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Ridership effects of real-time bus information system: A case study in the City of Chicago

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ABSTRACT

In this paper, using longitudinal data on route level monthly average weekday ridership in the entire Chicago Transit Authority (CTA) bus system from January 2002 through December 2010, we evaluate the ridership effects of the CTA real-time bus information system. This bus information system is called CTA Bus Tracker and was incrementally implemented on different CTA bus routes from August 2006 to May 2009. To take account of other factors that might affect bus ridership, we also include data on unemployment levels, gas prices, local weather conditions, transit service attributes, and socioeconomic characteristics during the study period. This combined longitudinal data source enables us to implement a quasi-experimental design with statistical controls to examine changes in monthly average weekday ridership, before and after the Bus Tracker system was implemented, on each bus route. Based on a linear mixed model, we found that the provision of Bus Tracker service does increase CTA bus ridership, although the average increase is modest. Further, the study findings suggest that there are temporal variations of the ridership effects among the routes, with the "winning" routes more likely to have the technology implemented in the later phases of the overall "roll-out" period. However, the results are less conclusive regarding geographical variations in the effects of Bus Tracker.

1. Introduction

Strategies to increase public transit ridership and to improve user satisfaction are an active and ongoing area of research. A voluminous literature has commented on the roles that transit service quantity and quality, pricing and fares, land-use, housing, and employment patterns play on public transit ridership. Within this broader literature, the role that real-time transit information systems, which belong to the transit service quality category, can play in increasing transit ridership levels and to improve customer satisfaction has been receiving increasing interest.

With the widespread dissemination of the Internet and personal mobile devices, the ways by which public transit agencies serve travel information to the public are undergoing great improvements. These trends, when combined with the rapid proliferation of Automatic Vehicle Location technology (AVL) in transit agencies, have led to novel ways in which the traveling public can access real-time transit vehicle location, arrival time, connection and other related pieces of information. Additionally, in 1991, the use of advanced Information and Communications Technology (ICT) received a significant boost from Title 6 (Intelligent Vehicle Highway Systems or IVHS) of the Intermodal Surface Transportation Efficiency Act (ISTEA). Over the next several years, the Intelligent Vehicle Highway Systems program was retitled "Intelligent Transportation

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Systems" (ITS) to reflect the multimodal uses of information and communications technology in transportation, including its use in public transportation modes. At the time of writing this paper, the US Department of Transportation (US DOT) has provided an ITS Transit Typology that improves safety and security to customers (including traveler information, automated fare payment and transportation demand management) (US Department of Transportation, 2010).

However, although many studies have considered real-time transit information to be one of the most important factors that will influence transit ridership (Federal Highway Administration, 2004; Taylor and Fink, 2003; The Victoria Transport Policy Institute, 2007), the current literature does not provide conclusive evidence regarding whether such information systems can successfully increase transit patronage. The objective of this paper is to fill the gap in the existing literature by presenting the results from a case study of system-wide changes in ridership (which we call "ridership effects") resulting from a real-time transit information system (i.e., CTA Bus Tracker) implemented by the Chicago Transit Authority (CTA), which is the operator of public transit within the City of Chicago, USA. We use data on monthly average weekday ridership for each bus route in the entire CTA bus system for the Chicago metropolitan area from January 2002 through December 2010, during which real-time bus location technology was incrementally introduced in the Chicago bus system, to examine such effects.

To account for alternative explanations for bus ridership changes during the study period, we control for other influential factors such as unemployment levels, gas prices, weather, transit service attributes, and socioeconomic characteristics in this study. These factors were identified by means of literature search on factors that affect ridership levels. The combined longitudinal data source enabled us to implement a quasi-experimental design with statistical controls to examine changes in monthly average weekday bus ridership, before and after the Bus Tracker system was implemented on each route. Including the control variables is essential to "net out" the residual effects of real-time transit technology on ridership, thereby addressing the attribution issue, although, as we note later, there are limitations in this study as well.

The paper is organized as follows: Section 2 gives the background and system information of Chicago Bus Tracker System. Section 3 reviews existing literature, discusses conceptual underpinnings for this research, and presents the research questions. Section 4 describes the data used and study approach adopted. Section 5 presents an exploratory analysis of bus ridership trends during the study period. Section 6 uses a linear mixed model to examine the ridership effects of Bus Tracker. Section 7 discusses the model results. Section 8 examines the spatial and temporal variations in the ridership effects. Finally, we present the conclusions in Section 9.

2. Technology background

The transit system under study, CTA, is a municipal corporation that provides public transportation service (bus and heavy rail) to the City of Chicago and 40 surrounding suburbs, in Midwestern United States. Based on the average weekday ridership, the CTA bus system is the third largest bus system in the US, after New York City and Los Angeles County (American Public Transportation Association, 2010). The CTA Bus Tracker is a real-time bus information system. It uses Global Positioning System (GPS) devices to position CTA buses and allows various information (such as the current location and expected arrival time of buses at a specific stop) to be mined for the benefit of the traveling public. Except for a single route for which Bus Tracker was launched in August 2006, the service for all other bus routes was incrementally implemented between April 2008 and May 2009. Bus Tracker was rolled out on routes depending on the garage with which it was associated, and these garages were randomly located throughout the Chicago area. In this study, we include all the CTA bus routes that are currently in service and several discontinued bus routes for which the information is still available to us to examine how the availability of Bus Tracker affects the ridership of each bus route. The total number of the routes in this study is 144, among which 141 routes are implemented with Bus Tracker service. Three of these 144 bus routes have never received Bus Tracker service, which are either special service or support service routes with relatively low ridership levels comparing with other routes.

The period of time during the implementation of Bus Tracker coincided with a general trend towards widespread use of Internet-based technology, smartphones and data services that connected users to a variety of Location-Based Services (LBSs), and in general, a heightened socialization in mobile applications via personal digital assistants. Such a trend has led to changes in the ways in which the public could access Bus Tracker information since the Bus Tracker system was initially launched. At the earlier stages when Bus Tracker was implemented, only general (non-customized) estimated bus arrival time information was available on the Bus Tracker website, which could be accessed from computers and web-enabled wireless devices. Beginning in spring of 2009, CTA customers could subscribe to receive customized scheduled emails or text messages that provide estimated arrival time of the next bus at the customer's preferred bus stop(s). Later that year, a "track by text" feature allowed customers to receive the arrival times of the next two buses at their bus stops via text messaging. Further, using the Bus Tracker data, third-party application developers have developed several "apps" (i.e., application software) over time that can be downloaded (for free or a fee) to handheld devices and smartphones. These "apps" give real-time bus arrival information for the user's selected bus stops and may also provide some additional information (for example, for a fee, a notification can be issued to the user's mobile device according to a user-defined number of minutes before the bus is expected to arrive). The information provided by these "apps" may vary depending on which "app" and the pricing scheme the user has chosen. These gradual developments of Bus Tracker delivery methods might affect the travelers' behavior as well as the presence of Bus Tracker service; however, the data for these gradual developments were not publicly available. Therefore, in this research, we assume homogeneity in the effect of information regarding the information delivery methods, which means that we assume that Bus Tracker has the same ridership effects on the travelers regardless of the media they were using to receive the Bus Tracker information.

