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Examining the Influence of Tolls on Commute Departure and Route Choice Behavior in the Chicago Region

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ABSTRACT

In the United States, a significant number of individuals depend on the auto mode of transportation. The high auto dependency, in turn, has resulted in high auto travel demand on highways. The resulting traffic congestion levels, surging oil prices, the limited ability to address increased auto travel demand through building additional transportation infrastructure, and the emphasis on reducing GHG emissions has led to the serious consideration and implementation of travel demand management (TDM) strategies in the past decade. Congestion pricing is a frequently considered TDM option to alleviate travel congestion in urban metropolitan regions. Congestion pricing might induce changes in activity location, travel route, departure time of day, and travel mode. The current study contributes toward understanding the influence of congestion pricing on commuter behavior by specifically examining what dimensions of commuter travel behavior are affected as a response to congestion pricing. Specifically, we formulate and estimate a joint disaggregate model of commute departure time and route choice drawing from the 2008 Chicago Regional Household Travel Inventory (CRHTI). The empirical analysis demonstrates the significance of individual and household socio-demographics on commuter behavior. The results also highlight how vehicle availability plays an important role in determining individual's sensitivity to travel time and travel cost. To demonstrate the applicability of the joint modeling framework to determine optimal toll fares, we compute value of travel time measures for different demographic groups.

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EXECUTIVE SUMMARY

This research study contributes to the existing literature on congestion pricing by analyzing the influence of pricing on travel behavior. Specifically, congestion pricing might induce changes in activity location, travel route, departure time of day, and travel mode. Commuter response to pricing might involve (1) shifting their departure time interval for both the home-to-work (HW) and the work-to-home (WH) segments, (2) altering their travel route and (3) shifting from auto mode to other modes of transportation. In this effort, we investigate the travel route and time of day choice for commuters who use the auto mode to travel to work. The data used in this study are drawn from the 2008 Chicago Regional Household Travel Inventory.

The current study examines the commuter departure time interval and travel route choice in a unified framework. Specifically, the departure time choice alternatives include a joint combination of time interval of travel for the home-to-work (HW) and the work-to-home (WH) segments. The travel route alternatives include “toll” and “no toll” routes. The route choice alternatives are not readily available in the travel data set. So, we manually compiled travel route characteristics using Google Maps (<http://maps.google.com>) for travel time information and the Chicago Toll Calculator for toll fare information (<http://www.getipass.com/tollcalc/TollCalcMain.jsp>). The classic multinomial logit model is employed for the empirical analysis.

The empirical analysis considered several variables to explain departure time and route choice, including level of service measures (travel time and travel cost measured as toll cost and operational cost), HW and WH departure interval duration, and interactions of individual attributes, (age, gender), household socio-demographics (household income, household vehicle availability computed as number of vehicles per licensed driver), and commuter employment characteristics (work schedule flexibility) with level of service attributes and departure time attributes. The results from this exercise provide several insights into commuter behavior. First, the model results highlight the significance of individual and household demographics on commute departure choice and travel route choice. Second, individuals, as expected, exhibit an overall disinclination towards using toll routes for commute unless the toll routes provide a reasonable travel time savings. Third, female commuters and commuters with high work flexibility are least likely to choose toll routes for their commute. Finally, the results highlight the importance of household vehicle availability on commuter route choice. These model

estimation results were employed to compute the implied money value of travel time for different demographic segments (males, females, high work flexibility *etc.*) and for different vehicle availability combinations. The value of time measures point out that commuters with restricted access to vehicles are less sensitive to travel time compared to commuters with higher access to vehicles. Further, the value of travel time measurements from the current research effort allow us to determine the optimal toll pricing schemes for different demographics. The model framework and the estimation results may be used in environmental justice studies and to determine toll fares in urban regions.

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CHAPTER 1: INTRODUCTION

1.1 Transportation in the U.S.

In the United States, a significant number of individuals depend on the auto mode of transportation, in part due to high auto-ownership affordability, inadequate public transportation facilities (in many cities), and excess suburban land-use developments. The high auto dependency, in turn, has resulted in high auto travel demand on highways. At the same time, the ability to build additional infrastructure to meet this growing auto travel demand is limited by capital costs, real-estate constraints, and environment considerations. The net result is that traffic congestion levels and air pollution levels in metropolitan areas of the United States have worsened substantially over the past decade. It is estimated that, in 2007, traffic congestion resulted in urban residents of the United States traveling 4.2 billion hours longer and purchasing 2.8 billions of extra fuel amounting to a total loss of 87.2 billion dollars to the economy (see Schrank and Lomax, 2009). Further, the auto-dependency in the U.S. and other developed countries, combined with the increasing auto-inclination of developing economies, has resulted in the high demand for oil which, in turn, has led to substantial fluctuations in oil prices that has adversely affected the economic growth of the United States (Fackler, 2008). Besides, there is increasing recognition, within the transportation community, that the transportation sector significantly contributes to Greenhouse Gas (GHG) emissions into the environment. Specifically, the GHG emissions from the transportation sector in the United States was estimated to account for about 29% of total GHG emissions in 2006 (EPA, 2006). With the recent emphasis on Global Climate Change, there is interest within the transportation community and growing political support to reduce GHG emissions in the U.S. (Burger *et al.*, 2009).

1.2 Commuting and Pricing Strategies

Commute-based travel constitutes an important part of transportation travel. The majority of the work commute travel is undertaken using a private vehicle. In fact, across the US, about 88% of the commute trips are auto-based (CIA III, 2006). Although, over the years, the fraction of travel attributable to commute has reduced from 40% of total trips in 1956 to only 16% of total trips in 2000 (CIA III, 2006), commuting still plays a significant role in determining peak travel demand

in urban areas. In addition to affecting the peak travel demand, individuals traveling to a work place also plan significant travel around the work place that affects individuals' choice of activity location, route, time and mode of travel. Hence, commuting remains an important element of overall travel and a significant contributor to peak period traffic congestion in urban areas.

The rising peak period traffic congestion levels, surging oil prices, the limited ability to address increased auto travel demand through building additional transportation infrastructure, and the emphasis on reducing GHG emissions has led to the serious consideration and implementation of peak period travel demand management (TDM) strategies. The main objective of TDM strategies is to encourage the efficient use of transportation resources by influencing travel behavior during the peak periods. TDM strategies offer flexible solutions that can be tailored to meet the specific requirements of a particular urban region.

