IMPACTS OF FLEXTIME ON DEPARTURE TIME CHOICE FOR HOME-BASED COMMUTING TRIPS IN AUSTIN, TEXAS

Mashrur Rahman
Community and Regional Planning, School of Architecture
The University of Texas at Austin
mashrur@utexas.edu

Krishna Murthy Gurumurthy
Department of Civil, Architectural and Environmental Engineering
The University of Texas, Austin
gkmurthy10@utexas.edu

Kara M. Kockelman
(Corresponding Author)
Dewitt Greer Professor in Engineering
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
kkockelm@mail.utexas.edu
Tel: 512-471-0210

ABSTRACT

Increasing number of corporations and workplaces have begun to provide flexible working hours, or flextime, for employees, which is expected to reduce congestions by redistributing the temporal pattern of commuters' departure time. This study examines the impacts of flextime on departure time choice using a Bayesian continuous-time hazard duration model. The model accommodates the time-varying effect of covariates and unobserved heterogeneity. Results from the Austin Household Travel Survey collected between 2017 and 2018 show that workers who have a flextime option choose to leave later, with a predominant effect deterring AM peak departures. Other trip and individual-specific variables such as travelers' job type, trip duration, number of trips during the travel day and household income were found to have significant impacts on departure time choice. The results also show that flextime is more effective shifting the departure time for retail and service sector employees, those who travel longer and perform more daily activities. The findings of this study reconfirm the theoretical underpinnings that implementing such policies may ease congestion by staggering the travel demand from peak to off-peak hours.

Keywords: Flextime; departure time; congestion relief; time-varying effect, proportional hazards.

INTRODUCTION

Departure time choice is an important component of commuters' trip-making behavior. At an individual level, the overall cost of commuting, including the penalties for travel-time delays and early or late arrival, depends on departure time choice. At the system level, departure time choice

determines the temporal pattern of vehicles occupying the network and the resulting level of service and congestion on urban roadways. The classic bottleneck theory was first formulated by Vickery (1969) to illustrate commuters' trip-making behavior and the resulting congestion during peak hours. According to this simplified model, the potential bottleneck in a fixed capacity roadway activates when flow exceeds capacity. As a result, commuters suffer delays from long queuing at congested bottlenecks. At the same time, they have to consider penalties for early and late arrival at their destination. Early arrival entails disutility considering the opportunity cost of time: the worker could enjoy their time better outside the workplace. Starting work early may not ensure higher wages earned in most cases. However, late arrival may entail greater disutility on grounds of punctuality. There may be various forms of penalties imposed by employers, such as a warning, salary deduction or even loss of the job. Thus, commuting cost is not simply a function of travel time, but is instead the total cost derived from travel time, delay, and early and late arrival (Small, 1982). A flexible working schedule plays a significant part in this decision. By choosing flexible working hours, commuters can avoid late or early arrival penalties and minimize overall commuting cost. If a large number of travelers depart before or after peak hours, travel demand may be spread over a wider time window, thereby reducing peak congestion.

Existing studies that explore the traveler-level benefits associated with flextime also reveal that the most obvious benefit is avoiding congestion. It was found that driver stress is lower for commuters who have a flextime alternative since they may choose to travel during off-peak hours (Lucas and Heady, 2002; Rowden et al., 2011). Moreover, flexible working hours allow for greater flexibility in lifestyle choices. For example, individuals may have time for other personal activities, such as shopping, taking children to school, and doing other household-related activities (Combs, 2010). Research has shown that early arrival to work is associated with an increase in time for leisure activities after work (Ott, 1980; Moore et al., 1984; Combs, 2010).

About 81 million workers, accounting for 57% of all full-time workers in the USA, had the ability to choose a flexible schedule in 2018 (Bureau of Labor Statistics, 2020). The Bureau of Labor Statistics (2020) found that public sector employees are more likely to have flexible working hours than private sector employees. The COVID-19 pandemic reflects the importance of flexible workplace policies to reduce the reliance on fixed infrastructure. Many organizations are increasingly embracing flexible working schedules and allowing their workers to adapt to alter their activity schedules. Such practices can help employees manage household responsibilities, avoid unreliable transportation, and take care of mental health.

