ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Boosting the eco-friendly sharing economy: the effect of gasoline prices on bikeshare ridership in three U.S. metropolises

To cite this article: Pan He *et al* 2020 *Environ. Res. Lett.* **15** 114021

Environmental Research Letters

OPEN ACCESS

RECEIVED
6 April 2020

REVISED
11 September 2020

ACCEPTED FOR PUBLICATION
24 September 2020

PUBLISHED
16 October 2020

LETTER

Boosting the eco-friendly sharing economy: the effect of gasoline prices on bikeshare ridership in three U.S. metropolises

Pan He[1,2], **Zhenpeng Zou**[3], **Yongping Zhang**[4,5] **and Giovanni Baiocchi**[6]

1 Department of Earth System Science, Tsinghua University, Beijing 100048, People's Republic of China
2 School of Earth and Ocean Sciences, Cardiff University, Cardiff CF10 3AT, United Kingdom
3 School of Architecture, Planning & Preservation, University of Maryland, College Park, MD 20742, United States of America
4 School of International Relations and Public Affairs, Fudan University, 220 Handan Road, Shanghai 200433, People's Republic of China
5 The Bartlett Centre for Advanced Spatial Analysis, University College London, 90 Tottenham Court Road, W1T 4TJ, London, United Kingdom
6 Department of Geographical Science, University of Maryland, College Park, MD 20742, United States of America

E-mail: baiocchi@umd.edu

Keywords sustainable transportation, sharing economy, gasoline price, emission reduction, bikeshare

Supplementary material for this article is available online

Abstract

Transportation has become the largest CO_2 emitter in the United States in recent years with low gasoline prices standing out from many contributors. As demand side changes are called for reducing car use, the fast-growing sharing economy shows great potential to shift travel demand away from single-occupancy vehicles. Although previous inter-disciplinary research on shared mobility has explored its multitudes of benefits, it is yet to be investigated how the uptake of this eco-friendly sharing scheme is affected by gasoline prices. In this study, we examine the impact of gasoline prices on the use of bikeshare programs in three U.S. metropolises: New York City, Boston, and Chicago. Using bikeshare trip data, we estimate the impact of citywide gasoline prices on both bikeshare trip duration and trip frequency in a generalized linear regression setting. The results suggest that gasoline prices significantly affect bikeshare trip frequency and duration, with a noticeable surge in short trips. Doubling gasoline prices could help save an average of 1933 gallons of gasoline per day in the three cities, approximately 0.04% of the U.S. daily per capita gasoline consumption. Our findings indicate that fuel pricing could be an effective policy tool to support technology driven eco-friendly sharing mobility and boost sustainable transportation.

1. Introduction

A demand-side approach is urgently called for in the U.S. transportation sector—a major greenhouse gas (GHG) emitter fueled by persistently low gasoline prices. In 2016, carbon dioxide (CO_2) emissions from the transportation sector have surpassed the electric power sector for the first time since the late 1970s (Dunn 2017). While the power sector has been transitioning from carbon intensive coal combustion to clean energy sources like natural gas and renewables, progress in the transportation sector has been slow mainly due to low gasoline prices that contribute to increasing vehicle miles traveled (Cortright 2019) and the popularity of suburban utility vehicles (SUVs) and trucks of low fuel efficiency (Puentes and Tomer 2008). Although fuel economy has been improving within each vehicle type and class globally, the trend has suspended in the United States since 2017, reflecting the rise in sales of light truck and SUVs and a slide in the sales of lighter cars (IEA 2018).

The emerging sharing economy provides new opportunities for demand-side mitigation of CO_2 emissions through the massive adoption of bikeshare programs across the U.S. cities. Current bikeshare systems are supported by advancements in information and communication technologies (ICTs), which drastically lower the marginal cost of reproducing information, remove the hurdle of finding a niche product like a rental bike, and support seamless transactions (Goldfarb and Tucker 2019). Thus, ICTs realize the potential of underutilized resources to improve efficiency and sustainability (Mi and Coffman 2019). Bikeshare has experienced brisk growth in the United

States, since the first public bikeshare program was launched in Washington D.C. in 2010. In 2018, about 84 million trips on shared micro-mobility were taken in the U.S., including station-based bikeshare, dockless bikeshare, and E-scooter share (National Association of City Transportation Officials 2019). With short auto trips replaced by more eco-friendly cycling trips, growing popularity and adoption of bikeshare has the potential to reduce traffic congestion and emissions (Hamilton and Wichman 2018).

Few studies attempted to understand how gasoline prices may impact the adoption of bikeshare. Extensive literature has been focusing on estimating the price elasticity of gasoline demand (Hughes *et al* 2008, Labandeira *et al* 2017), the price elasticity of gasoline on auto vehicle miles traveled (Goetzke and Vance 2018), and the gasoline price effect on public transport (Creutzig 2014). As for cycling, gasoline price was often treated as one of many exogenous variables to explain cycling activities. Previous research found a significant and positive correlation between gasoline prices and the percentage of work trips by cycling in both the U.S. and Canada (Pucher and Buehler 2006). Using health survey data, researchers found that an increase in inflation-adjusted gasoline price was significantly associated with an increase in leisure physical activities including cycling (Hou *et al* 2011). These studies, oftentimes relying on macro-level (e.g. state/province/metropolitan area) cross-sectional survey data, suffer from the issues of limited number of observations and the lack of granular analysis due to data aggregation. Trip level cycling data are rare prior to massive implementations of bikeshare programs with few exceptions (Smith and Kauermann 2011). Moreover, most studies were conducted prior to the emergence of bikeshare as a new mode of transportation, leaving it an open question about how responsive bikeshare usage is to fluctuations in gasoline prices.