TDM strategies include: (1) transportation options (such as promoting car sharing, increased non-motorized connectivity, enhancing existing public transportation services and building new services such as light rail transit), (2) incentives for reducing auto use and/or promoting alternate mode use (such as road pricing, entry vehicle charges for central business districts, promotion schemes for hybrid fuel vehicles, providing park and ride facilities, and encouraging tele-commuting), and (3) land use strategies (such as neo-urbanist development, parking pricing, and transit oriented development schemes) (see Litman, 2007 for more details on TDM strategies). Overall, TDM strategies have the effect of presenting travelers with a crisper set of commute choices in terms of the attributes characterizing activity location, travel route, time of day and travel mode alternatives (FHWA, 2008). The implementation of TDM strategies since 1970s has resulted in a number of studies evaluating how successful these strategies are in attaining their stated objectives.

Within the context of TDM strategies, congestion pricing is a frequently considered option to alleviate travel congestion in urban metropolitan regions (FHWA, 2008). Congestion pricing (also referred to as value pricing) is an economic strategy to shift trips away from congested routes, congested time periods and the solo-auto mode to less-congested routes, less-congested time periods, and non-solo auto modes/non-auto modes. Congestion pricing encompasses different schemes such as cordon tolls, expressway tolls, area-wide charges (for example entering a central business district), and high occupancy toll lanes (FHWA, 2008). These schemes, in addition to serving as congestion management tools, also generate revenue by monetizing the negative externalities associated with the environment and travel times because

of congestion. Congestion pricing is prevalent in several states in the U.S. (including California, Florida, Illinois, Massachusetts, New York, Ohio, Oklahoma, Pennsylvania, Texas, and West Virginia; see FHWA, 2006a), several countries in Europe (including the United Kingdom, France, Spain, Italy; see FHWA, 2006b), and other developed and developing countries. Consequently, there has been substantial research on evaluating the influence of pricing strategies and tolls on travel behavior.

1.3 Studying Commuter Response to Pricing

The current research contributes to the existing literature on congestion pricing by analyzing the influence of pricing on commute travel behavior. Commuter response to pricing can be rather complex, and may involve (1) shifting time intervals for departure from home-to-work (HW) and the time interval for departure from work-to-home (WH), (2) altering the commute travel route, (3) shifting from auto mode to other modes of transportation, (4) shifting responsibilities for some activities to other household members, (5) chaining or de-chaining non-work activity stops from the commute, or combinations of all of these. In addition, in the longer term, commuters may consider changing work locations and telecommuting. These complex shifts may be considered in a predictive land-use and activity-based modeling system, though such a system needs to have an underlying estimated model of commuter behavior. In this effort, we contribute to such commuter behavioral models by focusing attention on the commuter departure time of day choice (both to work and from work) and the commuter travel route choice, while assuming no change to other choices.

Commuter decisions regarding departure time and route choice are a function of individual work flexibility and travel time for different departure time/travel route combinations. For instance, an individual with a flexible work schedule has greater freedom in the choice of departure time. On the other hand, a person with no work flexibility will need to depart to work well in advance of the work start time to arrive at work prior to the work start time. This decision also implicitly incorporates *a priori* knowledge of travel time for the commuter. To illustrate this, consider that a commuter without work flexibility has a work start time of 8:30 AM. Also, the commuter has two possible travel routes A and B to arrive at work with travel times of 25 and 35 minutes, respectively. For the home-to-work departure time alternatives prior to 7:55 AM, the commuter has the option of choosing either route A or B. However, for HW departure time alternatives after 7:55 AM the commuter has the option of route A only. The choice process

at hand needs to incorporate this explicitly. Similarly, the WH departure time interval choice might also be constrained for the commuter based on his/her destination after work. For example, if the commuter needs to pickup his/her kid from school, the departure time from work is constrained based on the school end time of the child. In the current study, because we model departure time and route choice in a joint framework, we are able to accommodate travel considerations.

To summarize, the choice framework developed in this study simultaneously models the home-to-work (HW) departure time, the work-to-home (WH) departure time, and the commute route. The remainder of the report is organized in five sections. Section 2 presents a summary of earlier literature, discusses implications of available data and positions the current research. Section 3 describes the modeling methodology employed for the analysis. Section 4 describes the data compilation effort in detail. Section 5 discusses the empirical results and implications from the research. Section 6 concludes the report and identifies future directions of research.

CHAPTER 2: EARLIER STUDIES AND THE CONTEXT OF THE CURRENT STUDY

There has been considerable research undertaken to examine the influence of congestion pricing on travel behavior. It is not within the scope of the current research effort to review all these earlier research. The different aspects related to congestion pricing that have been examined (and examples of research studies investigating these aspects) include: (1) implementation and methodological advances of congestion pricing projects (for example see Small and Gomez-Ibanez, 1998, Lindsey, 2003, Bonsall *et al.*, 2007, Maruyama and Sumalee, 2007, Wichiensin *et al.*, 2007, Tsekeris and Voß, 2009), (2) feasibility and acceptability of congestion pricing among road users (for example see Bhattacharjee *et al.*, 1997, Verhoef *et al.*, 1997, Harrington *et al.*, 2001, King *et al.*, 2007), (3) lessons learned from implementation of congestion pricing projects (for example see Goh, 2002, Litman, 2006, Santos and Fraser, 2006, Santos, 2008), (4) equity and welfare cost distribution related to congestion pricing projects (for example see Kitamura *et al.*, 1999, Parry and Bento, 2001, Lindsey and Verhoef, 2001, Santos and Rojey, 2004, Armelius and Hultkrantz, 2006, Schweitzer and Taylor, 2008, Ecola and Light, 2009), (5) changes to travel behavior induced by congestion pricing (for example see Golob, 2001, Bhat and Castelar, 2002, Brownstone and Small, 2005, Loukopolous *et al.*, 2005, Bhat and Sardesai, 2006, and Hensher and Puckett, 2007), and (6) transportation network impacts of congestion pricing (for example, see Yang and Meng, 1998, Kuwahara, 2007, Stewart, 2007).

