The effects of public transportation and the built environment on the number of civilian vehicles in China[1]

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Abstract

As in many developing countries, the number of vehicles in China is increasing rapidly; as the economy develops, more people own and use cars. This paper examines the effects of public transportation and the built environment on the number of civilian vehicles in China. We use a 2-step GMM instrumental variables model and apply it to city-level panel data over the period 2001 to 2011. The results show that increasing the road area increases the number of civilian vehicles, which provides empirical support for the "fundamental law of traffic congestion" in China. In contrast, increasing the public transit passenger load decreases the number of civilian vehicles, suggesting that public transportation and civilian cars are substitutes. The effects vary by city population, however. For larger cities, increases in the number of public buses increase the number of civilian vehicles, but increases in the number of taxis and in road area decrease the number of civilian vehicles. We also find that land use diversity increases the number of civilian vehicles, especially in the higher income cities and in the extremely big cities. There is no significant relationship between civilian vehicles and per capita disposable income except in mega cities.

Keywords: cars; public transportation; built environment; China
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1. Introduction

China's economy has been developing rapidly ever since China implemented economic reforms introducing market principles in 1978 (Chen, Li and Xu, 2007). Along with rapid economic development, China has also experienced accelerated urbanization and an increase in the number of vehicles on its roads. By 2013, over 50 percent of China's population resided in urban areas. Evidence from Chinese cities suggests average annual growth rates in per capita vehicle ownership of 10% to 25% (Darido, Torres-Montoya and Mehndiratta, 2014). According to data from the China Statistical Yearbook, over the period 1990 to 2011, GDP per capita increased by nearly 16 times, per capita disposable income of urban residents increased by about 11 times, and vehicle ownership increased by nearly 56 times.

The rapid growth in vehicle ownership and vehicle usage associated with urbanization is linked to increasing congestion, global warming, emissions, air pollution, and other problems (Pickrell and Schimek, 1999; Kahn, 2000; Brownstone and Golob, 2009; Lin and Prince, 2009; Lin and Zeng, 2014; Beaudoin, Farzin and Lin Lawell, 2015; Beaudoin and Lin Lawell, 2015; Beaudoin, Farzin and Lin Lawell, forthcoming). Furthermore, these trends are inconsistent with the planning objectives which cities and governments are attempting to achieve.

Policy-makers are becoming increasingly aware of the need to find effective policy tools to tackle vehicle ownership-related problems such as congestion and air pollution. Policies to change mobility that have been proposed or implemented include driving restrictions, urban planning policies, or policies to restrict the number of private car licenses

(Newman and Kenworthy, 1989; May, 2013; Lin Lawell, Zhang and Umanskaya, 2015). But in practice, these policy instruments have been ineffective. For example, Lin Lawell, Zhang and Umanskaya (2015) find that under certain circumstances, due to substitution, the purchase of a second car, the use of alternative modes of transportation, and/or atmospheric chemistry, it is possible for driving restrictions to increase air pollution.

Policies to provide public transportation are not always effective either. Duranton and Turner (2011) find no evidence that the provision of public transportation affects vehicle-kilometers traveled in U.S. cities, and conclude that increased provision of roads or public transit is unlikely to relieve congestion. Beaudoin, Farzin and Lin Lawell (2015) find that increases in public transit supply lead to a small overall reduction in auto traffic congestion, but the magnitude of the effect is subject to heterogeneity across urban areas. Beaudoin and Lin Lawell (2015) find no evidence that increased transit supply improves air quality.

Likewise, policies to build additional road area may be ineffective in reducing congestion. According to the "fundamental law of traffic congestion", while investment in infrastructure may lead to short-term reductions in congestion, in the long run it will be ineffective in the absence of efficient pricing (Beaudoin, Farzin and Lin Lawell, 2015; Beaudoin, Farzin and Lin Lawell, forthcoming). As Hau (1997) states:

> "Latent demand -- demand that has heretofore been suppressed as a result of peak-hour congestion -- emerges as soon as the traffic situation is improved. Travelers that are currently discouraged from taking a trip during their most preferred times by the major form of abatement -- traffic congestion itself --

> will respond by traveling closer to their desired time of travel. Because of the fundamental law of traffic congestion, traffic will converge on preferred places and times until there is congestion. Thus the sole reliance on supply measures would not be helpful in solving the congestion conundrum without further differentially pricing road use via peak/off-peak charges." (Hau, 1997, pp. 267)

This "fundamental law of traffic congestion" has been demonstrated empirically for auto travel in the U.S. by Duranton and Turner (2011), who show that auto travel volumes increase proportionally with the available auto capacity.

In this paper we examine the effects of public transportation and the built environment on the number of civilian vehicles in China using city-level data from 2001 to 2011. The results show that increasing the road area increases the number of civilian vehicles, which provides empirical support for the "fundamental law of traffic congestion" in China. In contrast, increasing the public transit passenger load decreases the number of civilian vehicles, suggesting that public transportation and civilian cars are substitutes.

The effects vary by city population, however. For larger cities, increases in the number of public buses increase the number of civilian vehicles, but increases in the number of taxis and in road area decrease the number of civilian vehicles. We also find that land use diversity increases the number of civilian vehicles, especially in the higher income cities and in the extremely big cities. There is no significant relationship between civilian vehicles and per capita disposable income except in mega cities.