Understanding departure time choice is important to assess the true impact of increasing flexibility at the workplace (McCafferty and Hall, 1982), especially in special instances brought about by a pandemic. Decision making for departure time depends on personal heterogeneity and institutional constraints. Previous studies analyzed departure time choice to examine the effectiveness of policies that affect commuting cost, such as tolls, congestion pricing (Kalmanje and Kockelman, 2004; Ozbey and Yanmaz-Tuzel, 2008), information access and travel-time reliability (Jha et al., 1998; Ettema and Timmermans, 2003;; Hendrickson and Plank, 1984). However, empirical evidence of flextime's effect on departure time is relatively scarce (McCafferty and Hall, 1982; Saleh and Farrell, 2005; He, 2013). Discrete choice methods were used in earlier studies to analyze flextime impacts on departure time, although choices that are made in continuous time. This study applies a continuous-time proportional hazard duration model within a Bayesian framework using data from the Austin Household Travel Survey for travel between 2017 and 2018. The model accommodates time-varying effects of several covariates and unobserved heterogeneity in

departure time decision with a flexible framework for controlling other individual-specific effects. The remainder of the paper is organized as follows. A detailed literature review on flextime impacting departure time choice is presented next. This is followed by data description and model specification. Findings from the model estimation are discussed next, and the paper ends with conclusions.

LITERATURE REVIEW

Few studies focus on the impacts of flextime on work performance, mental wellbeing, work-family balance, wage difference and urban productivity (Ott, 1980; Christensen and Staines, 1990; Ezra and Deckman, 1996; Gariety and Shaffer, 2001; Lucas and Heady, 2002; Sharpe et al., 2002; Scroggins et al., 2010; Spieler et al., 2017). Even fewer papers analyze the impacts of flextime on travel outcome (Yeraguntla and Bhat, 2005; He, 2013). Most of these studies indicate flextime schedules have positive impacts.

McCafferty and Hall (1982) compared travel time choice before and after the closure of one CBD road exit in Ontario, Canada. Although the study considered flextime to indicate whether workers had flexibility to choose when to start work, flextime was used for sample selection instead of as an explanatory variable. The final sample included only those who had a flextime option. The only variable found to be significant was income. The authors maintained that the poor model fit indicated the effectiveness of flextime in altering temporal pattern of travel demand. However, due to the small sample size, the authors pointed out that their result was not conclusive to assess the effectiveness of flextime. The authors suggested including more explanatory variables over a larger sample size may improve the evaluation and accurately predict time choice behavior.

Chin (1990) studied the effect of location, individual demographic characteristics and occupational factors on departure time based on the implementation of the Area License Scheme (ALS) in Singapore. Results showed that ALS had heterogeneous impacts on departure time choice across different mode users. Car users, whose departure time share before 7:30AM rose from 28% to 42%, were impacted the most. The study also revealed that low-income travelers were more likely to work in production and manufacturing sectors which often follow a rigid work schedule due to the economies of production when all assembly lines must be staffed. However, high-income travelers, such as those who work in business, construction, administration, trade, sales, and clerical jobs, were also found to be less likely to vary their departure times.

He (2013) used a multinomial logit (MNL) model to analyze the influence of flextime on the departure time of commuters in the two largest cities of California: Los Angeles and San Francisco. Trip data were drawn from the National Household and Travel Survey (NHTS) 2009. Results indicated that workers from certain occupational categories, such as sales, professional, service, managerial, and technical jobs, were much more likely to depart during post-peak hours, whereas those in manufacturing, construction and production chose to leave home during pre-peak hours. Similar findings were also reported by Chin (1990) and Yoshimura and Okumura (2001). Among other factors, travel distance, number of non-work trips and family composition were significant factors in departure time choice. The model included flextime alternative as an explanatory variable. Those who had a flextime option preferred to depart later. Flextime increased the probability of post-peak departure by 7.41% and reduced the probability of departure in pre-peak and peak hours by 3.30% and 4.11%, respectively.

