CONTINUOUS DEPARTURE-TIME CHOICE MODELS FOR HOME-TO-WORK COMMUTE

By

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To my parents

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This study contributes to the literature by developing continuous-time models for the home-to-work commute timing decisions of full-time workers with flexible and non-flexible work schedules using the hazard-duration structure. Further, the estimated departure time choice models include the effect of travel time at a fine temporal resolution of 15 minutes. In order to generate the travel time data at this resolution, a second set of regression models is developed. The models were estimated using data from the 2000 San Francisco Bay Area Travel Survey. The regression models for inter-zonal travel times produce smoothly time-varying travel duration profiles that capture the effects of temporal and spatial congestion appropriately. Both the hazard duration models indicated a statistically significant effect of commute speed/travel duration on the choice of departure time. Specifically, individuals are less likely to depart home at times when the commute speed is lower (or travel duration is higher). In addition, the model also captures the impact of several other explanatory factors such as individual and household socio-demographic characteristics, employment related characteristics and land use characteristics of the home and work zones on the choice of departure time to work.

CHAPTER 1
INTRODUCTION

1.1 Background

Workers constitute a substantial fraction of the population and their commute to and from work constituted 16% of all travel undertaken. The average national commute travel times grew about 40 seconds from 21.7 minutes in 1980 to 22.4 minutes in 1990, with more than 22 million single occupant drivers added. This was followed by a gain of three minutes to 25.5 minutes from 1990 to 2000, with an increase of another 13 million SOV users (Pisarksi, 2006). In addition, Pisarksi (2006) also reports a shift in commute trips away from the "peak" period. Specifically, the 6-9 AM period in 2000 constituted only 64% of all work travel in contrast to 67% of all work travel in 1990. These large volumes of commute travel along with their changing temporal patterns underscore the need to model the commute patterns of workers towards developing effective strategies for congestion alleviation. The objective of this study is to broadly contribute towards this end by modeling the home-to-work commute timing decisions (i.e., choice of departure time) of workers.

1.2 Motivations

In the context of modeling the departure time choices for home-to-work commute travel, two issues are important. First, the models should recognize the continuous nature of the departure time choices. This is because evaluation of policy actions such as dynamic pricing schemes and provision of real-time information require estimates of travel-demand patterns at a fine temporal resolution. Further, continuous-time models do not require apriori discretization of the day into periods and hence can be more flexible in capturing the temporal shifts in the commute patterns into the future. Also, modeling the effect of vehicular emissions on the air quality can also benefit from continuous models for the choice of commute departure time. Since the commute is typically the first trip made during the day, the departure times for commute travel provide information on the soak times (defined as duration of time in which the vehicle's engine is not operating and that precedes a successful vehicle start) in an area which can potentially be used as inputs to air-quality models (see for example, Nair et al. 2001). Second, disaggregate models that capture the impacts of changing life styles and emerging population trends on commuting should be developed. For instance, Pisarksi (2006) indicates that increasing vehicle ownership levels especially in African-American households, increasing fraction of women as a part of work force, alternate work arrangements such as compressed work week and telecommuting, increasing car-pool shares, increasing trip chaining activity (stop making during commute), changing commuter flow patterns such as the shift from CBD to suburban for work, peak spreading phenomenon, etc can all impact the choice of departure time to work. Consequently, it is necessary to develop disaggregate, continuous-time models that control for these trends for accurate forecasting.

1.3 Focus of Research

In the above section the importance of developing disaggregate, continuous-time models for the choice of commute departure times was highlighted. The objective of this study is to contribute to the literature in this area. Specifically, we develop continuous-time models for the home-to-work commute (morning commute) timing decisions using the hazard-duration structure. These models include the effect of travel time at a fine temporal resolution of 15 minutes. In order to generate the travel time data at this resolution, a second set of regression models are developed. Further, this study also contributes to the understanding of the systematic differences in the commute timing decisions across population groups. Specifically, the empirical models incorporates several explanatory factors such as individual and household socio-economic characteristics, employment characteristics, commute characteristics and land-use patterns to capture heterogeneity in the departure time preferences. Separate models are developed for flexible and fixed-schedule (full-time) workers. Finally, a demonstration exercise is also presented for a better understanding and also to highlight the ease of application of these models in practice.

1.4 Structure of the Thesis

The rest of this thesis is organized as follows. Chapter 2 gives a brief overview of the literature on departure time choice modeling for work trips. Chapter 3 discusses the development of the Inter-zonal travel time models which will serve as inputs to the commute-timing models. This is followed by the description of departure time models of workers with flexible work schedules in Chapter 4. Chapter 5 discusses the commute-timing models in the context of workers with fixed work schedules. Later Chapter 6 summarizes the study, identifies the major conclusions, and highlights areas where this work can be extended and further developed.

CHAPTER 2
LITERATURE REVIEW

In recognition of the overall importance of modeling commute timing decisions, there have been an increasing number of studies in this area especially in the recent past. In the next several sections, we present a synthesis of literature on empirical modeling studies focused on commute departure choices using cross-sectional travel-survey data. For literature on the time-of-day choices for non-commute travel, see for example, Bhat and Steed (2002), Steed and Bhat (2000), Hunt and Patterson (1996) .For research on the day-to-day variability in the commute-timing decisions, the reader is referred to Mahmassani and Chang (1986), Mannering (1989), Hamed and Mannering (1989), and Saleh and Farrell (2005).

Section 2.1 presents the synthesis of the literature from a methodological standpoint. Later, Section 2.2 presents the empirical findings documented in the literature on departure time choice of individuals. This is followed by a summary Section 2.3 that identifies the shortcomings in the literature that this study intends to address.

2.1 Methodological Issues

Table 2-1 lists several studies that have developed empirical models for home-to-work commute timing decisions. All these are disaggregate models and capture the effects of several factors such as individual and household socio-economic characteristics, employment characteristics, residential and work location characteristics, and the transportation system characteristics. Four important dimensions of these studies are identified in this table and discussed below:

- The model structure used
- The temporal resolution of the choice alternatives
- The source and temporal resolution of the inter-zonal travel-time data, and
- Incorporation of schedule delay in the specifications.

Table 2-2 lists several evening commute and non-work studies that have relevantly contributed to the methodology of the departure time choice in our context. From the Table 2-1 and Table 2-2 several broad observations can be made.

2.1.1 Model Structure Employed

On examining the model structure employed, we find that almost all studies have used the unordered discrete-choice methods (such as the multinomial and nested-logit models). These approaches do not capture the inherently "ordered" nature of time and hence could lead to undesirable patterns (such as the equal proportional draws) in the departure-time shifts due to transportation system changes. Gadda and Kockelman (2007), however, develop continuous time models using the accelerated failure time specification. Several studies modeled departure time using further advanced econometric frameworks such as hazard duration structure (see Bhat and Steed 2002) or OGEV models (see Steed and Bhat 2000) but in the context of non-work trips. For a comprehensive synthesis on the various other approaches to departure time the reader is referred to Xia and Chiao (2008).

2.1.2 Temporal Resolution of the Choice Alternative

The second issue of interest is the temporal resolution of the choice alternatives. Models developed by Purvis (1999) and Pendyala (2002) include few aggregate time periods as alternatives, but the alternatives collectively span the entire day. On the other hand, models developed by Abkowitz (1981), Small (1982), Hendrickson and Planck (1984) and Chin (1990) incorporate a finer temporal resolution of the alternatives (5-15 minutes) but focus only on specific parts of the day. Thus, all these models have relatively less number of choice alternatives and hence could be estimated easily using the MNL structure. However, when the discrete departure time periods have fine temporal resolutions and, together, have to span the entire day, then the number of choice alternatives increase. This can be problematic to address within the MNL framework as it would involve the estimation of a large number of parameters. To address this, functional approximations to alternative-specific parameters have been employed (Hess et al. 2005; Vovsha and Bradley 2004, Cambridge Systematics 2004a; and Guo et al. 2005).

2.1.3 Temporal Resolution of the Inter-zonal Travel Time Data

The third issue that needs to be addressed with increasing temporal resolution is the availability of inter-zonal travel time data at a fine temporal resolution. Some studies including the continuous-time models of Gadda and Kockelman (2007) did not include time-varying transportation system characteristics. Many of the past studies have used peak and off-peak skims from equilibrium assignments. Thus, the travel times are available only at an aggregate-level even though departure time choice alternatives themselves are at a finer resolution. Other researchers have used methods such as interpolation between the peak and off-peak skims and explicit field data collection for developing the travel-time measures at the required time-of-day resolution. The most rigorous methodology to date involves the development of regression models of travel time as a function of time-of-day using data from household travel surveys (Cambridge Systematics, 2004b).

2.1.4 Incorporating the Concept of Schedule Delay

One of the objectives of this current research is to also model fixed-schedule workers, and therefore incorporation of schedule-delay assumes critical importance. It is useful to note here that the past empirical models that account for schedule delay (using primarily the multinomial-logit structure) have had explicit data on the desired work start times (see for instance, Coslett et al. 1977; Abkowitz 1981; Small 1982, and Hendrickson and Planck, 1984). However, such data are not commonly available from conventional household travel surveys (such as the one used in this study) that are most widely used for developing models for transportation planning purposes.

Therefore, Ben-Akiva and Abou-Zeid (2007) have recommended a theoretical modeling approach assuming latent work-start-time preferences. One alternative approach was to use market segment specific utility functions of time-of-travel. The second one is to use a probability density function of the latent desired time-of-travel. Although there are few studies which incorporate the concept of schedule delay by using a stated preference dataset (Hunt and Patterson 1996; Hess et al. 2004).

2.2 Empirical Findings

Our primary focus is the departure time of morning home-to-work commute journeys. This section describes in detail the factors that influence the departure time choice of morning commute. It is important to note that these studies have used different “universal” sets of time-of-day choice alternatives. Also, difference exists in terms of modeling the journey to work as trips and as joint home-to-work and work-to-home tour while making the departure time choice decision. Moreover, differences in terms of modeling the departure time to work from home or modeling arrival time at work, dataset used (Revealed preference data or Stated preference data) should also be noted. Due to these differences, it is not easy to generalize the impacts of the explanatory variables on the departure time choice of commuters.

Table 2-3 presents a summary of the empirical factors included as explanatory variables in the literature of departure time choice of morning commute. These factors may be broadly classified into the following categories: (1) Individual Socio-Economic Characteristics, (2) Household Socio-Economic Characteristics, (3) Employment Characteristics, (4) Transportation System Characteristics, and (5) Commute Characteristics. In the next several paragraphs, the impacts of each category of factors are discussed in detail.

2.2.1 Individual Socio-Economic Characteristics

Among the individual socio economic characteristics, age impacted departure time choice. Specifically, older workers (greater than 50) were found more inclined to depart so as to arrive earlier than the official work start time (Abkowitz 1982, Mannering 1988, and Bhat 2005). Female with kids was often involved in drop-off activities at school and hence chose early departures (Abkowitz 1982, Saleh and Farrell 2005). But on the contrary, Chin (1990) reported that employees with longer commute were generally male and hence chose early departures so as to get to work on time. According to Vovsha (2004) relative to children age 6-15, children of age 16+ tend to leave home earlier. Very few studies explored the impact of ethnicity; it was found (Bhat 2005) that more Afro – Americans chose early departure to work. High income workers showed a tendency to choose early departures (Pendyala 2002). Students preferred later departures, which might be reflective of the fact that most jobs taken up by students are part time jobs which are normally scheduled in the later periods of the day.

2.2.2 Household Socio-Economic Characteristics

The next set of factors is the household level socio-economic characteristics. The presence of kids or higher household size favored earlier departures (Pendyala 2002, Mannering 1988). It was expected that because of fewer family demands single workers are more flexible in their preference with regard to early arrival. But this could not be statistically established (Small 1982). Purvis (1999) and Cambridge Systematics (2004) implied that commuters from higher income households chose to travel in the peak period (8 AM). Vovsha and Bradley (2004) indicated that tours made by high-income households (to CBD) were more likely to be of longer duration and are also less likely to depart extremely early.

2.2.3 Employment Characteristics

On examining the employment related characteristics it was found that longer work durations favored early departures (Bhat 2005) and part time workers chose later time periods to commute to work (night or evening shifts). The effect of part time or full time was more predominant for students (interaction variables) as mentioned above. Similar effect was observed for work flexibility, availability of a flexible work schedule was considered important for people planning to arrive exactly on time and extremely important for those planning a late work arrival (Abkowitz 1982). Later departures were preferred by commuters who have flexible work schedules (Hess et al. 2004, Cambridge Systematics 2004, Guo et al. 2005). Occupation or the type of job played an important role too, individuals employed in a professional, technical, management, or administration capacity typically avoid departure such that arrival at work will be early (Abkowitz 1982). Small (1982) also confirmed the affect that white collared employees were less averse to late arrival.

2.2.4 Transportation System Characteristics

The effect of level of service variables was observed next. Longer travel times and travel cost in peak periods hindered commuters to depart in such periods. Small (1982) found that urban commuters were willing to alter their schedules in order to save travel time to work. Chin (1990) further reinforced this issue by concluding that commuters would not mind an early departure to work in order to avoid congestion. Similar results were obtained in other studies as well.

2.2.5 Commute Characteristics

Commute characteristics like mode also influenced the departure time choice to work. Auto travelers were found more likely to plan on arriving at work exactly on time, while bus travelers were not likely to depart so as to arrive extremely early for work. Small (1982) confirmed through his specifications that the need to match their schedules with other riders could make the car pool commuters to arrive early at work. Moreover, Hendrickson and Planck (1984) concluded that departure time decisions were found to be more flexible than mode choice decisions which have large implications on policy measures.

2.3 Summary of the Literature

The synthesis of literature presented in this chapter highlights that commute-timing decisions have been predominantly modeled using the MNL structure. However, the increasing need for finer temporal resolution has raised the issues of identification, interpretation, and computational effort involved in estimating the numerous parameters that go into the utility equations. To address this problem within the MNL framework, functional approximations have been suggested to reduce the number of alternative-specific parameters. An alternate approach for modeling commute-timing at a fine temporal resolution is to use continuous-choice methods such as the hazard-duration structure. However, such methods have not yet been adequately explored in the context of time-of-day decisions for commute. Hence, we contribute to the literature by developing continuous-time hazard-duration models for commute departure-time decisions.

The second issue that needs to be addressed with increasing temporal resolution is the availability of inter-zonal travel time data as a continuous function of time-of-day. In the past, researchers have employed methods such as explicit field data collection, interpolation between the peak and off-peak skims, and regression models based on travel surveys to develop the required time-of-day specific travel time measures. In this study, we develop and estimate inter-zonal travel time models which produce travel durations as a function of time-of-day using travel-survey data. These are further used as inputs to the commute-timing models.

Further, this study also contributes to the understanding of systematic differences in the commute-timing decisions across population groups. Specifically, the empirical models developed incorporates several explanatory factors such as individual and household socio-economic characteristics, employment characteristics, commute characteristics and land-use patterns to capture heterogeneity in the departure time preferences and also in the response to changes in transportation system characteristics. Finally, this study presents the empirical analysis of modeling the departure time choice incorporating the concept of schedule delay in the absence of preferred work start times in the dataset.

Table 2-1. Overview of morning commute-timing models

Sl.no	Key	Citation	Dataset (Sample size)	Model Type	Choice Alternatives		Inter-zonal Travel Time		Schedule Delay incorporation
					Arrival / Departure	Temporal Resolution	Temporal Resolution	Data Source	
1	Man	Mannering and Hamed (1988)	1987 Survey conducted in Seattle (117 commuters)	Poisson regression	Morning departure to work from home	NA	NA	User provides information on travel time on the most frequently used/alternate route	None
2	Pu	Purvis C (1999)	1990 San Francisco Bay Area Household Travel Survey	BL	Departure time for home-work trips	AM peak (6:30 - 8:30) or not	Same as choice alternatives	Network skims	None
3	Ro	Pendyala (2002)	Tampa Bay Household Travel Survey (3208 HW trips)	MNL	Mid point time of home-to-work trips	Morning peak (7:15 - 9:15), mid-day (9:15 to 3:15), afternoon peak (3:15 - 6:15), and off peak (6:15 PM to 7:15 AM)	None	None	None
4	Ab	Abkowitz, M D. (1981)	1972, San Francisco Bay area survey (425 commuters)	MNL	Arrival time at work	Twelve 5 min intervals (42.5 min before to 17.5 min after work start time)	Same as choice alternatives	Linear interpolation between peak and off-peak skims	Linearly 40 min early to 15 min late from official work start time
5	Sm	Small, K A. (1982)	1972, San Francisco Bay area survey (527 commuters)	MNL	Arrival time at work	Twelve 5 min intervals (42.5 min before to 17.5 min after work start time)	Same as choice alternatives	Floating car observations on major expressways	Linearly SDE and SDL and its interactions on family type, occupation, flexibility
6	HP	Hendrickson, Chris, and Edward Plank. (1984)	Pittsburg, Pennsylvania (1800 commuters)	MNL	Departure time for home-work trips	Seven 10-minute discrete periods (from 6:40 to 7:40) with four modes	Same as choice alternatives	Quadratic travel time function estimated using several vehicle trips to the CBD	Quadratic terms for later and early arrival

Table 2-1. Continued

Sl.no	Key	Citation	Dataset (Sample size)	Model Type	Choice Alternatives		Inter-zonal Travel Time		Schedule Delay incorporation
					Arrival / Departure	Temporal Resolution	Temporal Resolution	Data Source	
7	SF	Saleh and Farrell (2005)	2002 SP Survey conducted in Edinburgh (658 observation)	MNL	Morning departure to work from home	No change, depart earlier than usual, depart later than usual	NA	Travel time savings given in the stated preference experiment	Single linear SD term
8	Ch	Chin, Anthony T. H.	1983 household survey in Singapore (956 commuters)	Nested Logit	Departure time for home-work trips	Eleven 15 min intervals from 6 am to 8.45 am classified into "very early", early", and "morning" nests	Peak and off-peak	Network skims	Single linear SD interacted with gender, occupation, income, CBD dummy
9	HPB	Hess, S., Polak, J.W., Bierlaire, M. (2005)	2000, Dutch National System (1000 travelers)	MNL with functional approximations to alternative specific constants	Departure time for home-work trips	24 one hour time periods (full day)	Unknown	Unknown	None
10	VB	Vovsha, P., and Bradley, M. (2004)	1999, Mid-Ohio region household travel survey (6005 work tours)	MNL with "continuous shift" specification of the utilities	Departure-from-home and arrival-back-home time for each tour	19 one-hour periods (5 AM - 11 PM) with a total of 190 departure/arrival combinations)	4 discrete periods (am peak, midday, pm peak and night)	Network skims	None
11	CS	Cambridge Systematics, Inc (2004)	2000, San Francisco Bay area survey (21675 person-days)	MNL with functional approximations to coefficients on alternative specific variables	Departure time for work tours	35 time periods (33 half hour and 2 extreme long duration intervals) with a total of 630 departure /arrival combinations)	Same as choice alternatives	Travel time regression by time of day using household travel survey	None