This research aims to investigate the relationship between gasoline prices and bikeshare usage and evaluate the potential of using gasoline pricing tools to promote bikeshare and achieve sustainable transportation. We find empirical evidence of environmental benefits associated with higher gasoline prices through increasing bikeshare usage. We focus on three U.S. metropolises: Boston, Chicago, and New York City. They are early adopters of a citywide bikeshare program and represent metropolitan areas with large populations and considerable demand for the alternative modes of transportation. We take advantage of their diversities in spatial typology, demographic composition, economic prosperity, infrastructure development level, and other socio-economic attributes for an inter-city comparative analysis. In this way, we try to identify actionable implications for urban planning and transportation policy that could promote green transportation modes in heterogeneous urban contexts.

We match trip-level bikeshare data with weekly city-level gasoline price data in 2012–2018. The time series analysis allows us to control for confounding factors and estimate long-range gasoline price elasticity of bikeshare usage in terms of frequency and duration. Since the trips generated by all transportation modes and gasoline prices are simultaneously affected by macro and localized economies, we adopt an instrumental variable (IV) estimation using crude oil prices as the instrument to mitigate possible endogeneity biases. We further conduct heterogeneity analyses on bikeshare trips of different duration, across cities, between casual and membership users, as well as during rush and non-rush hours to provide the full scope of how gasoline prices affect bikeshare usage. In addition, we compute the shortest roadway network path of each bikeshare trip by origin-destination station pairs to derive bikeshare distances traveled. Based on the distance, we calculate the system-wide environmental benefit of increasing bikeshare travel associated with an increase in gasoline prices.

Our findings provide quantitative evidence that can be used in a cost-benefit analysis on gasoline pricing tools to incentivize a modal shift towards a more sustainable transportation system. Gasoline price has been pivotal in shaping energy policies. Studies on short- and long-run price elasticities of gasoline consumption on vehicle miles/kilometers traveled suggest that auto travel can significantly decline as long as gasoline prices stay high—as consumers will either switch to a more fuel-efficient vehicle (Small and Van Dender 2007) or consider alternative transportation modes (Currie and Phung 2007, Lane 2012, Smart 2014). Our study indicates that such shift can be environmentally beneficial in the presence of bikeshare programs. As a result, a pricing tool like fuel tax can disincentivize driving and reduce emission on environmental grounds (Santos *et al* 2010).

2. Results and discussion

2.1. The effect of gasoline price

We find that gasoline price leads to longer total duration across all trips mainly because of an overall increase in trips. Table 1 shows the effect of gasoline price on bikeshare ridership. The naïve generalized least squared (GLS) model shows that a 1% increase in gasoline price leads on average to a 0.726% increase in total bike trip duration, *ceteris paribus* (Column 1) and a 0.824% raise in trip frequency (Column 3). On the other hand, average trip duration decreases slightly by 0.098%, although the decrease is not statistically significant (Column 5). Taken together, these results suggest that a higher gasoline price encourages more bikeshare usage, especially short-distance trips. The IV estimations show larger effects of gasoline price (a 1% increase) on both the total duration and the total frequency by 1.210% and 1.565%, respectively (Column 2 and 4). An increase in gasoline prices also significantly reduces average trip duration. This is largely the result of increased trips with short duration which decrease average duration. The coefficient on prices is negative and significant (Column 6). One explanation for this result is that when gasoline price rises, citizens use bikeshare services more often with a large proportion of the newly increased trips lasting for a shorter duration compared with those in the context of lower prices. Such an interpretation can be further supported by the fact that mean duration of trips in the sample is approximately 15 min, while the trips lasting for 5–10 min increase most with increases in gasoline price (See analysis below and table S2 (available online at stacks.iop.org/ERL/15/114021/mmedia)). In the first stage of the IV regression, we find that our instrument, the crude oil price, is statistically significant and the F-statistics are larger than ten for three first-stage models, meaning that the instrument is strong and valid. The IV models yield estimates of larger magnitudes, suggesting an attenuation bias due to the measurement error in the GLS identification. Correcting for the attenuation bias resulting from measurement error in the GLS identification significantly increases the estimates of ridership impact of gasoline price. We find that doubling the gasoline price (from \$2.78 per gallon to \$5.56 per gallon) would lead to 4594 h longer the ridership (a 121% increase from 3797 h following the method from (Wooldridge 2015)[1]) for all three cities, and 23 796 more trips (a 156.5% increase from 15 205 trips).

We further explore whether people change the extent of their reaction to the gasoline price changes over time after the introduction of the program by separating the effects by periods. As our study period covers approximately 5–7 years after the launch of bikeshare programs, we divide the records of each city by three phases: the 1st and 2nd year, the 3th and 4th year, and after the 4th year of the project launch. We used a dummy variable approach to allow for changes in the estimated coefficient over the different periods. Considering the first phase as reference, two binary dummy variables are defined indicating whether an observation belongs to the second/third phase and then interacted with gasoline price. As shown in table S2, the interaction terms in both the total duration and total frequency regression are negative and significant, indicating that the effect of gasoline price has declined over time (Column 1–4). This could be explained by novelty effects wearing off over time and causing price changes to be less effective in increasing bikeshare use as time goes by. This novelty effect has been established in many mobility sharing programs including bikes (see, e.g. (Godavarthy *et al* 2017)). Nevertheless, an increase in gasoline price has still a significant impact in the last period as the sum of the coefficient of lnprice and lnprice* after the 4th year are positive in all the regressions. Higher prices have also triggered a larger reduction of average trip duration in later periods, indicating that the increased number of journeys have even shorter length.

