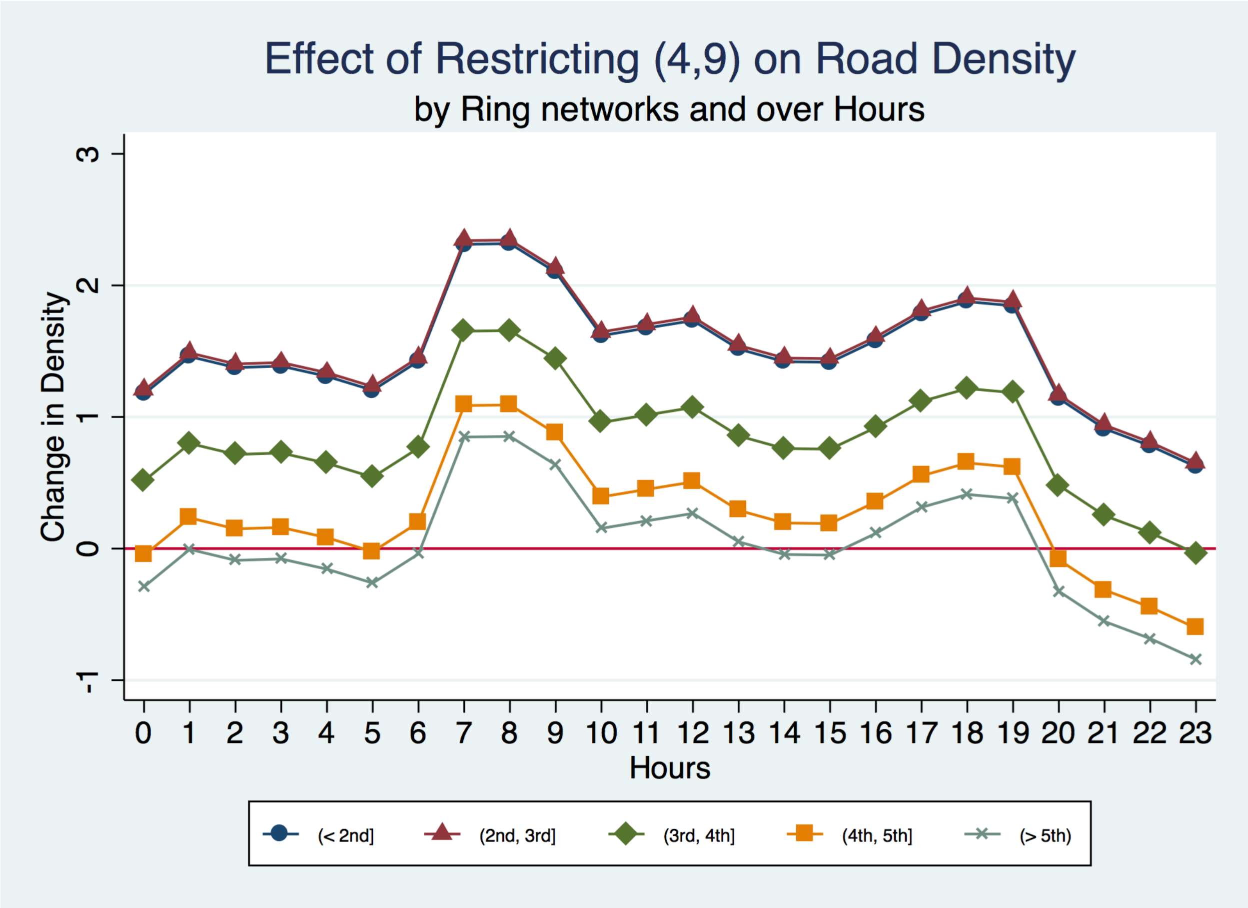
Note: The figure plots the observations of the variables pairwise: (top left) average vehicle speed (km/hour) versus traffic density (cars/lane-km); (top right) average vehicle speed (km/hour) versus traffic volume (cars/hour); and (bottom left) traffic volume (cars/hour) versus traffic density (cars/lane-km).