Among these studies, research efforts that investigate changes in travel behavior as a result of pricing are of particular relevance to the current study. For instance, Del Mistro *et al.*, 2007 examined the triggers for changes in different dimensions of travel choice including residential location, work location, travel mode and departure time. The study involved descriptive analyses of a retrospective survey that posed questions regarding potential triggers for changes in each of several choice dimensions. The study found that changes to work place, change in access to a car, and transportation cost are the primary triggers for changes to travel behavior. Bhat and Castelar (2002) formulated a mixed logit approach to jointly analyze revealed and stated preference data. The choice alternatives included mode and time of day combinations. The authors concluded that congestion pricing during the peak period reduces the likelihood of

using drive alone mode during peak periods, and increases off-peak travel, car pooling and travel by public transportation.

The focus of the aforementioned studies, and several other studies (de Jong *et al.*, 2003, Bhat and Sardesai, 2006, Washbrook *et al.*, 2006, Hensher and Rose, 2007), has been to compare and contrast the various characteristics that influence travel mode choice in an effort to understand how auto-oriented travel behavior can be altered. However, these studies do not explicitly consider route choice decisions. For example, in an urban region with toll highways, an individual may choose the auto mode of travel to work, but use a non-toll route to get to work. The current effort investigates the determinants of such route choice decisions for commuters using the auto mode of travel. In the rest of this section, we confine our review to studies that investigate responses in auto-based travel behavior due to pricing.

2.1 Studies Examining Auto-Based Travel Response to Pricing

Calfee and Winston (1998), in their research, highlight the need to explicitly consider only auto alternatives to estimate how much the automobile commuter is willing to pay for reducing travel time. They employ a stated preference approach to estimate the value of travel time. The authors concluded that the money value of travel time obtained is low. Loukopolous *et al.* (2005) examined possible changes induced in personal vehicle travel in the central business districts due to congestion pricing. The study observed that introducing congestion pricing would reduce auto trips, particularly those undertaken by males and low income individuals. Brownstone *et al.* (2003) analyzed travel lane choice (characterized as free lanes, car pool lanes and toll lanes) during peak periods on Interstate Highway 15 to determine the value of travel time for road users. They report a very high value of travel times of up to 30\$/hour. Small and colleagues have also conducted a host of studies on passenger lane choice (between toll lanes versus free lanes). Small *et al.* (2005) applied a joint framework to analyze stated and revealed preference data to understand the behavior of commuters to choose between toll and non-toll lanes. The study concluded that road pricing should take advantage of the heterogeneous preferences of travelers in designing pricing policies by offering travelers with the option of choosing between the toll and the non-toll option. Brownstone and Small (2005) extended the same framework employed in Small *et al.* (2005) to compare results from two road pricing studies. The study found that the value of time measurement is very close to those estimated in Small *et al.* (2005). Small *et al.* (2006) conducted a study where, in addition to the passenger lane choice, the choice of acquiring

an electronic transponder (that permits car users the option to use toll lanes) and the number of people in their vehicle were modeled.

2.2 The Current Study

The preceding discussion provides an overview of earlier research on the influence of pricing on commuter route (or lane) choice behavior. While these earlier research studies have provided important insights on commuter responses to pricing, they have not adequately examined joint decisions regarding travel route choice and departure time choice. Some other earlier studies have examined the effect of pricing on commuter mode choice (for example, see Bhat and Sardesai, 2006) or departure time choice (see Noland and Polak, 2002), but these studies also have not paid attention to the effect of pricing on combinations of choice decisions. The current study attempts to fill this gap by focusing on the effect of pricing on the joint decision of route and departure time choice for commute trips. In doing so, we focus only on personal auto trips and leave the inclusion of mode choice for future research. Further, data constraints lead us to consider the case of a time-invariant pricing strategy (*i.e.*, tolls). However, note that this does not negate the value of jointly modeling route and departure time choice, since the choice of whether to use a tolled route or not is intricately linked to when the commuter would have to depart home to arrive at work at a certain time (with a certain desired level of reliability). Finally, in the current study, we consider both the morning commute departure time from home as well as the evening commute departure time from work, along with route choice, in a joint analysis framework. This is achieved by formulating and estimating a joint disaggregate model of commute departure time and route choice, using data from the 2008 Chicago Regional Household Travel Inventory (CRHTI).

2.3 Data Considerations

An important aspect of modeling commuter departure time and route choice travel behavior is the availability of data for empirical investigation. In practice, it is difficult to obtain data on route choice. The information on commute travel collected via conventional travel surveys is generally limited to commute tour departure time intervals (both for the home-to-work or HW trip, and the work-to-home or WH trip) and travel mode. In some surveys, such as the 2008 Chicago Regional Household Travel Inventory (CRHTI) survey used in the current study, information on whether the commuter used a toll facility or not is also collected. But, even, in

such cases, the actual route alternatives considered by the commuter and the actual route chosen are not collected. The main reason for not collecting such revealed preference (RP) information is to avoid burdening the survey respondent and to ensure a reasonable survey response rate. Some studies by Brownstone and Small (Brownstone *et al.*, 2003, Brownstone and Small, 2005, Small *et al.*, 2005, and Small *et al.*, 2006) have used RP data, but have focused on a specific highway segment on which both toll and non-toll options are available to undertake a choice analysis for users of the highway segment. However, this approach is rather restrictive and cannot be employed to study response to congestion pricing in urban regions as a whole. The approach is also unable to examine other dimensions of choice such as time-of-day choice. Another alternative data collection strategy to examine pricing effects is based on stated preference (SP) data, where respondents are presented with carefully controlled and designed “priced” and non-priced” alternatives and asked to choose a particular alternative. SP data have their own advantages and limitations vis-à-vis RP data sources. For instance, since SP exercises provide respondents with the attributes of alternative competing routes, and ask respondents to choose their preferred route, the resulting data immediately enables route choice modeling. However, SP data collection methods can suffer from “non-reality” effects, since the choices are being made in a hypothetical context rather than in a real decision-making context.