2.2. Effects on heterogeneous groups

2.2.1. Trips of different duration

Gasoline prices have the largest positive effect on bikeshare trips that last 5–10 min. (figure 1(a)). As the duration increases, the price elasticity starts to decrease due to longer trips (figure 1(a), full results shown in table S3). These results indicate that there is more flexibility in mode choice for medium-distance trips as compared to long (10 min or more) or short (0–5 min) trips. When a destination is further away, it is less likely for people to switch from driving to cycling due to a higher cost of time and laboring physical activity. Meanwhile, individuals are essentially more likely to cycle or walk than drive for a short trip and thus are less responsive to switch modes according to gasoline prices. Nevertheless, a rise of gasoline price may lead to a mode shift to a combination of bikeshare and the public transit system, i.e. cycling to the nearest metro station or bus stop for the first-/last-mile commute. Therefore, gasoline prices still show a positive effect on short trip frequency. Similar to previous analyses, the IV estimates produce larger regression coefficients than those from GLS, indicating an attenuation effect in the GLS setting.

2.2.2. Trips in different cities

The effect of gasoline prices also differs by city. Boston shows the largest effect of gasoline prices on both the total duration and the total frequency (figure 1(b), full results included in table S4). Such an effect is largely driven by the high number of short trips in Boston, which yield a larger price effect as aforementioned in the previous paragraph. People still use bikeshare more often when gasoline prices rise in the other two cities, though they are not as responsive as Bostonians. According to our estimates, doubling the average gasoline price (\$2.78 per gallon) in Boston would lead to about 1285 h longer bikeshare usage (141.1% increase from 911 h) and 6289 more trips (190.7% increase from 3298 trips). It is 8607 more hours (a 101.1% increase from 8513 h), and 48 839 more trips (a 138.1% increase from 35 365 trips) in New York City if the gasoline price doubles from \$2.86 per gallon. and 2753 more hours (a 111.8% increase from 2462 h) and 11 380 more trips (a 128.4% increase from 8863 trips) in Chicago if the gasoline price doubles from \$2.71 per gallon.

[1]According to Wooldridge, J M (Wooldridge 2015), the percentage change of the dependent variable is inaccurately approximated by the coefficient when the coefficient is large. Instead, the change should be calculated using $100 \cdot [\exp(\hat{\beta}\Delta x) - 1]$.

Table 1. The effect of gasoline price on the frequency and duration of bikeshare ridership.

	(1)	(2)	(3)	(4)	(5)	(6)
	Total duration (ln)		Total frequency (ln)		Average duration (ln)	
	GLS	IV	GLS	IV	GLS	IV
lnprice	0.726***	1.210*	0.824***	1.565***	−0.098	−0.355*
	(0.184)	(0.506)	(0.159)	(0.440)	(0.058)	(0.174)
Temperature	0.064***	0.064***	0.055***	0.055***	0.009***	0.009***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Temperature^2	−0.000***	−0.000***	−0.000***	−0.000***	−0.000**	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visibility	0.144***	0.144***	0.127***	0.127***	0.017***	0.017***
	(0.006)	(0.004)	(0.006)	(0.004)	(0.002)	(0.001)
Wind speed	−0.033***	−0.033***	−0.027***	−0.027***	−0.006***	−0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Precipitation	0.000	0.001	0.004	0.004	−0.003	−0.004
	(0.024)	(0.020)	(0.020)	(0.018)	(0.007)	(0.007)
Constant	7.469***	6.054***	3.999***	2.635***	3.470***	3.419***
	(0.373)	(0.733)	(0.306)	(0.637)	(0.164)	(0.252)
Fixed effects						
City*Day-of-year	Y	Y	Y	Y	Y	Y
City*Day-of-week	Y	Y	Y	Y	Y	Y
Day-of-Week*Month*Year	Y	Y	Y	Y	Y	Y
N	5860	5860	5860	5860	5860	5860
R^2	0.731	—	0.776	—	0.723	—

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The signs of control variables are as expected: Temperature changes affect ridership in a non-linear way as a deviation from the most comfort temperature (either too hot or too cold) would reduce the number of trips as well as shorten their duration. Meanwhile, lower visibility or stronger wind also discourages cycling in both frequency and duration.