Figure 5: Average Traffic Density and Average Speed of Vehicles



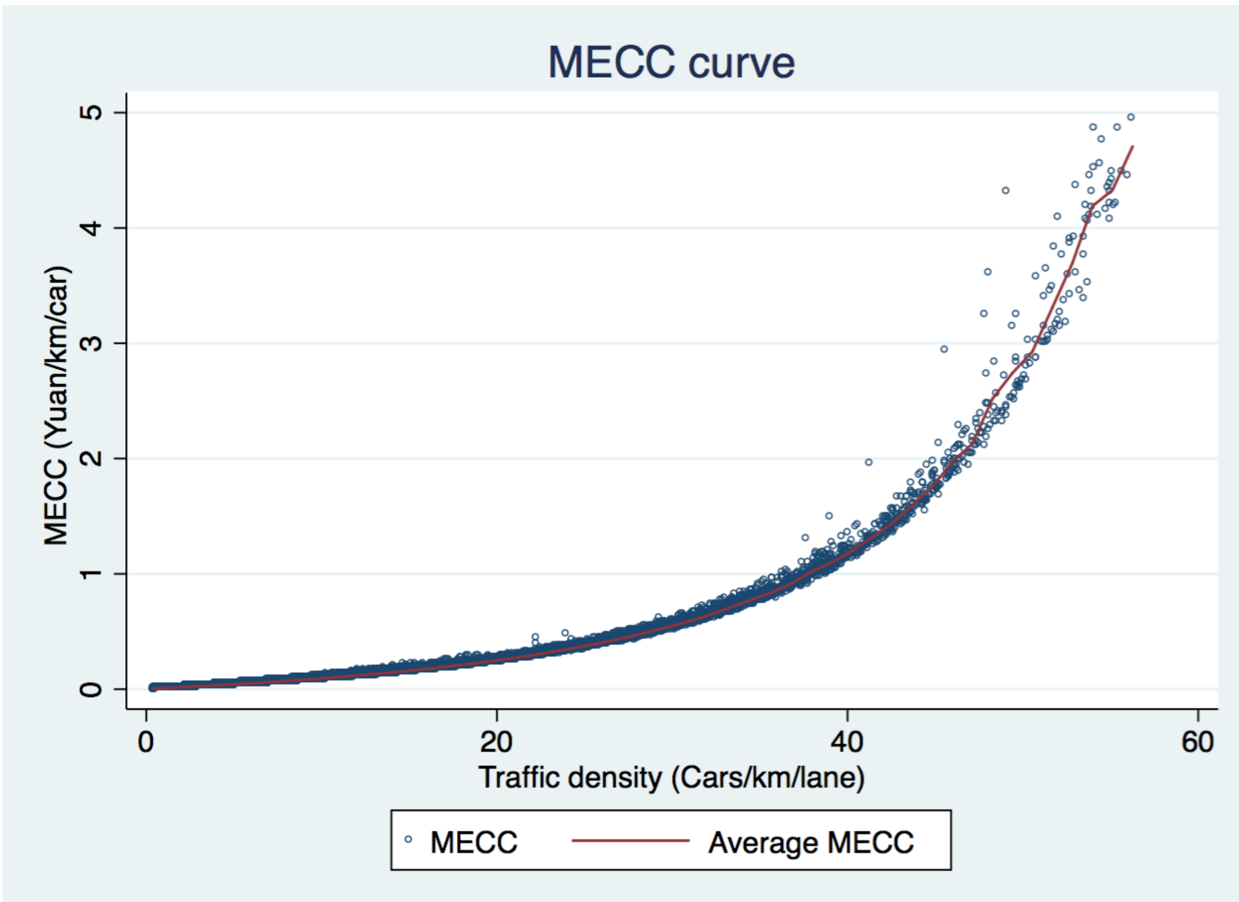
Note: The figure compares the hourly variation of average traffic density (left) and average vehicle speed (right) between the (4, 9) days and other weekdays for different locations (based on the ring roads). The data shows that the average traffic density is denser (or average speed is slower) during the days on which the plate numbers ending with four or nine are restricted and the difference vary over different times of the day and across ring roads.