3. Literature review and research questions

Although extensive studies have been conducted on travel behavior changes as a result of ICT in general, and traveler information systems for auto in particular (Al-Deek et al., 1988; Avineri and Prashker, 2006; Abdel-Aty et al. 1997; Abdel-Aty and Abdalla, 2004; Ben-Elia and Shiftan, 2010; Ben-Elia et al., 2008; Boyce, 1988; Chen and Jovanis, 2003; Heathington, 1969; Kirson et al., 1991; Mobility 2000, 1990; Schofer et al., 1993; Sparmann, 1991; Wardman et al., 1997; Yumoto et al., 1979), studies of the nature in the case of real-time transit information systems are relatively few. Even among these limited studies examining the potential effects of real-time transit information systems in attracting more users, the research results are quite inconclusive. While some of research findings suggest positive effects of such information systems on transit ridership (Abdel-Aty and Jovanis, 1995; Abdel-Aty, 2001; Cham et al., 2006; Peng et al., 1999), other studies indicate limited impact of such information on transit mode share (Chorus et al., 2006; Holdsworth et al., 2007; Zhang et al., 2008).

Studies based on comparing actual observed transit ridership statistics before and after the implementation of such systems seemingly provide the strongest evidence supporting the hypothesis that the provision of real-time transit information systems leads to ridership gains. Using such a method, several authors found that increases in transit ridership result in routes where real-time information is provided (Body, 2007; Cross, 2003; Lehtonen and Kulmala, 2001; Infopolis2, 1998; Rolefson, 2003; Schweiger, 2003). However, such type of evaluation that uses simple before-and-after comparison of ridership statistics does not provide convincing evidence for ridership gains due to the provision of real-time transit information, since many other factors (such as population, gas price, transit fare, and employment levels) might also influence transit ridership when and after the transit information systems were being implemented. Thus, it would be problematic to conclude that the observed increase in ridership is "a direct result of the (traveler information) system" based on this type of study (Schweiger, 2003, p. 3).

Although there is no conclusive empirical evidence showing the ridership effect of real-time transit information, several earlier studies have provided theoretical underpinnings for the hypothesis that the provision of real-time transit information will lead to increased transit patronage. Using a conceptual framework developed based on the cognitive models of behavior, Tang and Thakuriah (2011, p. 12) suggest that the psychological effects of the provision of real-time information system will eventually "lead to transit ridership gain". Additionally, the Socio-Technical Systems (STSs) literature (Pasmore and Sherwood, 1978; Salembier, 2003) implies that the complex interplay between the technical sub-systems and the social sub-systems, in terms of actors, institutions, rules, procedures and policies involved in the Bus Tracker technology, governs the extent to which the information may be effective in leading to desirable outcomes regarding overall increases in public transportation ridership.

Spatial variations in ridership outcomes of Bus Tracker technology are also to be expected according to the literature. General Purpose Technology (GPT) theory (Bresnahan and Trajtenberg, 1995), which explains pervasive use technologies across a wide range of sectors, suggests geographic variations in diffusion (for example, Greenstein and Prince (2006), for the case of the Internet; Wareham and Levy (2002), for the case of adopters of mobile computing devices), with implications for us to consider the socioeconomic attributes of bus users along the routes.

The period in which technology is implemented can also have substantial effects on its use. Earlier research indicated that "according to intuition and theories of diffusion, consumer preferences develop along with technological change" (Axsena et al., 2009, p. 221). Although we have not explicitly considered period effects in this research, we surmise that Bus Tracker users have gone through a learning and adaptation phase, where they have to integrate new technologies in their travel practices and routines, as the technology is being domesticated, resulting in myriad impacts on the way travelers benefit from technology and use it.

Based on the above discussions, we hypothesize that the provision of CTA Bus Tracker will increase the ridership for each CTA bus route that is provided with such service. We also hypothesize that there are spatial and temporal variations of such effects among these CTA bus routes. Therefore, we pose the following major research questions:

- What is the ridership effect of CTA Bus Tracker, controlling for other factors?
- What are the spatial and temporal variations in the ridership effect?

4. Research design and data source

4.1. Research design

The data used in this study are longitudinal data at equally spaced time intervals, which means the data comprise of repeated observations/measurements on the same study units at successive times at uniform time interval. This type of data can also be considered as a pooled time series and cross sectional data (TSCS), since it contains "observations both cross-sectionally and over time" (Worrall and Pratt, 2004, p. 35).

The research design for this study is a quasi-experimental design with statistical controls (Cook and Campbell, 1979). The unit of analysis is the CTA bus route, with repeated measures over time at monthly intervals. Since we expect monthly variations of CTA bus ridership, the study period chosen in this study should cover at least 1 year before the Bus Tracker started to implement (i.e., August 2006) to 1 year after of the implementation completed (i.e., May 2009). We choose January 2002–December 2010 as the study period.

As mentioned earlier, all the CTA bus routes that are currently operating are included in this study. As the research questions state, there is one treatment/intervention of which the effects need to be examined in this study – the provision of Bus Tracker service to the bus route. Bus routes that had the Bus Tracker service in use during the month when the ridership data were recorded are considered as received this treatment during that month. For the cross-sections before the implementation date of Bus Tracker for that bus route, we consider there is no such treatment for that route, and the time-series observations taken at the before-treatment (i.e., before the Bus Tracker's implementation) period for this bus route will serve as comparison to examine the effects of the treatment on this bus route. Since the technology was launched incrementally over time starting from year 2006, not all the bus routes received the treatment at the same time. The bus routes which had not received Bus Tracker service at a certain cross-section can serve as the control group for those bus routes on which the Bus Tracker had been implemented in that month. Using this multiple time-series design, for most of the bus routes, the effects of treatment are "twice demonstrated" (Cook and Campbell, 1979, p. 55), once against each of these bus routes' own before-treatment values, and once against the control series (i.e., bus routes with Bus Tracker implemented at a later time or without Bus Tracker implementation).

4.2. Outcome, independent and control variables

Ideally, a treatment group will differ from the control group only on the treatment under study. However, this requirement is almost always violated in reality due to lack of random assignment. As a result, we need to introduce control variables to correct for this non-random assignment with the assumption that we have sufficient information on the critical factors that account for systematic differences between the treatment and control group.

In order to do a statistical controlled quasi-experimental analysis, we need to identify and collect information for outcome, treatment and control variables. For the outcome measure, we use the reported monthly average weekday bus ridership.

The treatment variable is a binary variable identifying whether the bus route received treatment during the observation month (*Tracker* = 1 if tracker-based information is available for the bus route during the observation month). The control variables are those factors which may also affect the outcome (also called outcome-controls). They are identified based on our knowledge and previous studies and will be discussed in detail in the next section.

Table 1 lists all the variables used in this analysis. Although there are additional factors that might affect ridership according to the literature, information for such factors was not available to us at the time of this study (for example, data for the monthly average income among the residents within the service area of each bus route). As discussed shortly in Section 6, we use random intercept to correct for the omission of these variables in this study. The effect of these additional control factors will be considered in future research.

4.3. Data source

This study uses several secondary sources to obtain the data for the identified variables. As shown in Table 1, these variables include monthly average weekday ridership for each route for the entire CTA bus system (available from Regional Transportation Asset Management System or RTAMS website), gas prices, weather, population, unemployment rates, and CTA service attributes.

