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Factors influencing the choice of shared bicycles and shared electric bikes in Beijing

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ABSTRACT

China leads the world in both public bikeshare and private electric bike (e-bike) growth. Current trajectories indicate the viability of deploying large-scale shared e-bike (e-bikeshare) systems in China. We employ a stated preference survey and multinomial logit to model the factors influencing the choice to switch from an existing transportation mode to bikeshare or e-bikeshare in Beijing. Demand is influenced by distinct sets of factors: the bikeshare choice is most sensitive to measures of effort and comfort while the e-bikeshare choice is more sensitive to user heterogeneities. Bikeshare demand is strongly negatively impacted by trip distance, temperature, precipitation, and poor air quality. User demographics however do not factor strongly on the bikeshare choice, indicating the mode will draw users from across the social spectrum. The e-bikeshare choice is much more tolerant of trip distance, high temperatures and poor air quality, though precipitation is also a highly negative factor. User demographics do play a significant role in e-bikeshare demand. Analysis of impact to the existing transportation system finds that both bikeshare and e-bikeshare will tend to draw users away from the "unsheltered modes", walk, bike, and e-bike. Although it is unclear if shared bikes are an attractive "first-and-last-mile solution", it is clear that e-bikeshare is attractive as a bus replacement.

1. Introduction

Public bikeshare systems are among the world's fastest growing mode of public transportation, if not the fastest, growing at an average of 37% annually since 2009 (Meddin, 2015). The greatest growth is occurring in China, a country also experiencing rapid expansion of the use of electric bicycles (e-bikes). E-bike sales outpace all other personal motorized modes in China (CAAM, 2015a, 2015b; Jamerson and Benjamin, 2013). Fig. 1 shows the rapid growth of two emerging technologies, e-bikes and bikeshare systems. The rapid growth in personal e-bike ownership brings both benefits and costs. There are significant concerns about safety, disruption to traffic, and environmental impacts of these vehicles. However, e-bikes play an important role in the radically transforming Chinese urban form. Hyper urbanization, coupled with

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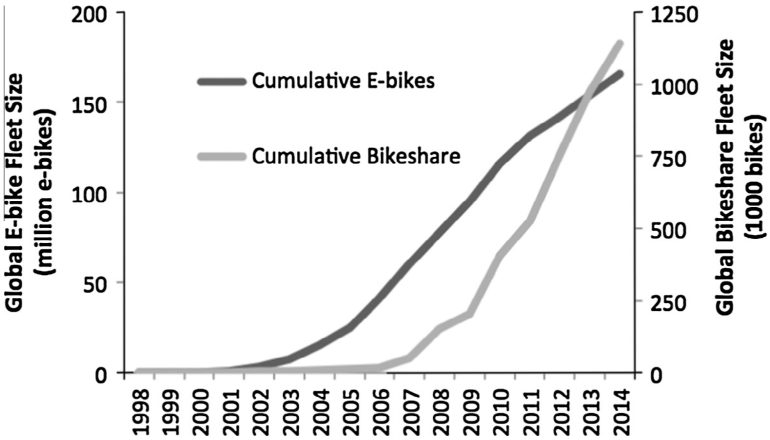

Fig. 1. Growth in personal e-bike and public bikeshare systems Note: Bikeshare data are developed and provided by Russell Meddin, head of research for the Bikesharing World Map (Meddin, 2015). E-bike sales data are reported in the Electric Bike World Reports (Jamerson and Benjamin, 2013, 2015). This chart uses combined annual sales data with an estimated five-year scrapage rate to estimate cumulative e-bike fleet size.

decentralization, has caused a host of transportation problems: runaway motorization, gridlock, increasing travel demand, tailpipe emissions, and decreasing accessibility. While in recent years, dozens of Chinese cities have implemented bikeshare systems in efforts to mitigate some of these problems, there are no known large-scale shared e-bike systems in existence. The current trajectory of bikeshare adoption, the popularity of e-bikes, and the presence of e-bikeshare pilot projects in other countries all support a future of e-bike sharing in China. Given the rapid evolution of transportation in China, it is not well understood how such a system will differ from standard bikeshare and how both types of shared bikes (hereafter "shared bike" is used to refer to both bikeshare and e-bikeshare) systems can best address the needs of urban China.

Although current trajectories suggest the emergence of e-bikeshare, as well as continued bikeshare propagation, there is little research investigating how cities can plan and implement these systems in a way that best suits their unique transportation, weather, and demographic markets. There have been some small e-bikeshare pilots (most notably in Japan, Europe, and on the campus of the University of Tennessee, Knoxville (City Bike, 2013; Langford et al., 2013)), and larger deployments recently in Europe (e.g. Madrid). Commercial e-bikeshare products are offered by companies in Europe and China, with about 4000 pedelecs in bikeshare systems in 2014 (Meddin, 2015), yet there exist no known investigation into how a large-scale system would be used (Ji et al., 2014). The majority of extant bikeshare research is backwards looking, focusing on user surveys and system-use data analysis (DeMaio, 2009; Fishman et al., 2013; Shaheen et al., 2011). These works have identified common factors that influence bikeshare usage, such as land-use, demographics, and environmental conditions, but they do not describe methods for investigating new markets or new technologies such as e-bikeshare. Furthermore, much of the research is qualitative or based on survey data from which general trends in travel behavior and usage among a self-selected sample can be identified. Recent bikeshare research quantifies the effects of environmental conditions and population demographics, yet these works are based on revealed preference data and thus retrospective (Buck et al., 2013; Buehler, 2013; Gebhart and Noland, 2014; Martin and Shaheen, 2014; Parkes et al., 2013).

Cities that are in the early phases of planning for new shared bike systems need tools to inform goals, budgets, and design. Questions of usage and demand forecasting are critical to achieving a successful system. We develop and implement a stated preference survey and estimate a multinomial logit (MNL) mode switching model for new shared bike markets. Our objective is to understand the factors influencing the decision to switch from existing modes to bikeshare or e-bikeshare and how a new shared bike system will interact with the existing transportation system. We expect that the adoption and usage of shared bike systems is contextually sensitive to transportation, environmental, and population variables that are unique to each market. To this end, we test trip and environmental factors as well as population factors that include travel habits and socio-demographic characteristics. The method is employed in a case study in Beijing introducing both bikeshare and e-bikeshare options. The policy and planning implications are considered in the Beijing context, a city with unique characteristics. But, the results are cautiously generalizable and can be applicable to many Chinese cities with diverse mode options.

Four aspects of this research are innovative. First, it is the only known study to introduce the concept of large-scale e-bikeshare and to investigate the factors influencing the choice to use such a system. Second, we quantitatively investigate a new bikeshare market through stated preference data, in contrast to the extant research using retrospective revealed preference data. Third, we introduce a novel stated preference (SP) pivoting design that allows for quality data collection through single-interview pen-and-paper surveys. Last, we explicitly quantify the effects of environmental variables that influence demand, but are often discounted in existing demand studies; in quantifying variables such as air quality, a particular concern in the Chinese market, we link China's unique environmental concerns to transportation demand.