Figure 6: Effect of Restricting (4, 9) on Traffic Density



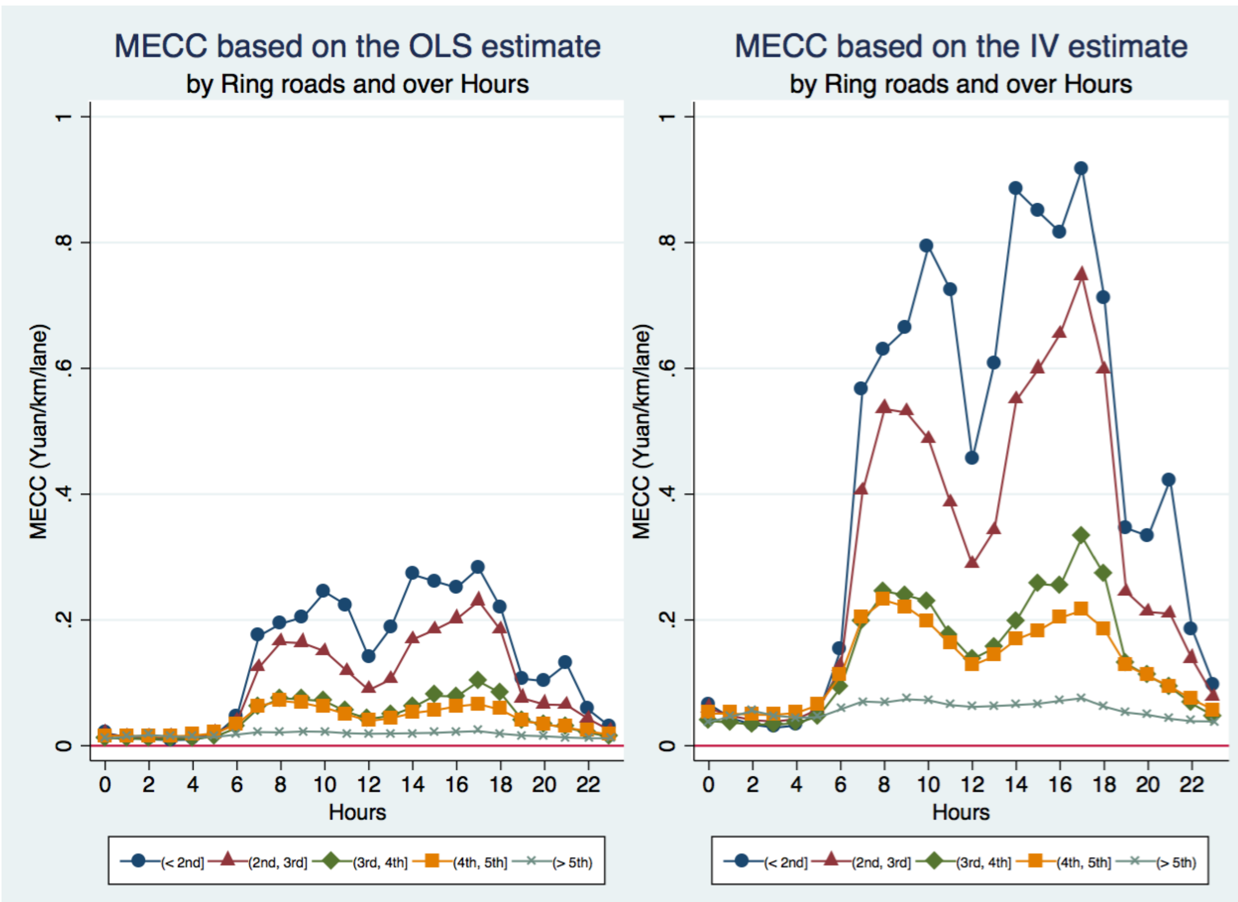
Note: The figure shows the effect of restricting vehicles with the plate numbers ending with four or nine on the traffic density. When the plate numbers ending with four or nine are restricted, the traffic density on the road located inside the 3rd Ring Road is higher by around 1.5 vehivles and the magnitude of the effects decreases as roads ar located outer ring roads such as between the 3rd and the 4th Rind Roads; between the 4th and the 5th Ring Roads; and outside the 5th Ring Roads.

Figure 7: Marginal External Cost of Congestion



Note: The figure depicts the marginal external cost of congesion (MECC) curve based on the empirical speed-density relationship. First, the MECC is estimated for each oversation of road-hour, then those are averaged over levels of traffic density. The MECC incrases nonlinearly as the traffic density increases.

Figure 8: MECC by Ring Roads and over Hours



Note: The figure illustrates the that the marginal external cost of congestion (MECC) differs over different hours of the day and across roads since the traffic conditions vary over time and space. The left figure shows the estimates of the MECC based on the OLS whereas the right figure shows the estimates of the MECC based on the 2SLS.