Overall, cost of alternative modes of transportation and weather conditions have been identified in the literature as having a significant bearing on public transit ridership (Guo et al., 2007; Mattson, 2008; Taylor and Fink, 2003). The data on gas prices, an important component of the variable cost of operating cars, are available from US Energy Information Administration. We include Chicago area monthly retail gasoline prices on all grades and formulations in this study.

Monthly weather data for O'Hare Airport (the weather station in the major international airport in the Chicago metropolitan area) for the same period were taken from National Weather Service Weather Forecast Office. This source includes data on average daily temperature, monthly depth of snow fall and precipitation. We use dummy variables *Very_cold*, *Cold*, *Chilly*, and *Hot* to categorize the local temperature as shown in Table 1. The temperature category with monthly average temperature between 62 and 77 °F serves as the base for the temperature dummy variables. This division of temperature categories is based on previous research (Koetse and Rietveld, 2009; Sabir et al., 2008) and model calibration/modification.

We also included factors relating to major socioeconomic factors that may affect bus ridership, such as population and employment level (Mattson, 2008; Taylor and Fink, 2003; Chung, 1997). The data on Chicago population are obtained from US Census Bureau; these data are only available to 2010 currently. The data on monthly unemployment rates in Chicago are obtained from US Bureau of Labor Statistics. We do not consider data on land-use changes in this study because the city witnessed negligible changes in land-use patterns, being a heavily built-up area throughout the period considered.

Table 1
Outcome, independent and control variables.

Variable	Label	Type	Coding for dummy	Classification
Outcome/response variable				
Ridership	Monthly average weekday bus ridership	Continuous		Time-varying
Independent variables – system internal factors				
Tracker	Whether Bus Tracker is provided for the bus route during the data collection month	Dummy	1 = Yes	Time-varying
Ad_busfare	Adjusted (to January 2005 value) bus fare (cents/ride)	Continuous		Time-varying
Ad_railfare	Adjusted (to January 2006 value) rail fare (cents/ride)	Continuous		Time-varying
Keyservice	Whether the bus route is a key service route	Dummy	1 = Yes	Not time-varying
Owlservice	Whether the bus route provides 24-hour service	Dummy	1 = Yes	Not time-varying
Frequency	Weighted average for bus frequency for each bus routes (number of buses/hour)	Continuous		Time-varying
VRH_rail (thousands)	Monthly Vehicle Revenue Hours of CTA Rail (thousands)	Continuous		Time-varying
VOM_rail	Number of CTA Rail Vehicles Operated in Maximum Service (Peak Vehicles)	Count		Time-varying
Independent variables – system external factors				
Ad_gasprice	Adjusted (to January 2005 value) monthly average gas price (cents/gallon)	Continuous		Time-varying
Unemploymentrate	Monthly average for Chicago unemployment rate	Continuous		Time-varying
Population (thousands)	Monthly estimates for Chicago area population	Continuous		Time-varying
Total_snow	Monthly total snow fall (inch)	Continuous		Time-varying
Total_preciptation	Monthly total precipitation (inch)	Continuous		Time-varying
Very_cold	Whether monthly average temperature is below 32 °F	Dummy	1 = Yes	Time-varying
Cold	Whether monthly average temperature is between 33 and 47 °F	Dummy	1 = Yes	Time-varying
Chilly	Whether monthly average temperature is between 47 and 62 °F	Dummy	1 = Yes	Time-varying
Hot	Whether monthly average temperature is above 77 °F	Dummy	1 = Yes	Time-varying
Independent variables – monthly effect				
Feb	Whether the measurements were taken during February	Dummy	1 = Yes	Time-varying
Mar	Whether the measurements were taken during March	Dummy	1 = Yes	Time-varying
Apr	Whether the measurements were taken during April	Dummy	1 = Yes	Time-varying
May	Whether the measurements were taken during May	Dummy	1 = Yes	Time-varying
Jun	Whether the measurements were taken during June	Dummy	1 = Yes	Time-varying
Jul	Whether the measurements were taken during July	Dummy	1 = Yes	Time-varying
Aug	Whether the measurements were taken during August	Dummy	1 = Yes	Time-varying
Sept	Whether the measurements were taken during September	Dummy	1 = Yes	Time-varying
Oct	Whether the measurements were taken during October	Dummy	1 = Yes	Time-varying
Nov	Whether the measurements were taken during November	Dummy	1 = Yes	Time-varying
Dec	Whether the measurements were taken during December	Dummy	1 = Yes	Time-varying

Transit internal factors (i.e., transit fare, service quantity and service quality factors) have been identified in the literature as having an impact on transit ridership (Taylor and Fink, 2003). At the system level, we include the variable for CTA bus fare, since the bus fare is the same for all CTA bus routes. At the bus route level, we compiled information on service type (i.e., whether it is a key service route[2]), service hours, service frequency, and the presence of Bus Tracker-based real-time bus arrival information for a route during the observation month. These data are obtained from CTA website directly, except for the bus service frequency data.

We used different sources to compile the data for service frequency variable, because the longitudinal data for route level frequency are not publicly available. First we looked on the CTA website to collect the data for the current service frequency for each bus route. Then through personal communication with Urban Transportation Center at University of Illinois at Chicago, by which CTA bus service data were collected in 2005, we obtained the 2005 cross-sectional data for CTA bus frequency for each route. Further, by checking press releases on the CTA website we collected the historical information on service changes (including bus service frequency changes) for each bus route. In order to accurately measure the average frequency at bus route level, we adopted the methodology used in the studies by Sriraj et al. (2006) and Minocha et al. (2008), and calculated the weighted hourly frequency for each bus route. In this weighted methodology, AM and PM peak times frequencies were assigned a 35% weight, midday times received a 20% weight, and the overnight period account for 10% of the weighted value for service frequency. The service hours for the AM peak, midday, PM peak, and overnight are considered to be between

[2] Key routes are the backbone of the CTA bus service. Such routes provide the basic geographic coverage for the service area. In 2001, 47% of the CTA rides are provided by key routes. Support routes are the remaining routes, which "by serving a variety of important specialized functions" to "enhance the quality of service and improve market share". (Chicago Transit Authority, 2002, p. 9)

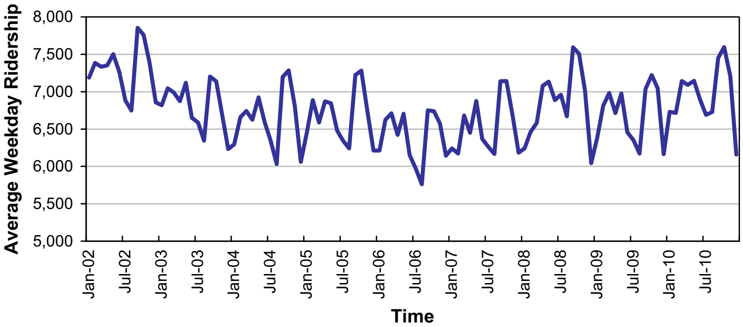

Fig. 1. Monthly route level average weekday ridership for CTA bus system.

7 and 9 am, 12 and 2 pm, 4 and 6 pm, and 2 and 4 am, respectively. Only bus routes provide 24-hour services during the observation month are measured for the overnight frequency.