The balance of this paper proceeds as follows. We review the previous literature in

Section 2. We present data on the number of civilian vehicles in China in Section 3. We present our empirical model in Section 4 and the data in Section 5. We present our results in Section 6. Section 7 concludes.

2. Previous Literature

Our paper builds upon previous studies of the relationship between economic development and car ownership. Button, Hine and Ngoe (1992) and Dargay (2007) find that per capita income is the deciding factor for car ownership, with an S-shaped relationship between them. In their study of China using aggregate city-level data from 1995 to 2009, Huang, Cao and Li (2013) find that the urbanization level is a significant indicator of private car ownership except in mega cities.

Our paper also builds upon previous studies of the relationship between the built environment and transportation. Also known as land use, urban form, spatial planning, or urban geography (Litman, 2012), the built environment refers to various land use factors including density, regional accessibility, transit quality, and transit accessibility. Naess (2005) argues that urban structure contributes to travel behavior, but is not the only factor. Bento et al. (2005) find that population centrality is important in explaining vehicle ownership in cities, but that the impacts of built environment measures are frequently statistically insignificant and small in magnitude. Similarly, Bhat and Guo (2007) find using data from the San Francisco Bay Area that built environment measures such as street block density, transit availability, and transit access time have a small effect on vehicle ownership.

Although most land use factors have modest individual impacts, density tends to receive the greatest attention. Ewing and Cervero (2001) and Badoe and Miller (2000) point out that as an indicator of urban sprawl, density can be interpreted as a proxy for access to employment, shopping, and other travel destinations. Several studies have shown a negative relationship between urban density and vehicle miles traveled or energy consumed in private transport (Newman and Kenworthy, 1989; Travisi, Camagni and Nijkamp, 2010). Newman and Kenworthy (1999) find a large significant inverse effect of density on vehicle miles traveled. Studies of Europe point to the existence of several important relationships at an aggregate level among land use patterns, travel behavior, and transit supply; they argue that an increasing density is strongly correlated with an increase in the supply of public transport both in vehicle kilometers and the presence of rail-based systems (de Abreu e Silva, Golob and Goulias, 2006).

In addition to density, another land use factor that is receiving increasing attention is the land use diversity. An increase in the land use diversity can reduce travel distances and allow more walking and cycling trips. Ewing and Cervero (2010) find that the land use diversity reduces vehicle travel. Frank et al. (2011) find that per capital vehicle travel and pollution emissions tend to decline with increased land use diversity.

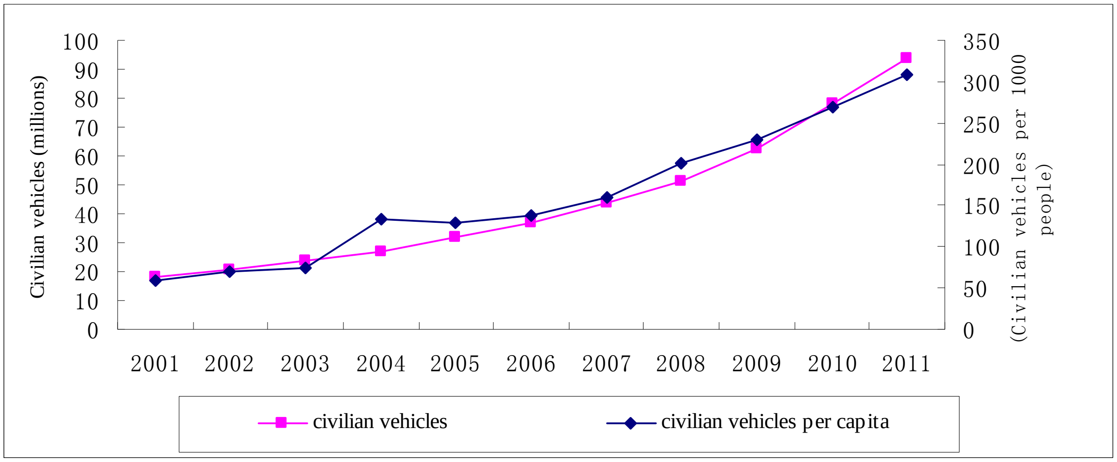
In addition to economic development and the built environment, another set of variables that can affect car ownership are socioeconomic characteristics. While land use characteristics may explain up to 40% of the variation in car ownership, socioeconomic variables often explain more of the variation in mobility patterns than land use variables (Stead, Williams and Titheridge, 2001).

We build upon the literature in several ways. First, unlike most of the previous studies, which have focused primarily on economic factors, land use factors, socioeconomic characteristics, and public transportation factors as determinants of civilian vehicle ownership and use, in this paper we examine the effects on the number of civilian vehicles of not only of income, land use diversity, population density, and public transportation, but also of road area and urban development. A second way in which we build upon the literature is that we use 2-step GMM IV regression to address potential endogeneity in our empirical model of the number of civilian vehicles.