In this research, we use RP data, but supplement the RP data with route generation procedures (including tolled and non-tolled routes) based on the home and work locations of commuters (as we indicate later, we focus attention only on those commuters who travel directly to work from home without any intermediate stops and who return home in the evening from work without any intermediate stops). Then, since the 2008 Chicago Regional Household Travel Inventory (CRHTI) survey did collect information on whether a toll or a non-toll route was used by the commuter, we are able to combine the route generation exercise with a choice of route to estimate a joint departure time-route choice model for the commute.

CHAPTER 3: ANALYSIS FRAMEWORK

In the current section, we discuss the framework employed to study how commuters respond to toll pricing in the Chicago region. Prior to detailing the actual framework, we outline the assumptions in formulating the study framework. First, in developing the commuter tour departure time interval and route choice model, we consider the typical daily work start and end time as being exogenously determined. Most activity based frameworks model daily work departure time choice subsequent to determining typical work start and end times (see for example Bhat *et al.*, 2004). Second, we limit ourselves to commuters who travel from home-to-work and back without any intermediate stops. This is done to make the route generation effort manageable, given the home and work locations of each commuter. Specifically, in the current study, the generation of travel level of service information for each commuter was manually undertaken based on information from Google Maps. If we consider commuters with intermediate stops during the commute, the level of this manual effort increases quite substantially. At the same time, about half of the commuters in the Chicago region are observed to commute without any stops. Thus, we focus on this fraction of the commuting population, setting aside a more extensive analysis of other commuters for a future study.

As indicated earlier in the report, the choices examined in this research include the commute departure time interval choice (for home-to-work (HW) and work-to-home (WH) segments) and travel route choice. Each of these choice dimensions is discussed in turn in the subsequent sections.

3.1 Departure Time Interval Choice

The departure time choice interval alternatives include a joint combination of time interval of travel for the home-to-work (HW) and the work-to-home (WH) segments. To develop the discrete departure time alternatives, the day is classified into M discrete time periods for the HW segment departure time, and N discrete time periods for the WH segment departure time, resulting in a total of $M*N$ possible departure time alternatives. To determine the feasibility of these $M*N$ possible alternatives for each commuter, we employed information on the typical work day information (includes work flexibility, work start time, work end time, and work

duration) collected from respondents in the Chicago survey. The work flexibility information is collected in three categories: (a) no flexibility, (b) medium flexibility and (c) high flexibility. For individuals without any work flexibility, departure time alternatives for the HW trip that permit the commuter to arrive prior to the typical work start time and departure time alternatives for the WH trip that are after the typical work end time are considered feasible. For individuals with medium work flexibility, commuters are allowed to arrive at work later, up to within 2 intervals of their typical workday schedule. Similarly, these commuters are also allowed to end their work 2 intervals earlier than their typical work schedules. For individuals with high work flexibility, all HW and WH departure time alternatives are available. The feasible alternatives obtained based on the worker flexibility constraints are subsequently subjected to the work duration constraint. Of the feasible combinations based on work flexibility and work start/end times, only alternatives with work duration greater than the typical work duration are considered feasible. For example, consider the case where 9:00 AM – 9:15 AM is a possible HW departure alternative and 2:00 PM – 2:15 PM is a possible WH departure alternative, based on work flexibility and work start/end times. The work duration for this alternative combination is approximately 5 hours. However, if the commuter in consideration has a typical work duration of 8 hours, the alternative described above is infeasible. In this manner, there are bound to be several infeasible combinations (say K) from the possible MN alternatives, resulting in $(MN-K)$ feasible alternatives for the joint departure time choice dimension. The reader would note that the number of infeasible alternatives for each commuter is clearly a function of his/her work flexibility, work duration information, and travel time to work on toll and non-toll routes. This is where the route choice component becomes important, since the feasible alternatives for departure time (and the actual chosen departure time alternative) would be a function of whether a toll route or a non-toll route is chosen.

3.2 Travel Route Choice

The generation of alternatives for examining route choice behavior is not straightforward. In traditional household surveys, the analyst has detailed information only on the origin and destination of each trip, though the Chicago survey includes information on whether a tolled facility was used or not for each trip. So, for examining route choice behavior, the analyst needs to generate possible competing alternatives. Within a transportation network, generating all possible routes (and their attributes) between a commuter's home and work locations is

infeasible. In the current study, we generated two routes for each commuter. These are: (1) the best non-toll route between the commuter's home and work locations and (2) the best toll route between the commuter's home and work locations. To determine the optimal toll and non-toll routes between each home and work location pair, we used Google Maps. For all commuters, the optimal non-toll and toll routes were not substantially different for the HW and WH segments. So, we considered the same toll and non-toll routes for both these segments, and generated two possible routes for the entire commute tour. After the information was compiled, the joint choice set was obtained by combining the travel route choice dimension with departure time choice dimension. The overall joint choice model has $(MN-K)*2$ choice alternatives. The chosen departure time-route alternative is based on the observed departure times and the indication of the commuter whether or not s/he chose a tolled route during the commute.

3.3 Methodology

A simple classical Multinomial Logit (MNL) model is employed to examine the joint choice of commute departure time and route choice. The modeling framework is briefly presented in this section. Let q be the index for commuters ($q = 1, 2, \dots, Q$) and i be the index for the possible combinations of departure time and travel route choice ($i = 1, 2, \dots, (MN-K)*2$). With this notation, the random utility formulation takes the following familiar form:

$$u_{qi}^* = \beta' x_{qi} + \varepsilon_{qi} \quad (1)$$

In the above equation, u_{qi}^* represents the utility obtained by the q^{th} commuter in choosing the i^{th} alternative. x_{qi} is a column vector of attributes including: (1) level of service attributes (such as travel time and travel cost), (2) departure time interval characteristics (such as duration length of the interval), (3) interactions of individual and household socio-demographics (sex of individual, presence of children, *etc.*) with the above two categories, and (4) interactions of employment characteristics with the first two categories. β is a corresponding coefficient column vector of parameters to be estimated, and ε_{qi} is an idiosyncratic error term assumed to be standard type-1 extreme value distributed. Then, in the usual spirit of utility maximization, commuter q will choose the alternative that offers the highest utility. The probability expression for choosing alternative i is given by:

$$P_{qi} = \frac{\exp(\beta' x_{qi})}{\sum_i \exp(\beta' x_{qi})} \quad (2)$$

The log-likelihood function is constructed based on the above probability expression, and maximum likelihood estimation is employed to estimate the β parameter.