Table 2-1. Continued

Sl.no	Key	Citation	Dataset (Sample size)	Model Type	Choice Alternatives		Inter-zonal Travel Time		Schedule Delay incorporation
					Arrival / Departure	Temporal Resolution	Temporal Resolution	Data Source	
12	BhCS	Guo, J.Y., S. Srinivasan, N. Eluru, A. Pinjari, R. Copperman, and C.R. Bhat (2005)	1996 Dallas Fort worth household travel survey	MNL with functional approximations to coefficients on alternative specific variables	Arrival time at work	32 time periods (with a total of 528 arrival / departure combinations)	Peak and off-peak	Network skims	None
13	HPDH	Hess, Polak, Daly & Hyman (2006)	3 SP surveys conducted in UK & Holland	Error component logit	Segmented models for commute, business, other tours	Base, retime early, late, switch mode, no travel	Unknown	Unknown	Linear SDE, SDL terms
14	BhHD	Bhat, C.R., Srinivasan, S., and Guo, J. (2002)	1996 Dallas Fort worth household travel survey	Hazard-duration model	Arrival time at work	Full day was discretized into 32 time periods	None	None	None
15	GK	Gadda, Shashank and Kara Kockelman (2007)	1996, Austin, Texas survey (1717 home-work trips)	Bayesian estimates using accelerated failure time specification	Departure time for home-work trips	Continuous time	None	None	None
16	KL2	Kumar and Levinson (1993)	1990 Montogomery county, Maryland data	Binomial logit	Full day: Work and Non work trips	Peak (3.30 pm to 6.30 pm) and shoulder	Same as choice alternatives	Network equilibrium skims with feedback	NA

Table 2-2. Overview of other time-of-day choice models

Sl.no	Key	Citation	Dataset (Sample size)	Model Type	Choice Alternatives		Inter-zonal Travel Time		Schedule Delay incorporation
					Arrival / Departure	Temporal Resolution	Temporal Resolution	Data Source	
1	MH	McCafferty and Hall (1982)	1997,Survey in Hamilton, Ontario (<200 households)	MNL	Departure from Work to home	Peak/off-peak; Pre, peak & Post peak; Peak (4.30 pm to 5.15 pm), shoulder, off-peak	Same as choice alternatives	Speed and delay studies (Constant travel times in each time period)	None
2	MC	Mahmassani & Chang	Simulation experiment with different values of parameters in the simulation	Macroscopic traffic simulation	Dynamics of departure to work	Departures on a 14 min time interval	Continuous time scale (measured as departure rate or veh/hr departing)	From simulation and heuristics (myopic and learning models)	Assumed distributions for SD with mean (5 , 10 , 15 min) and constant desired work arrival time of 8 AM
3	Jot	Jotinsaka, Hess and Polak (2004)	Simulated data sets	MNL, Mixed Logit	Modeling departure time of a generic trip	1 min to 30 min levels of aggregation (6.30 am to 9.30 am departures)	Same as choice alternatives	Weights for generating congested skims from free flow skims	Constant desired arrival time of 9 am assumed
4	BhSt1	Steed and Bhat (2000)	1996 Dallas Fort worth household travel survey	MNL and OGEV	Social recreation (3178 trips) and Shopping trips (2056 trips)	Morning, am peak (6.30 am to 9 am), am, off-peak, pm, pm peak (4 pm to 6.30 pm), evening	Peak and off-peak	Network skims	None
5	HPa	Hunt & Patterson (1996)	Stated preference experiment, Calgary, Canada (635 observations)	Exploded Logit for arrival at the movies	Departures such that travel time, SD are certain chosen values	NA	NA	Expected travel time values (10, 15, 30 min)	Expected SD (5, 10, 30 min) and the prob of that SD (5, 10, 20 %)
6	BhSt2	Bhat and Steed (2002)	1996 Dallas Fort worth household travel survey	Hazard-duration model	Departure time for Shopping trips	Continuous time (15 min resolution empirically)	Peak and off-peak	Network skims	None
7	HaM	Mannering and Hamed (1989)	Survey conducted in Seattle (204 commuters)	MNL for occurrence, Poisson regression for frequency, hazard duration for duration of delay	Occurrence, frequency and duration of departure delay from work to home (pm commute)	No change, depart early, depart later	NA	Network skims	None

Table 2-3. Factors impacting morning commute-timing decisions

Explanatory Factor	KEY															
	Pu	Man	Ro	Ab	Sm	HP	SF	Ch	HPB	VB	CS	BhCS	HPDH	BhHD	GK	KL2
Individual Socio-Economic Characteristics																
Age		Yes		Yes						Yes				Yes	Yes	
Gender								Yes								
Ethnicity														Yes	Yes	
Individual income				Yes												
Education level									Yes						Yes	
Student										Yes					Yes	
Household Socio-Economic Characteristics																
Mother											Yes	Yes				
Presence/Number of kids															Yes	
Household structure/size		Yes	Yes		Yes		Yes									
Household income	Yes		Yes							Yes	Yes				Yes	
Employment Characteristics																
Work Duration (Part-time/Full time)									Yes	Yes	Yes	Yes		Yes	Yes	
Flexibility				Yes	Yes				Yes		Yes	Yes		Yes	Yes	
Occupation Type	Yes			Yes	Yes			Yes								
Industry Type														Yes	Yes	
Self employed																
Retired																
Transportation System Characteristics																
Travel Time	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes			Yes
Travel Cost							Yes	Yes	Yes				Yes		Yes	
Transit Seat Availability						Yes										
Distance	Yes						Yes				Yes					Yes
Schedule Delay																
Late / Early Arrival at Work				Yes	Yes			Yes								
Other factors																
Mode/Number of vehicles	Yes		Yes	Yes	Yes						Yes		Yes			
Land-use at origin / destination	Yes							Yes		Yes	Yes					
Season of the year															Yes	

CHAPTER 3
INTER-ZONAL TRAVEL TIME MODEL

The contents of this chapter describe the modeling of inter-zonal travel times which will serve as inputs to the commute-timing model discussed in the later chapters. Section 3.1 presents the need for estimating the inter-zonal travel times as a function of time of day from survey data. Section 3.2 describes the dataset that has been used for the estimation. Section 3.3 presents the econometric modeling framework followed by a discussion of the empirical results in Section 3.4. Section 3.5 concludes this chapter with a summary.

3.1 Need for an Inter-Zonal Travel Time Model

Usually, the level-of-service variables (peak and off-peak travel time and costs) are obtained by performing equilibrium assignments on the transportation network for the peak and off-peak periods. Treating time of day as merely two discrete peak and off-peak time periods limits our ability to capture the variation of traffic congestion over the entire day. This limits the estimation of advanced continuous-time models, which require inter zonal travel times at a finer temporal resolution. One solution to counter this problem is to run the equilibrium assignment for several time periods. But this would give rise to several problems. Firstly, the travel time profiles may not be continuous across the time periods. Secondly, running so many static equilibrium assignments is a very time consuming process. Thirdly, as the temporal resolution increases there will be demand spillover across time periods (i.e. all the demand in a single time-of-day discrete time period may not be assigned to that time period) which require dynamic assignment techniques which are even more time consuming. An alternative approach to address is to develop models using reported travel times from household travel survey data. Further we can also use the free flow and peak period travel time obtained from the aggregate time equilibrium assignments as the independent variables. This will be discussed later in this chapter.

Therefore the objective of this chapter is to model travel time duration of a trip between any two zones as a function of network characteristics and time-of-day of departure of the trip. These estimated travel time durations functions (instead of just the aggregate peak and off peak travel time measures obtained from equilibrium assignment on the network) are incorporated into the continuous time models to better capture the effects of congestion across different time periods in a given day.

3.2 Data

The San Francisco Bay Area Travel Survey (BATS) conducted in the year 2000 by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission (MTC) is been used in this study. The nine county San Francisco Bay Area was divided into 1000 traffic analysis zones (TAZs) for this purpose. Activity information for two days was recorded from each of the respondent using an activity diary and the Computer Assisted Telephone Interview (CATI) method for recruitment and retrieval. The information was finally structured into four files namely the household file, person file, vehicle file and activity file. The household file provides information on the household level socio-economic characteristics like household size, number of children in the household, household income, location of the household, number of vehicles in the household and family structure of 14529 households. On the other hand, the person file provides information on individual level socio-demographic characteristics like gender, age, employment status, ethnicity for the 33402 members who participated in this survey. The vehicle file comprises information like make, model, year, and odometer reading for each vehicle owned by the surveyed households. Lastly, the activity file provides detailed information on activity purpose, location of activity participation (including latitude and longitude), start and end time of the activity.

These data were further augmented with land-use and level-of-service files obtained from MTC. The zonal characteristics of the TAZs like employment density, household density, area type (CBD, urban, suburban and rural), land-use mix index were included in the land-use file. The network characteristics like peak and off-peak travel time, travel cost and distance between zones were provided in the level-of-service file.

The data assembly for the estimation of the inter-zonal travel time models included the following steps:

First, weekday, inter-zonal, auto trips were extracted from the survey. The auto trips refer specifically to those in which the corresponding respondent indicated that he/she was the driver of the vehicle.Each trip is characterized by the start and end times (on a continuous-time scale), and the origin and destination locations (in terms of the Traffic Analysis Zones, TAZs). The reported trip duration was calculated as the difference between the end- and start-times of the trip.

Second, for each trip, the corresponding inter-zonal free-flow and peak-period travel times and distances were added from the level-of-service file.

Third, several consistency checks were performed to remove outliers and inconsistent information. Specifically, we removed trips for which the reported trip durations were less than one fourth or greater than four-times the corresponding free-flow travel times. The travel times in surveys are often reported for "door-to-door" travel whereas the free-flow travel times (obtained from network skims) represent the travel time between zone-centroids. Therefore, there could be considerable mismatch between the reported and free-flow travel times depending on the size of the zones. The threshold values of the ratios used here are what we think as empirically reasonable for the BATS data and the Bay Area Zoning system used in this study. In addition, we also removed long trips (reported travel times > 2 hours or distance > 50 miles). However, it is useful to point out that these checks did not result in a substantial reduction in the size of the data sample.

Fourth, the 24-hour day was divided into 96 15-minute intervals (2:52 AM – 3:07 AM, 3:07 AM – 3:22 AM, 3:27 AM – 3:37 M, and so on) i.e. the midpoint of each interval is an integral multiple of 15 minutes. All trips between the same origin-destination (OD) pair and departing within the same discrete time interval were aggregated to obtain average values of travel times between the corresponding OD pair and the departure time period. This averaged travel time is used to construct the dependent variable in the inter-zonal travel time model.

Fifth, details on the land-use at the origin and destination locations were added. The resulting estimation sample comprises 68,801 records. Each record represents travel between a particular OD pair and departing at one of the 96 discrete time periods.

Figure 3-1 presents the plot of % departures by time-of-day. Since there were not enough observations before 5.45 AM and after 10.30 PM they were removed from the estimations. The morning peak period occurs between 7 AM to 9 AM (18 % departures) and the evening peak occurs between 3 PM to 6 PM (35 % of departures). It can be observed from the Figure 3-1 that a more people round of their departure times to the nearest 30 minute than to the nearest 15 minute time slot. Hence the relatively higher percentage observed for time slot which are integral multiples of 30 minute than the adjacent time slots. Figure 3-2 plots of the distribution of trips based on the travel duration. It can be observed that 42.65 % of all the trips have travel duration between 7.5 to 17.5 minutes.

3.3 Econometric Structure

The empirical structure for the inter-zonal travel-time model is drawn from the earlier work of Cambridge Systematics (2004b). The travel duration for a trip from origin zone *i* to destination zone *j* when departing at time *t* (T_{ijt}) is related to the free-flow travel time between the zones (fft_{ij}), peak-period travel time between the zones (pkt_{ij}), time-of-day of travel (t), and other factors (X) as given by the following structure:

$$ln\left(T_{ijt}\right) = ln\left(fft_{ij}\right) * \left\{ \lambda_0 + \alpha X + \begin{bmatrix} \beta_1 e^{sin\left(\frac{\pi t}{12}\right)} + \beta_2 e^{sin^2\left(\frac{\pi t}{12}\right)} + ... + \beta_n e^{sin^n\left(\frac{\pi t}{12}\right)} \\ + \gamma_1 e^{cos\left(\frac{\pi t}{12}\right)} + \gamma_2 e^{cos^2\left(\frac{\pi t}{12}\right)} + ... + \gamma_n e^{cos^n\left(\frac{\pi t}{12}\right)} \end{bmatrix} * \left(\frac{pkt_{ij}}{fft_{ij}}\right) \right\} + \varepsilon_{ijt}$$

$$Where,\ \varepsilon_{ijt} \sim N(0, \sigma^2) \qquad \text{(Equation 3.1)}$$

In the above equation, λ_0 represents the constant term in the regression equation. X is the set of independent variables characterizing the trip. For example, this set of variables could include trip distance and land-use characteristics at the origin and destination locations. α Is the vector of coefficients on the explanatory variables X. The impact of time-of-day on the travel time is captured via a set of “sin” and “cosine” terms. $\beta = \left(\beta_{1,}\beta_{2,...,}\beta_n\right)$ and $\gamma = \left(\gamma_{1,}\gamma_{2,...,}\gamma_n\right)$ are the coefficients on these trigonometric terms. The number of such terms to be included (i.e., *n*) is determined empirically based on the model fits and the reasonableness of the profiles implied by the specifications with different values of *n*.

The peak-period travel time is obtained from static equilibrium assignment using the peak-period OD trip-table. Whereas, the free flow travel time is a function of the distance and the transportation system characteristics. The ratio of the peak to the free-flow travel times is included in the model to capture the effect of time-varying travel-demands between the zonal-pair on the variation of travel times over the day. As mentioned earlier, if the peak-period travel time were available at a finer temporal resolution (say 4 time periods) they can be incorporated into the estimations too. The *ln* of the ratio ensures that the predicted travel times are always positive.

An alternate piecewise linear specification (dummies from time-of-day) was also estimated. That specification did not provide smooth and continuous plot for travel time by time-of-day (“kinks” in the plot) which could have implications on the commute-timing models.

3.4 Empirical Results

A segmentation approach was adopted to allow for the travel duration profiles (over the day) to vary spatially and based on trip lengths. For this purpose, the data were first divided into the following four subsets based on inter-zonal distance: 0-5 miles, 5-15 miles, 15-30 miles, and 30-50 miles. Within the second and third distance categories, data were further segmented into four groups based on the trip-end location characteristics. That is, we identify whether the trips

(1) originate and end in the urban region (density[1] > 30), (2) originate in an urban region and end in a suburban region (density < 30), (3) originate in a suburban region and end in an urban region, or (4) originate and end in a suburban region. Such segmentation was not possible in the fourth distance category because of lack of data and deemed unnecessary in the first distance category (0-5 miles) because of very limited variations in travel times over the day. However, the trip-end location characteristics were included as explanatory variables in the models estimated for the first and fourth distance categories which yielded statistically insignificant coefficients. Overall, ten regression models were estimated and the best specifications are presented in Table 3-1. Note that the‘t' statistics have been suppressed in the table to avoid clutter and all reported estimated are statistically significant at at-least 90% level.

The impact of time-of-day on the travel time is captured via a set of "sin" and "cosine" terms. As the coefficients on these sin and cosine terms cannot be interpreted individually, we present the variability of travel time by time-of-day as implied by the models in the form of four illustrative graphs (Figure 3-3). In Case 1 ("short distance" trips with distance = 2.2 miles, free flow travel time = 7 minutes and peak travel time = 8 minutes) we find practically no variation in the travel duration over the entire day. Parameters from the first column in Table 3-1 are used in this plot. Cases 2 and 3 represent longer trips (distance = 9 miles and free flow time = 15 minutes, and peak travel time = 30 minutes) exhibit more variability (up to about 10 minutes over the day). Further, the trips from suburban to urban regions (case 2) have higher travel times during the morning peak period compared to an identical (*i.e.*, equal length) trip from urban to suburban regions (case 3). In contrast, the duration for travel from urban to suburban regions is higher during the evening peak compared to an identical trip in the opposite direction. Finally,

[1] Density is defined as (Total population in the zone + 2.5 * Employment in the zone) / (Residential + Commercial/Industrial Acreage)

case 4 represents a trip identical in all aspects to case 3 (9 mile trip from urban to suburban with free flow time = 15 minutes) except for a higher peak travel time (45 minutes). In this case we find a larger variation in travel time over the day compared to case 3. Parameters from the third and fourth columns in Table 3-1 were used to plot the graphs as shown in Figure 3-2 for travel from urban to suburban and suburban to urban respectively.

3.5 Summary

The need for developing the Inter-zonal travel time models was presented. Later the econometric structure of the model was presented. The models were estimated using data from the 2000 San Francisco Bay Area Travel Survey. The regression models for inter-zonal travel times produce smoothly time-varying travel duration profiles that capture the effects of temporal and spatial congestion appropriately. The empirical specifications were discussed in detailed. These models will serve as inputs to the commute timing models which will be discussed further.