3. The number of civilian vehicles in China

Figure 1 plots the trend in the number of civilian vehicles and the number of civilian vehicles per capita in cities in China over the period 2001 to 2011. Both the number of civilian vehicles and the number of civilian vehicles per capita in Chinese cities have been steadily increasing during the whole period. From 2001 to 2011, the number of civilian vehicles in Chinese cities increased rapidly from 18.02 million to 93.56 million, and the number of civilian vehicles per capita in Chinese cities increased rapidly from 58.83 to 268.48 vehicles per 1000 people.

Figure 1: Number of civilian vehicles and civilian vehicles per capita in China



Source: China Statistical Yearbook for Regional Economy, 2002 to 2012.

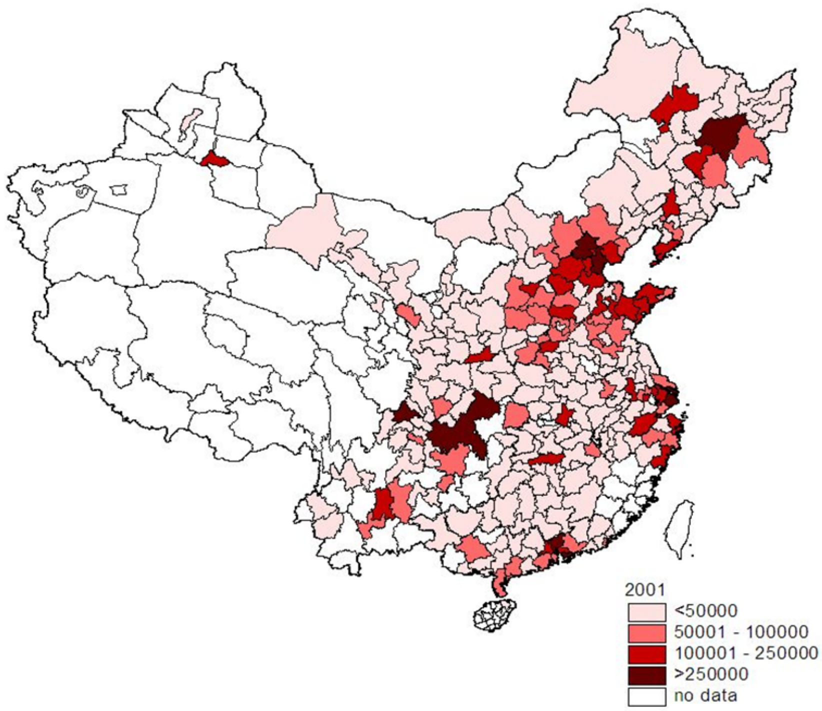
Figures 2, 3 and 4 map the number of civilian vehicles in cities in China in 2001, 2005 and 2011, respectively. From the spatial distribution of civilian vehicle ownership, we can find the number of civilian vehicles is higher in the coast than inland. The number of civilian vehicles is high in the eastern cities, particularly Beijing, Shanghai, Chongqing, and Guangzhou, while the number of civilian vehicles in the western cities is lower. In 2011, the average numbers of civilian vehicles in small cities, medium cities, big cities, extremely big cities, and mega cities are 166,533.4, 225,677, 428,763.5, 941,523.7, and 1,734,877, respectively.[2]

If we analyze the growth of number of civilian vehicles by city population, we find

[2] The classification of cities into small cities, medium cities, big cities, extremely big cities, and mega cities is based on population, in accordance with the new standard made by state council of China (State Councile, P.R. CHINA, 2014): small cities have less than or equal to 0.5 million people; medium cities have between 0.5 and 1 million people; big cities have between 1 and 3 million people; extremely big cities have between 3 and 5 million people; and mega cities have more than 5 million people.

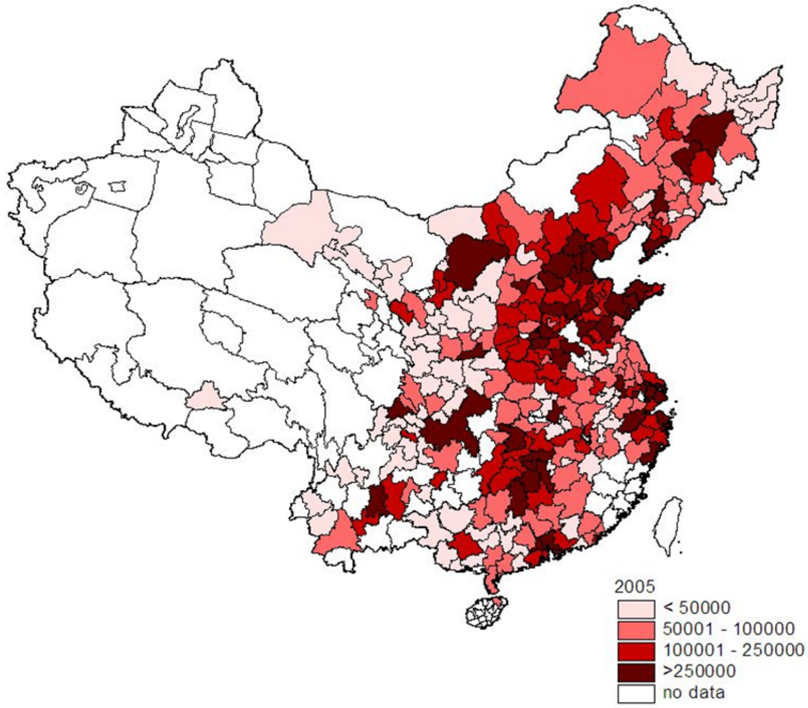
that during the period from 2002 to 2011, the number of civilian vehicles increased about 29.01 times in the mega cities; 5.97 times in medium cities, 5.75 times for big cities, 5.22 times for small cities, and 3.67 times for extremely big cities. We also find during the past decade, the number of civilian vehicles increased more in the latest five years than in the five years prior.