CHAPTER 4: DATA COMPILATION

4.1 Data Sources

The data used in this study are drawn from the 2008 Chicago Regional Household Travel Inventory (CRHTI), which was sponsored by the Chicago Metropolitan Agency for Planning (CMAP), the Illinois Department of Transportation (IDOT), the Northwestern Indiana Regional Planning Commission, and the Indiana Department of Transportation. The study area for the survey included eight counties in Illinois (Cook, DuPage, Grundy, Kane, Kendall, Lake, McHenry, and Will counties), and three counties in Indiana (Lake, LaPorte, and Porter). The survey was administered using standard postal mail-based survey methods and computer-aided telephone interview (CATI) technology through Travel Tracker Survey to facilitate the organization and storage of the data. For details of the survey design and implementation methods, the reader is referred to NuStats (2008). The primary objective of the survey was to collect data to aid the development of regional travel demand models for the Chicago region. The survey collected information on the activity and travel information for all household members (regardless of age) during a randomly assigned 1-day or 2-day period (the 1-day period sample focused only on weekdays, while the 2-day period sample targeted two consecutive days including the Sunday/Monday and Friday/Saturday pairs but not the Saturday/Sunday pair). Further, the survey respondents were also requested to provide information on household demographics and individual demographics of each household member, household vehicle ownership, employment characteristics, and geo-coded residence and work locations. The survey also collected information regarding toll road usage and corresponding toll fare for every travel episode.

4.2 Sample Formation and Description

The activity and travel information collected in the survey formed the basis of the empirical analysis. The data assembly process involved the following steps. First, employed individuals were identified and their work travel patterns were screened for detailed analysis. Second, of the employed individuals, workers who used the auto mode for their commute travel were selected. Third, among the auto commuters, individuals who traveled directly to work from home and

vice-versa were identified. Fourth, household and individual attributes, geo-coded residential and work location, and toll road usage and toll fare charges for these selected commuters were appended to the dataset. Fifth, the dataset obtained was checked for consistency and records with missing and/or inaccurate information were deleted. Sixth, the time periods for the HW and WH segment departure time intervals were determined. Figure 1 presents the HW departure time distribution and WH departure time distribution. The HW departure time distribution clearly indicates a peak between 5 AM to 8 AM. The WH departure time distribution identifies a peak between 2 PM and 5 PM. The peak hours of the day with large magnitudes of commuters departing were finely divided. Specifically, for the HW segment, the time period between 5 AM to 8 AM was classified in 15-minute intervals. Similarly, for the WH segment, the period from 2 PM to 5 PM was classified into 15-minute intervals. For the empirical exercise, we identified 24 time intervals each for the HW and WH departure times. These time intervals are listed in Table 1.

The final dataset contained 1760 commuters. The summary statistics of the final dataset are presented in Table 2. The dataset consists of a slightly higher share of male commuters than female commuters. The age distribution of the data sample is along expected lines with a substantially higher share of individuals between 45 to 60 years. The household vehicle ownership levels clearly indicate a large share of 2 vehicle households in the sample. Another variable of interest presented in the descriptive analysis is the number of licensed drivers in the household. There is a significant proportion of households with multiple licenses (82.8%).