2. Background

2.1. Transportation challenges and Chinese urban form

The favored development pattern in Beijing in recent decades has been super-blocks: large homogenous developments, ranging from 8 hectares (20 acres) to 40 hectares (100 acres), with limited internal vehicle circulation. Superblocks are bordered, and thus isolated, by high-speed multi-lane thoroughfares (Monson, 2008). The super-block is likely to continue as the main tool of Chinese development due to its efficient and profitable systems of planning, leasing, and construction. The net effects of market-driven sub-center development and super-block design have been to further divide land-use types, increasing motorized travel demand and reducing accessibility. Due to job-housing separation and lower land-use diversity, multiple studies have found that residents of peripheral communities travel farther, drive more, and walk, bike, and use transit less (Cervero and Day, 2008; Pan et al., 2009; Yang, 2006; Zhao, 2010).

Hyper-motorization and expanding urban form have contributed to problems of congestion and degrading levels of transit. Recent annual vehicle sales growth rate, driven by personal automobiles, has exceeded 18%, to the point that China is now the world's largest auto consumer (Wang et al., 2011). Chinese cities have responded with policies of road expansion, often at the cost of bike and pedestrian facilities, and more recently, license plate quotas and day-of-week restrictions on vehicle use (based on license plate numbers). But expansion has not kept pace and the average road-space-per-vehicle is decreasing, contributing to crippling congestion (Ng et al., 2010; Yang and Gakenheimer, 2007). At the same time, the growing average trip length has shifted travelers from walking and biking to public transit modes. Beijing's transit demand is highly periodic, with 32.4% and 50.1% of weekday bus and subway trips occurring during peak hours (Guo et al., 2011). During rush hours, long queues and uncomfortable crowding occur (Schipper and Ng, 2007).

2.2. Bikesharing and e-bikes in China

Bikesharing is a potential answer to some of the urban mobility challenges faced with Chinese development patterns. Bikeshare is the automated distribution of a public-use bike fleet for short term (usually less than 30 min) rental, aimed at providing a one-way urban transportation service (DeMaio, 2009). Asia is the world's fastest growing bikeshare market and China constitutes the majority of that growth (Shaheen et al., 2013). There are currently over 750,000 shared bikes in China and plans to increase that number to nearly a million (Fishman, 2015; Tang et al., 2013). A study from two years prior estimated fewer than 140,000 shared bikes throughout the entire world (Shaheen et al., 2010). While high profile systems in cities like Paris and Washington D.C. capture public attention in the west, China has been the world's bikeshare growth leader, as measured by number of bikes, since 2010. The expansion of bikeshare in China is bolstered by the Transit Priority policies first introduced by the Ministry of Housing and Urban and Rural Development (MHURD) in 2004, in order to curb carbon dioxide emissions (Shaheen et al., 2011). The policies call for transit to be the dominant mode of urban transportation, set performance guidelines, and pricing incentives (Wang et al., 2012).

The country's first bikesharing system was opened in Beijing in 2005 and was operated by several private rental companies. This system was not IT-based, requiring personnel to operate the fleet. Reports of fleet size growth, due to the transportation reforms for the 2008 Olympics, vary from 5000 to 10,000 bikes. Yet by 2010, the system had collapsed due to bad user experience, lack of a convenient network of rental stations, and poor bicycle maintenance (Liu et al., 2012; Tang et al., 2011). Since then, modern IT-based systems employing automated electronic access technologies have flourished in other Chinese cities. At present, Shanghai, Hangzhou and Wuhan boast modern fleets of 20,000, 60,000 and 70,000 bikes respectively (Tang et al., 2013). Beijing has deployed a new bikesharing system utilizing the automated access technology. The first phase of the project opened in June 2012 with a 2000 bike pilot in core urban districts, Chaoyang and Dongcheng, and has since expanded (Beijing Municipal Commission of Transport, 2012).

The role of bikeshare is varied in different Chinese cities, both in user base (tourists versus residents) and the interaction with transit (feeder versus replacement) (Shaheen et al., 2011; Tang et al., 2011; Zhao et al., 2015). Successful implementation requires investigation of the role bikesharing will play in Beijing's unique market. Furthermore, the city's recent history of decentralization through the promotion of peripheral "suburban" communities introduces new transportation problems that bikeshare may not be able to address. For many in these communities, trip lengths have grown to distances requiring motorized solutions (Yang, 2006).

Studies show that the e-bike can be such a solution, often offering superior access than quality bus systems (Cherry and Cervero, 2007; Cherry et al., 2016; Montgomery, 2010). In the realm of private transportation, e-bikes have been the fastest growing mode in China since the early 2000s. E-bikes are available in two main body types: bicycle style e-bikes (BSEBs) and the more popular scooter-style e-bikes (SSEBs), which are larger, heavier, can travel at faster speeds. See Rose (2012) and Weinert et al. (2007a) for detailed descriptions of e-bike technologies. E-bikes can be much more energy efficient than most other motorized modes (Cherry et al., 2009; Mendes et al., 2015).

Sales of e-bikes now outpace motorcycle and automobile sales. Annual e-bike sales are on the scale of tens of millions and the current fleet size in China is estimated to be about 150 million (Jamerson and Benjamin, 2013). In 2004, the National Road Transportation Safety Law classified any e-bike equipped with pedals, including SSEBs, as a non-motorized vehicle, granting e-bikes access to bike lanes and eliminating requirements for e-bike operator licenses, vehicle registration, and the use of helmets. This law, combined with the proliferation of bans on fuel-burning two-wheelers, strong pricing competition, lenient enforcement of performance regulations, drove the national adoption of e-bikes (Ling et al., 2015; Weinert et al., 2007b; Weinert et al., 2008).

Although e-bikes remain an attractive mode choice, sufficient concerns exist to result in city-wide bans. The bans can be motivated by larger conventional motorcycle bans. Though many reasons are cited, main criticisms of e-bikes include increased congestion at intersections, safety risks, and environmental impacts. Although e-bikes make more efficient use of road space than automobiles, they are less efficient than buses and compete for space with other users of already congested urban roads. Furthermore, the erratic behavior of e-bike users causes increased (more-so than conventional bicyclists) conflicts with drivers (Bai et al., 2013; Du et al., 2013). From 2004 to 2007 the number of e-bike user deaths rose from 589 to 2469, and injuries jumped from 5295 to 16,486 (Wu et al., 2012). The loose enforcement of performance regulations has led to the proliferation of low-cost vehicles that are heavy, travel at high speeds, and have poor stopping ability; all factors that are included in existing safety regulations but are very difficult to enforce. Another factor contributing to e-bike bans is their environmental impact, namely lead pollution from the inefficient processing of lead-acid batteries that power roughly 95% of the e-bikes in China (Jamerson and Benjamin, 2013). Lifecycle analysis shows that the lead pollution per kilometer from e-bike batteries is up to 100 times greater than current bus lead emissions in China (Cherry et al., 2009) and e-bikes make up a very 37% of the Chinese lead market (van der Kuijp et al., 2013). Sharing systems could ameliorate some of these challenges since the bikeshare operator could choose and maintain appropriately safe bikes and control the battery waste stream. There are no shared bike platforms that include e-bikes in China. Therefore, this study relies on a stated preference approach to understand some of the factors that influence choice of shared e-bike and share bike technologies in Beijing.