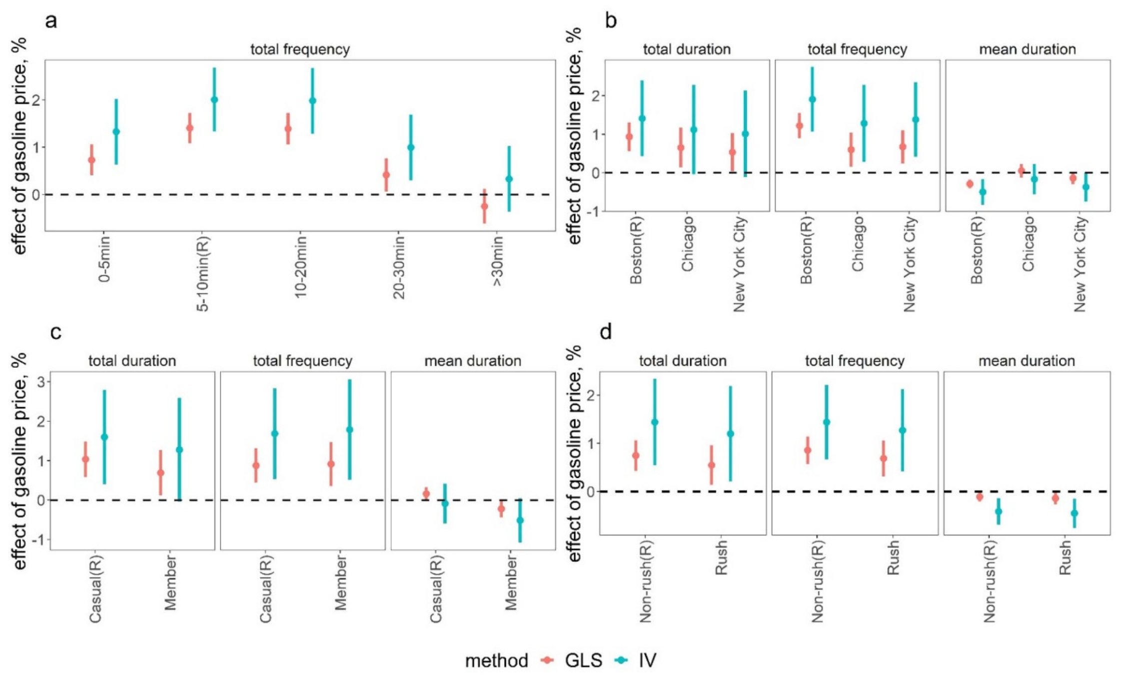

Figure 1. Effects of gasoline price on the frequency and duration of bikeshare ridership in different subsamples: (a) trips of different duration, (b) trips in different cities, (c) casual users and members, (d) rush and non-rush hours. The regression coefficients of gasoline price and its interaction terms with subgroups are plotted. The estimates and 95% confidence intervals for each group are included. (R) indicates reference group in the regressions. The confidence intervals are constructed using a method introduced by (Figueiras et al 1998) based on the regression results.

2.2.3. Casual users and members

Casual bikeshare users and members react differently to a change in gasoline price. Membership leads to a smaller price elasticity on total trip duration as compared to that for casual users, which is indicated by the negatively significant coefficient of the term *lnprice*member* (figure 1(c) and table S5, Column 1 and 2). However, the frequency of trips does not seem to differ (Column 3 and 4). Additionally, higher gasoline price further reduces the average trip duration for the members, indicating that members follow habitual usage of the system so that their travel patterns are less likely to change with gasoline prices as compared to casual users who can easily switch to/-from driving to bikeshare when gasoline prices rise/-fall. Such distinction between casual and membership trips is possibly a result of the pricing scheme of the bikeshare programs: Casual users do not invest in a membership and can quit bike-sharing anytime. Thus, the gasoline price elasticity is higher for them, whereas bikeshare members are loyal to use the system due to their financial investment. Moreover, the demand can be different for casual users and members: Members sign up the program with more habitual travel purposes, such as commuting, as opposed to casual rides for causal users. As a result, bikeshare members' trips are less likely to be affected by the fluctuations of gasoline price.

In addition, a rise in gasoline price may also encourage more individuals to join bikeshare membership. When driving becomes more expensive, casual users start to use bikeshare more frequently so that an annual membership may come at a lower price as compared to accumulating single trips. Although this assumption is not directly testable with our data, we are able to examine whether the daily percentage of membership trips in all the trips changes with the gasoline price. The results shown in Column 7 and 8 in table S5 do not suggest a significant difference, which means that higher gasoline prices alone may not be sufficient to persuade a causal bikeshare user to join the membership.

2.2.4. Rush and non-rush hours

The effect of gasoline prices may also differ by time of day. Rush-hour trips have a significantly smaller gasoline price elasticity for both the total trip duration and frequency, while the price elasticity for average duration does not seem to differ between rush and non-rush hours (figure 1(d) and table S6). This is largely due to the fact that most rush-hour trips are commute trips, which are expected to be less responsive to gasoline price changes.

2.3. Environmental benefits

Based on the estimated gasoline price elasticities of bikeshare trip frequency and duration, we further calculated the potential environmental benefits from increasing bikeshare usage as the gasoline price goes up. Here, we assume that higher gasoline prices would discourage driving and cause bikeshare trips to partially substitute driving trips (notice that people may also switch to public transit or a combination of bikeshare and transit). This assumption allows us to estimate the lower-bound of the environmental benefits from the energy saving and the subsequent reduction of air pollutant emissions from trip substitution (details of the calculation is included in the methodology section). The result indicates that 1% increase of gasoline price would lead to 1.415% increase in bikeshare trips that replace driving trips in all three metropolises—an equivalent to 74 663 km less driving mileage when the average gasoline price increases from \$2.78 per gallon. Suppose we double the average gasoline price to \$5.56, the increased bikeshare trips would help save 1933 gallons of gasoline per day in all three cities. In addition, the doubled gasoline price would also reduce emissions of CO_2, PM2.5, PM10, NO_x, SO_x, and NH_3 by 0.243t CO_2e, 17 g, 30 g, 145 g, 170 g, 5973 g, and 24 g, respectively, as a result of trip substitution from auto to bikeshare.

3. Concluding remarks

This research examined the effect of gasoline price on bikeshare usage and the associated environmental benefits. We focused on three municipal bikeshare programs in the United States with extended bikeshare trip time series data. We regressed both bikeshare trip duration and trip frequency on gasoline prices and other determinants in a generalized linear regression setting and applied an instrumental variable approach using regional crude oil prices as an instrument to overcome the potential endogeneity bias from local demand on fuel. Results suggest that gasoline prices have a significant impact on bikeshare usage: Doubling the average gasoline price would increase the total bikeshare trip duration by 121% and trip frequency by 156.5%. We also found that the impact of gasoline price fluctuation is larger on casual rides than on membership rides, as well as during non-rush hours than during rush hours. Doubling the average gasoline price would help save 1933 gallons of gasoline per day in a city, approximately 0.04% of the daily gasoline usage per capita in the United States.[2] It should be noted that the environmental benefit of increasing gasoline prices can be greater than those from the impact on bikeshare usage only, possibly by encouraging densification of the city through a commuting tax (Borck and Brueckner 2018), increasing public transit ridership