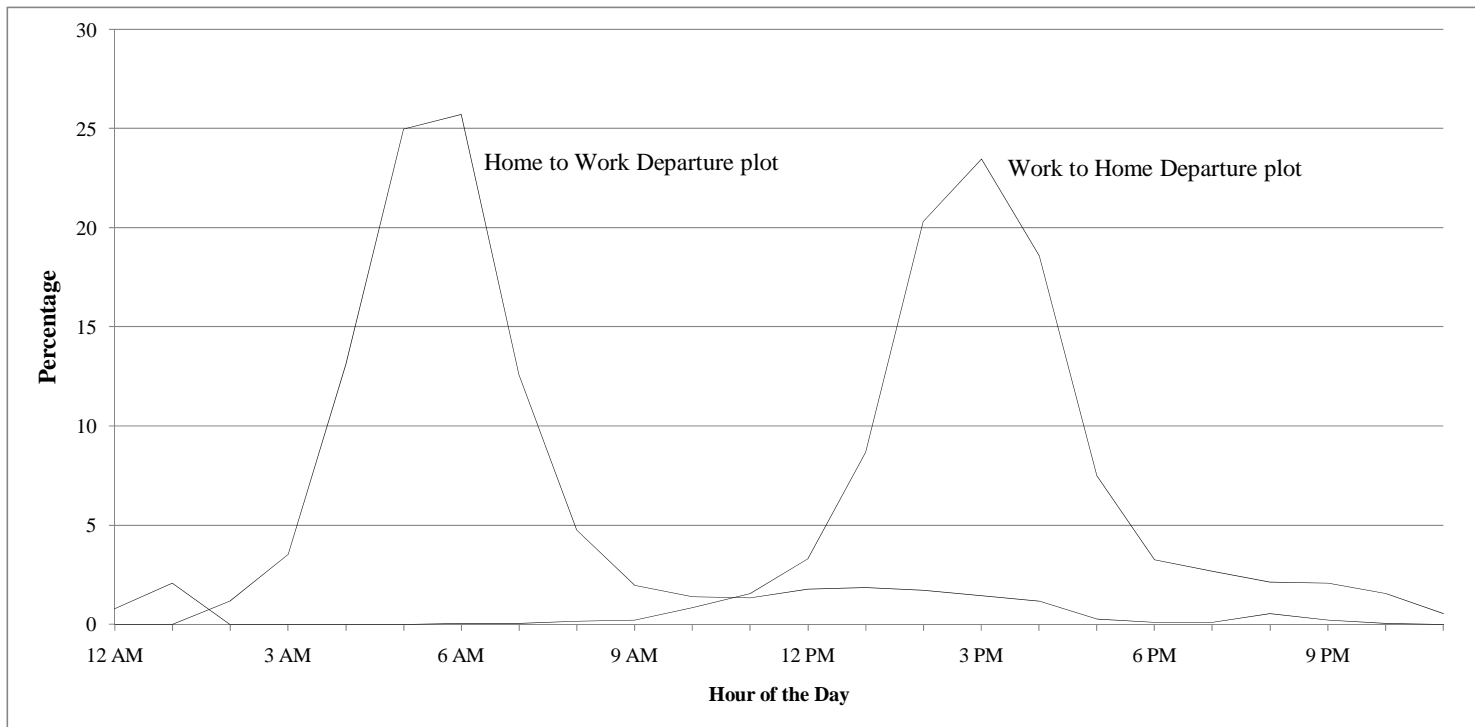


Figure 1. Distribution of WH and HW Commute Departure Times in the Sample

Table 1. Home to Work and Work to Home Departure Intervals

Serial No.	HW Departure Intervals	WH Departure Intervals
1	12:00 AM – 4:00 AM	12:00 AM - 12:00 PM
2	4:00 AM - 4:30 AM	12:00 PM - 1:00 PM
3	4:30 AM - 5:00 AM	1:00 PM - 2:00 PM
4	5:00 AM - 5:15 AM	2:00 PM - 2:15 PM
5	5:15 AM - 5:30 AM	2:15 PM - 2:30 PM
6	5:30 AM - 5:45 AM	2:30 PM - 2:45 PM
7	5:45 AM - 6:00 AM	2:45 PM - 3:00 PM
8	6:00 AM - 6:15 AM	3:00 PM - 3:15 PM
9	6:15 AM - 6:30 AM	3:15 PM - 3:30 PM
10	6:30 AM - 6:45 AM	3:30 PM - 3:45 PM
11	6:45 AM - 7:00 AM	3:45 PM - 4:00 PM
12	7:00 AM - 7:15 AM	4:00 PM - 4:15 PM
13	7:15 AM - 7:30 AM	4:15 PM - 4:30 PM
14	7:30 AM - 7:45 AM	4:30 PM - 4:45 PM
15	7:45 AM - 8:00 AM	4:45 PM - 5:00 PM
16	8:00 AM - 8:30 AM	5:00 PM - 5:30 PM
17	8:30 AM - 9:00 AM	5:30 PM - 6:00 PM
18	9:00 AM - 10:00 AM	6:00 PM - 6:30 PM
19	10:00 AM - 11:00 AM	6:30 PM - 7:00 PM
20	11:00 AM - 12:00 PM	7:00 PM - 8:00 PM
21	12:00 PM - 1:00 PM	8:00 PM - 9:00 PM
22	1:00 PM - 3:00 PM	9:00 PM - 10:00 PM
23	3:00 PM - 6:00 PM	10:00 PM - 11:00 PM
24	After 6:00 PM	After 11:00 PM

Table 2. Sample Characteristics

Variable	Sample shares
Gender	
Female	44.7
Male	55.3
Age categories	
16-30 years	15.6
30-45 years	30.9
45-60 years	42.8
> 60 years	10.7
Number of Vehicles in the household	
1 vehicle	18.2
2 vehicles	52.4
3 vehicles	20.6
4 or more vehicles	8.8
Number of licensed individuals in the household	
One	17.2
Two	58.9
Three or more	23.9

4.3 Level of Service Attributes Compilation

As previously discussed, any revealed preference dataset contains information only on the chosen alternatives *i.e.* for commuter opting for the “no toll” route the “toll” route information is unavailable and vice-versa. The examination of the choice behavior necessitates generation of information regarding other alternatives in the choice set. To do so, we need to obtain, for every commuter, the travel time and travel cost for the optimal “no toll” and “toll” routes. For this purpose, we used Google Maps web application to identify the two optimal routes and obtained detailed level of service information (<http://maps.google.com>). Google Maps allows us to generate potential travel routes by providing as input the geo-coded home and work locations (latitude and longitude). In fact, the website provides up to three alternate routes for each origin and destination. Under the default settings, Google Maps provides us the shortest route to the destination by time. The application allows us to opt for “no toll” routes via the “avoid toll”

option that allows the identification of the shortest “no toll” option. For some commuters in the dataset, it is possible that a “toll” route might not exist.

The level of service information provided by Google maps includes travel time information during uncongested and congested time periods.¹ In the current study, this information was used to obtain travel times for peak and off-peak periods.² However, the website does not provide the toll cost for the “toll” routes. For this purpose, we used the Chicago Toll Calculator (<http://www.getipass.com/tollcalc/TollCalcMain.jsp>). The Toll Calculator tool allows the computation of the toll cost by the entry and exit points by vehicle type on all major toll routes in the Chicago region. So, in this study effort, we manually identified the toll route entry and exit points from the Google maps travel route and computed the toll cost from the Calculator tool. The level of service information generated in this form was appropriately appended to the commuter’s characteristics. Specifically, the level of service information collected via Google Maps and Chicago Toll calculator is collated to obtain the total travel time and travel cost for each HW, WH and travel route (“toll” versus “no toll”) combination. In this process, and based on the time periods of the HW and WH segments, appropriate peak or non-peak travel times were included in the travel time computation. The toll cost for each of the alternative combinations does not vary for peak and off-peak periods because the Chicago city employs a time invariant toll pricing scheme.

¹ Google Maps does not explicitly provide information on the time of day for the congested travel. In this study, we assume that the congested travel occurs during the peak periods.

² For this study, the 6 am to 9 am and 3 pm to 6 pm periods were considered peak travel periods.

CHAPTER 5: EMPIRICAL ANALYSIS

5.1 Variables Considered

Several variables including level of service measures (travel time and travel cost for toll and operational cost), HW and WH departure interval duration, and interactions of individual attributes (age, gender), household socio-demographics (household income, household vehicle availability computed as number of vehicles per licensed driver), and commuter employment characteristics (work schedule flexibility) with level of service attributes and departure time interval attributes were considered. The estimation effort involved the selection of variables and their interactions based on prior research, removing statistically insignificant variables, and combining variable effects when they were not statistically different from each other. Further, for the continuous variables in the data (such as age), we tested different alternative functional forms that included a linear form, a spline (or piece-wise linear) form, and dummy variables for different ranges.