2.3. Weather effects on cycling demand

Several studies have explored the impact of weather on bicycle and e-bike demand around the globe. Early survey studies in Australia (Nankervis, 1999) and Sweden (Bergström and Magnusson, 2003) focus on cycling subject to seasonal variation and weather, including temperature categories, wind, and precipitation, with large decreases in cycling in colder conditions. Brandenburg et al. (2007) used a Psychological Equivalent Temperature rating system, taking into account a number of factors ranging from physical exertion and clothing to humidity and wind speed, resulting in a nine point perception scale ranging from "very cold" (<4 °C) to "very hot" (>41 °C). They found that recreational cyclists are most sensitive to temperature and precipitation, and commute cyclists are less sensitive, but both groups show marked reductions on cold weather days. Looking solely at bicycle commuters, Flynn et al. (2012) found that rainy days reduced the likelihood of cycling, while higher temperatures increased the odds of cycling. Notably, the temperature range in that study ranged from −1 to 26 °C, i.e., the temperature ranged from very cold to comfortable, and did not reach uncomfortably hot temperatures as in Beijing. That study also investigated snow and wind, both negatively affecting cycling rates, similar to Bergström and Magnusson (2003).

Cycling-friendly infrastructure can compensate for some weather impacts. Canadians have higher cycling rates than the United States, likely because of better infrastructure (Pucher and Buehler, 2006). Even so, Canadian cyclists are negatively affected by weather. A large study of individual cycling behavior found that the number of days below 0 °C and number of days with precipitation both reducing the odds of cycling in Canadian cities (Winters et al., 2007).

Some work has begun to investigate bikeshare. A study of bikeshare data in Washington D.C. finds that demand is positively correlated with moderate temperatures (15–32 °C), negatively correlated with temperatures outside that range, and negatively correlated with the presence of precipitation (Gebhart and Noland, 2014).

Very little work has been done on weather impacts in China, particularly among e-bike riders. Though not focusing explicitly on weather, Du et al., 2013, investigated the behavior of e-bike users in Suzhou, China, collecting thousands of observations of riders at intersections throughout the city. Though not normalized for total vehicle volumes, the study does find that on rainy days, e-bike volume is 76–81% lower than on sunny and cloudy days. Of interest is that volume was highest on cloudy days, suggesting that the very hot and humid weather of the region may have been a deterrent. In our study we include weather indicators and distinguish between Chinese bicycle and e-bike demand.

3. Methodology

In July and August of 2012 a mode choice survey was conducted in the four main urban districts of Beijing. The data were used to develop a multinomial logit model for mode choice. We employed a unique SP pivoting design that allows data to be collected in a single pen-and-paper interview. Traditional pivoting techniques require the use of computer-assisted interviews or two-stage pen-and-paper surveys, both of which are less cost effective than our method for small and medium sized surveys. In the following section, we briefly explore the survey design and data collection effort (Campbell et al. (2014) provides a more detailed discussion of design and methodological contributions).

3.1. Survey design

The survey was designed to capture the advantages of leading state of the practice methods within tight time and budget constraints. The convergence of behavioral psychology and economic theory has led to the recognition that SP data is improved when the choice is made within a familiar context. A method known as pivoting does this by creating a SP choice set based on a real life choice, providing the respondent with a reference point and a familiar context in which to make the decision. Work by Rose et al. (2008) as well as Train and Wilson (2008) illustrate various pivoting methods to develop custom surveys based on the respondent's RP choices. Traditionally, this is accomplished by either using computer-assisted-per sonal-interviews (CAPI) or two-stage pen-and-paper-interviews (PAPI). The two-stage PAPI method has significantly higher labor costs and increased incompletion rates than single-interview surveys. CAPI is the preferred mechanism for most SP studies due to quality control and analytical advantages, but it has considerably higher fixed costs and may be less economical than PAPI for small to medium sized surveys (Caeyers et al., 2012).

Time and budget constraints motivated the development of a lean and robust data collection effort. We developed a single-interview PAPI design that captures three of the advantages of standard experimental SP pivoting methods: reference point valuation, familiar decision context, and the creation of an inertia variable. A detailed description of the method is presented in Campbell et al. (2014). An abbreviated description is presented here. The survey (Table 1, Part 1) begins by prompting the respondent to describe trip links from the previous day, recording distance and trip-end facilities (e.g., the destination or multimodal trip-tour transfer points). All future choices are based on (pivoted from) these trip links, allowing the respondent to easily consider experimental factors not observed in the survey mechanism. Those experimental attributes and levels are shown in Table 2. This improves response quality by creating a familiar decision context. In Part 2, we define the environmental conditions and have the respondent choose a mode from a set of all options that are available in the real market. This choice (hereafter referred to as "original mode choice") provides a reference point for valuing the SP options in later sections and it also creates an inertia variable. Inertia is a measure of how one's existing habits impact future decisions, often in the form of a reluctance to deviate from travel habits (Cantillo et al., 2007). In decisions ranging from dynamic route choice

Table 1
Example of survey mechanism (translated from Chinese). Shaded values in the text and shared bike cost and times are variables that vary across different survey versions (see Table 2).

		Provide response for each trip *link*				
		1	2	3	4	5
Part 1: Trip diary Think back to yesterday. Tell me about all the trip links you made that were less than 10 km	Trip length (within 1 km) Origin (e.g., home, work, transit stop, etc.) Destination (e.g., home, work, transit stop, etc.)					
Part 2: Stated preference pivot with controlled conditions Now suppose that it is **sunny**, **15** °C, the air quality is **bad** and congestion is **bad.** Also suppose, even though this may or may not be the reality for the trip link you indicated, that bike lanes are available for **all** of the trip. If you have access to an automobile, assume your license plate is **restricted** Given these conditions, please indicate the transportation mode you would typically choose for each of the listed trip links, and please indicate the approximate cost and travel time for each *selected* mode	What mode would you choose (e.g. bus, subway, drive alone, car passenger, etc.) What would the approximate trip cost be? What would the approximate travel time be?					
Part 3: New modes added with attributes Suppose for each of the above trips that you had the opportunity to instead use a shared bicycle or shared electric bike. The costs and travel times are as follows	Public bike cost Public bike travel time Public e-bike cost Public e-bike travel time					
Part 4: Stated preference pivot with new modes Now please consider the costs and travel times as well as all the attributes described in Part-2: it is **sunny**, **15** °C, the air quality is **bad**, congestion is **bad** and bicycle lanes are available for **all** of the trip	Which would you choose for each trip? Same as **Part 2** Public Bike Public E-bike					

Table 2
Variable levels for stated preference mode and environmental attributes.

	Factor level		
	1	2	3
Precipitation	Sunny	Light rain	Heavy rain
Temperature	−5 °C	15 °C	35 °C
Air quality	Good	Medium	Bad
Congestion	Good	Medium	Bad
Presence of bike lanes	None	Half	All
Shared bike travel cost [RMB]	0	1	2
Shared e-bike travel cost [RMB]	0	1	2
License plate number restriction*	Is	Is not	NA

to long-term travel behaviors, inertia variables can be employed to improve models' predictive power (Koppelman and Sethi, 2005; Srinivasan and Mahmassani, 2003). In our study, the inertia variable does not represent a true habitual (or revealed) choice since the original mode choice was made under hypothetical environmental conditions. However, given that the environmental conditions described are likely to be experienced in real life, and the trip link is a familiar one, we believe the original mode choice variable is a strong representation of behavioral inertia. In Part 3, the respondent is presented with new modes, bikeshare and e-bikeshare, along with cost and travel time attributes. Finally, in Part 4, the respondent is asked to choose between three modes for revealed trips with hypothetical variables (i.e., characteristics presented in Part 2). The modes include their original choice (Part 2), bikeshare and e-bikeshare.