In this study, we also control for the service attributes of CTA rail, which serves as an alternative transit mode to CTA bus in the CTA service area. We expect increasing the level of service of CTA rail will negatively affect CTA bus ridership; while increasing the fare of CTA rail will increase CTA bus ridership. We use monthly Vehicle Revenue Hours (VRHs) of CTA rail and the number of CTA rail Vehicles Operated in Maximum Service (VOM) in each month as the indicators for service level for CTA train. These data are obtained from National Transportation Database (NTD) website.

Merging the above data together, we obtained a combined longitudinal data set for a total of 144 CTA bus routes from January 2002 through December 2010. The information for each route is on a monthly basis. Using Consumer Price Index (CPI) data available from US Bureau of Labor Statistics, the values for transit fares and gas prices are adjusted to January 2005 values.

5. Exploratory analysis

Fig. 1 illustrates how the CTA bus route level average weekday bus ridership changed over time from January 2002 to December 2010. From the figure, we can see that there are monthly variations of the ridership. The ridership tends to become higher during the fall and spring months and decrease during the summer and winter months. In general, the ridership levels appear to decrease when weather conditions become adverse (during the summer and winter).

From the ridership figure, it appears that the route level average weekday bus ridership was decreasing from January 2002 to August 2006; however, it started to increase from September 2006 (around the time when Bus Tracker was experimentally implemented in one route) to late 2008. During this 2-year time period from mid-2006 to mid-2008, gas prices were also higher than historical levels except for November and December in 2008 (Fig. 2). This high level of gas prices may lead to ridership increases according to the literature. During the same 2-year time frame, unemployment rates (Fig. 3) started to go up, as a result of a nationwide economic recession that was dated by the National Bureau of Economic Research to have started in the last quarter of 2007 and ended by the second quarter of 2009 (NBER, 2010). Economic researchers estimated that job growth in Metropolitan Chicago halted during this period and unemployment rates jumped, largely due to the region's dependence on financial services, manufacturing, and construction – three core industries that account for 20% of the area's economy (Transwestern and Delta Associates, 2008). These economic trends should have resulted in ridership decline during the 2006–2008 period. Thus the increase in bus ridership from mid-2006 to mid-2008 might be explained by the collective effects of energy price, economic trends, the implementation of Bus Tracker and some other factors.

In the third and fourth quarters of 2008, there was a sharp drop in gas prices. And unemployment rates kept rising. The changes in these two factors should lead to a decline in bus ridership. However, although the bus ridership did decline, starting in the third quarter of 2008, as per historical seasonal trends, it returned to even higher levels in 2009 than the ridership for the corresponding seasons in 2006 and 2007 when the majority of the bus routes were not implemented with Bus Tracker, despite the unemployment rates were much higher and the gas prices were lower in 2009 than in 2006 and 2007 for the corresponding months during the first two seasons. This analysis indicates that additional factors, including the provision of Bus Tracker services, appear to have buffered the drop in bus ridership to the pre-Bus-Tracker-period level that may otherwise have resulted in from the decrease in gas price and increase in unemployment rate. In the next section, we will present a longitudinal model to examine the effects of these factors on CTA bus ridership.

6. A longitudinal model of bus ridership

This section presents a longitudinal model that allows us to examine the effects on bus ridership of the provision of Bus Tracker, controlling for other influential factors. The model posited in this study is called linear mixed-effects model (or

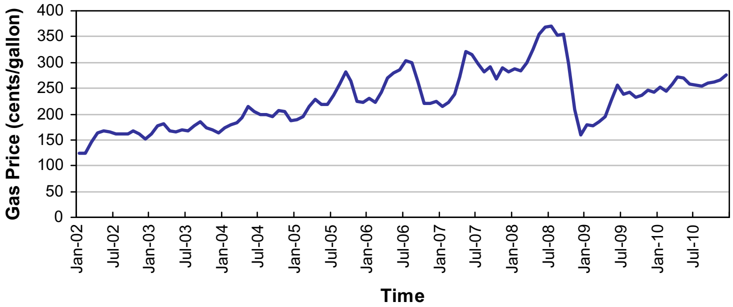

Fig. 2. Monthly average gas prices in Chicago (cents/gallon, adjusted to January 2005 prices).

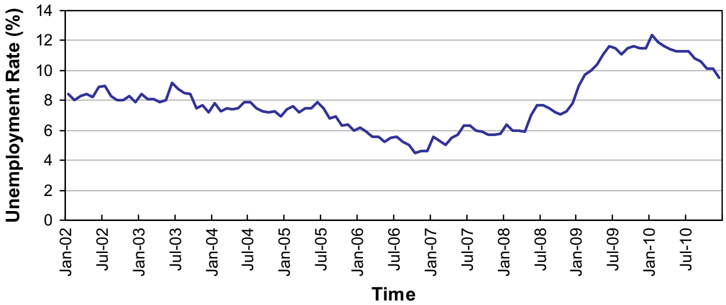

Fig. 3. Unemployment rate (%) in Chicago.

simply called linear mixed model), which contains both fixed effects and random effects (Diggle et al., 2002; Verbeke and Molenberghs, 2009). This model in this study is specified as:

$$ridership_i = X_i\beta + Z_i b_i + \varepsilon_i \tag{1}$$

where $ridership_i$ is the n_i dimensional response vector of ridership for route i, $1 \leqslant i \leqslant N$, N is the number of bus routes, X_i and Z_i are $(n_i \times p)$ and $(n_i \times q)$ dimensional matrices of known covariates, β is the p dimensional vector containing the fixed effects, b_i is the q dimensional vector containing the random effects, and ε_i is an n_i dimensional vector of residual components. The presence of the random effects explicitly recognizes natural heterogeneity amongst the bus routes. The design matrix X consists of the potentially influential factors that affect monthly average weekday bus ridership given in Table 1.

We choose a linear demand function for transit demand as specified in Eq. (1), instead of the more widely used double-log format. Using a linear demand function, we assume that the transit demand is "approximately linear over the range (of the explanatory variables that are) of interest"; while using the double-log function, one assumes the elasticity of demand is constant with respect to the explanatory variables (Meyer and Miller, 2001, p. 268). Both of the assumptions are common assumptions and have been used in previous transit demand studies (Meyer and Miller, 2001; Al-Sahili and Sadeq, 2003; Guerra, 2010). The reason we choose linear function instead of double-log function is that the model estimates produced by the various double-log format models that we have tested did not pass the judgment-based test (i.e., some of the model estimates are counter-intuitive), while the final linear model we have selected produces reasonable model estimates.

In the model presented here, we consider only one random effect, the intercepts, which are assumed to be route-specific. The random intercepts allow us to account for natural heterogeneity amongst bus routes as well as omitted variables relating to intrinsic factors that are not easily available from the observed data (such as the income variable discussed earlier). We could have introduced additional random effects for those covariates that vary over time; however, our purpose here is to start with an initial model that allows us to model the mean of ridership adequately, which is enabled by the introduction of random intercepts.

We model $\varepsilon_i \sim N(0, \sigma^2 I_{n_i})$ which assumes that all the variability in the data, which is not taken into account by the random effects (which model the stochastic variability between routes) is purely measurement error. The random effects are taken to be $b_i \sim N(0, D)$; the covariance structure for the random effects are modeled to be a general unstructured covariance matrix, i.e., a symmetric positive (semi-) definite matrix D, which does not assume the random effects covariance matrix to be any specific form.