Table 3-1. Empirical results: Inter-zonal travel duration regression models

	0-5 miles	5-15 miles				15-30 miles				30-50 miles
		Origin-Urban & Dest-Urban	Origin-Urban & Dest-Suburban	Origin-Suburban & Dest-Urban	Origin-Suburban & Dest-Suburban	Origin-Urban & Dest-Urban	Origin-Urban & Dest-Suburban	Origin-Suburban & Dest-Urban	Origin-Suburban & Dest-Suburban	
λ_0	1.295	1.135	1.152	1.076	1.051	1.032	1.059	1.057	0.955	1.088
$\alpha_{distance}$	-0.044	-0.007	-0.007	-0.005	-0.007	-0.001	-0.004	-0.003	-0.002	-0.002
β_1	-0.066	-0.067	-0.085	-0.056	-0.052	-0.056	-0.074	-0.040	-0.045	-0.019
β_2	--------	--------	--------	--------	--------	--------	0.022	--------	--------	--------
β_3	0.086	0.088	0.101	0.092	0.082	0.071	0.077	0.057	0.080	0.023
β_4	--------	--------	--------	--------	--------	--------	--------	--------	--------	--------
γ_1	--------	--------	--------	--------	--------	--------	0.028	0.025	--------	--------
γ_2	0.086	0.120	0.108	0.133	0.137	0.073	0.119	0.063	0.148	--------
γ_3	--------	--------	--------	--------	--------	--------	-0.048	--------	--------	--------
γ_4	-0.079	-0.108	-0.098	-0.121	-0.113	-0.061	-0.097	-0.054	-0.118	0.017
Number of cases	35463	2656	4081	4010	10436	834	2321	2106	3932	2962
Adjusted R^2	0.956	0.980	0.980	0.980	0.974	0.984	0.986	0.986	0.984	0.987

Note1: Only statistically significant variables are reported at 90 % CI
Note2: The high Adjusted R^2 values are due to absence of a constant term in the model specification

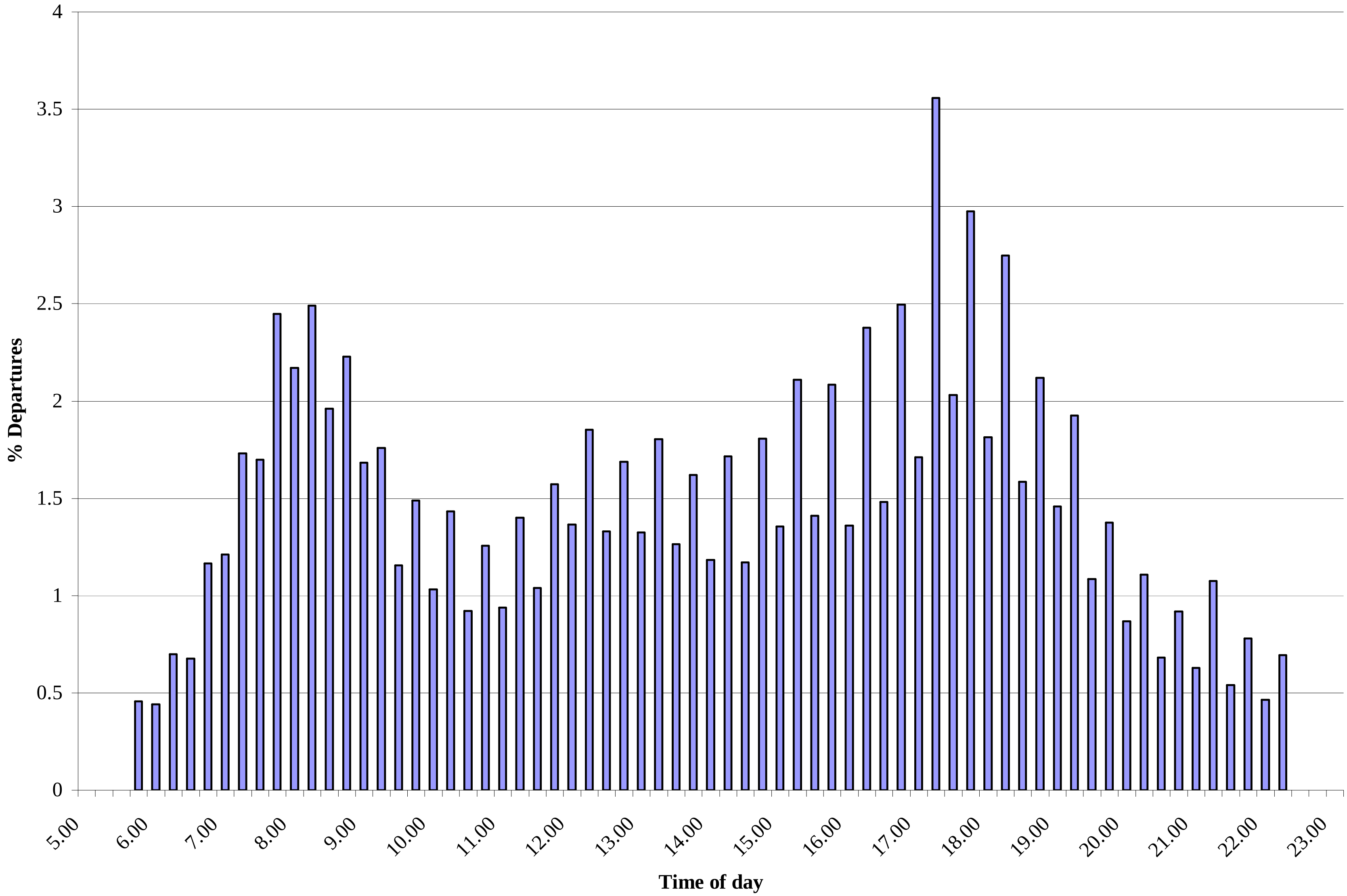

Figure 3-1. Distribution of departure times by time-of-day

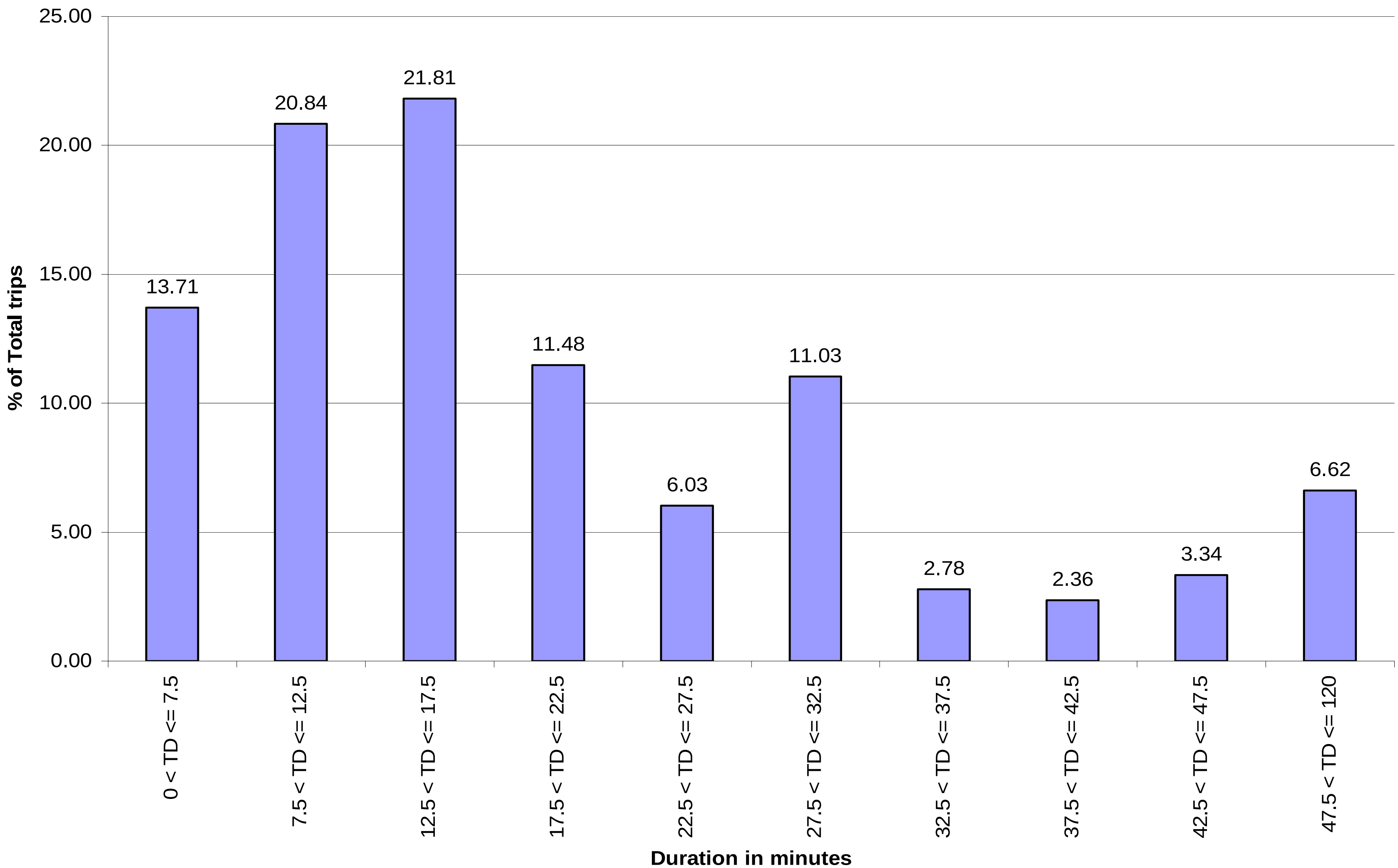

Figure 3-2. Distribution of travel time duration

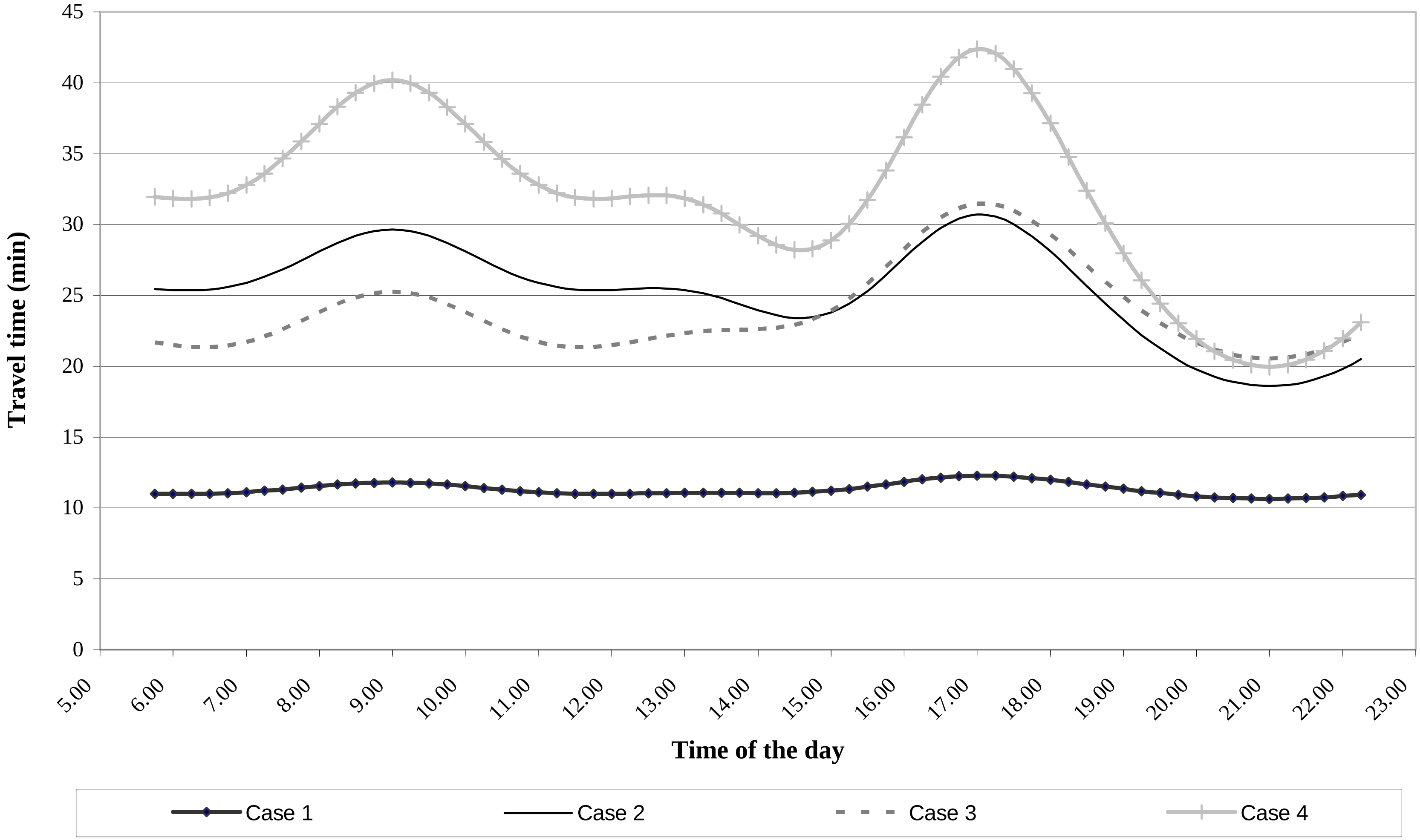

Figure 3-3. Variation of inter-zonal travel duration by time-of-day: Illustrative graphs

CHAPTER 4
COMMUTE-TIMING MODEL FOR FLEXIBLE SCHEDULE WORKERS

This chapter describes in detail the methodology behind the commute timing model for workers with flexible work schedules. Section 4.1 describes the sample that has been used for the estimation of the hazard duration structure. Section 4.2 presents the modeling framework followed by a discussion of the results in Section 4.3. Section 4.4 summarizes the chapter.

4.1 Data

As mentioned the primary source of data is the San Francisco Bay Area Travel Survey (BATS) conducted in the year 2000. The procedure for assembling the dataset for estimating commute-timing models comprised four major tasks.

In the first task, the home-to-work commute was extracted from the overall activity-diary of the respondent. The home-to-work commute includes the entire journey from home to work including any possible intermediate stops. This extraction began with identifying and characterizing (location, start time, mode of travel to episode, etc.) the first and last out-of-home work episodes. This was followed by identifying and characterizing (location, start time, etc.) the last in-home activity episode before the first work episode (the LHBFW episode). Next, all activity episodes before the LHBFW episode and those after the first out-of-home work episode were removed. The retained activity episodes constitute those undertaken during the home-to-work commute. Further processing was done on the commute activities to determine additional characteristics of the commute such as number of stops, activity type at the intermediate stops, and journey duration. All commute characteristics were then compiled into a home-to-work commute file. In this file each record represents a commute journey and is completely characterized by home location, work start location, departure time to work, work start time, mode used in various legs of the journey, number of stops, and activity type during the stop making.

In the second task, relevant household-, individual-, residential-, and level-of-service characteristics from the appropriate data files were added to the home-to-work commute file.

The third task involved cleaning to remove records with missing, outlier, and/or inconsistent data. For example, working spending less than 30 minutes at an out-of-home location for work or traveling for more than 2 hours to work were removed. In addition, only cases that had the complete data on all the relevant explanatory variables were retained.

In the final fourth task, restrictions were imposed to define the empirical scope of the study. Specifically, only weekday auto-based commutes of full time, workers aged 18 years or older are retained in the final estimation sample. Further, we also retain only those individuals who had two or fewer work episodes during the day and a single out-of-home work location. That is, we do not include workers who undertake a lot of work-based travel in our analysis. It should also be noted that we restricted to only inter-zonal commute journeys. All the above tasks were performed for all workers i.e. workers with both flexible and fixed work schedules.

This chapter is focused on a subset of the above data that reports fully flexible workers. A user is said to have full flexible work schedule when the individual has complete freedom to start and end work at will. On the other hand a fixed schedule worker does not have any freedom to alter the work start and end times. The corresponding dataset comprises of 4008 commute journeys to work obtained from 2742 persons and 2536 households. 15 % sample (615 records) of the 4661 commute journeys is set aside for the demonstration exercise which is discussed in the later sections. This leaves 3393 commute journeys to work obtained from 2496 persons and 2328 households for the estimation. Descriptive statistics on selected explanatory variables from the above estimation dataset are presented in Table 4-1. Note that the mean and standard deviation are presented for continuous variables (such as age, work duration, and household income) and the sample shares (percentages) are provided for categorical variables (such as ethnicity and household structure). In general we find that the fully-flexible, full-time workers analyzed in this study are middle-aged, more likely to be men, and hold executive/managerial/professional positions. The sample also includes considerable numbers of single-person households and individuals of Asian ethnicity.

The commute timing profile (*i.e.*, the percentage of departures to work in the estimation sample during each discrete time-of-day period) is presented in Figure 4-1. The mid-point times of the discrete periods are presented in the X-axis. That is, 5:30 refers to departures between 5:23 AM and 5:38 AM; 5:45 refers to departures between 5:38 AM and 5:53 AM, and so on. The bulk of the departures (60.5%) are concentrated in the 7-9 AM period with peaks at 7:30 and 8:00 AM. Few people leave before 5:30 AM or after 10:30 AM. The reader will also note that departures at half-hour periods (*i.e.,* 6:30, 7:00, 7:30, 8:00, and so on) are generally higher perhaps reflecting inherent biases in the reporting of departure times in travel surveys.

4.2 Methodology

This section presents the hazard-duration structure for modeling the commute-timing (*i.e.,* departure time) decisions. The model has a proportional-hazard structure incorporating the effects of the exogenous covariates in a multiplicative form, a non-parametric baseline-hazard distribution, and a parametric (gamma distribution) control for unobserved heterogeneity. Further, the model structure captures the impact of time-varying covariates (in this context, the home-to-work travel times vary as a function of time-of-day). Overall, the model structure adopted here is similar to the one adopted in Bhat and Steed (2002). However, we do not incorporate time-varying coefficients as these authors do. In this rest of this section, the model structure is presented in our application context.

The "hazard" for departing to work at any time of the day *u* (measured on a continuous scale, say in minutes from 3 AM) is defined as the probability that a worker will depart immediately after time *u* conditional on not departing until time *u*. This hazard is assumed to have the following functional form:

$$\lambda(u) = \lambda_0(u)\exp\left(\beta X + \gamma Z\left(u\right)\right)w \qquad \text{(Equation 4.1)}$$

In the above equation, $\lambda_0(u)$ is the baseline hazard. *X* and *Z(u)* are vectors of non-time varying and time varying covariates respectively. For example, *X* could include the socio-demographic characteristics of the worker whereas *Z(u)* includes the travel times / speeds between home and work locations at time *u*. β and γ are the vectors of coefficients on the non-time varying and time varying covariates respectively. w is the unobserved heterogeneity term assumed to follow a gamma distribution (with variance = σ^2) and independent of the covariates.

As already indicated, we adopt a non-parametric distribution for the baseline hazard (i.e., $\lambda_0(u)$) in our specification. For this purpose, we discretize the continuous time into *K* unique time intervals. Let *p* denote the index for the time intervals (*p* = 1, 2,…, *K*) and a_p represent the upper bound time corresponding to discrete interval *p*. Therefore discrete period *p* represents the time interval [a_{p-1}, a_p] and the duration of this discrete period is given by, $\Delta_p = a_p - a_{p-1}$. The baseline hazard is then assumed to be a constant within each of these discrete periods (*i.e.,* $\lambda_0(u)$ = exp(δ_p) if *u* element of discrete period *p*). In addition, we assume that the value of time-varying covariates remain constant within each discrete time period (*i.e., Z(u)* = Z_p if *u* element of discrete period *p*).

The "survival" function, *S(u)*, is defined as the probability that the worker did not depart to work until time *u* and is given by the following expression:

$$S(a_p) = \exp\left(-\int_{-\infty}^{a_p} \lambda(u)\, du\right) \quad \text{(Equation 4.2)}$$

$$S(a_p) = \exp\left(-\sum_{j=0}^{p}\left[\exp\left(\delta_j\right)\exp\left(\beta X + \gamma Z_j\right)w\right]\Delta_j\right) \quad \text{(Equation 4.3)}$$

The probability that a worker departs in discrete time period *p* conditional on the unobserved heterogeneity term *w* is therefore given by:

$$\begin{aligned}\text{Prob}[t = p] \mid w &= \text{Prob}[a_{p-1} < u < a_p] \mid w \\ &= S(a_{p-1}) \mid w - S(a_p) \mid w\end{aligned} \quad \text{(Equation 4.4)}$$

The unconditional probability of departure in interval *p* is given by (See, Bhat and Steed, 2002 for details)

$$\text{Prob}[t = p] = \left[1+\sigma^2\left\{\sum_{j=0}^{p-1}\Delta_j \exp\left(\delta_j + \beta X + \gamma Z_j\right)\right\}\right]^{-\sigma^{-2}} - \left[1+\sigma^2\left\{\sum_{j=0}^{p}\Delta_j \exp\left(\delta_j + \beta X + \gamma Z_j\right)\right\}\right]^{-\sigma^{-2}} \qquad \text{(Equation 4.5)}$$

Where $\delta_0 = -\infty$ and $\delta_K = +\infty$.

4.3 Empirical Results

The empirical results of the hazard duration model for departure time choice are presented in Table 4-2. The set of explanatory factors included in the model specification can be broadly classified as follows: (1) Individual and Household Socio-Economic Characteristics, (2) Individual Employment Characteristics, (3) Day of the Week, and (4) Location Characteristics, and (5) Transportation System Characteristics. Each of these sets of variables is discussed in detail below. Consistent with the notation specified in the formulation, a positive coefficient on a time invariant covariate increases the hazard and hence increases the likelihood of departure at any time. Therefore, a positive coefficient can be interpreted, in general, as favoring earlier departures. The interpretation of the coefficients on time varying covariates is described later.