[2]The calculation goes as follow: The total population of Boston, Chicago, and New York City are 692 600 (www.census.gov/quickfacts/bostoncitymassachusetts), 2693 976 (www.census.gov/quickfacts/chicagocityillinois), and 8336 817 (www.census.gov/quickfacts/newyorkcitynewyork) in 2019. So the gasoline saving per capita is $1933*3/(692\,600 + 2693\,976 + 8336\,817) \approx 0.00049$ gallon per day. The gasoline consumption in the United States is estimated to be 389.51 million gallons per day in 2019 (www.eia.gov/tools/faqs/faq.php?id=23&t=10), and the total population of the United States in 2019 is 328 231 337 (www.census.gov/quickfacts/fact/table/US/IPE120218). Therefore, the gasoline consumption per capita is $389.51*10^6/328\,231\,337 \approx 1.19$ gallon per day. As a result, 0.00049/1.19 gives approximately 0.04% of the daily per capita gasoline consumption.

(Lane 2012), and decreasing induced travel demand (Noland 2001). On average, the short-run and long-run price elasticity of demand for gasoline are −0.34 and −0.84, respectively, from the previous meta-analysis (Brons *et al* 2008), indicating a significant reduction of gasoline usage when its price increases. The broader environmental benefit of higher gasoline prices is outside the scope of this research.

Our findings provide an important piece of empirical evidence in support of using gasoline pricing tools in a shared mobility setting to realize the environmental benefit of green transportation like cycling. Recent studies have highlighted the importance of changing consumer behavior as an effective way to meet sustainable development goals when faced with the global challenge of climate change (Dietz 2014). Sharing economy, as an emerging economic model, opens up new opportunities for such a change in consumer behavior particularly in transportation and hospitality (Mi and Coffman 2019). While its potential environmental and health impacts have been evaluated in some studies (Otero *et al* 2018, Zhang and Mi 2018), such impacts are usually discussed in counterfactual scenarios rather than proved on a concrete empirical ground. Moreover, seldom is sharing economy addressed in the policy context. Our findings fill in the research gap by providing a robust estimation of the gasoline price elasticity on bikeshare usage, which can be utilized to support the implementation of energy policy tools such as a gasoline tax. In the policy context, our results also provide additional support to previous empirical research showing the environmental benefit of higher gasoline prices, albeit in a cross-country context (Creutzig *et al* 2015). The gasoline pricing tool can also be deployed to complement other policy tools targeting GHG emission reductions, such as a compact urban development (Creutzig *et al* 2015, Borck and Brueckner 2018). In the presence of a bikeshare system, the gasoline pricing tool may even achieve larger environmental benefits in terms of reducing air pollutant emissions, by ameliorating traffic congestion, as well as yielding health co-benefits from increased physical activities. In summary, we see an opportunity for policymakers to reconsider using gasoline pricing as an effective policy tool to achieve transportation sustainability goals in the advent of bikeshare. The emergence of bikeshare reshapes the loss and gain of implementing price tools in managing the urban transportation systems, and policy makers should re-examine the cost and benefits of fuel taxation or transportation subsidies.

4. Methodology

4.1. GLS regression

To explore whether and by how much gasoline prices affect the usage of the bikeshare programs, we aggregate bikeshare trip data by day and combine the data of all three programs[3] in the estimation. In addition, we adopted time and city fix effects to control for invariant city characteristics and common time trends across all bikeshare trips in the GLS setting, which is specified in equation (1):

$$\begin{aligned} Y_{it} = \beta_1 \ln price_{it} + X_{it} + city\_dow_{it} \\ + month\_year\_dow_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where Y_{it} stands for the usage of the bikeshare program (in terms of total trip frequency or duration) on the ith day in a particular city of year t. We firstly focus on the total duration of all the trips during the day, and then break it into total trip frequency and average trip duration. $\ln price_{it}$ denotes the logarithm of the average gasoline price one week before the ith day of a year in a city. The lagged price is used here for two reasons. First, as gasoline prices vary weekly in the data, contemporaneous prices may contain information of prices ahead of early days of a week. Second, it takes time for consumers to respond to a gasoline price change. X_t is a vector of control variables that consist mostly weather factors, such as the average daily temperature and its quadratic form, visibility, wind speed, and precipitation. α_i is the day-of-year by city fixed effect, which controls for the invariant confounding factors by city and by day in a year (e.g. city-specific seasonal attractions). λ_t is the year fixed effect. We also included two day-of-week fixed effects that are city and month-of-year specific ($city\_dow_{it}$ and $month\_year\_dow_{it}$), which enable us to control for invariant confounding factors, such as the varying travel demand between weekdays and weekends, that differ by city and month in a year. They also capture the system-wide changes of the bikeshare programs over time, including the expansion of a program over time with more stations and available bikes, changes to the pricing scheme, as well as planned or accidental disruptions in the transportation system. ε_{it} is the error term. Here, we are interested in β_1, which are positive and statistically significant—suggesting increasing bikeshare usage as gasoline prices go up.