Figure 2: Number of civilian vehicles in cities in 2001



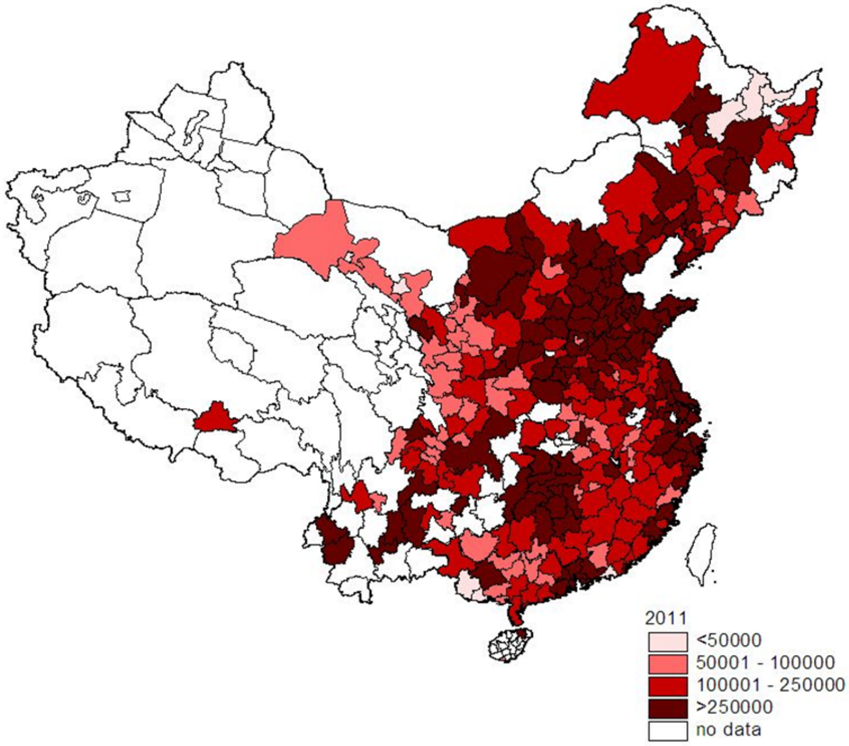
Source: China Statistical Yearbook for Regional Economy, 2002.

Figure 3: Number of civilian vehicles in cities in 2005



Source: China Statistical Yearbook for Regional Economy, 2006.

Figure 4: Number of civilian vehicles in cities in 2011



Source: China Statistical Yearbook for Regional Economy, 2012.

4. Empirical Model

In order to empirically analyze effects of public transportation and the built environment on the number of civilian vehicles in China, we estimate the following econometric model:

$$
\begin{aligned}
&\ln(civiveh_{it}) = \beta_1 \ln(taxi_{it}) + \beta_2 \ln(bus_{it}) + \beta_3 \ln(transit_{it}) + \beta_4 \ln(civiveh_{it-1}) \\
&\quad + \beta_5 \ln(popden_{it}) + \beta_6 \ln(inc_{it}) + \beta_7 \ln(urbdev_{it}) + \beta_8 \ln(road_{it}) \\
&+ \beta_9 \ln(landuse_{it}) + \alpha_i + \nu_t + \theta_{it} + \varepsilon_{it} \quad ,
\end{aligned}
$$

(1),

where $civiveh_{it}$ is the number of civilian vehicles in city *i* in year *t*; $taxi_{it}$ is number of taxis in city *i* in year *t*; bus_{it} is number of public buses in city *i* in year *t*; $transit_{it}$ is public transit passenger load in city *i* in year *t*; $civiveh_{it-1}$ is 1-year lag value of civilian vehicles; $popden_{it}$ is population density, which we define as the number of people per square kilometer in city *i* in year *t*; inc_{it} is per capita disposable income of residents in urban areas in city *i* in year *t*; $urbdev_{it}$ is urban development, which is defined as the fraction of the urban area that is developed; $road_{it}$ is urban road area in city *i* in year *t*; $landuse_{it}$ is the land use diversity in city *i* in year *t*; α_i is a city fixed effect, v_t is a year effect, θ_{it} is a region-year effect, and ε_{it} is an error term.

The public transportation variables in our model are the number of public buses bus_{it} and the public transit passenger load $transit_{it}$. Our built environment variables are population density $popden_{it}$, urban development $urbdev_{it}$, urban road area $road_{it}$, and land use diversity $landuse_{it}$.