4.3.1 Individual and Household Socio-Economic Characteristics

Among the set of individual-level socio-economic characteristics, only age impacts the choice of departure time. The coefficient on age is positive which means that older individuals are more likely to depart in the earlier time periods. Other characteristics like ethnicity and gender were also tested but were found to be insignificant.

The income of the household as well as the household composition is found to impact commute departure time choice. Specifically, we find that flexible full-time workers from higher income households depart later compared to identical individuals from lower income households. Workers in single-person households are found to be most likely to depart the latest. Workers from couple households depart earlier than the above persons but later than individuals from nuclear family, single parent, or any other type of household. Thus, it may be observed that individuals in households with children depart the earliest for work. This is perhaps because of their need to chauffer children to school on the way to work. In fact, we did explore the inclusion of a variable indicating whether the individual undertakes a drop-off activity during the commute. However, this was found to be insignificant after controlling for the household structure (but was significant with the positive sign in another model without the household structure variables).

Finally, the commute departure time decisions of flexible workers are also influenced by the presence of other non flexible commuters in the household. Specifically, the flexible worker is likely to depart earlier if another inflexible worker is also present in the household. This intra-household interdependency might be broadly capturing the desire of household members to synchronize their work timings perhaps to facilitate joint leisure pursuits during the later part of the day.

4.3.2 Individual Employment Characteristics

Work duration, work frequency, and the occupation type are individual-level employment characteristics found to determine the departure time choice for commute travel. Individuals who work long hours during the day also depart earlier for work, perhaps reflective of the overall time-budget constraints. Persons who do not travel to the out-of-home work location all five days of the week are found be more likely to depart later in the day. This is possibly reflecting a greater degree of flexibility in the work schedules of such persons among all flexible full-time workers. Finally, the occupation type of the person strongly influences the choice of commute departure time. Specifically, individuals employed in a professional, technical, management, or administration capacity are more likely to depart later in the day. However, those employed as executives or managers depart earlier.

4.3.3 Day of the Week

Individuals are more likely to depart earlier to work on Fridays compared to other four days of the work week. Perhaps, this is a manifestation of a desire to complete work earlier so as to have the evening available for the pursuit of leisure activities.

4.3.4 Location Characteristics

The residential- and work-location characteristics were tested in the specifications. It was found that only work location characteristics impacted the departure time choices of individuals. Individuals working in the CBD are more likely to leave earlier. This is perhaps because of the overall higher congestion prevailing in CBD area during the morning period.

4.3.5 Transportation System Characteristics

The effect of time-varying transportation system characteristics on the choice of departure time is captures via the commute speed variable. The commute speed when departing at time u is calculated as the ratio of commute distance to the travel time between home and work zones at time u (this is determined from the inter-zonal travel time model discussed in Chapter 3). The model also allows heterogeneity in the sensitivity to speed by interacting it with a categorical distance variable. For short distance trips, we find that the choice of departure time does not depend on the transportation system characteristics as indicated by a statistically insignificant coefficient on "speed for distance = 0 – 5 miles". For greater distances, we find a positive sign on the speed variables indicating that the probability of departing home at a certain time (conditional on not departing earlier) is higher if the speed at that time is higher. Further, the sensitivity to speed is also greater for longer commutes possibly reflecting the potential for greater time savings.

Note from equation 4-5 that the probability of departing during any discrete time interval is a function of commute speeds prevailing at all times *until* the discrete time interval under consideration and does not depend on the commute speed *after* the time interval under consideration. However, it is reasonable to expect that the probability that a person departs at a certain time is also dependent on "future" commute speeds. To capture this effect, we introduced measures of future commute speeds as a second time-varying covariate in our model. Specifically, this future speed variable corresponding to any discrete period is calculated as the difference between the commute speed during the next time period (say 15 or 30 minutes) and the current period as a percentage of the current speed. A negative coefficient on this variable could be expected implying that as the commute speed in the future increase relative to the currently prevailing times, the hazard for departure decreases (or a person is less likely to depart at a certain time if the commute speed in the future will be greater than the currently prevailing speeds). We explored the effect of this future speed variable at both 15 minute and 30 minute resolutions. However, these effects were not statistically significant. Additional empirical research on how to capture the effects of future travel times on the departure time choice is required.

The standard deviation of the unobserved heterogeneity term ("gamma" in Table 4-2) is estimated to be statistically different from zero. This reflects the strong presence of factors other than those controlled for in the model that influence the departure time choices of individuals.

The baseline hazard for the estimated model is as shown in the Figure 4-2. It can be seen that the longer an individual waits to depart for work, the more likely he/she is to depart. In other words, there is general positive duration dependence in the hazard function for departure to work.

4.4 Model Application

This section demonstrates an application of the commute timing model in predicting the aggregate departure time patterns of a sample of individuals. For this exercise, we use the validation sample containing the 615 observations. Section 4.4.1 presents the aggregate predictions on the choice of departure time on the validation sample. Sections 4.4.2 and 4.4.3 describe the aggregate sensitivity of changes in non time-varying and time-varying characteristics to the departure time choice.

4.4.1 Aggregate Prediction of Departure Time Profiles

We predict the average probability of the sample choosing different choice alternatives across time-of-day from the estimates obtained and compare it against the observed distribution of departure time choice. It can be noted from Figure 4-3 that the distribution predicted from the model closely approximates the observed distribution for the departure time choice of the individuals on an aggregate level. However, it can be found that the highest over-prediction is recorded at 6 AM at 1.65 % and the highest under-prediction of 2.24 % occurs at 8.30 AM. Overall, across the full day, the average over-prediction and under-prediction were 0.57 % and 1.06 % respectively. It should be noted that the above numbers are calculated by taking the difference of the predicted and observed percentages.

4.4.2 Aggregate Sensitivity to Changes in Time-Varying Characteristics

Further, we also test the impact of change in commuting speed (during the peak hour 7 AM to 9 AM) on the departure time choice of the individuals. The various scenarios for the change in the commute speed during 7 AM and 9 AM (we call this time period as policy time period) include doubling the speed and reducing the speed by half. The decrease in the commuting speed during the morning peak period may be due the increased congestion effects and the decrease in speed might occur in the case of reversible lanes. Here again the average predicted probabilities of all the individuals calculated for all the choice alternatives across the day are plotted. This is compared against the base case of no change in the speed variable. Figure 4-4 shows the impact of the change in a time varying covariate, in this case the travel time. Figure 4-5 presents the cumulative departures as a function of time-of-day. Several observations can be made from the figures. Firstly the predictions pattern before start of the policy time period does not change. This as mentioned earlier is manifestation of the fact that hazard duration implicitly doesn't recognize the impact of future time periods. The second observation that can be made is when the commuting speed in the morning peak period decreases in the policy time period, which is reflective of the increasing congestion during the peak period, the fraction of people choosing to depart at the start of the congested morning peak period decreases relative to base case of no change in the speed. In other words individuals tend to move away from the congestion as one would expect. Similarly if the commuting speed increases which may be reflective of a new reversible lane introduced in the direction of the congested traffic in the morning peak period, the fraction of people choosing to depart at the start of the congested morning peak period increases as compared to the case when the speed doesn't change? However a higher fraction of the individuals have already departed at the start of the policy period increases (due to the increased speeds), we would expect lower departures at the later time periods. These overall effects are more discernible in Figure 4-5 where the cumulative departures are plotted. It is clear that as the speed increases the fraction of people who have departed after the start of policy period is always higher than the base case of no change in the commute speeds.

4.4.3 Aggregate Sensitivity to Changes in Non Time-Varying Characteristics

We also test the sensitivity of a non-time varying covariate on departure time patterns of the individuals. The variable chosen for the purpose of demonstrating the impact of the change in a non time-varying covariate on the departure time pattern of the individuals is the binary variable for work frequency less than or equal to four per week. In order to simulate the change in the data we randomly pick 15 % of the individuals whose frequency to work is greater than equal to four per week and convert these individuals to individuals with work frequency less than or equal to four per week. Since the percentage of population with increased flexibility to depart to work has increased in the population sample, we expect a general increasing trend for later departures during the time-of-the-day. The effect can be observed from Figure 4-6 and Figure 4-7 (% departures and % cumulative departures as a function of time-of-day respectively). As the aggregate flexibility of the workers in the sample increases, it is easier to note from Figure 4-7 that at any given time across the time-of-day the fraction of individuals that have already departed for work is lower than the base case.

4.5 Summary

This chapter described the development of continuous-time model for the home-to-work commute timing decisions of flexible full-time workers using the hazard-duration structure. Further, the estimated departure time choice model includes the effect of travel time at a fine temporal resolution of 15 minutes. In order to generate the travel time data at this resolution, the regression models developed for the Inter-zonal travel times are used. The hazard duration model indicates a statistically significant effect of commuting speed on the choice of departure time. Specifically, individuals are less likely to depart home at times when the commute speeds are lower. In addition, the model also captures the impact of several other explanatory factors on the choice of departure time to work. Further we also presented a demonstration on how this model can be used for predicting the departure time patterns. This model application exercise also tries to present the sensitivities of the departure time patterns to the changes in the time varying transportation system and non-time varying characteristics.

Table 4-1. Sample characteristics of full-time workers with flexible work schedules

Attribute	Statistic	Attribute	Statistic
Individual Char.		**Household Char.**	
Age	42.69(10.48)	Number of persons	
Gender		1	18.42
Male	64.93	2	40.88
Female	35.07	3	16.00
Ethnicity		4	17.86
Caucasian	75.04	>=5	6.84
African American	2.30	Number of vehicles	
Hispanic	3.92	1	22.40
Asian/Pacific islander	13.14	2	52.20
Other	5.60	3	19.07
Work duration in hours	8.46(2.41)	>=4	6.34
Work frequency		Number of children	
<5 days per week	8.58	0	64.87
>=5 days per week	91.42	1	14.85
Occupation		2	15.30
Exec/Managerial	29.33	>=3	4.98
Professional	44.50	Presence of another fixed schedule worker	
Other	26.17	No	82.58
Transportation System and Land Use Char.		Yes	17.42
Commute free flow time (mins)	18.77(10.33)	Household structure	
Commute distance in miles	12.96(10.28)	Single person	18.42
Area type of home zone		Single parent	1.80
CBD (density >100)	1.18	Couple	34.04
Urban (density 30-100)	20.90	Nuclear Family	27.73
Suburban (density 6-30)	72.86	Other	18.01
Rural (density >6)	5.07	Household Income in 1000s of $	12.23(2.27)
Area type of work zone			
CBD (density >100)	10.88		
Urban (density 30-100)	47.54		
Suburban (density 6-30)	39.23		
Rural (density >6)	2.36		

The values mentioned are the mean (standard deviation) for continuous variables and the percentage shares for the categorical variables

Table 4-2. Empirical results: Covariate effects for the hazard duration model for departure time choice of flexible schedule workers

Variable	Parameter Estimate	t-statistic
Individual and Household Socio-Economic Characteristics		
Age	0.0202	7.423
Household Income	-0.0422	-3.469
Household structure		
Nuclear, Single parent, Other (Base)	-------	-------
Single person household	-0.2956	-3.687
Couple married or unmarried	-0.2167	-3.479
Presence of a non-flexible worker in the household	0.1261	1.751
Individual Employment characteristics		
Work duration	0.3112	19.009
Work frequency less than 4 days a week	-0.5363	-5.519
Occupation		
Executive/Managerial	0.2025	2.731
Professional	-0.1824	-2.784
Other	-------	-------
Day of the Week		
Day is Friday	0.1324	1.826
Location Characteristic		
Work location is CBD	0.1235	2.185
Transportation System characteristics		
Commute Speed (miles/hr)		
For distance = 0 - 5 miles	-0.0049	-0.705
For distance = 5 -1 5 miles	0.0129	3.22
For distance = 15 - 30 miles	0.0211	6.642
For distance = 30 - 50 miles	0.0248	8.361
Gamma	0.8334	16.434
Number of cases	3393	
Log Likelihood at convergence	-9621.67	
Log Likelihood at convergence for constants only model	-10107.8	

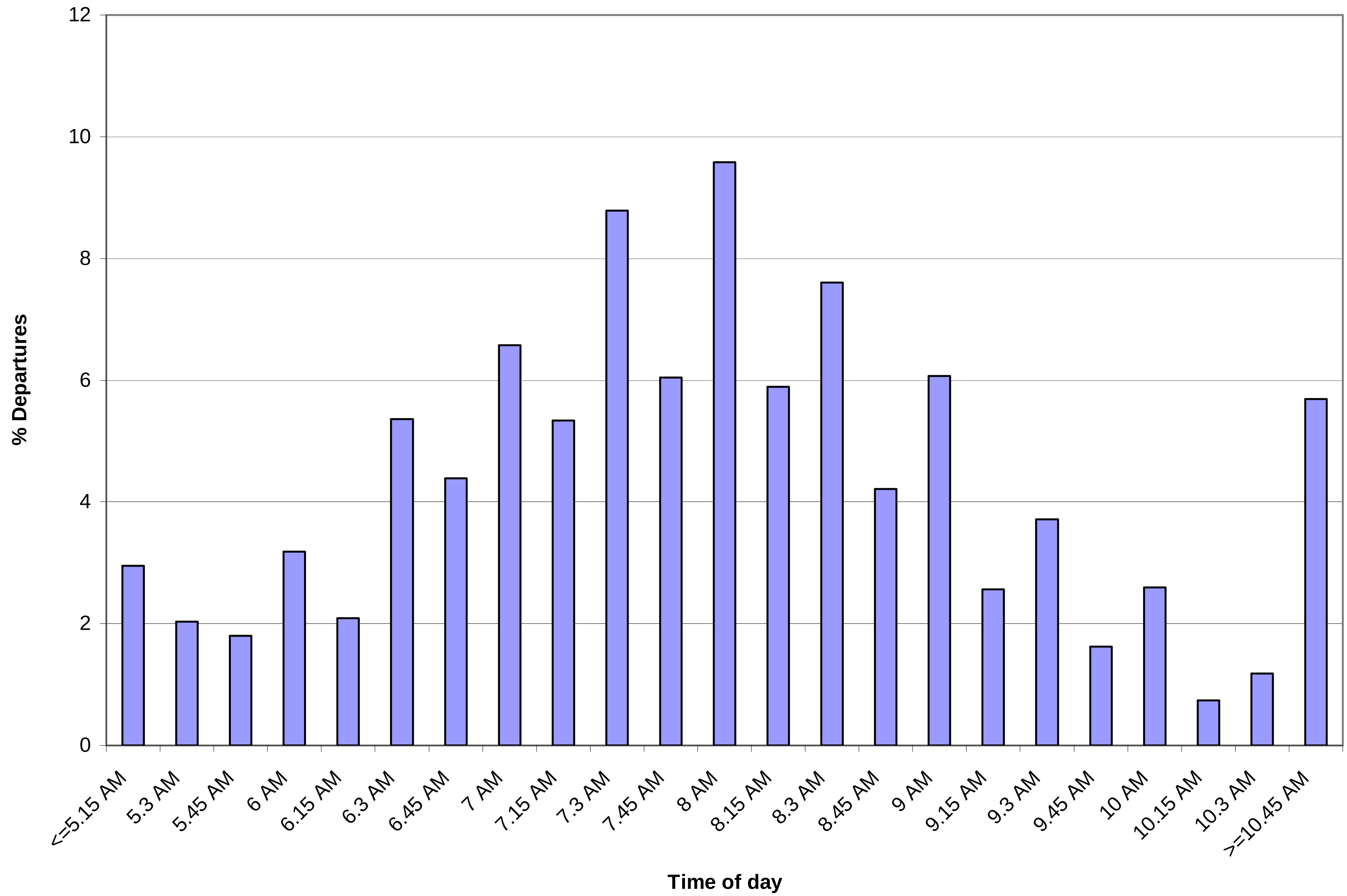

Figure 4-1. Distribution of departure times for home-to-work commute by time-of-day of flexible schedule workers