4.2. IV estimation

The GLS estimation is likely to suffer from an endogeneity issue due omitted variable biases and the reverse causality. Retail gasoline prices and travel demand can be simultaneously affected by localized factors, such as regional air pollution control policies and economic shocks (e.g. opening up new highways

[3]There is only one station-based bikeshare program functioning in each of the three cities. Pilot dockless bikeshare programs were launched in these three cities more recently (e.g. 2018 in New York City), in which the bikes are not required to be returned to a station. Dockless bikeshare is excluded from this study as the data are unavailable. We argue that the impact of their advent is limited on station-based bikeshare usage as the scale of these pilot programs is limited in these three cities.

or new warehouses that will attract a lot more traffic). (Liu 2016). These factors can hardly be captured by the control variables, leading to correlations between the variable of interest, $\ln price_{it}$, and the error term, ε_{it}. Furthermore, retail gasoline prices can be affected by changes in local travel demand and cause a reverse causality issue in a GLS estimation. To address the potential caveats of the GLS estimation, we conducted an IV estimation using an exogenous variable that only affects bikeshare usage through gasoline prices and nothing else. Previous literature considered multiple candidates for instrumental variables, including gasoline tax (Coglianese *et al* 2017), global crude oil price (Gillingham 2014), crude oil quality (Hughes *et al* 2008), and crude oil production disruptions (Hughes *et al* 2008). We were able to obtain weekly crude oil price data and constructed an instrument variable. The first stage regression is specified in equation (2):

$$\ln price_{it} = \beta_1' \ln crude\_price_{it} + X_{it} + city\_dow_{it} + dow\_month\_year_{it} + \alpha_i + \lambda_t + \mu_{it} \quad (2)$$

where $\ln crude\_price_{it}$ is the logarithm of the crude oil price in a specific city on day i in year t; μ_{it} is the error term; the other variables are specified the same as equation (1).

It should be noted that the effect of gasoline prices on bikeshare usage and the associated environmental benefits can be under-estimated. If a bikeshare station reaches its capacity limit, then there is no room for additional bikeshare usage to respond to higher gasoline prices. Such a capacity limit may only have a borderline impact on our conservative estimates of the environmental benefits. Besides, these programs kept expanding over the period of time in our study, which helps alleviate the concerns about the systematic capacity limits. Moreover, bikeshare stations are within a walking distance from each other in popular destinations so that users can easily find an available bike from a nearby station.

4.3. Effect by period

We test whether the effect of gasoline prices changes overtime with interaction terms of the price and period of years. For each city, we divide the study period into three phases: less than 2 years, the 3th and 4th year, and after the 4th year of the launch of bikeshare programs. The specification follows equation (3):

$$Y_{it} = \beta_1 \ln price_{it} + \beta_2 \ln price\_2_{it} + \beta_3 \ln price\_3_{it} + X_{it} + city\_dow_{it} + month\_year\_dow_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Where $\ln price\_2_{it}$ and $\ln price\_3_{it}$ are the interaction term of $\ln price_{it}$ and dummies indicating the period of the 3th and 4th year, as well as after the 4th year, respectively. In this way, the first two years after the launch of bikeshare is regarded as the reference group. The two interaction terms are instrumented by the interaction term of $\ln crude\_price_{it}$ and the period dummies following a similar identification as equation (2).

4.4. Tests on heterogeneous effect

We examined the heterogeneous effects of gasoline prices on trips of different duration. The specification follows equation (4):

$$Y_{ijt} = \beta_0 + \sum_j \beta_{1j} \ln price_{it} * dur_{ijt} + X_{it} + city\_dow_{it} + city\_month\_year_{it} + \alpha_i + \lambda_t + \varepsilon_{ijt} \quad (4)$$

where a series of dummy variables, dur_{ijt}, are included to indicate trips of different duration intervals, j. We defined five intervals: 0–5 min, 5–10 min, 10–20 min, 20–30 min, and >30 min. The total number of trips within each duration interval is specified as the dependent variable. To control for the endogenous variable $\ln price_{it} * dur_{ijt}$, we use a crude oil price instrument variable, $\ln crude\_price_{it} * dur_{ijt}$. We tested other heterogeneous groups following the same specification as equation (4), in which we interact the logarithm of gasoline prices with city/membership/rush hour dummy variables. For each, we constructed an instrumental variable accordingly using the interaction terms of crude oil prices and the dummy variables themselves.

4.5. Environmental benefit estimation

The primary environmental benefit comes from energy saving, which is estimated by dividing the total daily vehicle kilometers traveled (VKT) substituted by bikeshare trips by the average fuel efficiency (VKT per gallon of gasoline). Since bikeshare trip trajectories are not available, hence true VKT is not available, we calculated the shortest network distance in ArcGIS between the starting and ending station for each trip, taking into account the typology of roadways in different cities. In this way, we can obtain a conservative estimation of VKT because (1) bikeshare users may take a longer path than what the shortest distance suggests and (2) users can replace driving with a combination of cycling and public transit such that energy saving and emission reductions from transit are not included here.

The calculated VKT statistics as summarized in table S6. Average vehicle fuel efficiency p is set at 24 miles per gallon (i.e. 38.62 km per gallon) according to the Bureau of Transportation Statistics.[4] Upon the calculation of energy saving, we then calculated life-cycle emission reduction of major transportation pollutants, including CO_2, PM2.5, PM10, NO_x, SO_x, and NH_3. They include not only the direct emissions

[4]The data can be accessed from www.bts.gov/content/average-fuel-efficiency-us-light-duty-vehicles. We used the average fuel efficiency of light duty vehicles, short wheel base in 2016.

from fuel combustion, but also the indirect emissions from gasoline exploitation, processing, distribution, etc (Zhang and Mi 2018). We multiplied the amount of gasoline saved due to mode shift when the average gasoline price doubles by the emission factors to derive the amount of emission cut. The emission factors are set as 96.2 g CO_2e per MJ (Cooney *et al* 2016) (i.e. 12 675.31 g CO2e per gallon of gasoline with 131.76 MJ in 1 gallon) for CO_2, 0.037 g per mile (i.e. 0.023 g per km) for PM2.5, 0.064 g per mile (i.e. 0.040 g per km) for PM10, 0.315 g per mile (i.e. 0.196 g per km) for VOC, 0.368 g per mile (i.e. 0.229 g per km) for NO_x, 0.128 g per mile (i.e. 0.080 g per km) for SO_x, and 0.053 g per mile (i.e. 0.033 g per km) for NH_3 (Tessum *et al* 2012).