The survey tests trip attributes, and environmental and weather conditions in order to answer questions about shared bike adoption in Beijing. The environmental and traffic variables are represented as qualitative ordinal variables. For air quality, we expect respondents to be sensitive to different qualitative air quality levels given the public education campaigns in Beijing that report air quality in qualitative terms (i.e., rather than pollution concentration levels). Similarly, we expect qualitative measures for other variables (i.e., congestion levels, precipitation), though imprecise, to have more meaning to the respondent than quantitative measures. While this qualitative approach is limiting, interpretations of the results could attempt to validate how well residents' perceptions match quantitative metrics.

Bikeshare is often exhorted as a first-and-last mile solution for connecting to public transit (DeMaio, 2009; Shaheen et al., 2013). When Beijing's pilot bikeshare program was announced, improving transit connectivity was cited as a motivating factor (People's Daily, 2011). Recent research demonstrates the importance of considering trips links explicitly, particularly in the context of transit integration (Zhao et al., 2015). We structured the survey to investigate how shared bike use interacts with transit by explicitly querying trip links instead of multimodal trip chains. Surveys that query entire trips, by default, make bikeshare and transit competitors. By also querying trip-link-end facilities (Table 1, Part-1), this approach allows the evaluation of shared bike interaction with the transit system: as a feeder, replacement, or no relation.

We hypothesize that respondents will value and use the two shared bike modes differently, specifically, that the choice of e-bikeshare will be less sensitive to measures of effort and comfort because the rider is assisted by an electric motor. Distance is a clear measure of effort, but we also include other variables (Table 1, Part-2) that are of unique concern to self-powered travelers who are exposed to the outdoor environment: precipitation, temperature, and air quality. The effects of weather on cycling demand have been well studied, but the impact of air quality remains undocumented even though it is of great concern to Beijing residents. We also include traffic and infrastructure parameters, including congestion and bike lane variables as metrics of safety in the survey. A license plate restriction (car drivers cannot drive once every five days) variable was also tested.

The shaded attributes in Table 1 varied according to our factorial experimental design to allow modeling of those attributes on mode choice. Attribute levels are presented in Table 2. In Part 3, there would be instances when there were cost differentials between e-bike and bike, and instances where there were no cost differentials. We assumed fixed average speed of the different modes, empirically reflected in the literature, that were linked to their reported trip distance to calculate travel time. Bike and e-bike travel times were populated in the surveys in real-time from a lookup table linked to trip length. E-bike speed (including stops) was 12.1 km/h and bicycle speed was 9.1 km/h (Cherry and He, 2010). In terms of cost, all sets of costs are within the range of realism in the context of Beijing's heavily subsidized transit fares. Subway tickets cost 2 RMB at the time of the survey and bus fares were less than 1 RMB (about $0.30 and $0.15 in 2012 U.S. dollars). We assume that bikeshare would also include this subsidy and the user behavior would be reflected in the cost borne by the user. Other bikeshare systems in China tend to include a free hour and charge 1 RMB per hour after. Because of the experimental nature of the stated preference approach, we present realistic, but varying levels of price and system performance to assess the effect of changes.

3.2. Data collection

The survey was implemented in Beijing's four core urban districts: Haidian, Chaoyang, Dongcheng and Xicheng. Although Beijing consists of 16 districts covering an area of 16,800 km^2, over 60% of residents live in these four districts (National Bureau of Statistics of China, 2010). In 2010, Dongcheng and Xicheng annexed the former districts of Chongwen and Xuanwu, respectively. For purposes of data collection and analysis, these old districts are treated as distinct entities since they exhibit significant differences in population and land use characteristics (e.g., lower income, informal business sector) (Tian et al., 2010; Wang and Chai, 2009).

The target population for the study is adult consumers of transportation in the four core districts of Beijing. During the month of July 2012, a team of students from Tsinghua University conducted an intercept survey at transportation facilities throughout the target districts. Respondents were sampled while using transportation; for example, as they were entering or exiting a subway station. The surveyor would pick an arbitrary marker, such as a line in the sidewalk, and question the first user of the target mode to cross the marker. Other people would be ignored until the survey was completed. To capture any bias inherent to the mode currently being consumed, respondents were stratified by the seven main modes of transportation: walk, bike, e-bike, bus, subway, taxi, and private automobile. While collecting data, surveyors would sample one of the seven modes until they had completed a block of 18 surveys. To capture temporal effects, data were collected in each district between 9 am and 9 pm on multiple weekdays and at least one weekend day.

3.3. Survey limitations

A series of pilot surveys revealed limitations, particularly in the public understanding of shared bikes and the distinction between trips and trip-links. As a result, surveyors were trained to explain these concepts carefully. Respondents also reported difficulty estimating travel time. If respondents were unable to make an estimate, a time was suggested by surveyors, based on trip link distance. This estimate was informed by a simple lookup table, taped to the back of their clipboards, that provided shared bike travel times based on average commute speeds and distance reported in the Annual Transportation Development Report (Guo et al., 2011). Selection bias is a problem inherent to intercept surveys. The response demographics discussed in the proceeding sections suggest that the sample is likely not representative of the total population. However, accurate and detailed demographic data is not publicly available for Beijing. It is unclear how much the sample demographics differ from those of the areas surveyed.

4. Survey results

The survey was conducted over a three weeks period in July and August 2012. A total of 623 surveys with 1427 trip-link observations were collected. Many respondents declined to provide personal information about age, income or education. After removing samples with missing demographics and unreasonable trip link distances (above 30 km), a total of 496 surveys and 1188 observations were analyzed, averaging 2.4 observations per survey. E-bikeshare and bikeshare were chosen in 15% and 10% of the observations respectively.

4.1. Respondent demographics

The data in Table 3 provide sample demographics, highlighting some trends in mode switching behavior. The data are aggregated by final mode choice: the response to Part 4 of the survey mechanism (see Table 1). According to the 2010 National Population Census, the gender split in the case study districts is 52.5% male and 47.5% female. Our sample has a much higher percentage of male respondents, possibly due to gender travel patterns in China or a willingness of male respondents to be surveyed. Similarly, we undersample older (>64 years old) respondents (National Bureau of Statistics of China, 2010). Within the groups choosing shared bikes, there is a slight tendency for females to prefer bikeshare to e-bikeshare. The data suggest that response to the shared modes changes with age, with the over 55 group showing a strong preference for bikeshare over e-bikeshare, while the under 40 male group prefers e-bikeshare. As a result, it will be important to consider the possible non-linearities in the influence of age on mode choice in the choice framework.

Socioeconomic heterogeneities are reflected in the variables of income, education, and household access to vehicles. Based on previous studies and anecdotal evidence, it was expected that the shared modes would be favored by young, educated, middle income people with some level of environmental concern (Shaheen et al., 2011; Tang et al., 2011). It is not clear from this dataset that this is the case. Respondents who chose e-bikeshare show a tendency to come from the lower income and lower education categories. Both shared modes are favored by active students.

4.2. Respondent travel behaviors

Two important travel behaviors are observed in the sample: original mode choice influences final mode choice and significant differences exist in the distributions of trip link distances for the three choices. The data illustrate the distinction in behavior between respondents whose original mode choice was sheltered (bus, subway, drive alone, and taxi) and those whose original choice was not sheltered. The unsheltered modes are highly under-represented in the groups choosing shared bike options but the unsheltered modes, highlighted in Table 4, show large shifts toward the shared modes. Most of this shift occurs with conventional bikeshare, that where only 28% of those shifting to bikeshare are drawn from sheltered modes, compared to 47% of e-bikeshare users drawn from sheltered modes. This indicates that behavioral inertia could influence mode choice decisions. Those who are accustomed to traveling while exposed to the environment appear more likely to adopt the shared bike modes. This also shows that e-bikes can be more effective at drawing sheltered mode users toward shared bikes.