While most studies defined flextime based on binary options of having flexible working schedules or not, Saleh and Farrell (2005) used five factors to operationalize the level of flexibility: whether the employee could start work 30 mins before or after the official start time, presence of dependent children in the family, non-work family activity, and income. These factors reflect work schedule flexibility, non-work flexibility and financial flexibility. Using an MNL model, Saleh and Farrell (2005) found that a higher level of flexibility encouraged people to depart later. The findings also show that non-work flexibility and work schedule flexibility have a large influence on departure time choice. Those who have flexible work schedules may not be flexible in their work trips due to other non-work-related commitments.

DATA AND METHODOLOGY

STUDY AREA

This work focuses on the Austin, Texas region, that houses 2.2 million residents and is among USA's fastest growing metro areas (U.S. Census Bureau, 2019). Traffic congestion has become a major concern for Austin as the rising travel demand has outgrown the transportation infrastructure, at least during peak times of day. Across US regions, Austin ranks between 11th and 20th for metrics such as yearly delay per auto commuter, travel time index, commuter congestion cost per auto commuter, and commuter stress index (Texas Transportation Institute, 2019). It is expected that many Austin drivers already adjust their travel time to cope with traffic congestion, but little is known on what the specific effect of flextime is on departure time.

DATA

The Austin Household Travel Survey data for years 2017-2018 contains household-level, person-level, vehicle-level, and trip-level details. A total of 35,699 trips are collected across all trip types from 2,920 participant households. The survey area includes five counties in the Capital Area Metropolitan Planning Organization (CAMPO) boundary: Hays, Travis, Williamson, Bastrop and Caldwell counties.

The survey data includes a binary variable on travelers having flexible work hours. However, detailed information about the flextime policy is unavailable. For example, workers may have an informal arrangement instead of a formal one, or may have a limitation on number of days in week this flextime option may be used. This is a limitation since the effect of departure time choice for those with informal or limited flexible hours may not be uniform across all days, or the days reported in the dataset. Nevertheless, this study hypothesizes that any flexibility in work hours should have a non-zero effect on departure time choice, and the methodology is set up with that in mind.

The proportion of workers in the study area having flexible working schedule option is 30%. Two peak hour periods are expected during daily operation. Figure 1 shows that the morning peak hours are from 6 AM to 9 AM, and the afternoon peak hours are from 4 PM to 7 PM. With the focus of this paper being the impact of flextime on departure time choice, only home-based work (HBW) trips (n = 1,809) are considered, and their return trips were removed. People leave as early as 8 AM in the morning, and the busiest hour is expected to be between 8 AM and 9 AM. Overall, peak hours account for 62.5% of total trips, while the shares of pre-peak, post-peak (until midday) and after midday (12 PM) are 13.2%, 11.3%, and 13.0%, respectively.
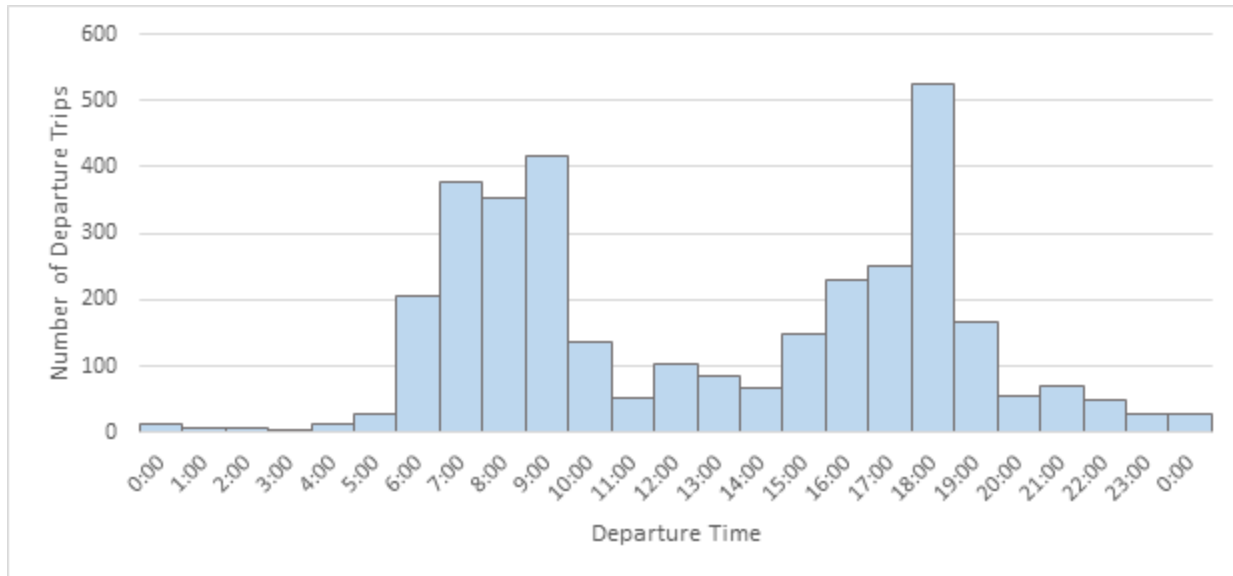
Figure 1 Departure time distribution over the course of a day