The covariance structure for repeated measurements on each bus route (i.e., the residual covariance structure) is specified as a first-order autoregressive moving-average structure (i.e., ARMA (1,1)) to account for the serial correlation. The selection of the residual covariance structure is based on comparing models with different serial correlation structures and using likelihood-based criteria as the selection criteria (i.e., a method recommended by Verbeke and Molenberghs (2009)). Restricted maximum-likelihood estimation is applied as the estimation method.

We use the informal judgment-based test (i.e., to check whether the sign and magnitude of the parameters are reasonable), goodness-of-fit measures (i.e., likelihood-based criteria in this study) and statistical tests to compare models with different model specifications with the same basic model specification in Eq. (1). SAS procedure PROC Mixed is used for model estimation (SAS Institute Inc., 2008). Table 2 presents the model estimates for the final selected model.

7. Model results

Table 2 shows that all the signs of the control variables are as expected in the final selected model. All these variables are statistically significant, except for the variables for population and hot temperature. However, we decide to keep these two variables in the final presented model for theoretical reasons (i.e., both the previous literature and our knowledge indicate that these two variables are very important factors that affect transit ridership and should be controlled for in the analysis).

The results of the system internal factor variables indicate that transit fares have significant effects on bus ridership. On average, for every cent increase in bus fare, the average weekday bus ridership will decrease by 11. On the contrary, for every

Table 2
Estimation results for linear mixed-effects model of bus ridership.

	Estimate	*SE*	*P*
Solutions for fixed effects			
Intercept	6013.2600	1571.4800	**0.0002**
Independent variables – internal factors			
Tracker	125.8400	48.9503	**0.0102**
Ad_busfare	−11.0192	2.0827	**<.0001**
Ad_railfare	6.1074	1.5804	**0.0001**
Keyservice	7801.2400	959.0700	**<.0001**
Owlservice	5384.1500	1399.4500	**0.0001**
Square root of Frequency	318.7900	124.9500	**0.0107**
VRH_rail (thousands)	−2.1900	0.5120	**<.0001**
VOM_rail	−2.4609	1.2563	**0.0502**
Independent variables – external factors			
Ad_gasprice	1.4034	0.3112	**<.0001**
Unemploymentrate	−302.2900	53.7029	**<.0001**
Square (quadratic) of Unemploymentrate	17.7614	3.1573	**<.0001**
Population (thousands)	0.6280	0.4490	0.1624
Total_snow	−5.7100	0.8216	**<.0001**
Total_preciptation	−6.7022	0.9048	**<.0001**
Very_cold	−338.1400	49.6725	**<.0001**
Cold	−235.2100	44.5161	**<.0001**
Chilly	−114.1000	46.6783	**0.0145**
Hot	−48.6864	29.8269	0.1026
Independent variables – monthly effect			
Feb	246.7400	19.0294	**<.0001**
Mar	262.8000	30.8771	**<.0001**
Apr	106.4000	52.5964	**0.0431**
May	289.0900	56.7787	**<.0001**
Jun	−158.5400	57.4728	**0.0058**
Jul	−364.9500	58.0558	**<.0001**
Aug	−483.9600	57.3708	**<.0001**
Sept	487.6800	57.1141	**<.0001**
Oct	546.7100	58.6140	**<.0001**
Nov	316.8600	34.2526	**<.0001**
Dec	−216.9300	23.0551	**<.0001**
Fit statistics			
−2 Res log-likelihood	226,418.00		
AIC	226,426.00		
BIC	226,437.90		
Covariance parameter estimates			
Rho (autoregressive parameter)	0.8489	0.0061	**<0.0001**
Gamma (moving-average parameter)	0.8652	0.0044	**<0.0001**
UN(1, 1)	22,650,478	2734,941	**<0.0001**
Residual	1293,236	43,116	**<0.0001**
Sample size			
N	144		
Total observations	14,540		

cent increase in rail fare, the average weekday bus ridership will increase by 6. Since we assume the transit demand function to be a linear function (Eq. (1)), the elasticities of demand with respect to the explanatory variables are not constant along the linear demand curve. Using the model estimates for transit fares and the predicted route level average ridership data and observed transit fare data for each month, we calculate the range for arc elasticity of bus ridership with respect to bus fare and rail fare to be from −0.23 to −0.32 and 0.13 to 0.20 during the study period, respectively. These results indicate that CTA bus ridership is inelastic to transit fare change. This finding is consistent with findings from previous research (Taylor and Fink, 2003). The model output shows that bus service type also significantly affects bus ridership. The key service bus routes, on average, have much higher ridership than non-key service bus routes. The average weekday bus ridership for routes with owl service (i.e., 24-hour service) is about 5384 higher than those without such service.

CTA bus service frequency has a significant and positive effect on bus ridership. The square root form of this variable indicates that there is a diminishing marginal effect of increasing bus service frequency, i.e., the higher frequency the bus route is currently served with, the less ridership increase the bus route will experience when the frequency is increased by one unit (e.g., one bus per hour).

As expected, the factors for the level of service of CTA rail system have significant and negative effects on CTA bus ridership. Both increases in Vehicle Revenue hours of CTA Rail and Peak Vehicles of CTA Rail will decrease bus ridership.

All of the weather-related factors have expected signs. Increases in the levels of snowfall and rain significantly reduce bus ridership. Both high and low temperatures will reduce the bus ridership. These estimates reflect the observations made earlier, regarding the effect of adverse weather during the winter (cold and snowy months) and summer months (hot and more likely to be rainy).

There is a positive quadratic effect of unemployment on bus ridership. Bus ridership reaches its minimum when Chicago unemployment rate is 8.51% and increases when the unemployment rate increases or decreases, controlling for other factors. This finding implies that when the unemployment rate is relatively low, increase in unemployment level will decrease the total number of commuters, thus reduce the transit ridership as well; however, when employment rate becomes high, many commuters might give up their car and start to use transit instead, thus the transit ridership starts to increase.

The increase in gas price has a positive and significant effect on bus ridership. On average, for every cent increase in gas price, the average weekday bus ridership will increase by 1.4, controlling for other factors. Using the same method as calculating the elasticity of bus ridership with respect to transit fares, the cross elasticity of bus ridership to gas price is estimated to range from 0.03 to 0.08 during the study period. This estimate is consistent with the findings in previous research on impact of gas price on transit ridership (Taylor and Fink, 2003; Mattson, 2008).

We have accounted for monthly variations in ridership by introducing monthly variables (dummies) in the model. From the model output, we can see that bus ridership is higher for the months during the fall (September–November) and spring (March–May), and lower during the summer and winter months (except for February) when controlling for temperature and other factors. This monthly variation of the ridership can be explained by school/work vacation periods during the summer months and December, when there are fewer commuters.

The estimate for the treatment/intervention variable of interest – *Tracker* – indicates that the provision of Bus Tracker significantly increases bus ridership, at the .05 level of significance. On average, monthly average weekday ridership of the bus routes, after Bus Tracker information is launched, is estimated to be 126 rides a day more than the ridership in the routes without such information, when controlling for all other factors. However, comparing this gain with the average route level weekday bus ridership during the year before the implementation of Bus Tracker (i.e., August 2005–July 2006), which varies from 5761 to 6876 rides per day (as shown in Fig. 1), this increase is quite limited (i.e., equal to around 1.8–2.2% of the route level average weekday bus ridership).