Land use diversity can be measured using entropy indices or dissimilarity indices; both methods result in scores from 0 to 1. In this paper, we measure the land use diversity using the following Gibbs-Mirtin index (Chen et al., 2009):

$$landuse_{it} = 1 - \frac{\sum S_{ijt}{}^2}{\left(\sum S_{ijt}\right)^2} = 1 - \sum S_{ijt}{}^2,$$

where S_{it} represents the proportion of area for each land use type *j* in the total urban construction land area of city *i* in year *t*. The types of land use *j* we consider are: residential; industrial; storage; public facilities; transportation systems; roads and plazas; municipal utilities; green space; and land for special purposes. Land use diversity ranges from 0 (least diverse) to 1 (most diverse).

In the regression in equation (1), one may worry that the number of taxis, the number of public buses, and the public transit passenger load may be endogenous to civilian vehicles. To test for their endogeneity, we run an IV regression of equation (1) with year and city fixed effects using lagged values of the number of taxis, the number of public buses, the public transit passenger load as instruments for number of taxis, the number of public buses, the public transit passenger load, respectively, and then test for the endogeneity of the number of taxis, the number of public buses, and the public transit passenger load.

Under the null hypothesis that the specified endogenous regressors can actually be treated as exogenous, the test statistic in our endogeneity test is distributed as chi-squared with degrees of freedom equal to the number of regressors tested. The test statistic is based on the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where the suspect regressor(s) are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous. Under conditional homoskedasticity, this endogeneity test statistic is numerically equal to a Hausman test statistic (Hayashi, 2000; Baum, Schaffer and Stillman, 2007). Unlike Durbin-Wu-Hausman tests, the test statistics we use are robust to various violations of conditional homoscedasticity (Baum, Schaffer and Stillman, 2007).

According to the results of our endogeneity test, the p-value for the number of taxis is greater than 0.1 (p-value = 0.7075), so we do not reject the null hypothesis that the number of taxis is exogenous. When we test for the endogeneity of the number of public buses and the public transit passenger load using lagged values of the number of public buses and the public transit passenger load as instruments, we reject the null hypothesis that the number of public buses is exogenous at a 5% level (p-value = 0.0469) but do not reject the null hypothesis that the public transit passenger load is exogenous (p-value= 0.1681). Since we reject the null hypothesis that the number of public buses is exogenous and since it is likely that public transit passenger load is endogenous to the number of civilian vehicles, we use the lagged values of the number of public buses and the public transit passenger load as instruments for the number of public buses and the public transit passenger load, respectively.

Given that our panel data has large *n* and small *t*, we use 2-step GMM methods to estimate our IV regression (Roodman, 2009). We also conduct Arellano-Bond tests for AR(1) and AR(2) in first differences (Roodman, 2009). Our results (not shown) reject the null hypothesis of zero autocorrelation in the first-differenced errors at order 1 at a 5% level. Serial correlation in the first-differenced errors at order 2 is not significant at a 5% level.

In addition, we also address potential endogeneity by including city fixed effects, year effects, and region-year effects to control for time-invariant city-level unobservables, nation-wide shocks that vary year by year, and region-wide shocks that vary year by year, respectively.

5. Data

We use annual city-level panel data for 284 cities in China over the years 2001 to 2011. The data in this study are from the China City Statistical Yearbook and the China Regional Statistical Yearbook.

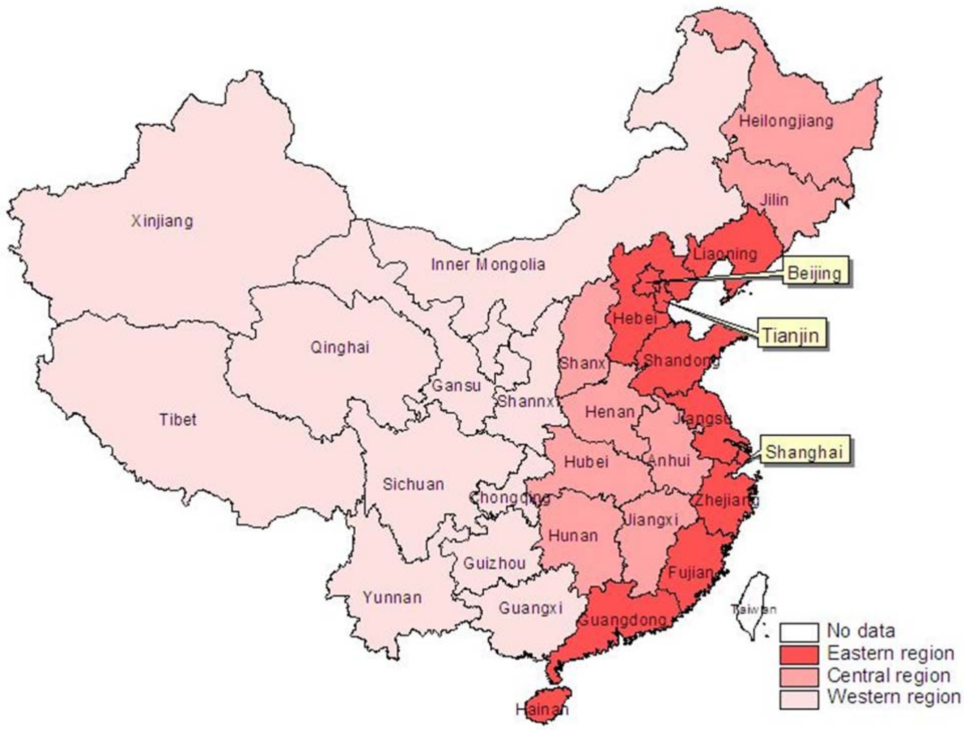
Table 1 presents summary statistics of the variables in our data set. Over the period 2001 to 2011, the number of civilian vehicles ranges from 1816 to 4,732,124, with an average of 188,072. For the population density, there is a large gap between the maximum value and the minimum value: the minimum value of 12.98 people per km^2 appeared in Heihe city in 2001, and the highest value of 5324.123 people per km^2 occurred in Shanghai in 2011. The average value for per capita disposable income is 12,105 constant 2001 yuan. The average urban development, as measured by the fraction of the urban area that is development, is 0.077. The road area varies greatly by city, with an average value of 11,089,000 m^2. The average land use diversity is 0.771, which is relatively diverse. There is also great spatial disparity in number of taxis: the maximum value is 70,373, but the minimum is only 36. The average number of public buses is 1020. The average public transit passenger load is 166,480,000 people.