The data also suggest a general trend for the impact of shared bikes on the existing transportation system: the majority of trips will be drawn from so-called "green" modes, those that generally have lower emissions per passenger-kilometer. Bikeshare draws 66% of its users from the non-motorized walking and biking modes. E-bikeshare draws a much smaller portion from the walking mode, but it draws more heavily from the private e-bike mode. From the sheltered motorized modes, the majority of shared bike users are switching from the bus. This suggests that planners should not a priori treat shared bikes as a transit feeder; they may also act as competitors.

The data indicate that e-bikeshare will be used for considerably longer trip link distances than bikeshare. The cumulative distribution of trip link distances, broken out by final mode choice, is seen in Fig. 2. The e-bikeshare distribution tracks much more closely to the original mode choice distribution while the majority of bikeshare trip links cover shorter distances. For bikeshare the mean and median distances are 2.9 km and 1.5 km (3.4 km standard deviation). For e-bikeshare the mean and median distances are 4.5 km and 4 km (3.9 km standard deviation). These are very close to the average distances of morning

Table 3
Demographic statistics.

Total $N = 1188$	Total sample	Aggregated by final mode choice[a]		
		E-bikeshare $N = 167$	Bikeshare $N = 117$	Original mode $N = 904$
Age (% 30 years or younger)***	57%	50%	60%	58%
Income (% under 6000 RMB/month)[b,**]	74%	82%	78%	71%
Male****	64%	66%	62%	64%
Mean education index[c,*]	2.63	2.44	2.71	2.65
Mean environmental concern index[d,**]	1.45	1.57	1.50	1.43
Currently enrolled as student**	15%	18%	22%	13%
Average household vehicle access				
Bikes**	0.97	1.04	1.15	0.94
E-bikes****	0.44	0.47	0.42	0.44
Automobiles****	0.50	0.53	0.53	0.49

The values for the three sub-samples, aggregated by final mode choice, were tested for statistical difference at the 0.05 significance level using the log-likelihood ratio test.
[a] Final mode choice is the response to Part 4 of the survey mechanism (see Table 1).
[b] The average monthly wage in Beijing was 5200 RMB/month in the survey year.
[c] The index was calculated using the following ordinal values. If the highest level of education achieved was: grade school (1), high school or basic technical school (2), undergraduate or advanced technical degree (3), graduate (4).
[d] The index was calculated with the following ordinal values: not at all concerned (0), somewhat concerned (1), very concerned (2).
* All three sub-samples significantly different.
** Only Bikeshare and E-bikeshare *not* significantly different.
*** Only Bikeshare and Original mode *not* significantly different.
**** No significant difference between any sub-samples.

Table 4
Mode shift from original mode choice to shared bike mode.

Original mode choice		Aggregated by final mode choice		
Total sample $N = 1188$		E-bikeshare $N = 167$	Bikeshare $N = 117$	Original mode $N = 904$
Sheltered original mode				
Bus**	22%	22%	17%	23%
Subway*	14%	8%	3%	17%
Auto solo***	10%	6%	3%	12%
Carpool****	1%	1%	3%	0%
Taxi****	10%	10%	2%	12%
Total	57%	47%	28%	64%
Unsheltered original mode				
Private e-bike*****	7%	15%	6%	6%
Bike*	9%	11%	17%	7%
Walk*	27%	27%	49%	23%
Motorcycle[a]	0%	0%	0%	0%
No trip[a]	0%	0%	0%	0%
Total	42%	53%	72%	36%

The values for the three sub-samples, aggregated by final mode choice, were tested for statistical difference at the 0.05 significance level using the log-likelihood ratio test.
* All sub-samples significantly different.
** Only Original mode and Bikeshare significantly different.
*** Only Bikeshare and E-bikeshare *not* significantly different.
**** Only Original mode and E-bikeshare *not* significantly different.
***** Only Original mode and Bikeshare *not* significantly different.
[a] No observations.

commute trips, 3.2 km and 4.5 km for private bike and e-bike across Beijing (Guo et al., 2011). Although e-bikeshare distances are significantly longer than bikeshare, roughly 80% of the trip links fall short of the average commuter bus trip, 9.6 km. One limitation of this study is that we asked users to only include trips less than 10 km, the expected upper range of bikeable trips. Some respondents included all trips, including a few trips beyond 20 km. We limited our analysis to responses less than 20 km, which systematically underreports the 10–20 km trips, reflected in the discontinuity in Fig. 2.

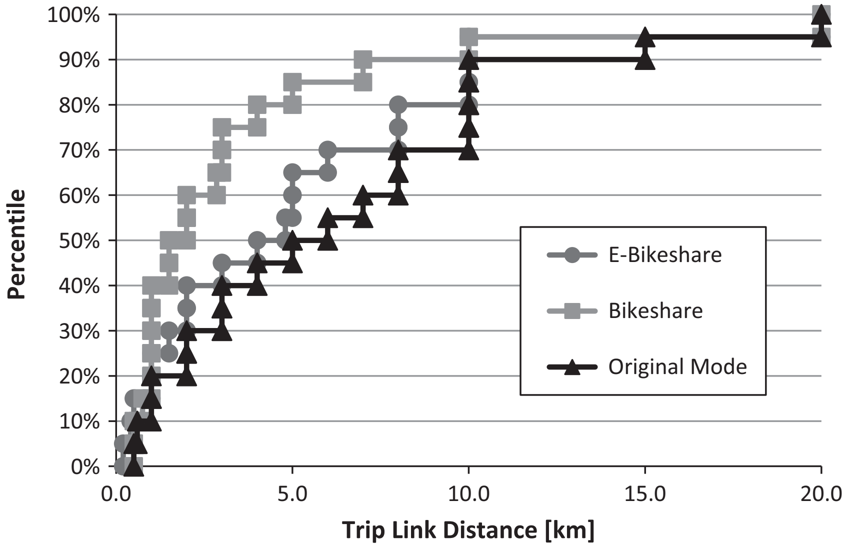

Fig. 2. Trip link distance CDF. * Reported trip links greater than 20 km have been removed.

5. Modeling results

The survey data were used to build a multinomial logit (MNL) mode switching model. A switching model estimates the likelihood of respondents switching from their original choice (a stated preference pivoted from revealed trip data) to a new option. In our model, there are three options in the choice set: original mode choice (which can be one of ten original mode options, see Table 1, Part-2), bikeshare, and e-bikeshare. To validate the use of the MNL, especially when employing panel data, the assumption of independence of irrelevant alternatives (IIA) needs to be verified. As there are multiple observations from the same respondent, unobserved factors may not be independent across repeated choices (Train, 2009). If IIA is not present, then a model that allows for correlation between error terms must be used in place of the MNL. We check for IIA using the Chi-squared test statistic described by Hausman and McFadden (1984). For each alternative, IIA is tested by estimating parameters on a subset where the alternative being tested has been removed. If the remaining choices are independent of the removed choice, that is if IIA holds, then the parameters estimated on the subset will not be significantly different than those estimated on the full choice set. For original mode choice and bikeshare, the IIA assumption is supported below the 0.01 significance level. For e-bikeshare, the test statistic is negative, which Hausman and McFadden (1984) assert also supports the IIA hypothesis.