8. Spatial and temporal variations in the ridership effects

Based on the above discussion, using a linear mixed-effects model, we found that the provision of Bus Tracker service does increase bus ridership, after accounting for other factors that offer alternative explanations for ridership change. As mentioned earlier, existing literature also suggests that spatial and temporal variations in ridership due to the provision of Bus Tracker technology are to be expected. Therefore, our next step is to examine whether, and how, Bus Tracker affects ridership on different bus routes differently over time and space. In order to achieve this purpose, first we will compare the predicted change in ridership before and after the treatment for each bus route. Such a comparison allows us to examine how the estimated ridership has changed after the implementation of Bus Tracker. There are several issues to be considered in doing so.

First, since there are within-year natural variations in bus ridership and potential lag effects in Bus Tracker technology adoption and usage, we will compare the averages of the predicted monthly weekday ridership for a year before Bus Tracker was implemented to the predicted monthly averages for the months following Bus Tracker implementation, for which data were available. We call the difference between the average of the predicted monthly average weekday ridership for the 1-year period after and before Bus Tracker implementation as *grossmeangain*. The selection of 1 year for the before and after comparison is arbitrary. But the period is long enough to smooth out monthly variations. Since three out of the 144 bus routes have never received Bus Tracker service, we only compute the *grossmeangain* values for those 141 bus routes on which the service was implemented.

Second, since routes originally having higher ridership may have greater opportunities to accrue increased ridership compared to routes otherwise, we estimate the percentage change in the average of the predicted ridership after Bus Tracker is implemented, compared to the before-period for each route. This variable is called *permean*. Same as in the previous discussion for *grossmeangain*, we calculate the values of *permean* for 141 bus routes.

Fig. 4 shows the distribution of *grossmeangain* (i.e., the difference between the averages of the before and after-period predicted monthly average weekday ridership). The mean of the distribution is 148.42; however, the distribution is quite skewed, with a median of 109.18. This indicates that many routes were estimated to have made a positive change between the 12-month before and after-period. There were a few, where ridership in the after-period was, in fact, lower. The distribution is trimodal, with close to 40% of routes gaining over 210 rides on a typical weekday, between the before and after-period, an additional 58% gaining more modest levels of rides, between 55 and 140 rides per day, and 0.7% (i.e., one route) estimated to have lower rides per weekday in the after-period.

The trimodal distribution of *grossmeangain* values appears to be strongly related to the date by which Bus Tracker was launched in a route. Fig. 5 shows *grossmeangain* values of routes plotted against the calendar dates on which Bus Tracker was implemented on the routes. The trend is positive. On average, the routes where Bus Tracker was introduced very recently have higher *grossmeangain* values compared to routes where Bus Tracker was introduced earlier in time. Fig. 6 shows the *permean* values, which illustrate a more obvious trend than in Fig. 5 – the routes that were implemented with Bus Tracker more recently are shown as having incurred higher percentage gains in ridership, relative to the baseline of the year before, compared to those where Bus Tracker was implemented in an earlier time.

One possible explanation for this temporal variation in ridership effects is that, during the later stages, the technology was launched on routes which had ridership comprising of individuals that were more likely to use the technology, such as higher levels of education and income, or other factors that have been identified in the literature as leading to greater adoption and use of location-based services technology. However, this is not the case. As discussed earlier, Bus Tracker was rolled out randomly throughout the Chicago area. This random roll-out of Bus Tracker makes it difficult to making associations between roll-out timing and areas with socio-demographics that lead to ridership attributes favorable to LBS adoption.

An alternative explanation for this association between ridership gains and Bus Tracker launch dates would be that bus users in routes where the technology was implemented later on had an opportunity to become more familiar with such information, since Bus Tracker technology had been widely reported in the news, technology blogs, social media and other sources early in the deployment phase, which might make the system familiar to residents of the entire metropolitan area well before the system was fully deployed on all routes. For the routes with Bus Tracker implemented at a later stage, their users experienced reduced learning and adaptation phases associated with new technologies, which will result in shorter lags between information availability and impacts on ridership. In another paper, we have presented a detailed discussion on how the prior experiences with transit information systems will help change travelers' mode choice behavior (Tang and Thakuriah, 2011).

Moreover, users of routes where the technology was implemented later on are more likely to have been beneficiaries of the additional connectivity between Bus Tracker and technologies such as Google Transit and other LBS technologies, thereby leading to a better overall integration of the technology to the person's travel, social and other needs. Changes in the Bus Tracker information itself, with more features and apps available to the public (such as the "track by text" and email subscription features of Bus Tracker from CTA, and the developments of more matured apps), potentially made Bus Tracker data more efficient and user-friendly.

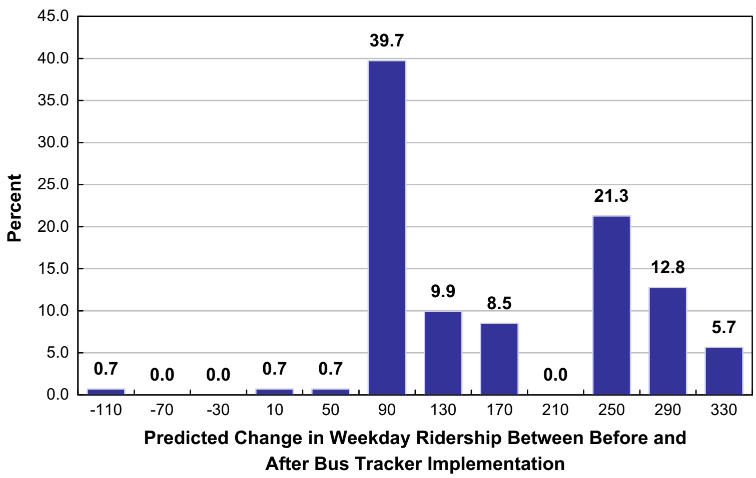

Fig. 4. Frequency distribution of the difference between average weekday ridership for a 1-year period after and before Bus Tracker implementation.

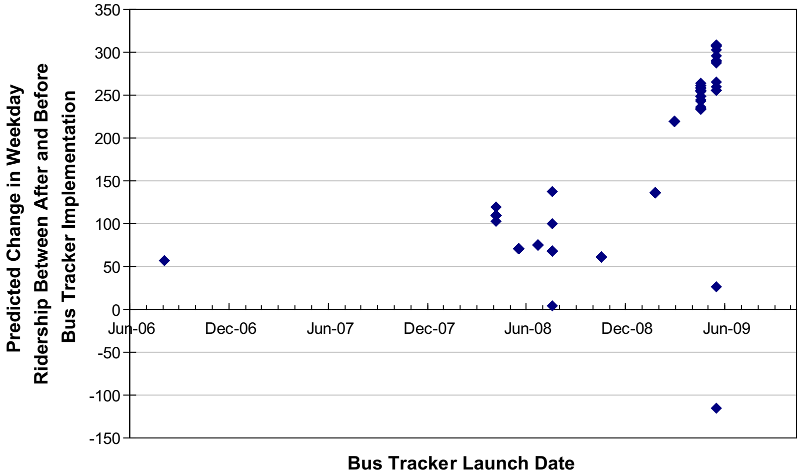

Fig. 5. Scatterplot of the predicted change in average weekday ridership of routes and the Bus Tracker launch date.