The trip data was further matched with Austin's traffic analysis zones (TAZs) to obtain land-use information. Two land use variables are derived from TAZ data – density and entropy. Density represents how intensively the land is being used for different activities such as housing, employment and other purpose. In this study, activity density of TAZ trip origin was measured in terms of sum of population and employment normalized by the TAZ's area. Entropy index shows the diversity of land use – how different activities are distributed across the space. The index is normalized by the number of distinct activities (natural log), to be bounded between 0 and 1 (Cervero, 2003). Entropy index close to one means perfect balance – different activities are uniformly distributed, while the index value close to zero means the balance is not proportionate – a single type of activity is dominating the land use.

MODEL SPECIFICATION

Previous studies have used a discrete choice approach for modeling departure time choice (McCafferty and Hall,1982;Saleh and Farrell, 2005; He, 2013). However, the fundamental limitation of this approach is the discrete portioning of time in large bins (e.g. peak, off-peak, morning, evening). Different time intervals and resolutions can largely affect model outcomes. Two neighboring time points might fall into different time intervals but may intuitively have the same effect on choice. For example, if we define the peak period as 6AM-9AM, then two spaced time points (e.g., 8:55 AM and 9:05 AM) will fall into two distinct alternatives (8:55 AM as peak and 9:05 AM as off-peak), but decisions made at both those instances may be the same.

Continuous cross-nested logit models for departure time choice have been widely used in previous studies to account for the correlation between two bins (Lemp and Kockelman, 2010; Lemp, Kockelman and Damien, 2010). A hazard duration model can also address the continuous nature of trip timing and trip duration (Gadda, Kockelman and Damien, 2009; Mannering et al., 1994; Niemeier and Morita,1996). Bhat and Steed (2002) proposed a continuous-time hazard duration model, which accommodates time-varying coefficients, time-varying covariates and unobserved heterogeneity in departure time choice. This approach splits the entire day into smaller grouped

intervals where the baseline hazard rate is assumed to be constant, and the coefficients vary in the pre-defined intervals. This frequentist approach helped overcome limitations in logit-based choices while respecting the continuous aspect of time.

In this paper, a Bayesian equivalent of the time-varying proportional hazards model (Bhat and Steed, 2002) is pursued. The Bayesian approach provides flexibility in specification while continuing to allow for uncertainty quantification. Traditional hazard models like the semi-parametric Cox proportional hazards model assume that the effect of a covariate on the hazard rate is constant at all points of time. This is limiting since travelers can make different choices depending on the time of day when controlling for other factors. The value of travel time is potentially perceived differently at different times of day. This is especially true when travelers have the flexibility in their work times or have the option to telecommute. There may be a delayed departure from home in such situations without compromising on daily work activities such that the effect size is higher later in the day. Travelers with such flexibility may make essential personal trips such as taking children to school or running an errand before traveling to work, or may choose to travel once peak hour congestion has passed. Similarly, other variables that do not vary across time may still exhibit differential effect at different times of day, and some others may have a constant effect throughout the day. The variation in decision-making for all factors G across the day is captured by including time-varying coefficients, $\beta(t)$, in the model. Finally, some other factors, X, may provide a constant, time-invariant effect, α, and is also included in the model.