Coefficients were estimated for 26 variables that are aggregated into five types (Table 5). The variety of variable types that enter the model demonstrate that the shared bike choice is nuanced, not only influenced by trip attributes and environmental conditions, but also by traditional travel behaviors and user demographics. Here, user demographics are included as mode-specific interactions, consistent with discrete choice modeling frameworks. The trip cost variable was not included in the model because it produced a statistically insignificant coefficient, likely due to insufficient variation in shared bike cost levels. While a question about the presence of bike lanes was included in the survey, respondents remarked that virtually every non-freeway road in Beijing has some sort of bike lane; this variable was therefore excluded from analysis. Trip distance was retained instead of travel time, as only one could be included because of high correlation. It was found that survey sampling methods do not significantly impact response. Indicator variables describing sampling location, mode sampled, time and day-of-the-week were all insignificant. This makes for convenient analysis; although sampling was stratified by mode, time and day, all responses can be pooled with equal weight.

The results (Table 6) strongly suggest that choice of bikeshare and e-bikeshare are influenced by distinct and different sets of factors. From the coefficient estimates we gain an understanding of the factors that influence the adoption of shared bikes: the bikeshare choice is most sensitive to measures of effort and comfort while the e-bikeshare choice is more sensitive to user heterogeneities. The disutility of distance is over twice as high for bikeshare, supporting our hypothesis that motorized assistance lowers effort and makes e-bikeshare users more tolerant of trip distance. Motorized assistance also appears to decrease sensitivity to measures of comfort, namely air quality and temperature. Both of these variables are interacted with distance, indicating that travelers consider their total exposure to these conditions when making mode choice decisions. In other words, travelers are not particularly concerned with uncomfortable temperature and air quality conditions if trip link distances are small. Although an e-bikeshare user is exposed to air pollution, the reduced physical effort should result in lowered respiratory activity, mitigating the impact of poor air quality. This may explain the statistical insignificance of the e-bikeshare air quality coefficients. On the other hand, the more physically demanding bikeshare option is

Table 5
Variable descriptions.

Variable	Description
Alternative specific constant	Captures all unobserved factors
Distance (km)	Self-reported distance, in kilometers, of trip link
Air quality bad indicator * distance (km)	Air quality is a categorical indicator variable. It is interacted with distance to capture exposure
Air quality medium indicator * distance (km)	
Air quality good indicator * distance (km)	
Congestion indicator	Congestion is a categorical indicator. It is equal to one if congestion is present
Congestion indicator * female indicator	
License plate restriction indicator	Indicates if respondent's hypothetical license plate number is restricted
Heavy rain indicator	Categorical indicator of precipitation level
Light rain indicator	
No rain indicator	
Temperature cold indicator * distance (km)	Temperature is a categorical indicator that is interacted with trip link distance to capture exposure
Temperature hot indicator * distance (km)	
Temperature comfortable indicator * distance (km)	
Original mode sheltered indicator	Indicates whether original mode choice was or was not in a sheltered vehicle
Original mode not sheltered indicator	
Original trip link by bus	Indicator variables describing the trip link's relationship to transit. A transit feeder link either originated or terminated at a transit facility, but not both. These variables are based on the Origin and Destination data
Original trip link was transit feeder	
Original trip link did not involve transit	
Original trip link by subway	
Age	Age in years. Allows non-linear contribution of age to utility
Age squared	
Higher education indicator	Indicates if respondent has or is currently receiving college education
Environmental concern indicator	Indicates if concern is medium or high
Gender female indicator	Indicates if respondent was female
Income	Respondent's income in 1000 RMB/month

Shading corresponds to the five variable types: alternative specific constant, trip attribute (distance), environmental conditions, travel behavior, and demographics. The demographic variables interact with choice alternatives.

Table 6
MNL estimation results.

Variable	Switch to shared e-bike		Switch to shared bike	
	Parameter	(*p*-val)	Parameter	(*p*-val)
ASC_O	−6.31	(0.00)	−4.39	(0.00)
Distance (km)	−0.0854	(0.01)	−0.175	(0.02)
Air quality bad indicator * distance	Fixed	(Fixed)	Fixed	(Fixed)
Air quality medium indicator * distance	0.0194	(0.53)	0.158	(0.04)
Air quality good indicator * distance	−0.0153	(0.66)	0.133	(0.06)
Congestion indicator	−0.581	(0.01)	0.169	(0.57)
Congestion indicator * female indicator	0.812	(0.05)	0.563	(0.25)
License plate restriction indicator	−0.066	(0.72)	0.415	(0.07)
Heavy rain indicator	Fixed	(Fixed)	Fixed	(Fixed)
Light rain indicator	0.527	(0.02)	0.78	(0.01)
No rain indicator	1.17	(0.00)	1.03	(0.00)
Temperature cold indicator * distance	−0.0247	(0.49)	−0.0907	(0.10)
Temperature hot indicator * distance	0.000619	(0.98)	−0.218	(0.00)
Temperature comfortable indicator * distance	Fixed	(Fixed)	Fixed	(Fixed)
Original mode sheltered indicator	Fixed	(Fixed)	Fixed	(Fixed)
Original mode not sheltered indicator	0.308	(0.19)	0.874	(0.01)
Original trip link by bus	1.67	(0.00)	0.632	(0.16)
Original trip link was transit feeder	0.319	(0.14)	−0.156	(0.54)
Original trip link did not involve transit	Fixed	(Fixed)	Fixed	(Fixed)
Original trip link by subway	0.696	(0.11)	−1.14	(0.27)
Age	0.321	(0.00)	0.0731	(0.07)
Age squared	−0.00451	(0.00)	−0.000907	(0.05)
Higher education indicator	−0.686	(0.00)	0.221	(0.40)
Environmental concern indicator	0.811	(0.00)	0.35	(0.11)
Gender female indicator	−0.783	(0.02)	−0.356	(0.39)
Income	−0.132	(0.00)	−0.0201	(0.54)
Number of observations = 1181				
Number of parameters estimated = 42				
Log likelihood = 1154.154				
Adjusted rho-square = 0.412				

Shading corresponds to the five variable types: alternative specific constant, trip attribute (distance), environmental conditions, travel behavior, and demographics.

significantly sensitive to air quality. As expected, bikeshare air quality parameters are positive for good and medium (relative to bad air quality).

In the case of temperature, the e-bikeshare coefficients are statistically insignificant, in contrast to the bikeshare choice that is particularly sensitive to hot conditions. This is reasonable considering that summer weather in Beijing often exceeds 30 °C and 75% relative humidity. The bikeshare mode has a weakly significant ($P = 0.10$) negative response to cold weather. Both modes have negative reactions to rain, with similar magnitude and high statistical significance. The rain variable produces statistically more significant results when it is not interacted with distance. This suggests that physical effort is not related to the impact of rain. It also suggests that the negative effect of rain, namely getting one's clothes and goods wet, does not scale with distance.