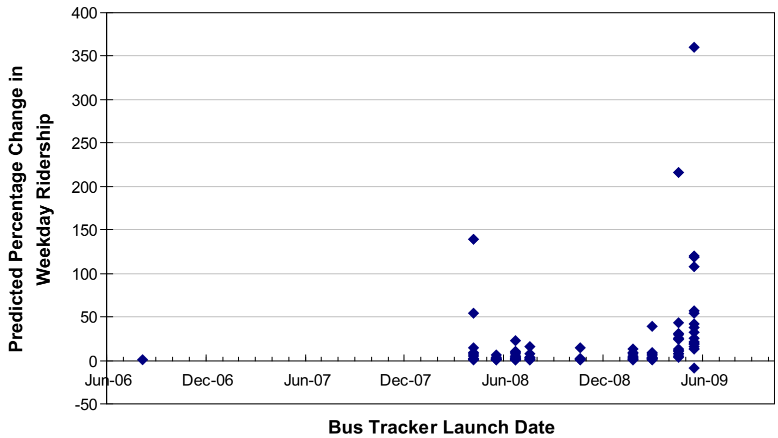

Fig. 6. Scatterplot of the percentage change in predicted ridership after Bus Tracker is implemented and the Bus Tracker launch date.

Furthermore, users of routes where the system was implemented later in the roll-out schedule, and whose entire trip may require the use of several bus routes, may have also benefited from the fact that the real-time arrival times of more bus routes were provided, leading to greater possibilities of real-time bus connection information. Therefore, they may have been more likely to choose the bus mode, or to make more trips using buses, than at an earlier time when the bus connection information was absent.

As the research questions stated, our next step is to examine the spatial variations in ridership due to the provision of Bus Tracker. This can be done by the examination of the distribution of random effects estimated by the linear mixed model. Such estimates can be interpreted as residuals, which represent historical route-specific deviations from the overall mean, and may be helpful for detecting special or outlying profiles (or routes that have gained or lost ridership more than other routes over time) or groups of routes that have evolved differently over time. Routes with negative values of random effects are those which have negatively deviated from the overall growth trends in ridership – i.e., they have historically, over the entire period considered, experienced lower growth in ridership compared to those routes which have positive values of the random effects.

Fig. 7 shows the spatial distribution of the values of the random effects of the bus routes. It is difficult to draw any specific conclusions from the figure. Although none of the bus routes with negative random effects serve downtown Chicago, and it seems that most of the routes with larger random effects serve the north side of Chicago, the route with the largest random effect is located at the south of Chicago with east–west direction and does not serve downtown Chicago. The routes with lower positive and negative random effects values seem to distribute evenly spatially. These observations imply that the geographical diffusion of ridership increases and the socio-demographic underpinnings of these increases are not obvious. This

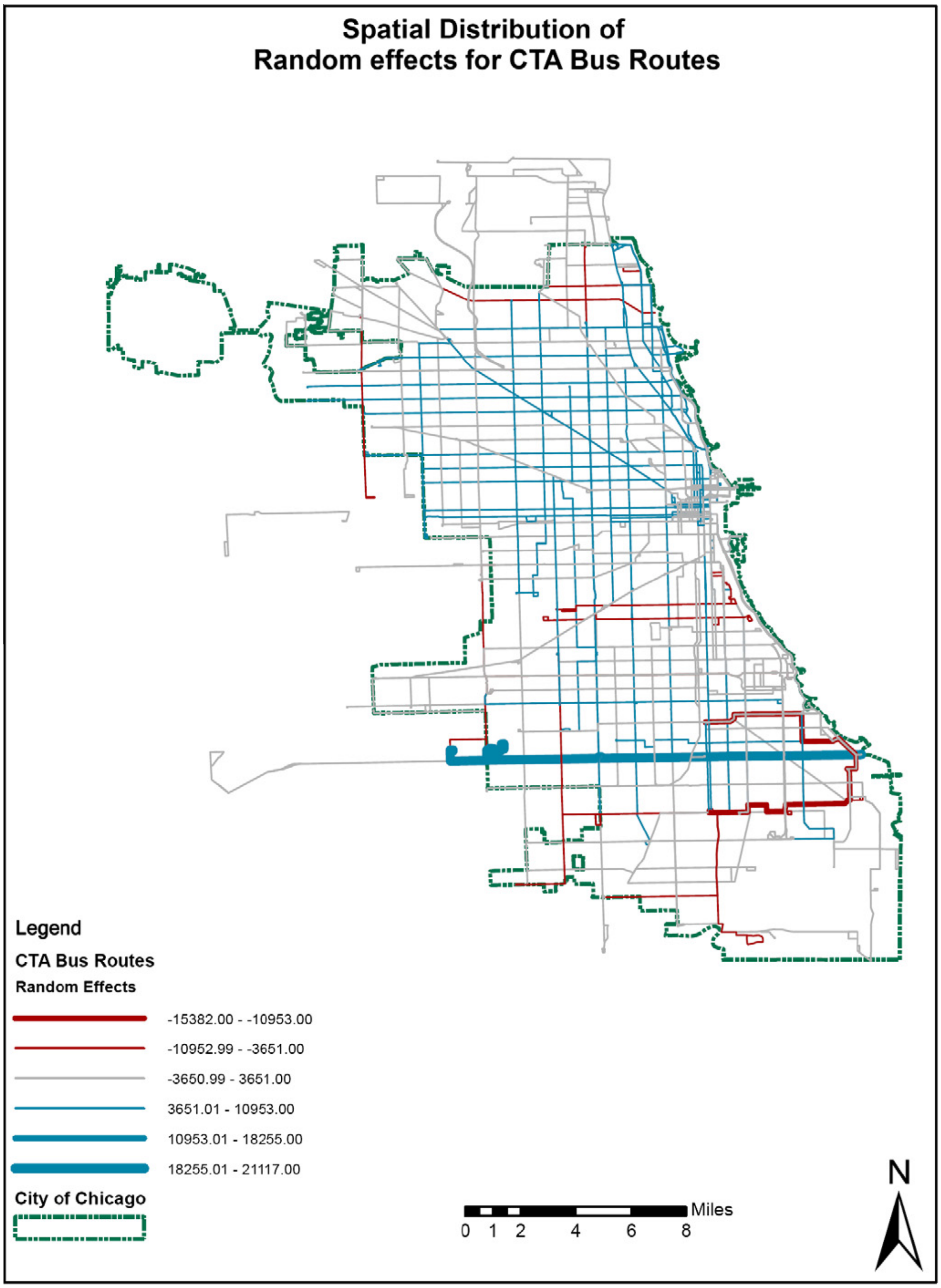

Fig. 7. Spatial distribution of random effects.

ambiguity in geographical implications reflect the complex mix of dates of bus information technology implementation, and the variations of the socio-demographics of the riders who live or work within the service areas of the bus routes.

9. Conclusions

In this paper, we use secondary data on route level monthly average weekday ridership in the entire Chicago Transit Authority bus system for the Chicago metropolitan area from January 2002 through December 2010, combined with data on gas prices, weather conditions, unemployment rates, population, CTA service factors, and other socioeconomic characteristics of the CTA bus service area, to evaluate the system-wide ridership effects of the CTA Bus Tracker, a real-time bus location technology. The combined longitudinal data source enables us to implement a quasi-experimental design with statistical controls to examine changes in average weekday ridership before and after the Bus Tracker system was implemented on each route.