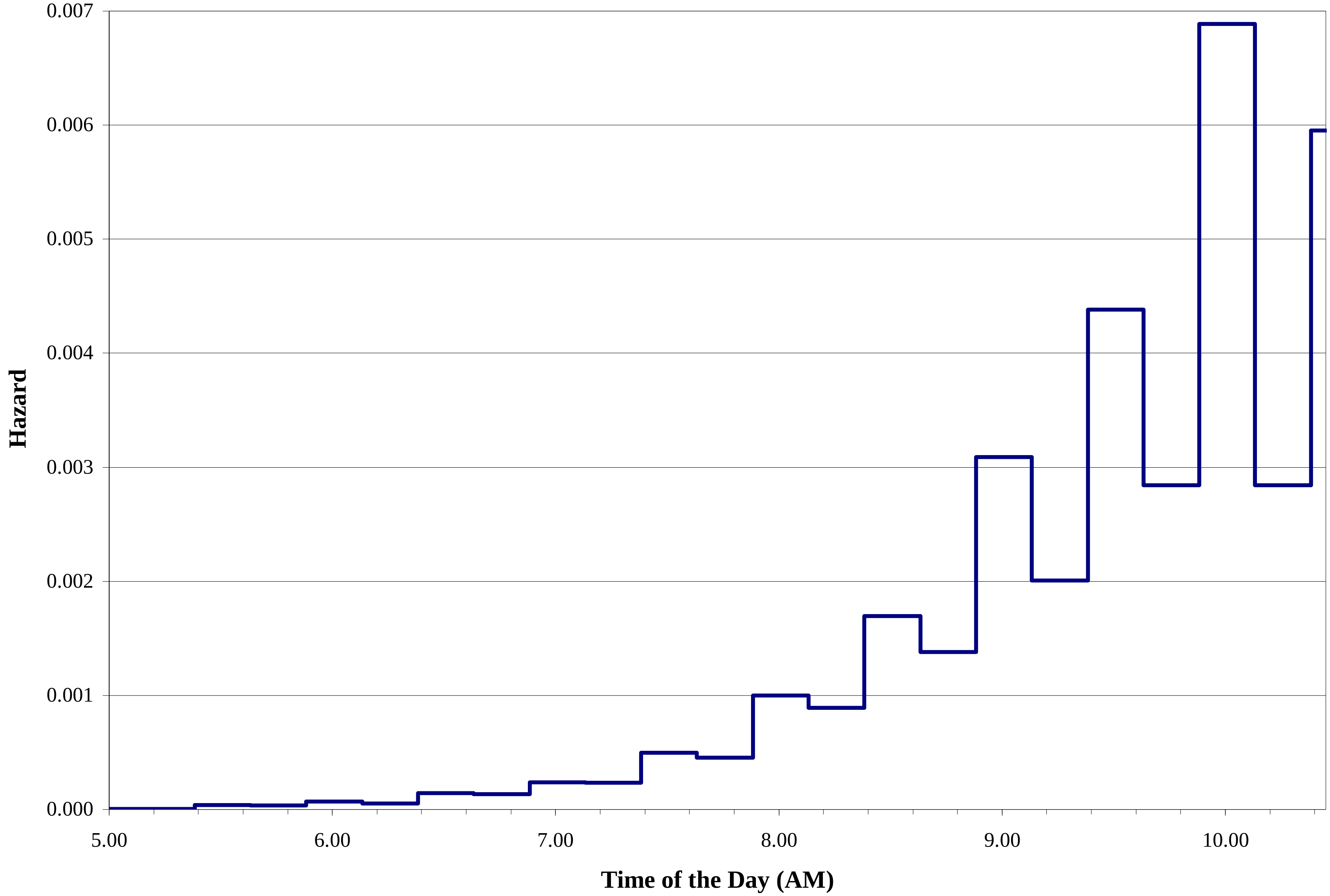

Figure 4-2. Estimated baseline hazard distribution of flexible schedule workers

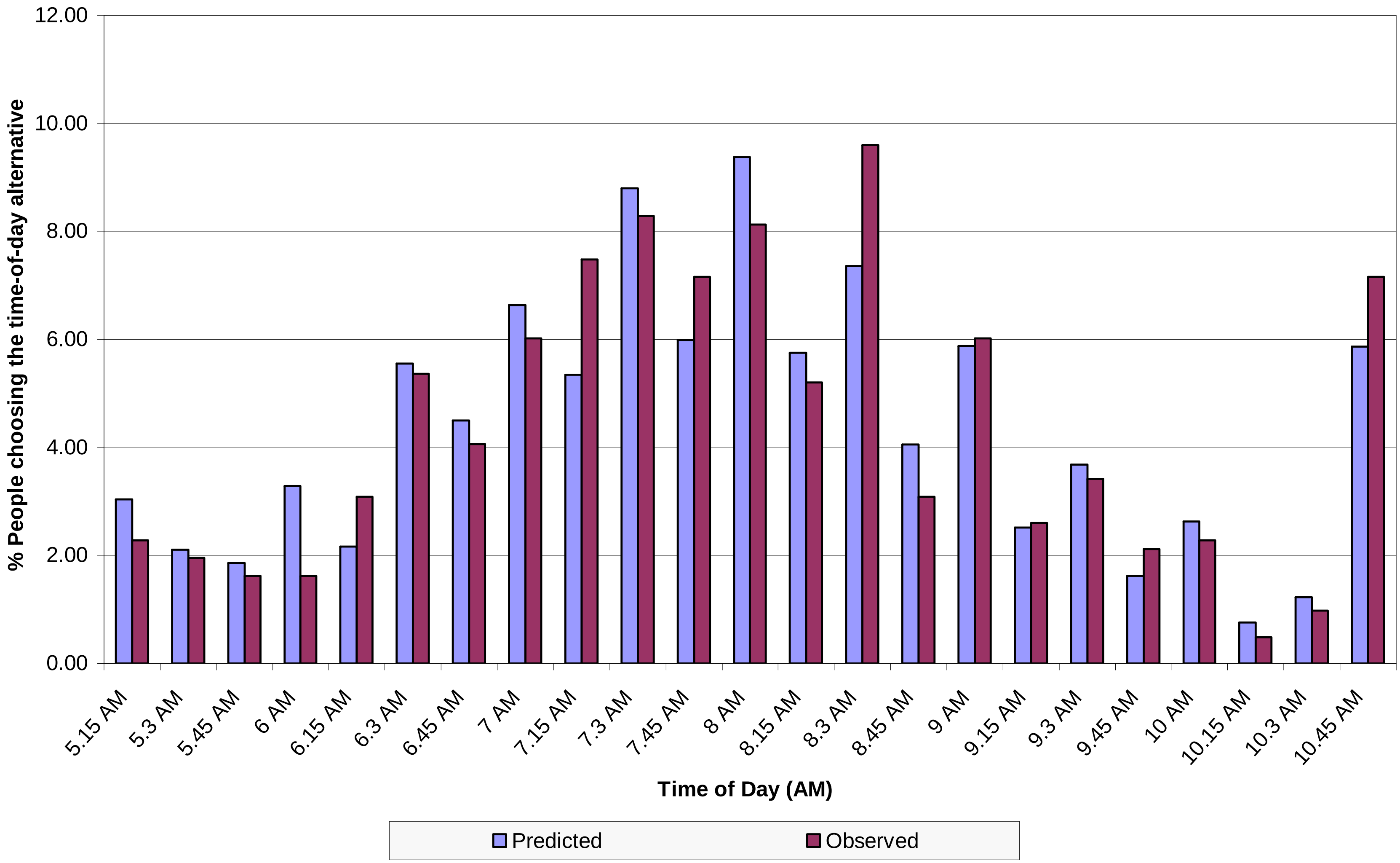

Figure 4-3. Observed vs predicted distribution of departure time patterns of flexible schedule workers

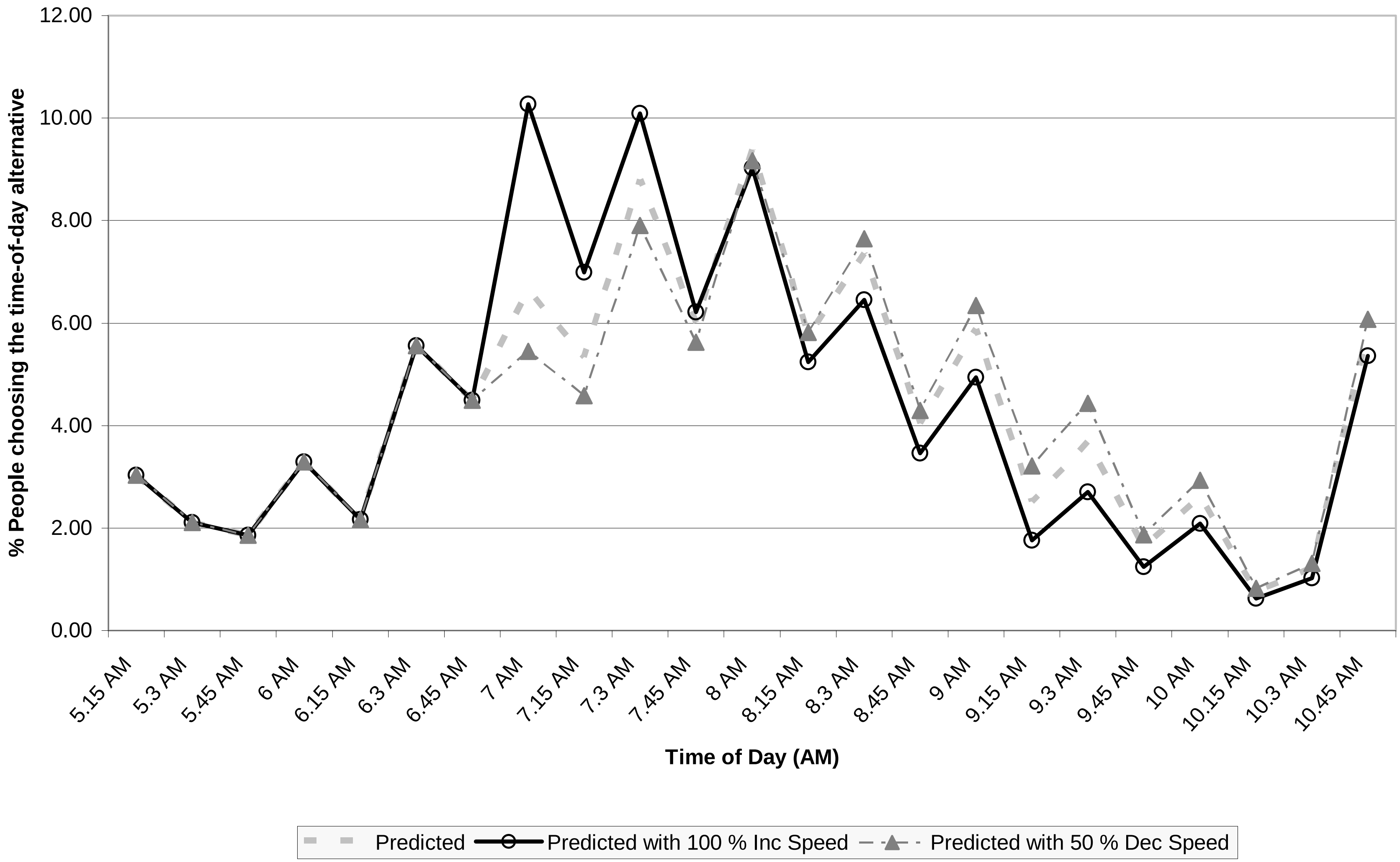

Figure 4-4. Impact of change in commuting speed in the morning peak period (7 AM to 9 AM) for flexible schedule workers

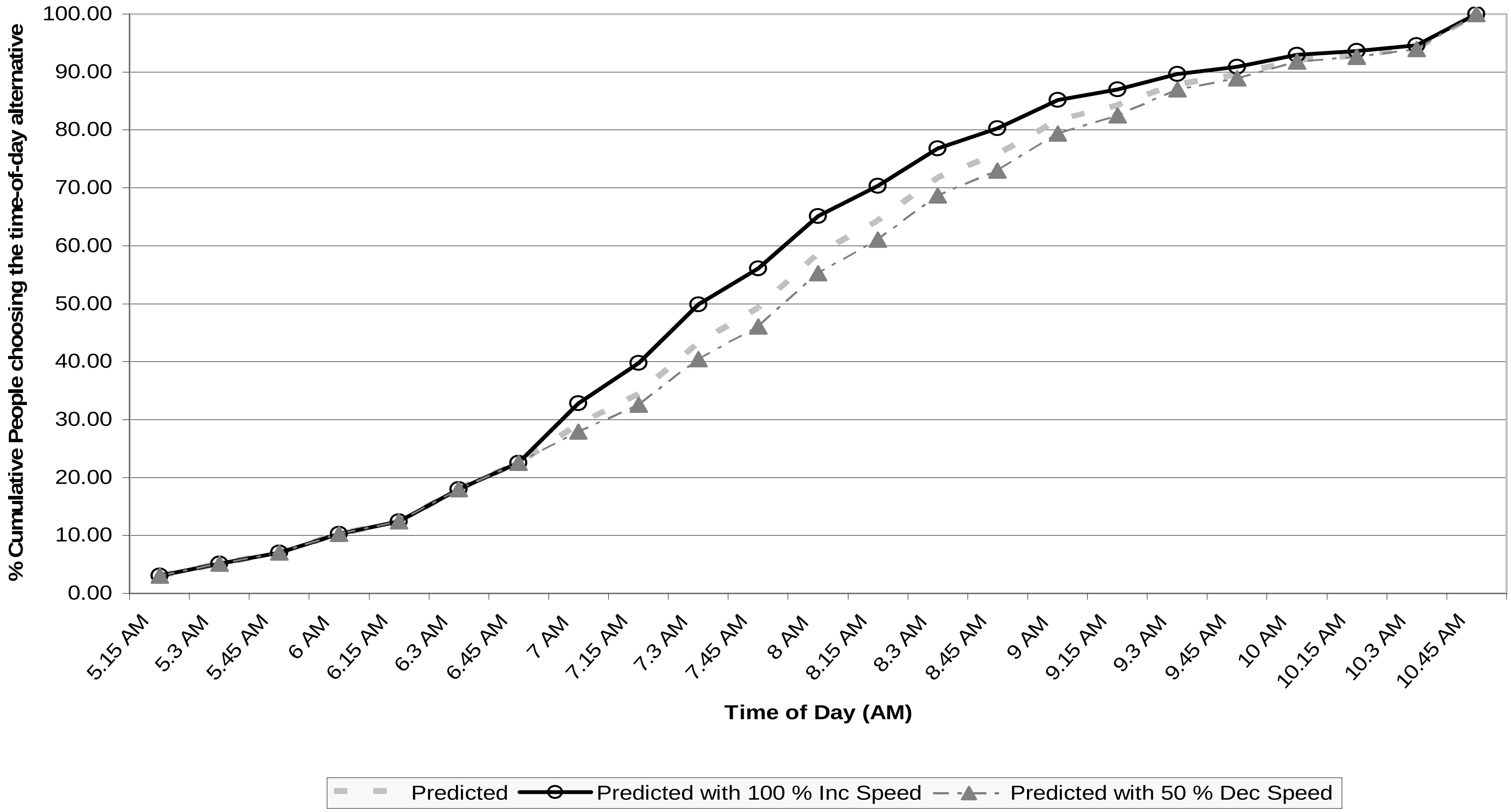

Figure 4-5. Cumulative impact of change in commuting speed in the morning peak period (7 AM to 9 AM) for flexible schedule workes

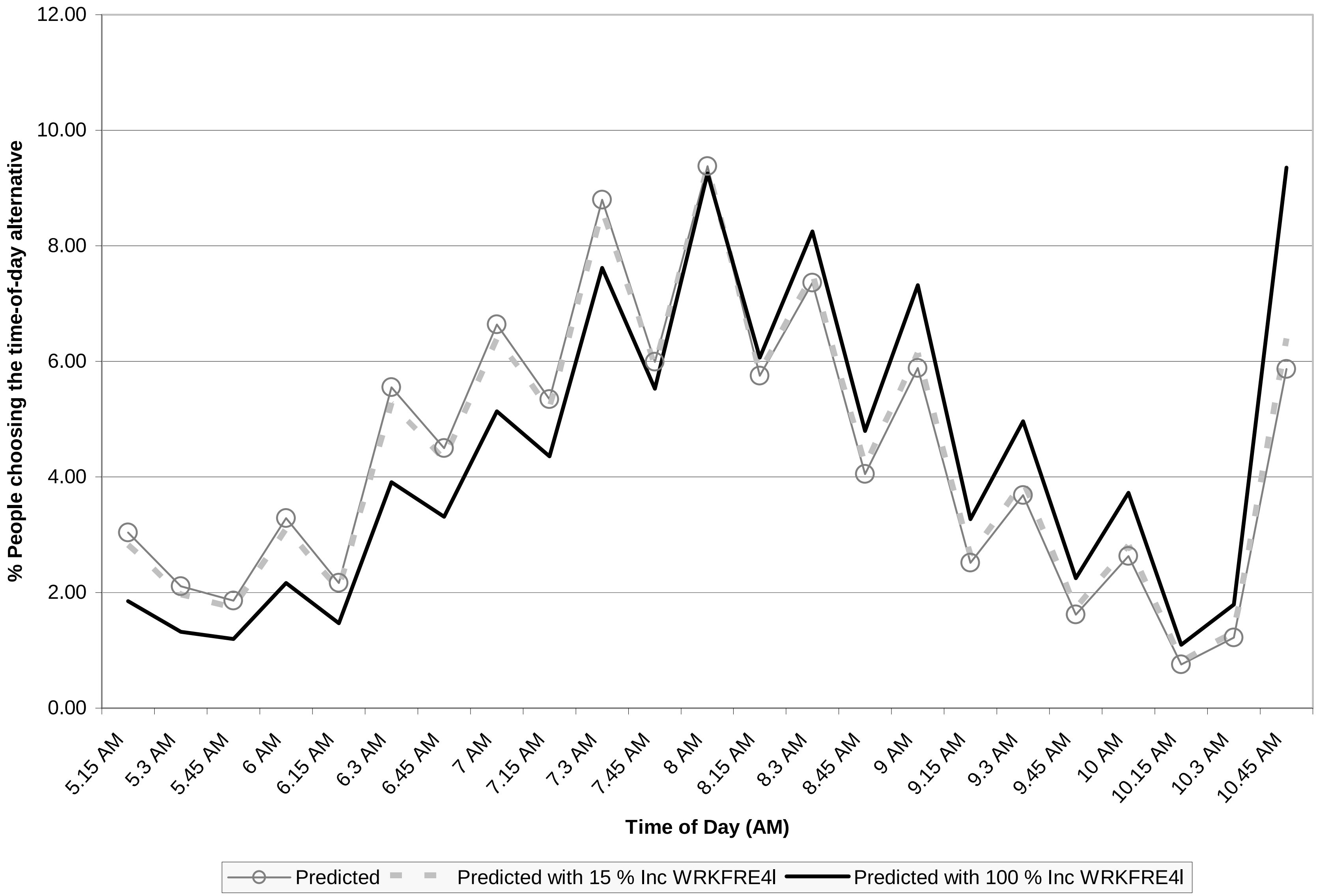

Figure 4-6. Impact of change in % departures with work frequency less than or equal to four for flexible schedule workers

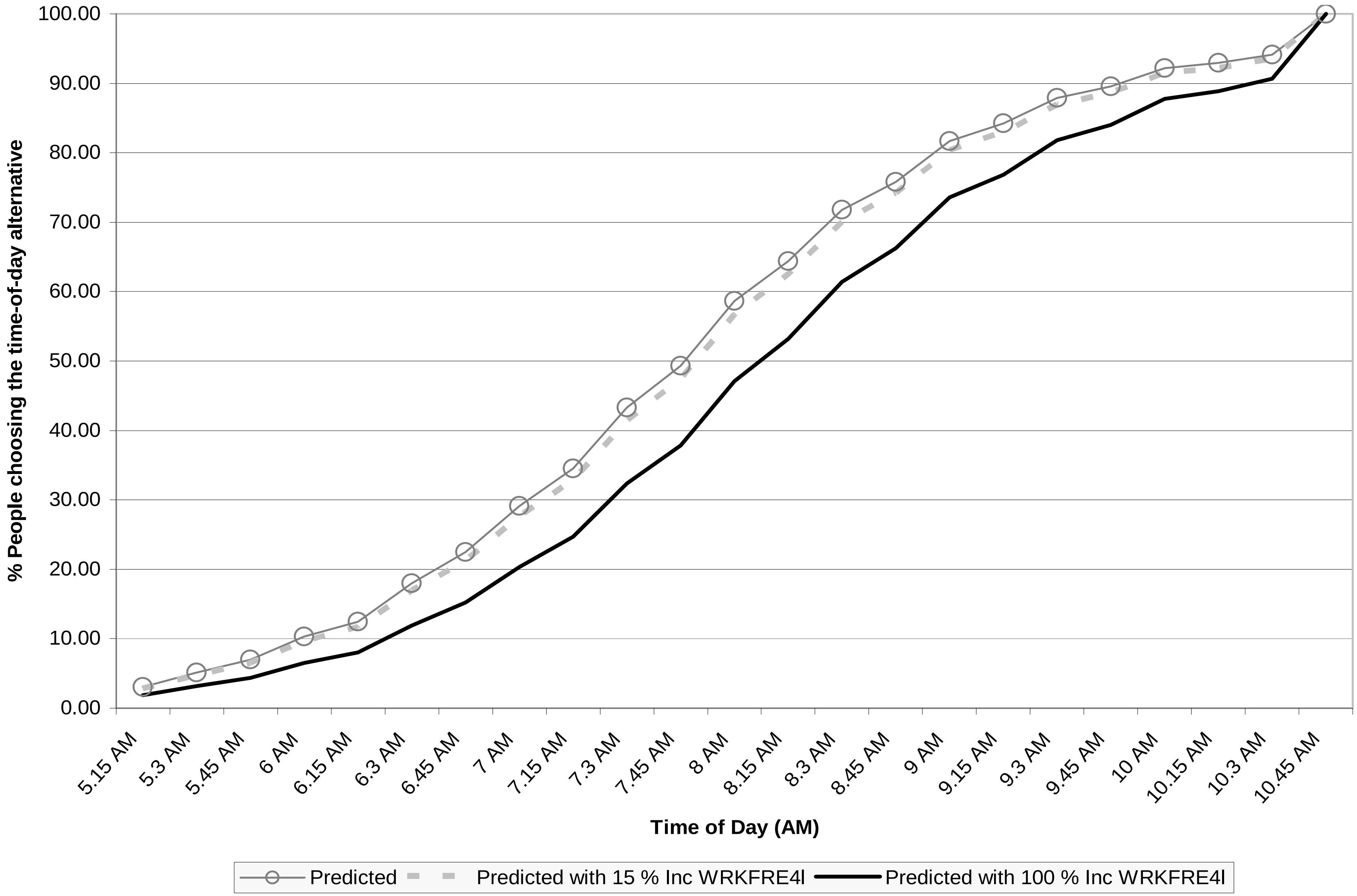

Figure 4-7. Cumulative impact of change in % departures with work frequency less than or equal to four for flexible schedule workers

CHAPTER 5
COMMUTE-TIMING MODEL FOR FIXED SCHEDULE WORKERS

This chapter presents the description of commute- timing models for workers with fixed work schedules in detail. Section 5.1 describes the dataset used for the estimations. Section 5.2 presents the modeling framework followed by a discussion of the results in Section 5.3. Section 5.4 presents an application of the commute timing model in the case of workers with fixed work schedules. Finally the chapter concludes with a summary in Section 5.5.