5.2 Model Estimation Results

Table 3 provides the results of the MNL model. In the current research effort, the coefficient on operational cost was statistically insignificant. We examined various interactions and different plausible functional forms for the operation cost variable in the specification, but it consistently turned out to be statistically insignificant. So, the travel cost variable used in the final specification corresponds only to the toll fare.

The results of the joint departure time and travel route choice model are discussed in the subsequent sections.

Table 3. Estimates of the Joint Departure Time and Travel Route Choice Model

Variables	Coefficient	t-stats
Level of service attributes		
Travel cost (toll lanes)	-0.2355	-0.674
Individual characteristics * Level of service attributes		
Female * Travel cost	-0.2863	-1.654
Age >60 * Travel cost	-2.0747	-2.943
Employment characteristics * Level of service attributes		
High Flexibility * Travel cost	-0.8674	-2.351
Household characteristics * Level of service attributes		
Household vehicle availability * Travel cost	-0.3789	-1.54
Household vehicle availability * Travel time	-0.0116	-2.029
Household income 60,000 – 100,000 * Travel cost	0.3389	1.230
Household income > 100,000 * Travel cost	0.6322	2.556
Departure time alternative characteristics		
HW alternative duration	0.0022	2.005
WH alternative duration	0.0002	0.186
HW alternatives between 5 AM – 8 AM	0.7351	8.456
Alternative Work Duration – Actual work duration	-1.0402	-5.133
Individual characteristics * Departure time alternative characteristics		
HW alternative duration * Age < 30	0.0060	2.507
HW alternative duration * Age > 60	-0.0025	-0.749
WH alternative duration * Age 45 - 60	0.0033	1.732
WH alternative duration * Age > 60	0.0147	2.277

5.2.1 Level of Service Attributes and their Interactions

The level of service attributes (travel time and toll cost) and their interactions with individual, household demographics and employment characteristics significantly influence the probability of choosing an alternative. The impact of travel cost (captured as toll fare) on the joint choice process is captured directly as well as in the form of interactions with other variables. The results indicate the negative impact of toll fares on departure and route choice (similar to most earlier research on toll lane choice; see Brownstone *et al.*, 2003, Brownstone and Small, 2005, Small *et al.*, 2005, and Small *et al.*, 2006). The negative impact is particularly high for women, individuals above the age of 60 years, those with high work flexibility and high accessibility to

vehicles, and individuals in low income households (note that the household vehicle availability variable is computed as the ratio of the number of household vehicles to the number of licensed drivers in the commuter's household; this variable provides an indication of how accessible a vehicle is to the commuter). That is, women, older commuters, individuals with high work flexibility and high vehicle access, and low income individuals are less likely to use the toll road alternative relative to their peers.

The travel time effect indicates that commuters with higher access to vehicles are more sensitive to travel time.

5.2.2 Departure Time Alternative Characteristics

The departure time interval alternative characteristics, as expected, affect commuter travel behavior. As expected, the likelihood of choosing the HW and WH interval alternatives is directly proportional to the interval duration (see Guo *et al.*, 2005 for a similar result in work start and end time modeling). Further, the results indicate a strong general propensity to choose a HW departure between time periods 5 AM to 8 AM. The result clearly highlights commuters' preference towards starting work early in the day. These findings are consistent with commuting facts reported by Commuting in America report (CIA III, 2006). Another result of significant interest from this group of variables is the influence of the difference in commuter work duration for the chosen alternative and the commuter's typical work duration. The result indicates that commuters opt for HW and WH departure times such that the resulting work duration is not substantially different from their typical work duration.

Within the departure time interval alternative characteristics, only the interactions with individual characteristics affect commuter choice behavior. In particular, the interactions of departure time interval with age of the commuter are statistically significant. Specifically, commuters aged less than 30 years are positively influenced by HW departure interval duration compared to commuters aged between 30 and 60 years. However, commuters aged more than 60 years exhibit lower proclivity to be affected by HW departure interval duration. Interactions of a similar nature for the WH departure intervals yield slightly different results. These findings indicate that commuters aged more than 45 years are positively influenced by alternative interval duration with the effect being even more pronounced for older commuters (age >60).

5.3 Model Application

5.3.1 Value of Travel Time

An important product of the examination of the joint departure time and travel route choice is the value of travel time savings to commuters (see Hensher, 2001, Bhat and Sardesai, 2006 for examples of travel time value computations in transportation research). However, in the model framework we developed, only toll fares turned out to be statistically significant (and even that only for some segments).

The computation of the implied money value of travel time requires the consideration of all travel time and travel cost interactions with other variables. The resulting values vary substantially based on the demographics of the commuter. The base commuter for the joint model has the following attributes: (1) male, (2) age < 60 years, (3) work schedule is not highly flexible, and (4) household income is less than 60,000. The base commuter's value of travel time is also influenced by household vehicle availability. So, for different vehicle availability values the commuter's value of travel time varies. The formulation of money value of travel time (v in dollars/hr) for the base commuter as a function of vehicle availability is given by

$$v = \frac{\beta_{ttva} * vehavail}{\beta_{tc} + \beta_{tcva} * vehavail} * 60 \quad (3)$$

where β_{ttva} is the coefficient representing the interaction of travel time in minutes and vehicle availability (-0.0116), β_{tc} is the coefficient on travel cost (-0.2355) and β_{tcva} is the coefficient corresponding to the interaction of travel cost and vehicle availability (-0.3789). The value of travel time measure (dollars/hour) computed for the base commuter is reported in Table 4a, where we provide the values for different combinations of household vehicles and number of licensed drivers instead of reporting the values for different vehicle availability values. This method of reporting is more intuitive and presents interesting trends in the value of travel time measures. The table indicates an increasing money value of travel time from the top right corner to the bottom left corner, indicating that commuters from households with fewer constraints on vehicle availability are willing to pay higher toll fares for travel time savings. Further, the value of travel time measures range from 0.53 \$/hr to 1.63 \$/hr. The current research effort is unique because we compute the money value of travel time for toll prices directly as opposed to computing money value of travel time as a whole (including operational cost). The comparison of this money value of time measure with earlier research efforts is not meaningful because earlier studies have considered total travel cost (operational + toll) in their analysis.