Based on a linear mixed-effects model, we found that the provision of Bus Tracker service does help increase bus ridership. These findings bear out predictions from the cognitive models of behavior and Socio-Technical Systems literature described earlier in the paper. The linear mixed-effects model estimates that, on average, the weekday ridership for the CTA bus route with Bus Tracker service is about 126 more than the bus route without such information, controlling for all other factors. This effect is significant at the .05 level. This may seem to be a modest gain; however, when considering that the ridership effects may expand over time after the lag periods if the learning and adaptation phases are overcome, and additional user benefits that may accrue due to connectivity to related LBS and social media systems, the return on investment from the additional fares raised may more than offset the investment cost, and may lead to new revenue sources. Furthermore, the increased ridership due to the provision of Bus Tracker will also lead to social welfare gains. Thus the benefits of the provision of real-time bus information should not be overlooked.

The model results also indicate that many control variables have significant effects on bus ridership. These variables include CTA transit fares, CTA transit service attributes, Chicago gas price, unemployment level, and weather conditions.

Further, through an examination on how Bus Tracker has affected different routes differentially, we found that there are temporal variations in the ridership effects among routes in the extent to which ridership gains occurred. Those routes where Bus Tracker technology was rolled out at a later stage of the entire deployment period tend to have greater positive percentage change in ridership compared to those that were provided with such information at an earlier stage. This finding is consistent with our hypothesis based on intuition and theories of diffusion.

The results are less conclusive regarding geographical variations in the effects of Bus Tracker. This ambiguity reflects the complex mix of the dates of technology implementation, the dynamic processes within the city regarding the spatial patterns of demand for residency and job growth over the time period considered, and the socio-demographics of the riders who live or work within the CTA bus service area. Hence, the geographical diffusion aspects of theory are not clearly borne out by the analysis.

The major contribution of this study is that it fills a gap in the existing literature by providing empirical evidences showing that real-time bus information does help increase bus ridership. This finding will be useful for transit service providers and decision makers in their decisions regarding investments on such systems. However, this study also shows that the ridership increase due to the provision of real-time bus information may be quite modest. Thus it is necessary to find out the reasons that limited this increase and adopt corresponding marketing strategies to help promote transit use. Possible reasons that might limit the ridership increase include:

(1) It is possible that many travelers, especially those who do not typically use transit, were unaware of the Bus Tracker service during the period of time considered in this paper. It is possible that if more people were aware of this service, the ridership increase might be more.
(2) Bus Tracker service is only available to travelers who have the devices that can get access to such information (e.g., computer or handheld devices with Internet access); thus, many people who do not have such access or who were not willing to use such technologies will not be able to take advantage of such service. This also implies that with more people starting to use these technologies, the number of the riders might continue to increase.
(3) There may be additional delayed effects of the Bus Tracker service on transit ridership that cannot be captured by our current model, or are not evident within the time frame considered. In order to estimate such effects, additional studies should be conducted to investigate this issue when more after-intervention (i.e., after the provision of Bus Tracker service) data become available, especially in the latest set of routes where the technology was implemented.

One of our earlier studies (Tang and Thakuriah, 2011), in which we surveyed Chicago area commuters during July–December 2008, indicates that the first reason discussed above might be a valid one. In this earlier study, around 43% of the respondents had never seen or used real-time information system by the time of the survey, when Bus Tracker had started its implementation for 2 years. Additionally, in this earlier study, using stated preference questions, we also found that transit users are more likely to increase transit usage than transit non-users when real-time information is provided; however, once these non-users are familiarized with such information, they might break their old habit of not using transit and start to ride transit (Tang and Thakuriah, 2011). This finding suggests that marketing strategies for real-time information should be targeted not only to transit users but also to transit non-users in order to bring about larger increase in transit ridership. Furthermore, since one major purpose of providing real-time transit information is to increase transit mode share and attract transit non-users, greater effort is needed to promote this system among those transit non-users.

Traditional examples of programs to promote real-time transit information systems include advertisements through TV, and newspaper, although such technology applications have been receiving wide publicity through blogs, social networks and other technology-focused outlets. These types of facilitating programs should work for both transit users and non-users.

One way of marketing real-time transit information systems to non-users may be through application software recommender systems (Adomavicius and Tuzhilin, 2005). Such systems can be made available through application market places, when non-users are looking for assistance with driving tasks. For example, when these users are searching for ways to complete their daily itinerary (e.g., where to shop), such recommender systems would provide a recommendation for real-time transit applications in search results. Recommender systems could also be more strongly integrated with eco-feedback technologies to appeal to a broad range of potential transit users. Some other marketing strategies include exploring the business models to tie incentives and LBS technologies to direct customers, especially non-users of transit, to transit options. This type of strategy will potentially lead to Public–Private Partnerships. Additionally, the current trend to integrate public transit real-time information feeds to third-party LBS offering services of value to customers should be significantly expedited and further research is needed to examine how this may be done in a variety of circumstances. Some multiple technology service providers such as Google have already started to add real-time transit information into their web mapping services, bundled with traveler information for other travel modes (such as driving, walking and bicycling). It is likely that this type of traveler information service with multimodal options will help attract non-users to transit.

As stated earlier in this paper, there are several limitations of this study. The first limitation comes from the research design. In this study, we used a binary variable to identify whether an individual bus route received the treatment (i.e., with Bus Tracker information provided) during the observation month. As discussed in Section 2 in the paper, ways in which users can receive information from Bus Tracker have changed greatly since the basic technology was implemented, which may have had differential impacts on people's use of the bus system. However, as also discussed in Section 2, we could not control for these gradual developments of Bus Tracker delivery methods due to information limitations. Therefore, we assume that the ridership effects of Bus Tracker will not be affected by the media through which the information is delivered. Thus, the analysis results based on this assumption will not provide detailed information on how gradual developments of Bus Tracker delivery methods will influence the effects of Bus Tracker.

Second, this study only examined the ridership effects of Bus Tracker on CTA bus routes, but did not examine how other transit modes in the Chicago area (i.e., CTA heavy rail) might be affected. Therefore, even though we found that Bus Tracker positively affected bus ridership, the study results do not provide conclusive evidence to support the statement that real-time bus information will help increase transit mode share, since some of the observed changes may be caused by the modal shifts from CTA train to bus.

Third, there are data unavailability related issues in this study. According to the literature, there are other factors that might also affect bus ridership (e.g., monthly income information for Chicago area); however, they are not included in this study since the longitudinal data for these variables are not currently available. Further, data on some of the control variables that are included in the analysis, such as socio-demographic factors (e.g., population, unemployment rate), are only available at the city/bus system level instead of at the individual bus route level. These data limitations might affect predicting power of the model presented in this study for each individual route.

Finally, there is some limitation in using the results from this analysis to predict the outcome for the future investment on real-time transit information systems. The traveler behaviors, as examined in this research, are situated with the technology during the last decade. It is possible that as information becomes more personalized, with newer trends in technology design strategies that support behavior change in everyday life through persuasive technologies (Fogg, 2003), behavior modification approaches (Nawyn et al., 2006; Consolvo et al., 2009), and other trends in mobile information processing and delivery, new technology models driving transit real-time information systems in the future will lead to substantially different results in transit ridership change.

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