An individual's departure time T, representing the duration from midnight until departure has the hazard, $\lambda(t)$, at any time t less than T. This hazard rate is the instantaneous probability that the traveler will depart in a small time interval Δt after time t, given that departure has not occurred until time t. The definition of hazard in terms of probability can be expressed as follows:

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{P(t < T < t + \Delta t \mid T > t)}{\Delta t}$$

This formula makes it possible to calculate the cumulative distribution function for departure at time t, $F(t)$, and survival function denoting cumulative probability of not departing until time t, $S(t)$, as shown in the following expression:

$$\lambda(t) = \frac{f(t)}{S(t)} = -\frac{\frac{dS(t)}{dt}}{S(t)} = -\frac{d}{dt} \ln S(t)$$

$$S(t) = P(T > t) = 1 - F(t) = \exp\left(-\int_0^t \lambda(x)\,dx\right)$$

This definition of hazard rate is transformed to accommodate time-varying, time-invariant and unobserved heterogeneity effects. The following equation denotes the use of the time-varying hazard rate $\lambda(t)$, estimated in bins of departure. It is expected that the proportional effect of a covariate remains constant in smaller buckets of time during the morning peak, and may remain constant over mid-day. So, these bins of departure are allowed to vary in size across the day, with finer granularity of 15-min in the morning peak, and larger bins of 120 and 240 min depending on anticipated departures in the data at those times of day. As shown below, $\lambda(t)$ is estimated by using a non-parametric time-varying baseline hazard rate $\lambda_0(t)$, the zero lower-bounded exponent

consisting of observed covariates X and G, corresponding coefficients α and $\beta(t)$, and unobserved component ω_i for each individual i. Therefore, an individual's hazard at time t (after dropping subscript i for the individual) is given by:

$$\lambda(t) = \lambda_0(t) \exp\big(\alpha X + \beta(t) \times G(t)\big) \omega$$

The parameters available for G is exploded for each time bin used in the model. The Bayesian hierarchical model is set up to estimate the hazard rate from the data. Observed departure times need to be discretized into bins corresponding to the bins used for the time-varying β(t). A variable, d_{ij}, is created to identify whether an individual i departed during the bin j. Correspondingly, survival time is computed as t_{ij}, that denotes the time in the bin j that individual i survived or did not depart. A convenient Poisson approximation for d_{ij} allows for estimating the hazard rate when the mean of the Poisson is t_{ij} times the hazard rate in bin j (Ibrahim et al., 2014). The resulting Bayesian hierarchical model used is, therefore:

$$d_{ij} \sim Poisson\left(t_{ij} \times \lambda_{ij}\right)$$

$$\lambda_{ij} \leftarrow \lambda_{0j} \times \exp(\alpha X_i + \beta_j G_{ij})\, \omega_i$$

$$\alpha \sim Normal(0, \sigma_k^2)$$

$$\beta_1 \sim Normal(0, \sigma_k^2)$$
$$\beta_j \sim Normal(\beta_{j-1}, \sigma_k^2)$$

$$\omega_i \sim Gamma\left(a_0, a_0\right)$$

The variance for parameters was allowed to vary based on bin size with each bin size variance estimated through a series of hierarchical priors σ_k^{-2} distributed Gamma(b_0, b_0) and b_0 distributed Gamma(0.1,0.1). Since all parameters used were normalized, the expected variance from the priors alone was selected such that it was 1. The time-varying parameter is expected to be correlated between bins, so a random walk is assumed, where the prior imposes a mean based on the β in the previous time bin. The unobserved heterogeneity is also expected to have a mean of 1, if all heterogeneity is accounted for, so the Gamma prior with the same parameters allows for mean 1, with variance allowed to be dictated by a hierarchical prior Gamma(1, 0.1). The baseline hazard rate is hard to know before hand, so an uninformative prior Gamma(0.001,0.001) is chosen.

RESULTS

The Bayesian model discussed above was implemented in the R interface to JAGS (Denwood, 2016; Plummer, 2019). Three chains were simulated in parallel with a 2,000 iteration burn-in, and 1,000 iterations were analyzed for estimates and 95% credible intervals.