For the region-year effects in our model, we classify the provinces in China into 3 regions: the eastern region, the central region and the western region. The regions are mapped in Figure 5. The eastern region includes the following 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes the following 8 provinces: Shanxi, Heilongjiang, Jilin, Anhui, Jiangxi, Henan, Hunan, and Hubei. The western region includes the following 12 provinces: Sichuan, Guizhou, Shaanxi, Inner Monglia, Yunnan, Qinghai, Ningxia and Xinjiang, Guangxi, Sichuan, Chongqing, and Tibet. Owing to limits on data availability, and because they are separate from mainland China, Macao, Taiwan and Hong Kong are not included in any region nor in any regression.

Table 1. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
number of civilian vehicles	3044	188,072	323,621	1816	4,732,124
population density (people/km^2)	3103	90.449	406.964	12.980	5324.123
per capita disposable income (constant 2001 yuan)	2974	12,105	9795	1136	167,783
urban development (fraction of the urban area that is developed)	2818	0.077	0.084	0.001	0.763
road area (10,000 m^2)	3089	1108.900	1679.021	14	214,900
land use diversity	2991	0.771	0.0772	0.024	0.8639
number of taxis	3092	2997	6096	36	70,373
number of public buses	3089	1020	2259	22	29,608
public transit passenger load (10,000 people)	3081	16,648	42,385	9	525,606

Figure 5: Regions in China



Notes: The eastern region includes the following 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes the following 8 provinces: Shanxi, Heilongjiang, Jilin, Anhui, Jiangxi, Henan, Hunan, and Hubei. The western region includes the following 12 provinces: Sichuan, Guizhou, Shaanxi, Inner Monglia, Yunnan, Qinghai, Ningxia and Xinjiang, Guangxi, Sichuan, Chongqing, and Tibet. Macao, Taiwan and Hong Kong are not included in any region.

6. Results

The results of our instrumental variables model with city fixed effects and year effects, and with and without region-year effects are reported in Table 2. We find that there is no significant relationship between the number of civilian vehicles and disposable income, which is different from previous studies (Huang, Cao and Li, 2012). The variables that have a significant effect on the log number of civilian vehicles include the log public transit passenger load, which has a significant negative effect; the lagged value of the log number of civilian vehicles, which has a significant positive effect; and the log road area, which has a significant positive effect.

The positive coefficient on road area in Table 2 shows that increasing the road area leads to an increase in the number of civilian vehicles in China. This result is consistent with the "fundamental law of traffic congestion": while investment in infrastructure may lead to short-term reductions in congestion, in the long run it will be ineffective in the absence of efficient pricing (Beaudoin, Farzin and Lawell, 2015; Beaudoin, Farzin and Lin Lawell, forthcoming).

In order to further explore whether increasing the road area can lead to traffic congestion, Brackman, Grarretsen and van Marrewijk (2001) compare the growth rate between civilian vehicles per capita and civilian vehicles per road length, and find that traffic congestion increases if civilian vehicles per capita increases more than civilian vehicles per road length. In our data set, civilian vehicles per capita increased 5.23 times from 2001 to 2011, while civilian vehicles per road area increased 2.54 times; thus, since civilian vehicles per capita increased more than civilian vehicles per road length, this discordance could result in traffic congestion. Thus, according to our results, increasing road area is not an effective policy instrument to curb traffic congestion in China.

In order to explore how the effects of public transportation and the built environment on the number of civilian vehicles vary by city population, we classify the cities into 5 categories according to population, in accordance with the new standard made by state council of China (State Councile, P.R. CHINA, 2014): small cities (less than or equal to 0.5 million people), medium cities (between 0.5 and 1 million people), big cities (between 1 and 3 million people), extremely big cities (between 3 and 5 million people), and mega cities (more than 5 million people). We then run our econometric model in equation (1) separately for each category of city.