Figure 9: Uniform Road Pricing

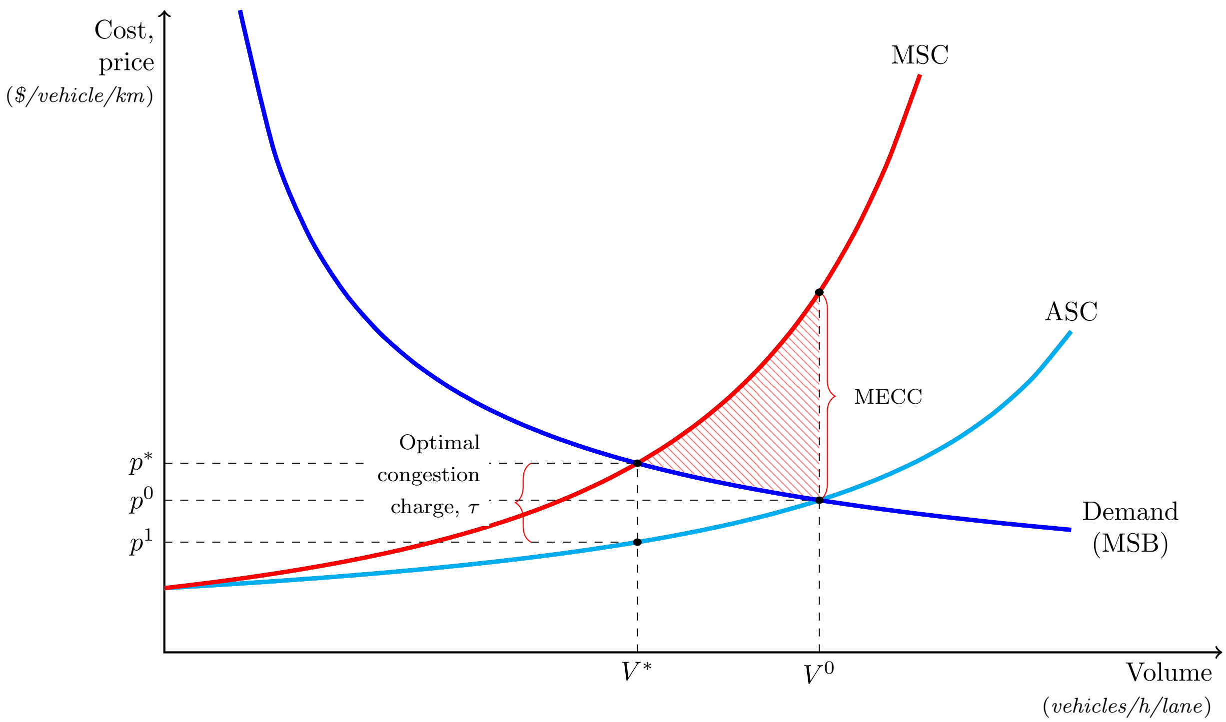


Figure 10: Time-Varying Road Pricing

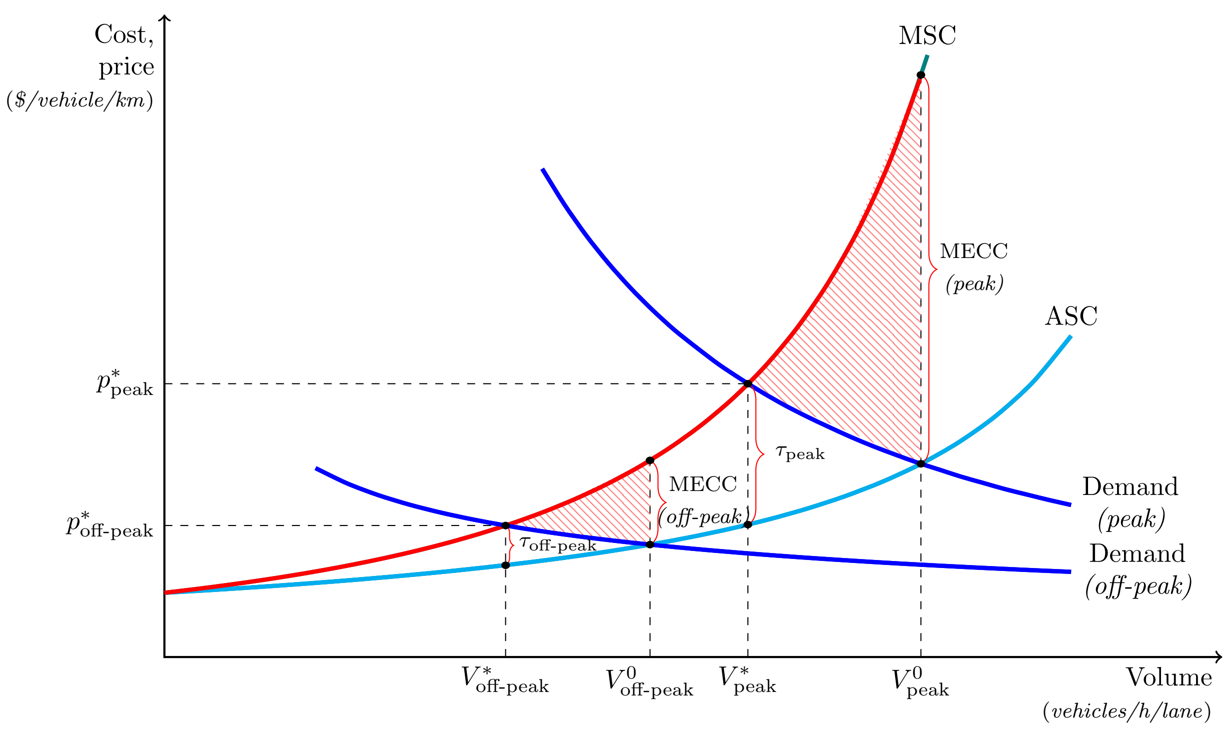