Baseline Hazard

Figure 2 shows the baseline hazard for the estimated model. The baseline hazard used here is non-parametric and captures differential baseline hazard across different departure times for the average person. There is a general positive time dependency, as expected, meaning that the longer a commuter waits to depart, the higher their probability of departure in the next time period. The baseline hazard is small until 6AM, larger during peak hours, and eventually fades after 8 AM.

This is expected as a majority of work trips with or without flextime prefer to start their work during the morning hours, on average.

Flextime Effect

The time-varying effect of flextime on commuters' departure time choice is captured by the corresponding coefficient estimates in $\beta(t)$. A negative value of $\beta(t)$, at any time t, suggests that flexible work hours decreases a commuter's propensity to leave at that time t. The coefficient values sharply decline starting 6 AM in the morning, reach a maximum negative value at 7:45 AM, and then shifts back to 0 after 8:30 AM (Figure 3). The hazard multipliers represent the magnitude of covariate effect, determined by $\exp(\beta)$. Percentage change in the hazard can be further derived by $\{\exp(\beta)-1\} \times 100$. Thus, the effect of flextime can be interpreted at any instantaneous point of time in terms of percentage change in hazard rate. Accordingly, flextime decreases the hazard rate or the propensity to depart at 6 AM by 40.3%. The effect further goes higher as time progresses until it reaches its peak at 7:45 AM with 53.1% decrease in hazard rate. This time-varying effect of $\beta(t)$ clearly shows that effect of flextime on departure time is not constant but significantly varies throughout the day. Most importantly, the effect of flextime is predominant in deterring AM peak departures. Although many coefficients' credible intervals estimated at off-peak hours include 0, the large deterrence in morning peak departures are quite significant.
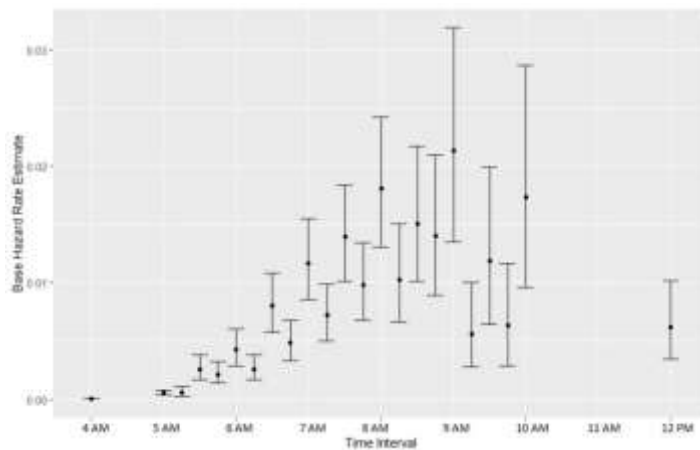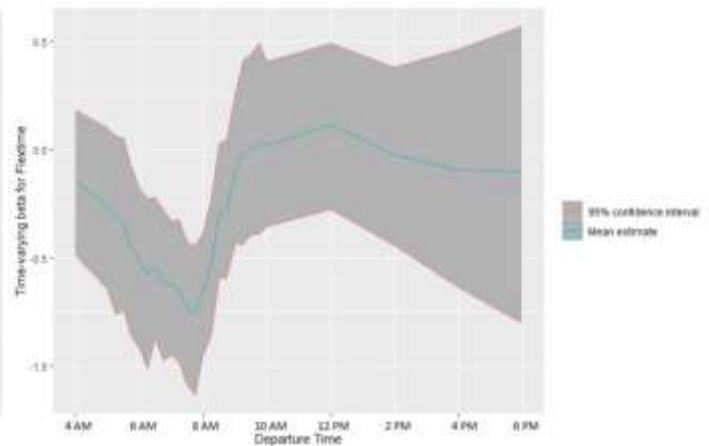