According to the results by city population in Table 3, we can find that the determinants of the number of civilian vehicles vary by city population. For small cities (specification 1), the road area has a significant positive effect on the number of civilian vehicles. For medium cities (specification 2), which account for 40 percent of all cities in China, increases in public transit passenger load decrease the number of civilian vehicles, which provides support for the Chinese government's policy to develop public transportation to address the transportation issue. For big cities (specification 3), however, increasing the number of public buses increases the number of civilian vehicles also increased. For extremely big cities (specification 4), the results show that increases in the number of public buses and in land use diversity increase the number of civilian vehicles, but increases in the number of taxis and in road area decrease the number of civilian vehicles. For mega cities (specification 5), increases in disposable income increase the number of civilian vehicles.

In order to explore how the effects of public transportation and the built environment on the number of civilian vehicles vary by disposable income, we classify the cities into low and high income cities with 11,000 yuan as the cut-off point, which is close to the mean disposable income over all cities. According to the results by income in Table 4, in high disposable income cities, both road area and land use diversity significantly increase the number of civilian vehicles. For the low disposable income cities, none of the variables are significant.

We also estimate the model by urban development. According to the results in Table 5, in low development cities, increases in public transit passenger load decrease the number of civilian vehicles, but increases in road area increase the number of civilian vehicles. For the medium and high development cities, none of the public transportation or built environment variables has a significant effect.

Table 2. IV Results

Dependent variable is log number of civilian vehicles		
	(1)	（2）
Log number of taxis	-0.00526	-0.00614
	(0.0198)	(0.0195)
Log number of public buses	0.0908	0.0836
	(0.0585)	(0.0585)
Log public transit passenger load	-0.0749*	-0.0618
	(0.0357)	(0.0350)
Lagged log number of civilian vehicles	0.136***	0.137***
	(0.0209)	(0.0209)
Log population density	0.0716	0.0577
	(0.0634)	(0.0626)
Log disposable income	-0.0571	0.00255
	(0.0726)	(0.0765)
Log urban development	-0.0406	-0.0310
	(0.0412)	(0.0406)
Log road area	0.105**	0.101**
	(0.0328)	(0.0324)
Log land use diversity	0.133	0.143
	(0.0989)	(0.0985)
City fixed effects	Y	Y
Year fixed effects	Y	Y
Region*year effects	N	Y
First-stage F-statistic for log number of public buses	4374.38	
First-stage F-statistic for log public transit passenger load	2990.47	
p-value from under-identification test	[0.000] ***	
p-value from weak instrument-robust inference test	[0.000] ***	
p-value from test for endogeneity of the log number of taxis	[0.7075]	
Observations	2,560	2,455
Number of cities	284	284
R-squared	0.705	0.718

Notes: Standard errors in parentheses. We use the lagged values of the number of public buses and the public transit passenger load as instruments for the number of public buses and the public transit passenger load, respectively. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3. IV Results By Population

	Dependent variable is log number of civilian vehicles				
Population (million people)	⩽0.5	∈(0.5, 1]	∈(1,3]	∈(3,5]	>5
	small cities	medium cities	big cities	extremely big cities	mega cities
	(1)	(2)	(3)	(4)	(5)
Log number of taxis	0.0180	-0.0412	0.0338	-0.614**	0.00883
	(0.0518)	(0.0331)	(0.0335)	(0.209)	(0.0581)
Log number of public buses	0.0459	0.0682	0.245*	0.603**	0.968
	(0.156)	(0.0996)	(0.102)	(0.204)	(0.599)
Log public transit passenger load	-0.126	-0.118*	0.0115	0.193	0.194
	(0.0877)	(0.0504)	(0.0800)	(0.275)	(0.407)
Lagged log number of civilian vehicles	0.0554	0.133***	0.147***	-0.373***	-0.0687
	(0.0518)	(0.0337)	(0.0351)	(0.0813)	(0.151)
Log population density	0.244	-0.0641	0.0105	0.586	1.171
	(0.156)	(0.147)	(0.113)	(0.450)	(0.643)
Log disposable income	0.265	-0.226	0.147	-0.315	1.476***
	(0.232)	(0.121)	(0.168)	(0.276)	(0.346)
Log urban development	-0.180	0.0381	-0.0650	0.448	-0.965
	(0.143)	(0.0818)	(0.0653)	(0.281)	(0.504)
Log road area	0.196**	0.0316	0.0741	-1.050***	0.0122
	(0.0709)	(0.0596)	(0.0637)	(0.185)	(0.225)
Log land use diversity	0.0166	0.233	-0.0112	1.617*	-0.282
	(0.210)	(0.144)	(0.231)	(0.733)	(1.148)
City fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Region*year effects	Y	Y	Y	Y	Y

First-stage F-statistic for log number of public buses	497.90	1812.61	1960.76	177.34	179.64
First-stage F-statistic for log public transit passenger load	311.13	990.85	1090.90	266.57	563.31
p-value from under-identification test	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***
p-value from weak instrument-robust inference test	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.010] *
p-value from test for endogeneity of the log number of taxis	[0.9485]	[0.8949]	[0.9515]	[0.1390]	[0.9804]
Observations	468	971	853	68	72
Number of cities	68	124	110	11	11
R-squared	0.618	0.696	0.774	0.971	0.954

Notes: Standard errors in parentheses. We use the lagged values of the number of public buses and the public transit passenger load as instruments for the number of public buses and the public transit passenger load, respectively. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. IV Results by Disposable Income