The other two environmental variables, congestion and license plate restriction, describe transportation conditions. The presence of license plate restriction has very little influence on the e-bikeshare choice and some weakly significant ($p = 0.07$) positive influence on the bikeshare choice. This may indicate that those who would choose to switch from car to e-bikeshare do so willingly, that they see e-bikeshare as a viable automobile replacement, even when the automobile option is not removed by license plate restriction. The switch from car to bikeshare however may involve an element of compulsion. The presence of congestion has small positive utility for bikeshare, but it is statistically insignificant. Congestion reduces the probability of choosing an e-bike for male respondents and increases the probability for female. The issue of safety may be responsible for the negative sign of the e-bikeshare congestion indicator parameter. However it seems unintuitive that women prefer e-bikeshare in the congested condition. One explanation may be found in previous research that shows that Chinese women feel safer crossing intersections on e-bikes than bicycles (Weinert et al., 2007b). Another possible explanation is that the congestion variable is confounded with transit crowding since surveyors explained congestion in terms of peak commute hours. Perhaps women prefer e-bikeshare to avoid crowding on Beijing transit during peak hours. Studies in other nations have found sexual harassment of women to be a serious concern (Horii and Burgess, 2012; Stringer, 2007).

The travel behavior variables allow for modeling the influence of travel habits as well as the interaction with public transit. Many specifications were tested in which the original mode choice options were grouped according to different parameters: each mode as an individual variable, motorized and non-motorized, and public versus private transit transportation, to name a few. Grouping original mode choice options by the property of being, or not being, sheltered provides the simplest and most compelling way to capture the impact of behavioral inertia. The modeling results corroborate the trend described in the discussion of Table 4 in the previous section. Controlling for weather and environmental effects, the habit of traveling by unsheltered mode is one of the strongest factors positively influencing someone to choose bikeshare. It also positively impacts the e-bikeshare choice, though with lower magnitude and significance. The important implication for the impact of bikeshare on Beijing's transportation system is that it will draw most of its users from modes that are similar to bikeshare: walk, bike, and e-bike.

We additionally use the results to investigate the role of shared bikes as an attractive first and last-mile solution. To do so, we model the interaction with public transit through Original Trip Link variables. For example, if the Original Trip Link by Bus variable is one, and the final mode choice is e-bikeshare, then the respondent chose to replace a bus trip link with e-bikeshare. The attractiveness of shared bikes, in terms of transit competition and complement, is varied. The most outstanding result is the significant positive utility of replacing bus links with e-bikeshare. This variable is one of the strongest positive influences on the choice of e-bikeshare in the model. The utility of shared bikes as transit feeders (first and last mile solutions), however, is called into question. For e-bikeshare, the coefficient is slightly positive, though at a lower significance level. For bikeshare, the coefficient is negative, though at a very low significance level.

The demographics coefficients identify a distinct group that will prefer e-bikeshare to their original mode: young to middle age males with low education and income. Bikeshare does not appear to provoke a strong reaction from any specific group and will likely draw users from across the demographic spectrum. Age (from Age and Age^2) is the only demographic that impacts both shared bike modes significantly. For e-bikeshare, age is the greatest contributor to utility for young respondents, with a peak effect at 36 years. The Age and Age^2 coefficients demonstrate that e-bikeshare may be strongly preferred to bikeshare by young to middle age respondents with diminishing advantage until age 69. The average marginal effect of age (average of derivatives of probability with respect to age) is much stronger for e-bikeshare than bikeshare. When worst-case weather and environmental conditions are assumed, the average marginal effect of age is 8.6 times greater for e-bikeshare than bikeshare. When ideal conditions are assumed, the ratio grows to 191. The significance and positive sign of the e-bikeshare Environmental Concern Indicator may be a product of marketing that dubs e-bikes as an environmentally friendly mode (despite bicycles being more environmentally friendly).

6. Discussion and conclusion

In the following section we explore the implications of the model results within the context of Beijing to gain Insight into planning and policy considerations for successful shared bike systems. We discuss demand forecasting and effective use scenarios for bikeshare and e-bikeshare. One of the challenges with this model is the reliance on some qualitative measures (e.g., "heavy rain") to simplify the modeling approach and response burden from the users, while capturing environmental conditions. We include these variables and offer some interpretation on the importance of environmental and meteorological conditions on demand. We also discuss traditional factors that influence demand, like distance and existing mode inertia. The factors influencing e-bikeshare demand create the potential to deploy these systems with targeted purposes: to relieve congested bus lines, provide an alternative to bikeshare when hot weather or poor air quality conditions are present, and to identify how bikeshare could influence ridership of transit systems.

6.1. Impacts of weather and air quality on demand

In order to successfully plan and budget a shared bike system, it is important to be able to realistically forecast demand. The modeling results demonstrate that shared bike demand in Beijing, especially for conventional bikeshare, will be quite sensitive to weather and air quality conditions. The choice of both shared bike modes is strongly negatively impacted by "heavy rain" as perceived by the users, which is a common occurrence in Beijing. Since bikeshare users are sensitive to levels of comfort and effort, temperature will also temper demand. Beijing frequently experiences both heavy rain and uncomfortable temperatures. These results are similar, though our effects for cycling are higher in magnitude to comparable variables reported in Flynn et al. (2012). For conventional bikeshare, our results are consistent with other studies that point to diminished demand during uncomfortably hot, cold, or rainy days. Mapping qualitative and perceptual responses to actual weather and pollution data is a challenge, but here we attempt to identify meteorological and air quality break points that could influence demand. In 2012, the city received a half inch or more of rain on approximately 58 days. That same year, approximately 67 days were uncomfortably hot, with peak temperatures exceeding 30 °C, and 77 were uncomfortably cold, with minimums below 0 °C (National Oceanic and Atmospheric Administration, 2013).[2] In Beijing, summer is the rainy season, so many of the heavy precipitation and hot weather days will overlap. Still, it appears that weather could reduce demand at least 40% of days in a year relative to good-weather days (the sum percent of uncomfortably hot and cold temperature days plus an allowance for an unknown number of days when rain deters demand independently of temperature). This alone does not preclude the implementation of a popular shared bike program. In the United States, two successful bikeshare systems, Boston Hubway and Denver B-Cycle, are closed for approximately 25% of the year due to winter conditions.

Air quality on the other hand will have a deleterious effect on bikeshare demand throughout the year. The United States Environmental Protection Agency developed the AQI to measure air quality in terms of health impacts instead of pollutant concentration (U.S. Environmental Protection Agency, 2013). That highly publicized rating system classifies air quality as Good, Moderate, and several levels of Unhealthy. These categories approximately translate to the three simplified levels of air quality presented in our experiment. Over the one-year period during this study, the average $PM_{2.5}$ Air Quality Index (AQI) was rated Unhealthy or worse on 47% of measured days. Although the worst readings are recorded in January and February, levels of Unhealthy and Very Unhealthy occur regularly throughout the year. This will have an overall effect of depressing bikeshare demand, especially for longer trips. Since e-bikeshare demand is not significantly impacted by air quality, it is possible that usage will shift from bikeshare to e-bikeshare on bad-air days. The erratic fluctuations of air quality, and thus demand, will place strain on system operations. The AQI can change radically from day to day. However, this masks the fluctuations that occur within a single day. During the hours of daytime activity, $PM_{2.5}$ AQI often experiences changes of over 100 points. If bikeshare demand proves highly sensitive to air quality, efforts to forecast near-term usage in order to optimize fleet redistribution operations will suffer from an extra source of volatility that is not experienced by Western bikeshare systems.