5.1 Data

Again, the San Francisco Bay Area Travel Survey (BATS) conducted in the year 2000 by is the source of data used in this set of estimations. The estimation dataset for the departure-time choice model comprises of 3600 weekday auto-based commute journeys of 2528 fixed-schedule full-time workers from 2262 households. The overall data processing procedure is similar to the one adopted in the context of modeling departure time choices of flexible-schedule workers.

The commute timing profile (*i.e.*, the percentage of departures to work in the estimation sample during each discrete time-of-day period) is presented in Figure 5-1. The mid-point times of the discrete periods are presented in the X-axis. That is, 5:30 refers to departures during the fifteen minute period from 5:23 AM to 5:38 AM; 5:45 refers to departures between 5:38 AM and 5:53 AM, and so on. The bulk of the departures (61 %) are concentrated in the 6:30 to 8:00 AM period. This occurs a little early as compared to the bulk of departures occurring between 7 and 9 PM as in the case of flexible schedule workers reflecting the constraint to get to work early. Departures before 4 AM or after 12:15 PM were relatively few and hence not included in this analysis. The reader will also note that departures at half-hour periods (*i.e.*, 6:30, 7:00, 7:30, 8:00, and so on) are generally higher perhaps reflecting inherent biases in the reporting of departure times in travel surveys.

Descriptive statistics on chosen explanatory variables from the above estimation dataset are presented in Table 5-1. In general we find that the fully-flexible, full-time workers analyzed in this study are middle-aged, equally likely to be male or female (as opposed to male slightly male dominate in case of flexible workers), and hold position in private profit making firm. The sample also includes considerable numbers of single-person households and individuals of Asian ethnicity like in the case of flexible schedule workers. It can also be observed that the average work duration of the fixed schedule workers is slightly more than that of the flexible schedule workers. The area type, household size, number of vehicles and children in the household distributions are pretty similar amongst both fixed and flexible schedule workers.

5.2 Methodology

The econometric structure presented in this section draws from earlier research of Steed and Bhat (2002) and Ben-Akiva and Abou-Zeid (2007). Specifically, we adopt the former researchers' approach to incorporate time-varying covariates in a hazard-duration framework (proportional-hazard structure with a non-parametric baseline-hazard distribution and a parametric control for unobserved heterogeneity) and the methodology prescribed by the latter researchers on accommodating latent work-start-time preferences.

The "hazard" for departing to work at any time of the day *u* (measured on a continuous scale, say in minutes from 3 AM) is defined as the probability that a worker will depart immediately after time *u* conditional on not departing until time *u*. This hazard is assumed to have the following functional form:

$$\lambda(u) = \lambda_0(u)\exp\left[\beta X + \gamma_1 Speed(u) + \gamma_2 SDE(u) + \gamma_3 SDL(u)\right]\omega \qquad \text{(Equation 5.1)}$$

In the above equation, $\lambda_0(u)$ is the baseline hazard. *X* is a vector of non-time varying and covariates such as the socio-demographic characteristics of the worker and β is the corresponding vector of coefficients. *Speed(u)* represents the commuting speed prevailing at time *u* and is defined as the ratio of distance and *TT(u)*. Where *TT(u)* is the travel time prevailing precisely at time *u*. *SDE(u)* and *SDL(u)* represent schedule delay terms as defined below:

$$SD(u) = u + TT(u) - WST$$
$$SDE(u) = \begin{cases} -SD(u) \text{ if } SD(u) < 0 \\ 0 \text{ otherwise} \end{cases} \qquad \text{(Equation 5.2)}$$
$$SDL(u) = \begin{cases} SD(u) \text{ if } SD(u) \geq 0 \\ 0 \text{ otherwise} \end{cases}$$

SD(u) represents the schedule-delay or the difference between the actual arrival time at work when departing at time u [i.e., u + TT(u)] and the preferred work start time (WST). Recognizing that earlier-than-preferred arrivals and later-than-preferred arrivals may be perceived differently by decision makers, the schedule delay term is further divided into early schedule delay (SDE(u)) and late schedule delay (SDL(u)). Note that both these schedule delay terms are always positive by definition. γ_1, γ_2, and γ_3 are the coefficients on the time-varying covariates (i.e.., the travel time and schedule-delay variables).Alternatively the schedule delay terms can also be defined as a fraction of free flow travel time or distance. The normalization is introduced to capture the sensitivity of delay terms to the commuting distance. In other terms a 5 min delay might imply different penalties to an individual commuting 10 miles (or 10 minutes of free flow time) and an individual commuting 20 miles (or 20 minutes of free flow time) to get to work. This allows us to estimate three different specifications based on how the schedule delay terms are specified. This will be discussed further in the next section.

The final term in equation 2 is the unobserved heterogeneity term (w) which is assumed to follow a gamma distribution (with variance = σ^2) and independent of the covariates.

As already indicated, we adopt a non-parametric distribution for the baseline hazard (i.e., $\lambda_0(u)$) in our specification. For this purpose, we discretize the continuous time into *K* unique time intervals. Let *p* denote the index for the time intervals (*p* = 1, 2,…, *K*) and a_p represent the upper bound time corresponding to discrete interval *p*. Therefore discrete period *p* represents the time interval [a_{p-1}, a_p] and the duration of this discrete period is given by, $\Delta_p = a_p - a_{p-1}$. The baseline hazard is then assumed to be a constant within each of these discrete periods (*i.e.*, $\lambda_0(u)$ = exp(δ_p) if *u* element of discrete period *p*). In addition, we assume that the value of time-varying covariates remain constant within each discrete time period (*i.e.*, $Speed(u) = Speed_p$ and $SD(u) = SD_p$ if *u* element of discrete period *p*) and are evaluated at the mid-point time of each discrete period.

The probability of departure in interval *p* conditional on knowing the preferred work start time (WST) is given by (See, Bhat and Steed, 2002 for details):

$$prob[t = p \mid WST] = \left[1+\sigma^2\left\{\sum_{j=0}^{p-1}\Delta_j \exp\left(\delta_j + \beta X + \gamma_1 Speed_j + \gamma_2 SDE_j + \gamma_3 SDL_j\right)\right\}\right]^{-\sigma^{-2}} - \left[1+\sigma^2\left\{\sum_{j=0}^{p}\Delta_j \exp\left(\delta_j + \beta X + \gamma_1 Speed_j + \gamma_2 SDE_j + \gamma_3 SDL_j\right)\right\}\right]^{-\sigma^{-2}}$$

(Equation 5.3)

Where $\delta_0 = -\infty$ and $\delta_K = +\infty$.

As the preferred work start times (WST) are not directly known from the traditional household travel surveys, we assume that the work-start-time preferences are latent and follow a discrete probability density function f(WST). In this research, we determine this density function from the distribution of work start times observed in the estimation data. Now, the unconditional probability of departure in a discrete period p can be obtained as:

$$prob[t = p] = \sum prob[t = p \mid WST]\, f(WST) \qquad \text{(Equation 5.4)}$$

Therefore the model parameters can be estimated by maximizing the following likelihood function:

$$L = \prod_{q=1}^{N} \prod_{p=1}^{K} \{Prob[t=p]\}^{M_{qp}}$$

$$M_{qp} = \begin{cases} 1 \text{ if individual } q\text{'s trip begins in period } p \\ 0 \text{ otherwise} \end{cases} \qquad \text{(Equation 5.5)}$$

5.3 Empirical Results

As described in the model formulation, the work-start-time preferences are assumed to follow a discrete probability density function determined from the distribution of work start times observed in the estimation data. This profile is presented in Figure 5-2. Note that work start times in our estimation sample range from 3:45 AM to 2:45 PM (there were relatively few very early or very late work starts and these are ignored in our analysis). This temporal range is divided into 43 equal 15-minute discrete periods and the probability of choosing to start work in any discrete period is determined as the fraction of the sample observed to start work during this period.

The results of our empirical specification of the hazard duration model for the departure time choice of the fixed schedule workers is as shown in Table 5-2. Three difference model specifications were developed. In Model (a), the schedule delay terms (SDE and SDL) were defined as in Equation 5.2. The schedule delay terms were normalized by distance in Model (b) and by free-flow travel time in Model (c) We now discuss the interpretation of the variables (remains same for any of the three specifications). We have classified the set of explanatory factors into the following four categories: (1) Individual and Household Socio-Economic Characteristics, (2) Individual Employment Characteristics, (3) Location and Commute Distance Characteristics, and (4) Time-Varying Characteristics.

5.3.1 Individual and Household Socio-Economic Characteristics

Among the set of individual-level socio-economic characteristics, age and gender impacts the choice of departure time. The coefficient on age is positive which means that older individuals are more likely to depart in the earlier time periods. Note that from equation 5.1, a positive coefficient on a time-invariant coefficient increases the hazard and hence increases the likelihood of departure at any time. Similarly men also chose to depart early relative to women. Other characteristics like ethnicity were also examined but were found to be statistically insignificant.

A positive coefficient on the number of children in the household indicates that workers with children depart earlier. This might be because of the need to drop off the children at school on their way to work. Household structure variables and the presence of other workers in the household were also tested but were found to be insignificant after controlling for number of children in the household. The number of vehicles in the household was also found not to impact the departure time decisions of fixed-schedule workers.

5.3.2 Individual Employment Characteristics

Work duration, work frequency, and the work type are individual-level employment characteristics found to determine the departure time choice for commute travel. Individuals who work long hours during the day also depart earlier for work, perhaps reflective of the overall time-budget constraints. Persons who travel to the out-of-home work location on all the five days of the week were found more likely to depart earlier in the day (relative to those who work less than five days a week). This is possibly reflecting a greater degree of fixity in the work schedules of such persons among all non-flexible full-time workers. This effect was only observed in Model a. The dummy for work frequency greater than four was found insignificant in the Models b and c. Finally, the occupation type of the person strongly influences the choice of commute departure time. Specifically, individuals employed in a governmental organization depart the earliest followed by those who work for private non-profit organizations. Self employed individuals depart the latest to work.

5.3.3 Location and Commute Distance Characteristics

The residential- and work-location characteristics were found to be insignificant in determining the departure-time choice of fixed schedule workers. However, we find that individuals who have to travel longer distances leave earlier in the day. The coefficients on the commute distance dummies were significant in Model a where the schedule delay was introduced as an absolute term. But in Models b and c where it was introduced relative to (fraction of) the distance and free-flow time some of the coefficients on the distance dummies turned insignificant. This might be due to the correlation that might exist between the relative schedule delay terms and the commute distance dummies.

5.3.4 Time-Varying Characteristics

The coefficient on the Speed (in miles per hour) variable was found to be statistically significant. The positive coefficient on the speed variable suggests that the individual is more likely to depart at a time with higher commuting speeds which is as expected.

The results show a negative coefficient on the early schedule delay terms. This indicates that an individual is less likely to depart at a certain time with increasing early schedule delay. Alternatively, this means that an individual who would get to work 30 minutes earlier than the desired work start time is less likely to depart at a certain time compared to an identical individual who would get to work only 20 minutes earlier than the desired work start time when departing at the same time.

The coefficient on the late schedule delay terms is positive and significant. This indicates that an individual is more likely to depart at a certain time with increasing late schedule delay. That is, a person who would get to work 30 minutes later than the desired work start time is more likely to depart at a certain time compared to an identical individual who would get to work only 20 minutes later than the desired work start time when departing at the same time. Note that these probabilities are conditional on not departing earlier.

Overall, the coefficients on the schedule delay terms indicate that commuters choose their departure times so as to arrive at work as close as possible to the preferred work start times. Another alternate specification to capture the sensitivity of the delay terms to commuting distance was estimated. The delay terms were partially segmented based on the four commute distance categories. We found that the coefficients across the distance categories were approximately the same. Hence this specification was deemed unnecessary.

The standard deviation of the unobserved heterogeneity term ("gamma" in Table 5-2) is estimated to be statistically different from zero. This reflects the strong presence of factors other than those controlled for in the model that influence the departure time choices of individuals. The baseline hazard for the estimated model is as shown in the Figure 5-3. It can be seen that the longer an individual waits to depart for work, the more likely he/she is to depart. In other words, there is general positive duration dependence in the hazard function for departure to work.

On the overall, Model a performed the best in terms of the likelihood fit measure. But if we have to capture the differential sensitivities on the delay term based on the commute distance Model b or Model c can be used. The results (sign of the coefficients) are same irrespective of whether the schedule delay is introduced into the specification as a fraction of distance of free-flow time. But amongst these two, Model c performed slightly better in terms of the likelihood fit.

5.4 Model Application

Similar to the structure in Chapter 4, we demonstrate an application of the commute timing model in predicting the aggregate time patterns of a sample of individuals. For this exercise, we use the validation sample containing the 612 observations. Section 5.4.1 presents the aggregate predictions on the choice of departure time on the sample followed by a description of the aggregate sensitivity of changes in time-varying and non time-varying characteristics to the departure time choice in Sections 5.4.2 and 5.4.3 respectively.

5.4.1 Aggregate Prediction of Departure Time Profiles

First, we predict the aggregate departure time choice patterns based on the estimates of the Model 'a' and Model 'b' respectively as shown in Figure 5-4. We find that, on an aggregate level the predicted departure choice patterns from both the models approximate to the observed departure time pattern in the sample. The maximum over and under prediction recorded were at around 1 % (at 7 AM) and 2 % (at 5.45 AM) respectively. Again, it should be noted that the reported numbers above are calculated as a difference of the observed and predicted percentages.

5.4.2 Aggregate Sensitivity to Changes in Time-Varying Characteristics

Secondly, we try to understand the influence of the sensitivity of the time-varying characteristics on the predictions of the departure choice patterns on an aggregate level. For this we consider two scenarios in which the commuting speeds during the peak period (7 AM and 9 AM) are doubled and halved respectively similar to the exercise in Chapter 4. The sensitivities of the departure time to the commuting speeds for Model 'a' and 'b' can be observed in the Figures 5-5 and 5-6 respectively. The time of the day is plotted on the X-axis and the cumulative percentage of departures is plotted on the Y-axis. Model 'a' suggests the highest number of departures in the case of reduced speed in the peak period, which is against our expectations (as compared to the base case of no change in speed and doubling the speed). This might be the manifestation of the trade-off between the commuting speed and schedule delay terms in the specification. Reduced speeds might be getting people closer to their work start times as opposed to higher speeds resulting in being at work much earlier than the preferred work start times. This suggests that the schedule delay dominates over the effect of commuting speed in the specification of Model 'a'. The opposite effect is observed in the case of Model 'b' i.e. doubling the speeds increases the departures and reducing the speed in the peak period reduces the departure in that period. This suggests that the commuting speed dominates over the schedule delay terms in the specification of Model 'b'.

5.4.3 Aggregate Sensitivity to Changes in Non Time-Varying Characteristics

Finally, we depict the sensitivity to non-time varying covariates on the choice of departure time. The variable chosen for the purpose of demonstration is the assumed aggregate distribution of the work start time. Specifically, we adjust the probabilities of the individuals to reflect a generic preference to start work earlier, than the base case (adjustment done in the 7 - 9 AM period). Models 'a' and 'b' predict an increase in the departures in the earlier time periods (before 7 AM) and also a decrease in the time periods after 9 AM as compared to the base case. These results observed in Figures 5-7 and 5-8 is as expected due to the increased generic preference to depart in earlier time periods.

5.5 Summary and Conclusions

In this chapter, a continuous-time model for the choice of departure time for the home-to-work commute for fixed schedule workers was formulated and estimated. A hazard-duration structure is adopted that accounts for latent work start time preferences. The model was estimated using data from the 2000 San Francisco Bay Area Travel Survey. The empirical results capture the strong effect of schedule delay on departure time decisions. Specifically, the model highlights that fixed-schedule commuters are likely to choose departure times so as to arrive at work as close as possible to their preferred work start times. The model also captures the effects of several socio-economic and employment characteristics variables on the commute timing decision. An application of the commute timing models that were estimated was also presented. The sensitivities of the time-varying and non time-varying factors on the prediction of the departure time choice patterns were analyzed.