To estimate the change of VKT due to gasoline price change, we conduct the IV analysis using the distance as the dependent variable. We also considered city and rush-hour heterogeneities with two city interaction terms and a rush-hour interaction term in the IV specification. The results are shown in table S7. The positive sign of the coefficients of gasoline prices are preserved, despite the loss of statistical significance in the second specification. The interaction terms are not significant in some cases. Nevertheless, the coefficients can still be adopted in estimating the change of VKT as we previously showed the effect of gasoline prices on bikeshare usage in terms of trip duration and frequency.

5. Data

5.6. Gasoline prices and crude oil prices

Gasoline price data are retrieved from the U.S. Energy Information Administration (EIA) website (U.S. Energy Information Administration, 2018). EIA reports the weekly average retail gasoline prices for selected regions, including the cities in our sample. The price data are available for the 1993–2018 period, which covers our study period. Gasoline prices are categorized by grade and formulation. We adopt the average price for all grades as a comprehensive indicator. Weekly crude oil prices in two markets—the West Texas Intermediate market in Cushing, Oklahoma, and the Europe Brent market—are also reported. We adopt the crude oil prices from the Europe Brent market as our instrument to avoid the endogeneity issue raised from domestic confounding factors (U.S. Energy Information Administration, 2018). We plot the temporal trends of both the gasoline price in each city and the crude oil price in figure S1. Overall, the gasoline prices in all the cities show similar trends over time to the crude oil price, indicating that crude oil prices can be a robust instrument.

5.7. Bikeshare ridership

We combine data of three bikeshare programs in the United States. Most municipal bikeshare operators publish the information of historical ridership on their websites. Despite the differences in data source, bikeshare trip records contain similar information, including starting and ending time, station, date, and membership status. The geographical coordination and the number of docks of a bikeshare station are also accessible. The three chosen metropolises—Boston (Bluebikes, 2018), Chicago (Divvybikes, 2018), and New York City (Citibike, 2018) [5]—also have gasoline price data. The bikeshare programs were launched on July 28, 2011, June 28, 2013, and May 27, 2013, respectively, and have been active since then. We therefore select data from their launch date to October 31, 2018. The trips of 1 min or shorter are excluded by the data providers to avoid false starts. In addition, we excluded the trips longer than 24 h. Less than 0.1% of the data were excluded. We calculate the total duration, total frequency, and average duration of each day in each city during the study period (approximately 7 years for Boston and 5 years for Chicago and New York City) which are then summarized here used as the dependent variables of our regression analysis. In the analysis on heterogeneous effects, the dependent variables are aggregated by duration/city/membership status/whether in rush hour or not of each day in each city, and thus show a different sample size compared with that for the main analysis. The descriptive statistics of the final sample are provided in table S1. We plot the temporal change of the gasoline price and the bikeshare trip frequency and total duration in figures S2 and S3. The bikeshare ridership shows a strong seasonality in each city, but both the frequency and duration have been trending up since the launch of the programs.

5.8. Weather factors

The weather factors come from the Global Surface Summary of the Day (GSOD) (NOAA National Centers for Environmental Information 2019b) and the Global Historical Climatology Network (GHCN) (NOAA National Centers for Environmental Information 2019a), provided by the US National Centers for Environmental Information. The GSOD dataset provides detailed global daily weather indicators from over 9000 land stations. We retrieved the average temperature, the average wind speed, and the average visibility to control for weather factors that will affect bikeshare usage in the regression analyses. The precipitation data for the stations located in the three cities are not available in the GSOD dataset, but in the GHCN dataset. We merged the GSOD data with the GHCN data to derive all the weather factors, the latter

[5] We identified four cities with available gasoline price data and bikeshare ridership data: Boston, Chicago, New York City, and Denver. However, the bikeshare system in Denver is not as frequently used as the other three. Besides, there are many outliers in its bikeshare data. Thus, we decided not to include Denver's data in our analysis.

of which also contain information about weather conditions collected from land surface stations that cover the areas similar to those covered in the GSOD data. For each of the city in our analysis, observations from more than one station are available. We use the daily average weather statistics from all the stations in a city in the regression analysis.

Data availability statement

The data that support the findings of this study are openly available. www.bluebikes.com/system-data

The gasoline prices and crude oil prices come from www.eia.gov/dnav/pet/pet_pri_gnd_dcus_nus_w.htm for gasoline prices and www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm , respectively. The bikeshare data for the three cities can be retrieved from www.bluebikes.com/system-data (Boston), www.divvybikes.com/system-data (Chicago), and www.citibikenyc.com/system-data (New York City). The Global Surface Summary of the Day (GSOD) data are available from www7.ncdc.noaa.gov/CDO/cdoselect.cmd?datasetabbv\protect$\relax=$GSOD&resolution\protect$\relax=$40. The Global Historical Climatology Network (GHCN) data are available from ftp.ncdc.noaa.gov/pub/data/ghcn/daily/.