In addition to the base commuter group, we also compute value of travel time measures for three other demographic groups including: a) female commuter with other characteristics being same as the base commuter, b) commuter with high flexibility with other characteristics being same as the base commuter and c) commuter with high flexibility and household income > 100,000 with other characteristics being same as the base commuter. To compute value of travel time measures for these demographic groups Equation (3) is slightly modified as follows: β_{tc} is replaced with the coefficient on cost for the demographic group under consideration. For example, for female commuters β_{tc} is replaced with -0.5218 (-0.2355-0.2863).

The values of travel time measures for the three demographic groups just identified are presented in Tables 4b through 4d. The overall trend in the numerical values is similar to the trends observed in the base commuter results, with an increase in the money value of travel time down the diagonal from the top right corner to the bottom left corner. The value of travel time measures range from (1) 0.23 \$/hr to 1.44 \$/hr for female commuters, (2) 0.15 \$/hr to 1.16 \$/hr for commuters with high flexibility and (3) 0.31 \$/hr to 1.47 \$/hr for commuters with high work flexibility and household income greater than 100,000. The comparison across the results (in Tables 4a through 4b) indicates that commuters with high flexibility have the lowest value of travel time, while the base commuter demographic exhibits the highest value of travel time.

Tables 4a-4d. Value of Travel Time Measures

Table 4a. Base commuter

No. of vehicles	No. of licenses			
	1	2	3	4
1	1.133	0.819	0.641	0.527
2	1.401	1.133	0.951	0.819
3	1.522	1.299	1.133	1.004
4	1.590	1.401	1.253	1.133
5	1.634	1.471	1.338	1.227

Table 4b. Female commuter

No. of vehicles	No. of licenses			
	1	2	3	4
1	0.773	0.489	0.358	0.282
2	1.088	0.773	0.599	0.489
3	1.259	0.958	0.773	0.648
4	1.366	1.088	0.904	0.773
5	1.440	1.184	1.006	0.874

Table 4c. Commuter with high flexibility

No. of vehicles	No. of licenses			
	1	2	3	4
1	0.470	0.269	0.189	0.145
2	0.748	0.470	0.342	0.269
3	0.932	0.625	0.470	0.376
4	1.063	0.748	0.577	0.470
5	1.161	0.849	0.669	0.552

Table 4d. Commuter with high flexibility and household income greater than 100,000

No. of vehicles	No. of licenses			
	1	2	3	4
1	0.819	0.527	0.389	0.308
2	1.133	0.819	0.642	0.527
3	1.299	1.005	0.819	0.692
4	1.402	1.133	0.951	0.819
5	1.471	1.227	1.052	0.921

CHAPTER 6: CONCLUSION

In the United States, a significant number of individuals depend on the auto mode of transportation, in part due to high auto-ownership affordability, inadequate public transportation facilities (in many cities), and excess suburban land-use developments. The high auto dependency, in turn, has resulted in high auto travel demand on highways leading to increased traffic congestion levels and air pollution levels in metropolitan areas of United States. Further, with the recent emphasis on Global Climate Change, there is increasing interest within the transportation community and growing political support to reduce GHG emissions in the U.S. The rising traffic congestion levels, surging oil prices, the limited ability to address increased auto travel demand through building additional transportation infrastructure, and the emphasis on reducing GHG emissions has led to the serious consideration and implementation of travel demand management (TDM) strategies in the past decade. Within the context of TDM strategies, congestion pricing is a frequently considered option to alleviate travel congestion in urban metropolitan regions. The current research contributes to the existing literature on congestion pricing by analyzing the influence of pricing on travel behavior. Specifically, congestion pricing might induce changes in activity location, travel route, departure time of day, and travel mode. Commuter response to pricing might involve (1) shifting their departure time interval for both the home-to-work (HW) and the work-to-home (WH) segments, (2) altering their travel route and (3) shifting from auto mode to other modes of transportation. In this effort, we investigate the travel route and time of day choice for commuters who use the auto mode to travel to work. The data used in this study are drawn from the 2008 Chicago Regional Household Travel Inventory.

The current study examines the commuter departure time interval and travel route choice in a unified framework. Specifically, the departure time choice alternatives include a joint combination of time interval of travel for the home-to-work (HW) and the work-to-home (WH) segments. The travel route alternatives include “toll” and “no toll” routes. The route choice alternatives are not readily available in the travel data set. So, we manually compiled travel route characteristics using Google Maps (<http://maps.google.com>) for travel time information and the Chicago Toll Calculator for toll fare information

(<http://www.getipass.com/tollcalc/TollCalcMain.jsp>). The classic multinomial logit model is employed for the empirical analysis.

The empirical analysis considered several variables to explain departure time and route choice, including level of service measures (travel time and travel cost measured as toll cost and operational cost), HW and WH departure interval duration, and interactions of individual attributes, (age, gender), household socio-demographics (household income, household vehicle availability computed as number of vehicles per licensed driver), and commuter employment characteristics (work schedule flexibility) with level of service attributes and departure time attributes. The results from this exercise provide several insights into commuter behavior. First, the model results highlight the significance of individual and household demographics on commute departure choice and travel route choice. Second, individuals, as expected, exhibit an overall disinclination towards using toll routes for commute unless the toll routes provide a reasonable travel time savings. Third, female commuters and commuters with high work flexibility are least likely to choose toll routes for their commute. Finally, the results highlight the importance of household vehicle availability on commuter route choice. These model estimation results were employed to compute the implied money value of travel time for different demographic segments (males, females, high work flexibility *etc.*) and for different vehicle availability combinations. The value of time measures point out that commuters with restricted access to vehicles are less sensitive to travel time compared to commuters with higher access to vehicles. Further, the value of travel time measurements from the current research effort allow us to determine the optimal toll pricing schemes for different demographics. The model framework and the estimation results may be used in environmental justice studies and to determine toll fares in urban regions.

The empirical approach developed in this report is not without limitations. In the current approach, the travel route alternatives were represented by a binary choice of a toll versus non-toll classification. Modeling travel route choice at a finer resolution might enable us to better characterize the effects of level of service measures on commute behavior. Another important aspect to be explored in further research is the consideration of commuters who make stops on their route to or from work.

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