Table 5-1. Sample characteristics of full-time workers with fixed work schedules

Attribute	Statistic	Attribute	Statistic
Individual Char.		**Household Char.**	
Age	43.37 (11.33)	Number of persons	
Gender	`	1	15.00
Male	49.08	2	39.17
Female	50.92	3	17.25
Ethnicity		4	18.44
Caucasian	74.31	>=5	10.14
African American	3.50	Number of vehicles	
Hispanic	6.78	1	19.472
Asian/Pacific islander	8.81	2	46.361
Other	6.61	3	23.972
Work duration in hours	8.68(1.95)	>=4	10.194
Work frequency		Number of children	
<5 days per week	6.78	0	65.19
>=5 days per week	93.22	1	15.14
Occupation		2	13.75
Private non-profit	10.36	>=3	5.92
Private profit	63.00	Presence of another fixed schedule worker	
Governmental organization	23.22	No	59.86
Self employed	3.42	Yes	40.14
Transportation System and Land Use Char.		Household structure	
Commute free flow time (mins)	18.34(11.15)	Single person	15.00
Commute distance in miles	12.57(10.43)	Single parent	2.17
Area type of home zone		Couple	30.97
CBD (density >100)	0.67	Nuclear Family	21.81
Urban (density 30-100)	18.11	Other	30.05
Suburban (density 6-30)	76.03		
Rural (density >6)	5.19		
Area type of work zone			
CBD (density >100)	6.64		
Urban (density 30-100)	33.83		
Suburban (density 6-30)	55.14		
Rural (density >6)	4.39		

The values mentioned are the mean (standard deviation) for continuous variables and the percentage shares for the categorical variable

Table 5-2. Empirical results: Covariate effects for the hazard duration model for departure time choice of fixed schedule workers

Attributes	Model a: Speed, SDE, SDP, discat		Model b: Speed, SDEd, SDPd, discat		Model c: Speed, SDEf, SDPf, discat	
	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic
Individual and Household Socio-Economic Characteristics						
Age	0.0161	8.21	0.0129	8.926	0.0131	8.018
Male	0.6946	11.77	0.4892	13.292	0.5785	13.015
Number of kids in the household	0.0908	4.716	0.0688	4.399	0.0671	3.901
Individual Employment characteristics						
Work duration	0.0049	15.391	0.0039	24.146	0.0042	20.78
Work frequency is >= 5 days per week	0.1481	1.871	0.0008	0.014	0.056	0.818
Work type (Self employed is Base)						
Private non-profit	1.4662	9.665	1.1751	11.267	1.2451	10.338
Private profit	1.1241	8.128	0.9378	8.638	0.9475	7.748
Governmental organization	1.5824	10.704	1.3496	12.812	1.3405	11.195
Location and Commute Distance Characteristic						
Commute Distance						
0 - 5 miles	--------	--------	--------	--------	--------	--------
5 -1 5 miles	0.1176	1.66	0.0466	0.766	-0.1009	-1.446
15 - 30 miles	0.4007	3.652	0.3124	3.899	0.1021	0.996
30 - 50 miles	1.1858	7.471	0.9927	9.325	0.7554	5.463
Time Varying characteristics						
Speed (miles/hr)	0.0107	2.925	0.013	4.624	0.0141	4.889
Schedule Delay on the early side (min)	-0.0157	-8.751	-0.009	-4.807	-0.0506	-5.576
Schedule Delay on the late side (min)	0.0142	2.072	0.0893	7.684	0.2959	4.603
Gamma	0.6957	9.084	0.7727	25.53	0.8638	22.45
Number of cases	3600		3600		3600	
Loglikelihood at Convergence	-30670.6788		-30692.6604		-30680.8956	

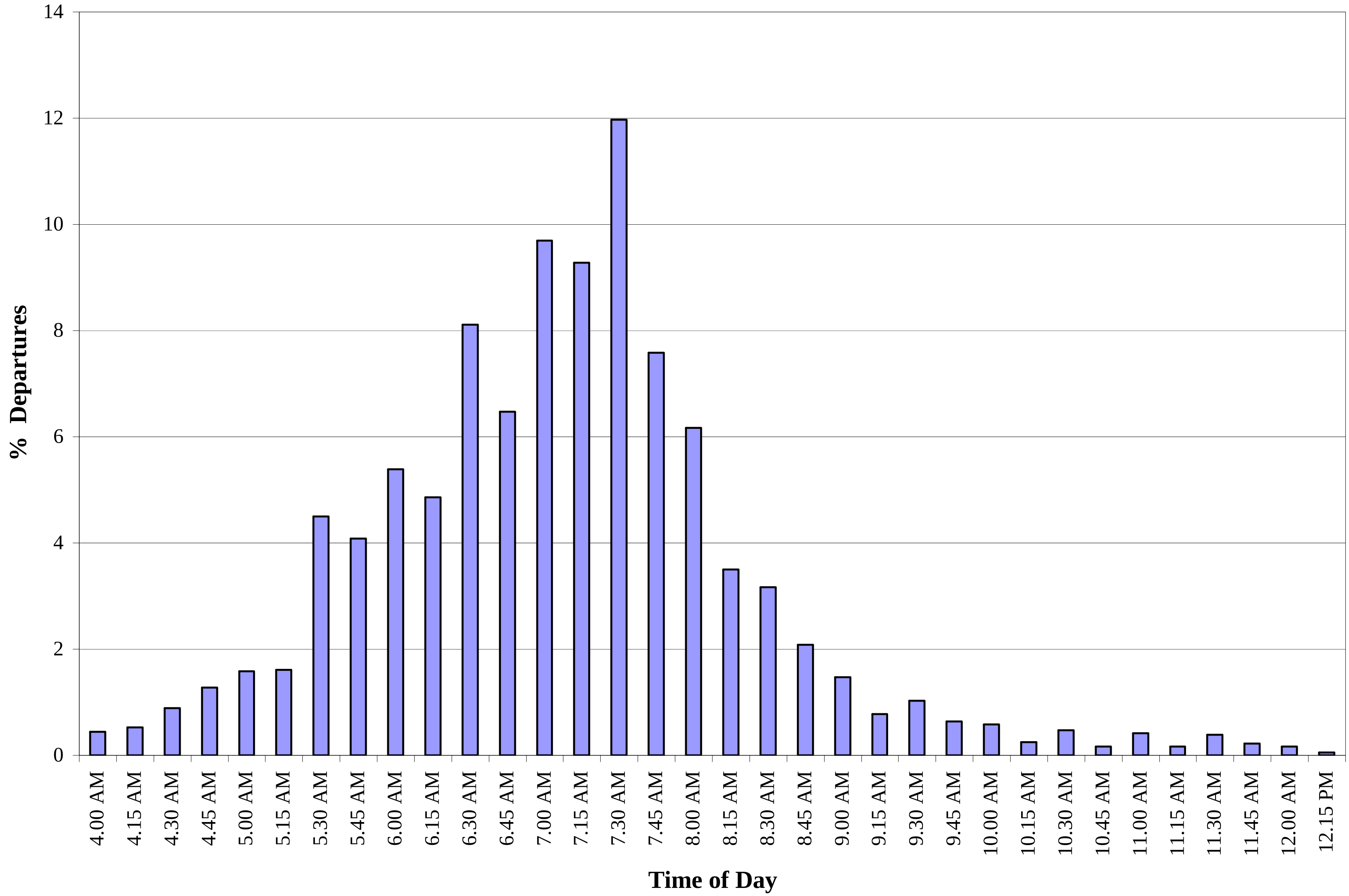

Figure 5-1. Departure time distribution over time-of-day fixed schedule workers

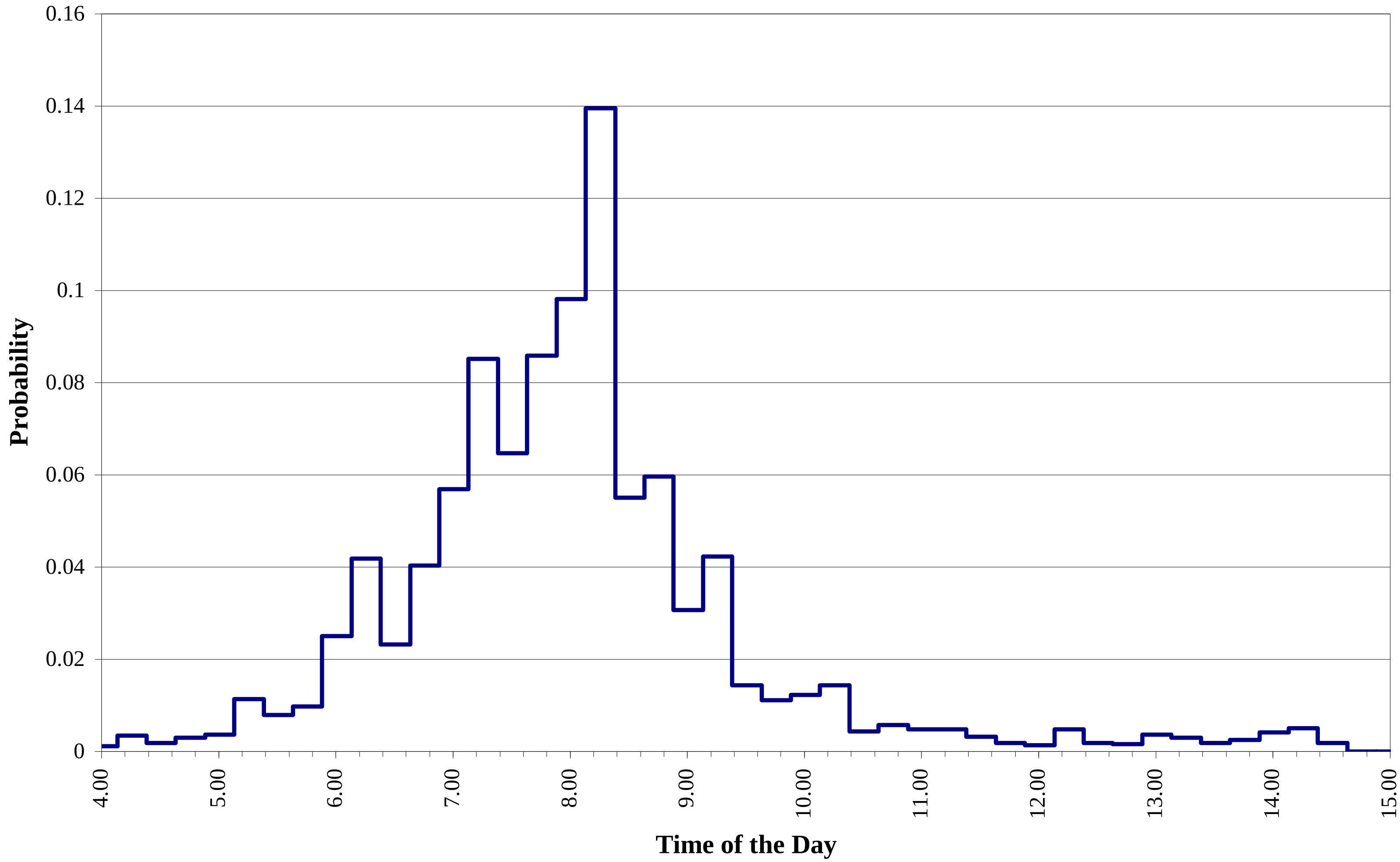

Figure 5-2. Probability density function for the preferred work start time of fixed schedule workers

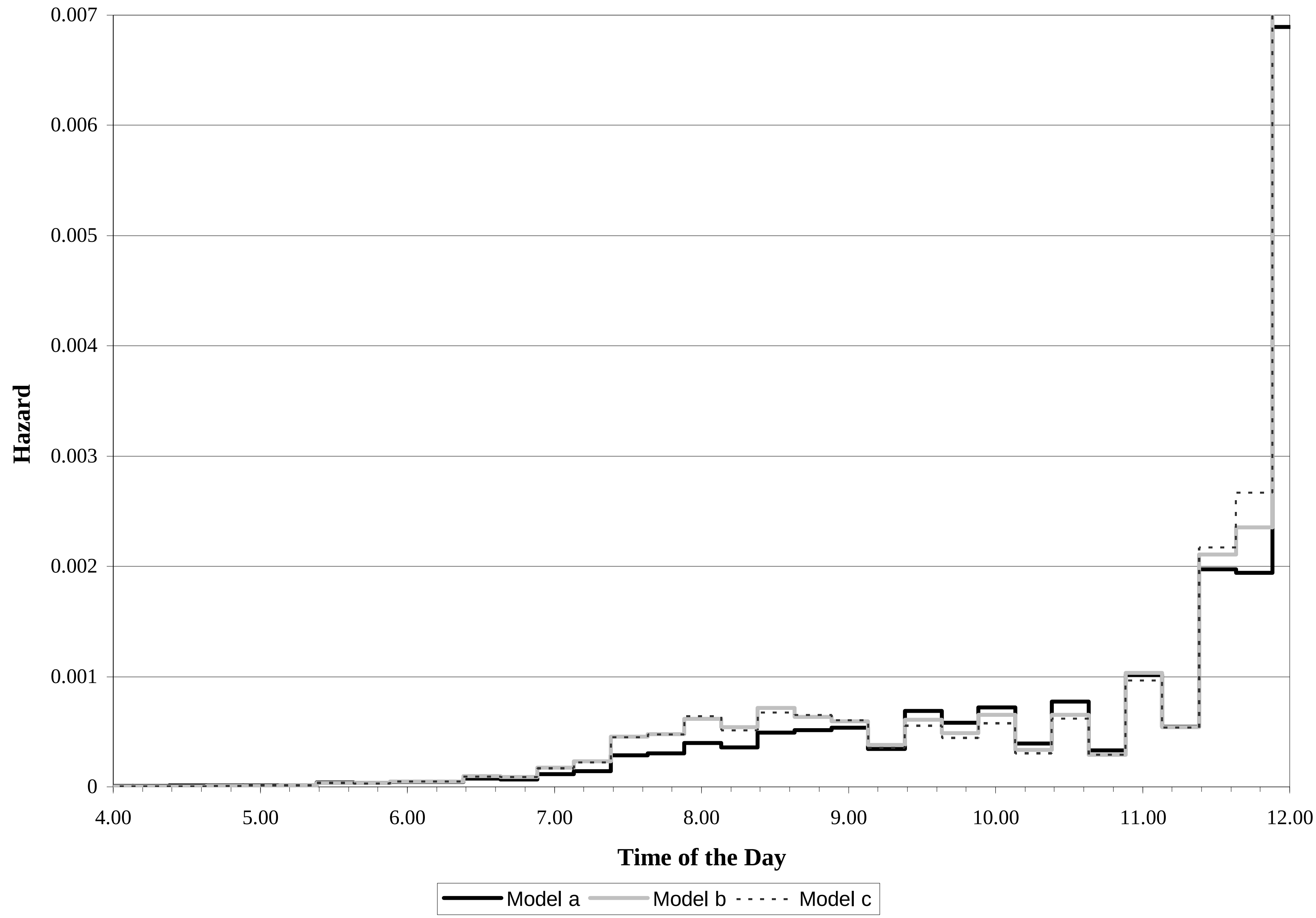

Figure 5-3. Estimated baseline hazard distribution of fixed schedule workers

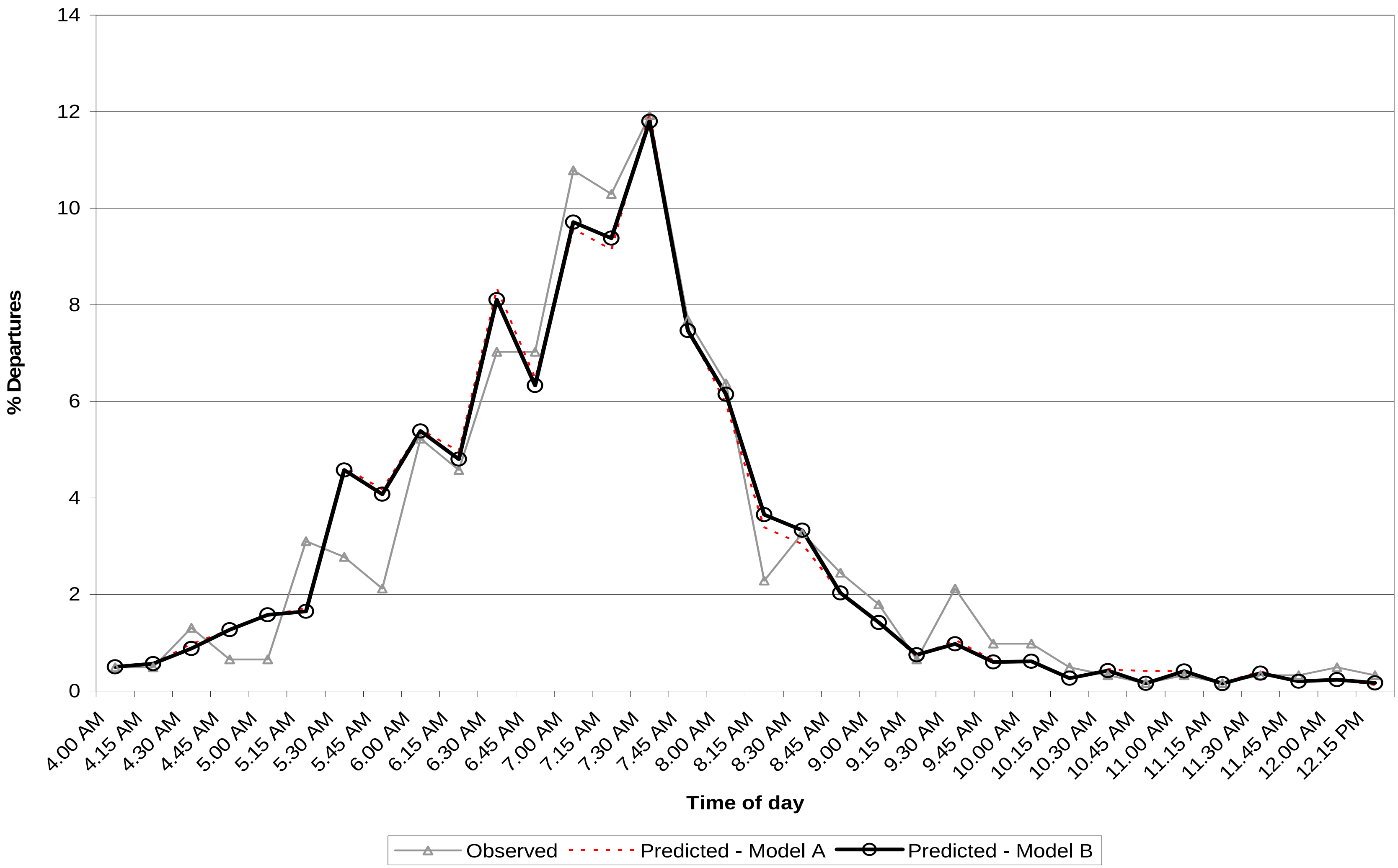

Figure 5-4. Observed vs predicted distribution of departure time patterns of fixed schedule workers

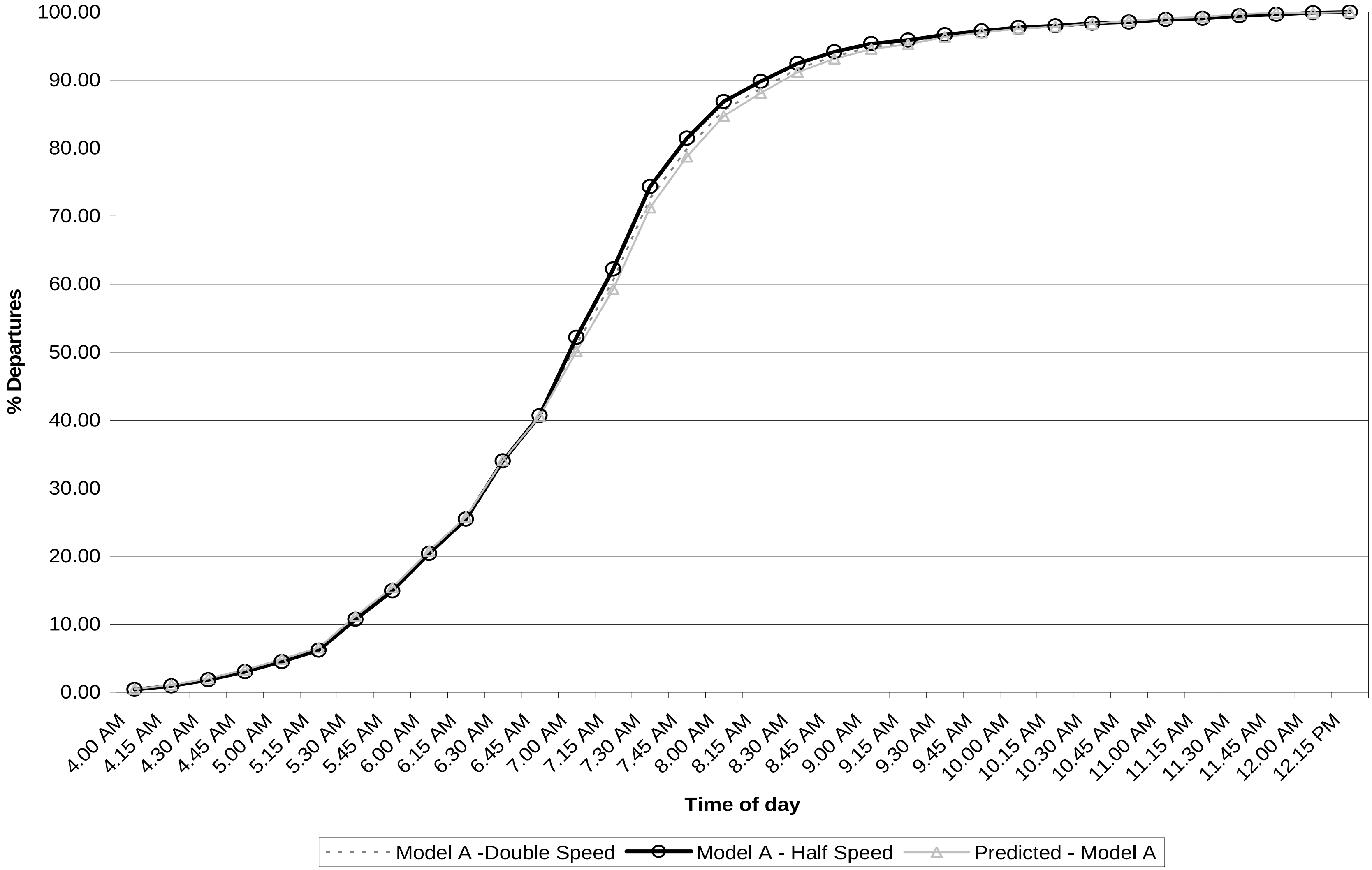

Figure 5-5. Cumulative impact of change in commuting speed in the morning peak period (7 AM to 9 AM) for Model 'a' for fixed schedule workers