ORCID iDs

Pan He https://orcid.org/0000-0003-1088-6290
Giovanni Baiocchi https://orcid.org/0000-0002-0319-7561

References

Bluebikes 2018 Blue Bikes Comprehensive Trip Histories, Boston www.bluebikes.com/system-data

Borck R and Brueckner J K 2018 Optimal energy taxation in cities *J. Assoc. Environ. Resour. Econ.* **5** 481–516

Brons M *et al* 2008 A meta-analysis of the price elasticity of gasoline demand. A SUR approach *Energy Econ.* **30** 2105–22

Citibike 2018 Citi Bike Trip Histories, New York City www.citibikenyc.com/system-data

Coglianese J, Davis L W, Kilian L and Stock J H 2017 Anticipation, tax avoidance, and the price elasticity of gasoline demand *J. Appl. Econom.* **32** 1–15

Cooney G, Jamieson M, Marriott J, Bergerson J, Brandt A and Skone T J 2016 Updating the US life cycle GHG petroleum baseline to 2014 with projections to 2040 using open-source engineering-based models *Environ. Sci. Technol.* **51** 977–87

Cortright J 2019 The high price of cheap gasoline (www.citylab.com/transportation/2019/02/high-price-cheap-gasoline/583867/)

Creutzig F J 2014 How fuel prices determine public transport infrastructure, modal shares and urban form *Urban Clim.* **10** 63–76

Creutzig F *et al* 2015 Global typology of urban energy use and potentials for an urbanization mitigation wedge *Proc. Natl Acad. Sci.* **112** 6283–8

Currie G and Phung J 2007 Transit ridership, auto gas prices, and world events: new drivers of change? *Transp. Res. Rec.* **1992** 3–10

Dietz T 2014 Understanding environmentally significant consumption *Proc. Natl Acad. Sci. USA* **111** 5067–8

Divvybikes 2018 Divvy historical trip data available to the public, Chicago www.divvybikes.com/system-data

Dunn D 2017 US Energy Information Administration Monthly Energy Review, August

Figueiras A, Domenech-Massons J M and Cadarso C 1998 Regression models: calculating the confidence interval of effects in the presence of interactions *Stat. Med.* **17** 2099–105

Gillingham K 2014 Identifying the elasticity of driving: evidence from a gasoline price shock in California *Reg. Sci. Urban Econ.* **47** 13–24

Godavarthy R *et al* 2017 Evaluation study of the bike share program in Fargo North Dakota

Goetzke F and Vance C 2018 Is gasoline price elasticity in the United States increasing? Evidence from the 2009 and 2017 national household travel surveys Ruhr Economic Papers

Goldfarb A and Tucker C 2019 Digital economics *J. Econ. Lit.* **57** 3–43

Hamilton T L and Wichman C J 2018 Bicycle infrastructure and traffic congestion: evidence from DC's Capital Bikeshare *J. Environ. Econ. Manage.* **87** 72–93

Hou N, Popkin B M, Jacobs, D R, Song Y, Guilkey D K, He K, Lewis C E and Gordon-Larsen P 2011 Longitudinal trends in gasoline price and physical activity: the CARDIA study *Prev. Med.* **52** 365–9

Hughes J E, Knittel C R and Sperling D 2008 Evidence of a shift in the short-run price elasticity of gasoline demand *Energy J.* **29**

IEA 2018 World Energy Outlook

Labandeira X *et al* 2017 A meta-analysis on the price elasticity of energy demand *Energy Policy* **102** 549–68

Lane B W 2012 A time-series analysis of gasoline prices and public transportation in US metropolitan areas *J. Transp. Geogr.* **22** 221–35

Liu W 2016 Estimating the elasticities of gasoline demand: an instrumental variable approach *Appl. Econ. Lett.* **23** 1153–6

Mi Z and Coffman D M 2019 The sharing economy promotes sustainable societies *Nat. Commun.* **10** 1214

National Association of City Transportation Officials 2019 Shared micromobility in the U.S.: 2018

NOAA National Centers for Environmental Information 2019a Global historical climatology network (GHCN) ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily/

NOAA National Centers for Environmental Information 2019b Global summary of the day files: 2011–2018 www7.ncdc.noaa.gov/CDO/cdoselect.cmd?datasetabbv\protect$\relax=$GSOD&resolution\protect$\relax=$40

Noland R B 2001 Relationships between highway capacity and induced vehicle travel *Transp. Res.* A **35** 47–72

Otero I, Nieuwenhuijsen M J and Rojas-Rueda D 2018 Health impacts of bike sharing systems in Europe *Environ. Int.* **115** 387–94

Pucher J and Buehler R 2006 Why Canadians cycle more than Americans: a comparative analysis of bicycling trends and policies *Transp. Policy* **13** 265–79

Puentes R and Tomer A 2008 The road… less traveled: an analysis of vehicle miles traveled trends in the US

Santos G, Behrendt H, Maconi L, Shirvani T and Teytelboym A 2010 Part I: externalities and economic policies in road transport *Res. Transp. Econ.* **28** 2–45

Small K A and Van Dender K 2007 Fuel efficiency and motor vehicle travel: the declining rebound effect *Energy J.* **28** 25

Smart M J 2014 A volatile relationship: the effect of changing gasoline prices on public support for mass transit *Transp. Res.* A **61** 178–85

Smith M S and Kauermann G 2011 Bicycle commuting in Melbourne during the 2000s energy crisis: a semiparametric analysis of intraday volumes *Transp. Res.* B **45** 1846–62

Tessum C W, Marshall J D and Hill J D 2012 A spatially and temporally explicit life cycle inventory of air pollutants from gasoline and ethanol in the United States *Environ. Sci. Technol.* **46** 11408–17
U.S. Energy Information Administration 2018 Weekly Retail Gasoline and Diesel Prices (2011-2018) www.eia.gov/dnav/pet/pet_pri_gnd_dcus_nus_w.htm
U.S. Energy Information Administration 2018 Spot Crude Oil Prices (2011-2018) www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm
Wooldridge J M 2015 Introductory econometrics: a modern approach Nelson Education
Zhang Y and Mi Z 2018 Environmental benefits of bike sharing: a big data-based analysis *Appl. Energy* **220** 296–301