6.2. Bikeshare use

Modeling results indicate that bikeshare demand will be primarily driven by environmental conditions and individual travel habits. Socio-demographics do not factor heavily, and thus bikeshare will draw users from across the social spectrum. Bikeshare will appeal to users of traditionally unsheltered modes for short trips during pleasant weather and air quality conditions. Given the importance of short trips, bikeshare will be most successful in areas with high density and diversity of attractions. In Beijing, such areas are found in the urban core and central business districts: areas that are already highly walkable, bikeable and well served by public transit. Although bikeshare is an intuitive first-and-last mile solution, it is not clear from the study that it will actually be used this way. Rather, bikeshare may compete with bus transit for complete trips, or simply draw most of its users from the unsheltered modes. These factors suggest that bikeshare systems should be deployed in areas with a dense network and high frequency of short trips. A large number of small to medium-sized docking stations should be diffused throughout the area, rather than fewer, larger stations being clustered around transit facilities and main attractions. This will increase access and lower travel distances by placing stations closer to trip ends. It will also increase the number of potential short trips by reducing the average inter-station distance.

From our results, we expect that bikeshare will likely have little effect on current motorization rates in Beijing. Instead, it will mostly shift users between low-impact modes; from walking, biking, e-biking, and buses to bikesharing. Pedestrians who switch to bikeshare will find their range, accessibility, and speed increased. Former private bike and e-bike users will

[2] Daily precipitation and temperature data were collected at a single weather station in Haidian district and may not be indicative of average values for the study area. Since data were not available for every day of 2012, totals were calculated by extrapolating values for the observed days to 366 days (2012 was a leap year): Estimate = (qualifying days)/(observed days) ∗ (366 days).

find bikeshare more convenient without maintenance, storage, or theft concerns. And the users who shift from buses will improve the comfort of those who remain on the buses by reducing crowding.

6.3. E-bikeshare use

Our study results indicate that e-bikeshare can be deployed with more targeted purposes than classic bikeshare in Beijing. Unlike bikeshare, e-bikeshare appeals to a distinct social demographic group: young to middle age males who tend to have low income and education levels. The increased user tolerance for trip distance suggests e-bikeshare can be used in different locations and ways than traditional bikeshare. It will be more viable than bikeshare in areas with low-density superblock forms. The tendency for users to take longer trips suggests e-bikeshare will appeal to workers commuting outside of their neighborhood. Design of an e-bikeshare network must consider the mode's considerably higher fixed costs, both for the bikes and for the docking stations, which are a likely to require trenching for power lines. This suggests a network structure based on a small number of large docking stations will be most economical. The tolerance for longer travel distances improves the viability of such a design. Since access costs will suffer in the sparser network, station location must be carefully considered to ensure a sufficient volume of attractions in proximity of docking stations.

We envision three use scenarios for e-bikesharing in Beijing. In the first scenario, bus-relief, e-bikeshare is deployed for the purpose of shifting users off of over-subscribed bus routes. As demonstrated in the choice model results, e-bikeshare is an attractive alternative to short and medium distance bus trips. Increasing bus demand and road congestion have degraded bus transit level of service to the point that studies in multiple Chinese cities have found e-bikes to offer superior mobility and operating speed (Cherry and Cervero, 2007; Guo et al., 2011; Montgomery, 2010). An e-bikeshare network can be deployed to deliberately compete with bus transit by co-locating docking stations along lines targeted for demand reduction.

In the second scenario, bikeshare-backup, e-bikeshare will be co-deployed alongside bikeshare. Docking stations will predominantly have spaces for bikeshare, but a small number of spaces will be reserved for e-bikeshare. The bikeshare-backup system will serve users when conditions are not conducive to bikeshare, specifically during uncomfortable temperatures or poor air quality. Such a system may also open up shared bikes to additional user groups, such as people carrying loads (Macarthur et al., 2014; Rose, 2012), or those with physical conditions that prevent pedaling a bicycle (Johnson and Rose, 2015).

The third scenario is e-bikeshare as sub-center circulator. In this scenario, a series of stand-alone e-bikeshare systems would be deployed in Beijing's sub-centers to improve internal circulation. As discussed in the Background, these sub-centers were intended to be self-contained areas with density and land use diversity comparable to the core. But a variety of redevelopment and marketization trends have converged to cause access and equity issues in Beijing's "suburban" sub-centers. E-bikeshare could mitigate the negative effects of lowered density and land use diversity, namely increased automobile use and congestion and decreased access. E-bikes travel at roughly 25% greater speed than bicycles and our modeling indicates e-bikeshare users are tolerant of twice the trip distance as bikeshare users. This suggests e-bikeshare trip range could be from 25% to 100% greater than bikeshare. Thus e-bikeshare users could access an area from 50% to 400% greater (assuming a simple circular access area) than bikeshare or private bicycle users, helping to curb the trend to turn to automobiles.

The access benefits of e-bikeshare could also help mitigate some of the equity impacts of Beijing's residential decentralization. Much of the outward movement, from core to peripheral residences, was voluntary, conducted by people seeking newer or higher quality housing. But for millions, the move was compulsory; traditional family homes were razed to make room for redevelopment and the creation of western style central business districts. Surveys of households relocated from core to peripheral communities found that in Shanghai, 51%, and in Beijing, 42%, of respondents stated that relocation was at least partially involuntary. Those forced to relocate from the urban core to these sub-centers tend to earn less money and suffer greater impacts to accessibility and commute time (Cervero and Day, 2008; Yang, 2006). Some of these equity issues could be addressed by targeted deployment of e-bikeshare in sub-center communities with high populations of forced relocations. Yang (2006) aggregates commute time into three types of commutes: within subdistrict, beyond subdistrict, and beyond district. He shows that those relocating to sub-centers, especially those forced to do so, have a greater tendency to commute beyond their subdistrict and district, thus increasing travel time and motorization rates. But commute time can at least be reduced by providing fast e-bikeshare transportation between home and subway stations. The same e-bikeshare system can improve job access within the local subdistrict, reducing the demand for long distance commuting. E-bikeshare should also reduce commute time for those who switch from buses since the travel speeds are comparable and service is on-demand, reducing wait times.

An e-bikeshare system is a tool local government can use to mitigate the problems of current private e-bike usage and still provide the mode's social benefits. As mentioned in Section 1, e-bike problems can be grouped in three categories: increased congestion, safety risks, and environmental impacts. These problems are largely due to lack of regulation. Some cities have addressed the problems through bans but Ling et al. (2015) and Cherry et al. (2016) have shown that the ensuing mode shift can have unintended consequences for safety, congestion and air quality. A government controlled e-bikeshare system could enforce safe performance standards and reduce lead emissions by sourcing higher quality batteries or even switching to the more expensive lithium ion options, enabled by amortizing the high cost over the life of the vehicle. Strategic placement of e-bikeshare stations would indirectly control the routes the vehicles are used on and thus their impact to other road users.

6.4. Future research

The work presented in this study indicates clear distinctions in the factors influencing the adoption of bikeshare and e-bikeshare in Beijing. Demand limiting factors, particularly weather and air quality, are identified using categorical descriptions. In order to more accurately forecast the impact to shared bike demand, further research should be done to quantify and validate the public perceptions of temperature, precipitation, and air quality in relation to objective measures.

As Beijing's bikeshare system deploys, and e-bikes are integrated into more bikeshare systems globally, empirical evidence of the role of e-bikes will be important. Revealed preference studies will soon be viable and will allow more nuanced understanding of differences between bike technology on adoption. We find that bikeshare may not have a significant impact on Beijing's transportation system, but there is reason to think that it can be an attractive mode for tourists and visitors (Lathia et al., 2012). A strong precedent of tourism demand for shared bikes exists in China, especially the Hangzhou system, as well as in many western systems. Given Beijing's many popular tourist destinations, using bikeshare to expand non-automobile access for visitors should be explored.

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