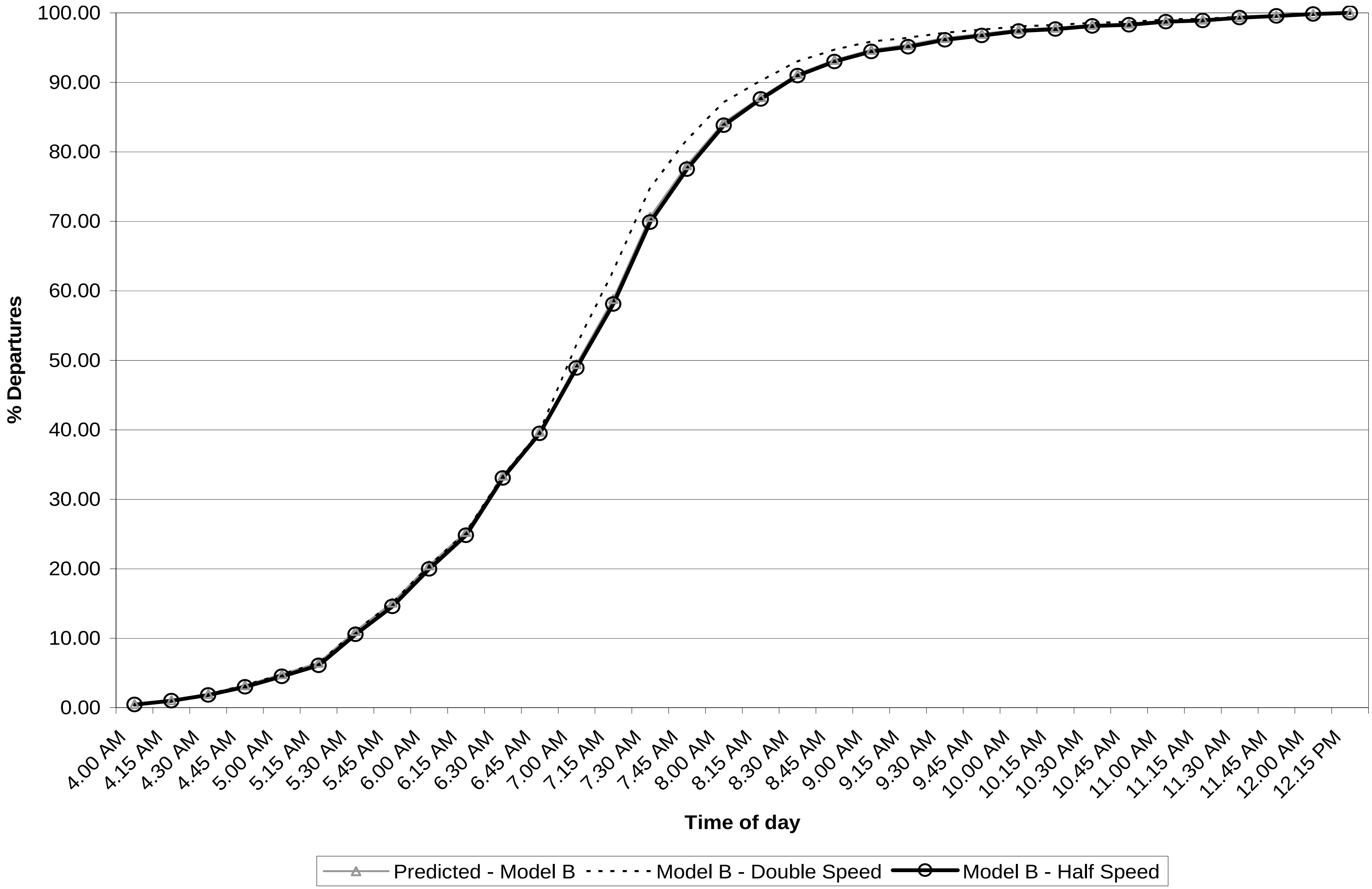

Figure 5-6. Cumulative impact of change in commuting speed in the morning peak period (7 AM to 9 AM) for Model ‘b’ for fixed schedule workers

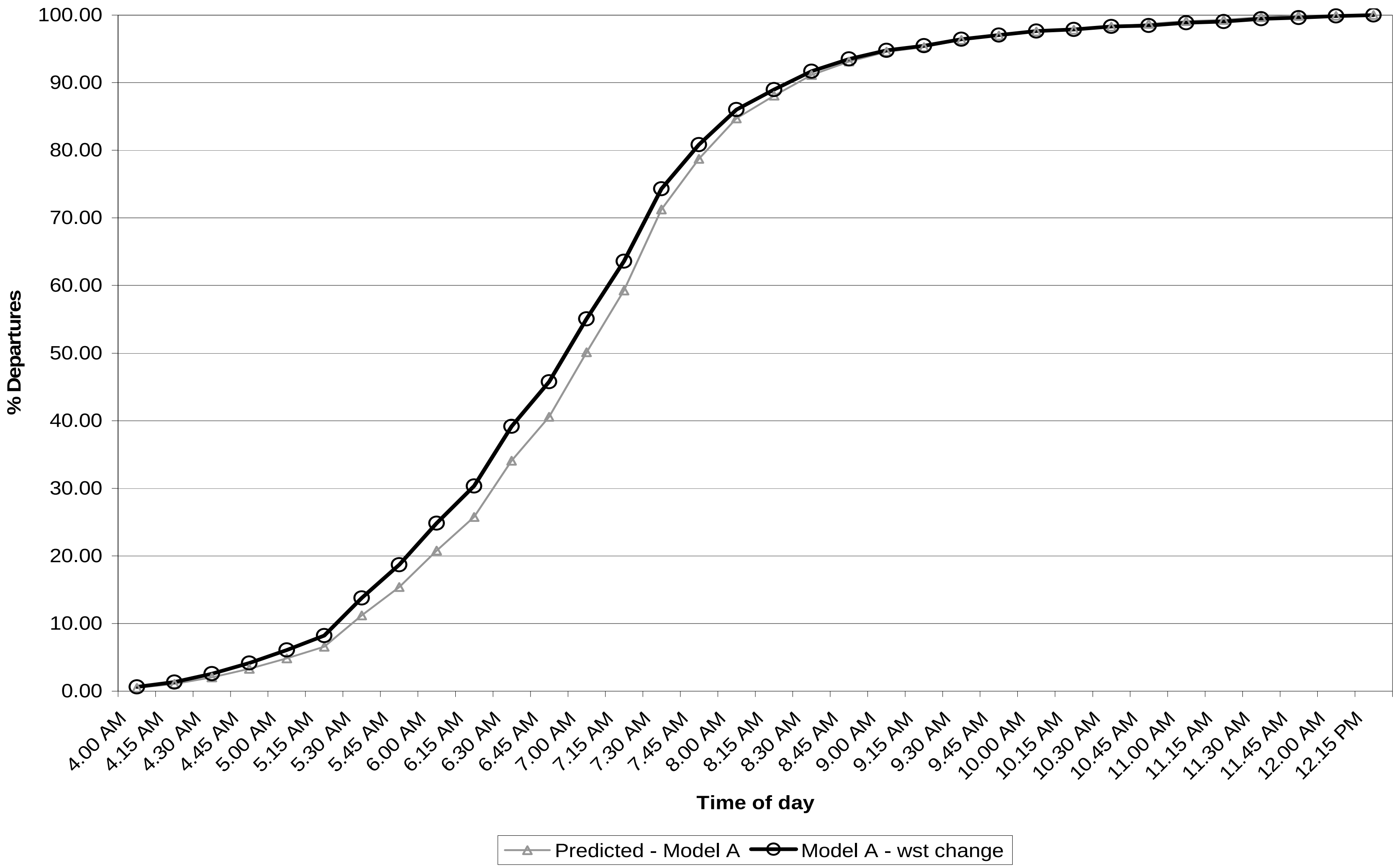

Figure 5-7. Cumulative impact of change in % departures with change in work start time preference for Model 'a' for fixed schedule workers

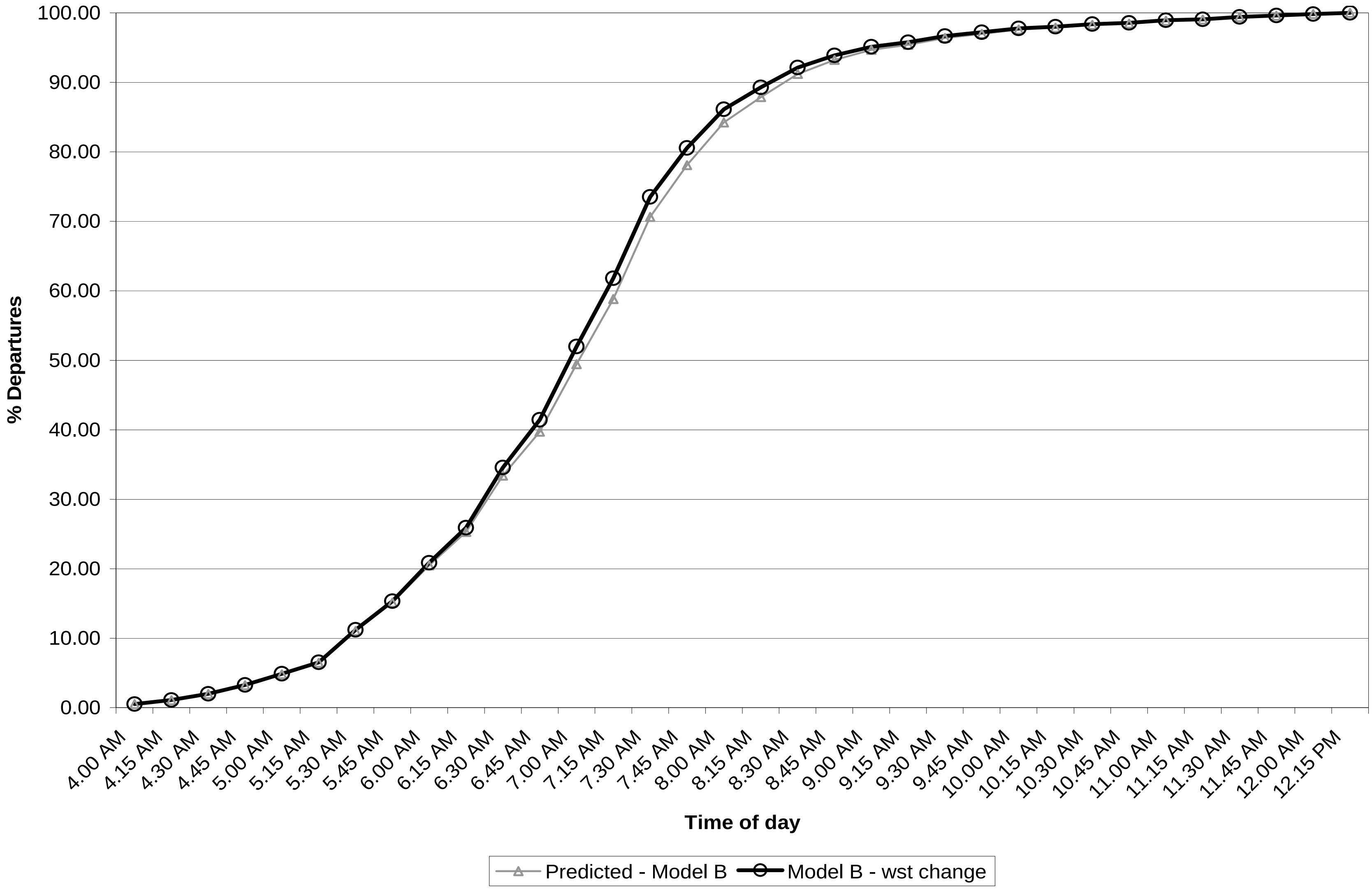

Figure 5-8. Cumulative impact of change in % departures with change in work start time preference for Model ‘b’ for fixed schedule workers

CHAPTER 6
SUMMARY AND CONCLUSIONS

A detailed understanding of departure time choice of commuters is necessary in the wake of increasing volumes of commute travel along with their changing temporal patterns due to increasing availability of work start flexibility, telecommuting behavior, shared ride services and increasing HOT/HOV lanes during the peak hour. Further, it is important to evaluate policy implications of introducing time-varying road pricing or congestion pricing schemes on the departure time patterns. Hence disaggregate departure time models for full-time fixed and flexible schedule workers were estimated. The emphasis in the commute-timing models was to incorporate the effects of time-varying transportation system covariates. For this a separate set of inter-zonal travel time regression models were estimated. Econometric models which adopted a hazard duration structure were estimated for both the commute-timing models. For the fixed schedule commuter, the constraint of being at work at a specified time was captured but introduced the concept of schedule delay. Several other factors found to impact commute departure time such as individual and household socio-economic characteristics, employment characteristics and land use characteristics were also introduced. Further an application of the commute timing models was also demonstrated indicating the ease of implementing these models in practice for policy evaluation. Data from the 2000 San Francisco Bay Area Travel Survey (BATS) were used in this study.

Section 6.1 will provide a brief summary of the empirical results followed by the limitations and directions for further research in Section 6.2.

6.1 Summary of Empirical Results

Section 6.1.1 will summarize the empirical results for the inter-zonal travel time models. Later, Section 6.1.2 will provide a brief summary of the empirical implications for the commute-timing models.

6.1.1 Summary of empirical results for inter-zonal travel time models

Inter-zonal travel time models were segmented based on the four commute distance categories. Further segmentation based on origin and destination land use categories was done. A total of 10 models were estimated. This segmentation was not possible in the case of very short distance trips (0-5 miles) and very long distance trips (30-50 miles) due to lack to variation in the observed travel time and data amongst different categories respectively.

Our empirical results on the inter-zonal travel time models indicate the influence of time-of-day and distance. In general longer the distance/ free flow time longer the travel duration. The variability across the time-of-day was very apparent in the case of long distance (5-30 miles) and very long distance trips. The travel times showed two smooth peaks indicating the morning (7 AM to 9 AM) and evening (3 PM to 6 PM) peak periods. It could also be observed that the travel durations were higher for a trip from a sub-urban region to urban regions when compared to that for a trip from sub-urban to urban region in the morning time period. The vice-versa was observed during the evening peak period. This indicated that the directionality effects of the congestion are appropriately captured by the model specifications.

6.1.2 Summary of empirical results for commute-timing models

Our empirical results on the commute-timing models reinforce several intuitive conceptions also documented in the literature. For example, workers in households where kids are present (or nuclear households) were found to depart later than workers in households with no children (single-person or couple households). Also early departures were observed when the commute distances grew or when individuals have to stay at work for longer durations. Further, people chose to depart in periods experiencing higher speeds (or lower travel times) or at times which could get them as close as possible to the preferred work start times. Another interesting variable we tested was the day of the week. The effect was however statistically insignificant for fixed schedule workers. This is in contrast to the result obtained in the case of flexible-schedule workers. Overall, this result reinforces that fixed schedule workers have very tight time constraints and hence travel at the same time irrespective of the day of the week. It was also found that presence of another fixed schedule worker in the household affected the departure time of only flexible schedule workers and not a fixed schedule worker. This effect is the manifestation of tighter constraints to start work at a specified time for a fixed schedule worker. Several other employment characteristics such as occupation and industry type impacted departure time of commuters. Apart from the above mentioned variables several variables such as ethnicity, dummy variable for student, origin and destination land use characteristics and several interaction variables between time varying covariates and demographic variables (to capture response heterogeneity) were tested but found to be insignificant.

For a better understanding of the model application for forecasting purposes, a separate set of demonstration exercises were carried for both the commute timing models highlighting the sensitivities of the departure time patterns to time varying and non-time varying covariates. Through this exercise, we found that the departure time patterns predicted compared very closely to the observed departure time pattern on an aggregate time scale.

6.2 Directions for Further Research

There are several directions for further research that can be explored in this area of research. In this section, we identify empirical and methodological enhancements:

Conventional revealed preference travel survey data do not collect data on the preferred or desired work start time of the individuals. This was dealt by simply assuming the observed work start time distribution in the dataset. A better approach would be to enhance the survey instrument to collect additional data on preferred work start times. Further, the inter-zonal travel time models estimated and forecasted from survey data seem to be the easiest way to produce travel times by time-of-day. With the available technology, travel time data by time-of-day can also be collected by instrumented vehicle experiments on the transportation network (to be used in building the travel time models). This essentially will eliminate the error in the travel times reported by individuals in the survey data. Also, if data on time-of-day specific data were available for travel/parking costs they can also be incorporated into empirical modeling. For example, policy evaluation on the impacts of commute departure time in response to congestion pricing can be evaluated by additional the appropriate costs such as travel costs and parking costs.

The models developed in this research could be enhanced methodologically is several of the following ways.

1. The hazard duration structure does not recognize the effect of future travel times (departure at time *t* conditional on not departing until time *t*) on departure time choice. We tried to overcome this limitation by introducing the future travel times into the model as explanatory variables. These variables were found to be insignificant in our estimations possibly due the presence of high correlation (less variability in travel times) across the adjacent time periods. More research on how to appropriately capture these future effects still needs to be addressed.

2. The main advantage of using a hazard duration type framework is the parsimonious structure it provides at fine temporal resolutions of choice alternatives as opposed to the MNL type models. At the same time, it lead to an overall restrictive relationship between the departure time choice and the explanatory factors. On the other hand, MNL or Ordered response type advanced formulations such as OGEV or the mixed multinomial logit type structures provide the flexibility to specific elaborate correlation structures. This will again have the issue of exploding alternatives at finer temporal resolutions. Studies which can quantify the trade-offs between using the hazard duration structure and OGEV type specifications need to be explored.

3. This study mainly focused on developing continuous departure time choice models for commuters. A broader perspective would be look at how these models fit into the current comprehensive demand forecasting frameworks.

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BIOGRAPHICAL SKETCH

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