Figure 11: Location-Specific Road Pricing

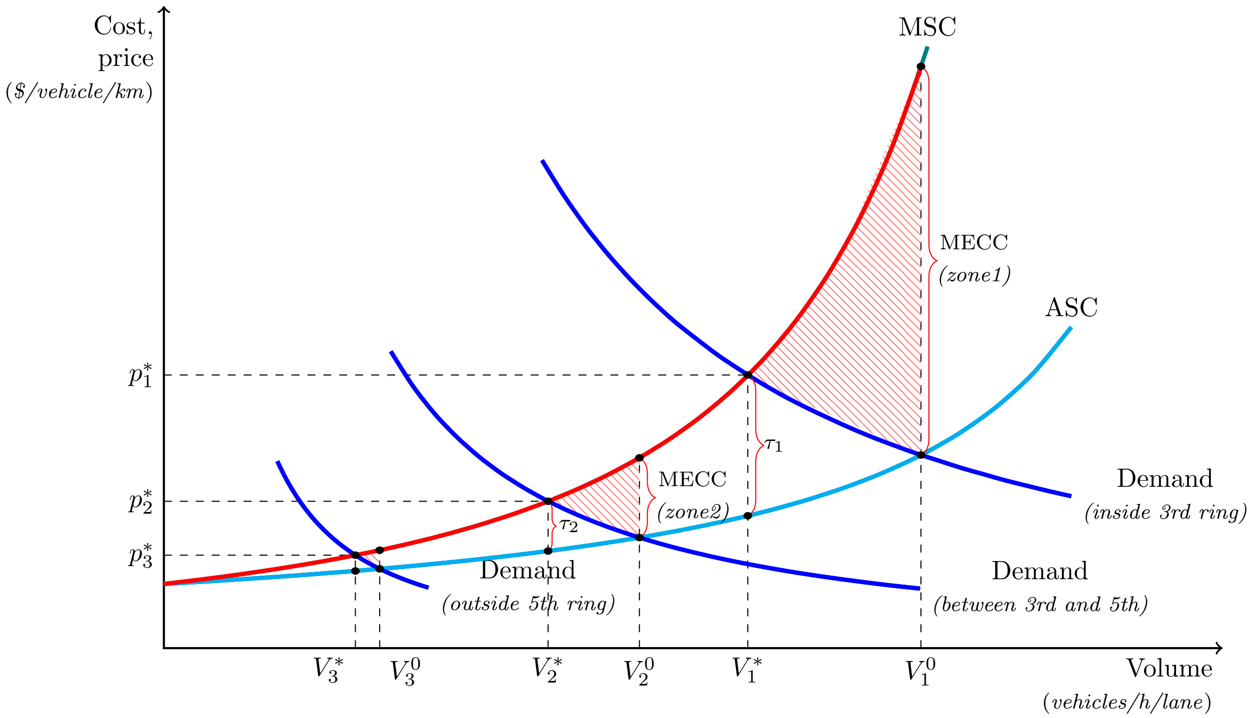


Figure 12: Location-specific and Time-varying Road Pricing