Dependent variable is log number of civilian vehicles		
Disposable income (yuan)	>11,000	⩽11,000
	(1)	(2)
Log number of taxis	0.00942	0.00990
	(0.0190)	(0.0385)
Log number of public buses	0.0203	0.160
	(0.110)	(0.189)
Log public transit passenger load	-0.0852	0.0330
	(0.0656)	(0.181)
Lagged log number of private cars	0.00808	-0.0181
	(0.0276)	(0.0357)
Log population density	0.00832	0.205
	(0.0645)	(0.133)
Log disposable income	-0.0158	0.0700
	(0.141)	(0.128)
Log urban development	0.0288	-0.150
	(0.0474)	(0.0891)
Log road area	0.0860*	0.0816
	(0.0374)	(0.0743)
Log land use diversity	0.562***	0.0459
	(0.149)	(0.161)
City fixed effects	Y	Y
Year fixed effects	Y	Y
Region*year effects	Y	Y
First-stage F-statistic for log number of public buses	1738.96	2707.27
First-stage F-statistic for log public transit passenger load	1124.11	1904.19
p-value from under-identification test	[0.000] ***	[0.000] ***
p-value from weak instrument-robust inference test	[0.000] ***	[0.000]***
p-value from test for endogeneity of the log number of taxis	[0.8718]	[0.6403]
Observations	1,281	1,142
R-squared	0.734	0.395
Number of cities	269	244

Notes: Standard errors in parentheses. We use the lagged values of the number of public buses and the public transit passenger load as instruments for the number of public buses and the public transit passenger load, respectively. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5. IV Results by Urban Development

	Dependent variable is log number of civilian vehicles		
urban development	<0.1	∈[0.1, 0.2)	⩾0.1
	(1)	(2)	(3)
Log number of taxis	-0.00405	-0.0329	0.0145
	(0.0232)	(0.0604)	(0.0400)
Log number of public buses	0.130	-0.176	-0.143
	(0.0689)	(0.153)	(0.111)
Log public transit passenger load	-0.0392*	0.0617	0.00940
	(0.0195)	(0.0763)	(0.0554)
Lagged log number of private cars	0.124***	0.109*	0.115**
	(0.0249)	(0.0541)	(0.0403)
Log population density	0.121	-0.171	-0.200
	(0.0765)	(0.264)	(0.168)
Log disposable income	0.0339	0.0435	0.0593
	(0.0946)	(0.162)	(0.142)
Log urban development	-0.0631	-0.000654	0.121
	(0.0515)	(0.199)	(0.115)
Log road area	0.0958**	0.0794	0.0877
	(0.0360)	(0.140)	(0.0949)
Log land use diversity	0.142	0.445	0.230
	(0.111)	(0.278)	(0.225)
City fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Region*year effects	Y	Y	Y

First-stage F-statistic for log number of public buses	3717.46	547.58	239.74
First-stage F-statistic for log public transit passenger load	2111.04	825.09	227.00
p-value from under-identification test	[0.000] ***	[0.000] ***	[0.000] ***
p-value from weak instrument-robust inference test	[0.000] ***	[0.000] ***	[0.000] ***
p-value from test for endogeneity of the log number of taxis	[0.5933]	[0.5670]	[0.9090]
Number of observations	1,773	416	666
Number of cities	222	69	88
R-squared	0.699	0.723	0.755

Notes: Standard errors in parentheses. We use the lagged values of the number of public buses and the public transit passenger load as instruments for the number of public buses and the public transit passenger load, respectively. Significance codes: $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.

7. Conclusion

China is facing increasingly serious environmental problems, and the number of civilian vehicles continues to increase even when the oil price increases and no matter how bad city traffic and pollution get. In this paper we analyze the effects of public transportation and the built environment on the number of civilian vehicles in China using city-level data from 2001 to 2011.

We draw several conclusions from our results. First, we find that increasing the road area increases the number of civilian vehicles, which provides empirical support for the "fundamental law of traffic congestion" in China. Thus, widening the roads or adding new roads are not effective tools for alleviating traffic congestion.

Second, we find that increasing the public transit passenger load decreases the number of civilian vehicles. Thus, improving public transportation to increase the public transit passenger load is an effective way to decrease the number of civilian vehicles.

Third, in contrast to Cao et al. (2009), our results show that there is no significant relationship between civilian vehicles and per capita disposable income except in mega cities. Many people living in cities in China can now afford to buy a car. But some mega cities have implemented government policies to limit the number civilian vehicles, such as a high license plate price or a license-plate lottery. For example, the cost of a license plate is over 70,000 yuan higher in Shanghai. Thus, in mega cities, only the richer can afford the buy a car.

Our fourth result is that land use diversity can increase the number of civilian vehicles, especially in the higher income cities and extremely big cities. In contrast, previous studies of developed countries have found that the land use diversity reduces vehicle travel (Ewing and

Cervero, 2001).

Our fifth result is that for cities with lower urban development, the public transit passenger load has a significant negative effect on the number of civilian vehicles. The Chinese government should therefore improve its transit passenger load by better transportation planning, lowering the transit fee, and designating exclusive bus lanes.

Possible avenues for future research include studying the emissions from cars in China, and analyzing and designing policies to alleviate car dependence.

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