Figure 2 Baseline Hazard Function

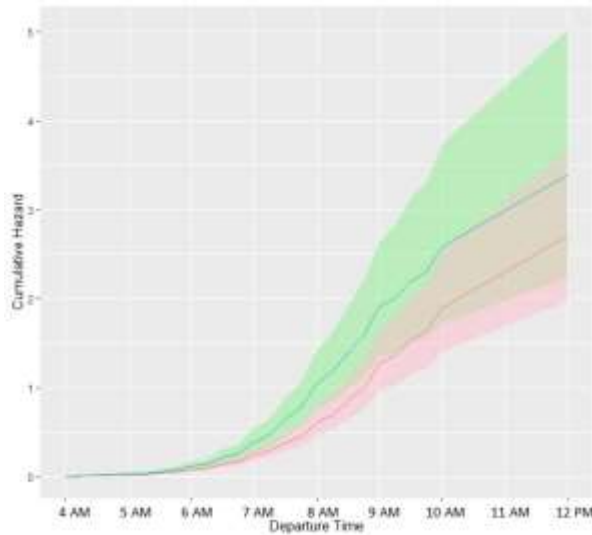**Figure 3** Time-Varying Coefficients of Flextime

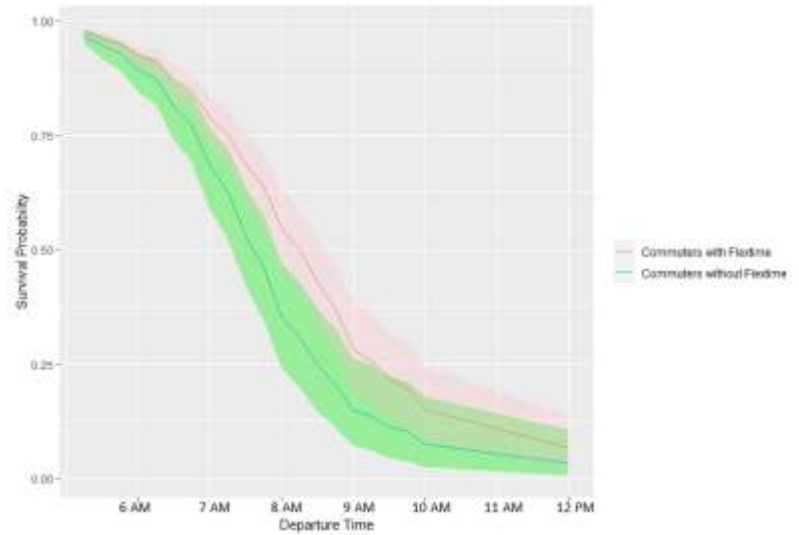**Figure 4** Estimated Cumulative Hazard Function

Figure 5: Estimated Survival Function

The effect of flextime can be further illustrated by cumulative hazards plots for two groups – commuters with and without flextime (Figure 4). The slopes of these lines indicate the instantaneous probability of departure. During the early morning hours before 5 AM the hazards are nearly zero which means probability of departure is very low. Starting at 6 AM probability continues to increase indicating more departure during peak hours. However, the slope declines after 10 AM as departure rate falls after peak hours. For commuters with flextime, the hazard rate grows slowly over time before being indistinguishable from non-flextime commuters, implying that they are more likely to depart later than commuters without flextime during the peak hours.

The survival function, which is actually the exponential of the negative cumulative hazard function, provides a better interpretation of the results (Figure 5). A closer look at the slopes shows a clear difference of survivals or likelihood to not depart between two commuter groups. Commuters without flextime option show higher probability of early departures, explained by the steep slope at the beginning and then gradual decline after the peak hours. Commuters having flextime option, on the other hand, prefer later departure as shown by less steep slope during early morning hours. Survival probabilities from the curves can be extracted into exact numeric values for any instantaneous time. The difference between cumulative survivals at the end of two time periods provides the probability of departure during that time interval. The predicted shares of departures of two commuter groups at an aggregate level are presented in Table 1. Accordingly, 89.3% of commuters without flextime are expected to leave before 9 AM while this value reduces to 76.0% for commuters with flextime option. Flextime commuters show 8.2% less probability to depart during peak hours compared to their counterparts without flextime. The difference is more evident in post-peak hours: having flextime option increases the probability of post-peak departure from 8.0% to 18.4%.

Table 1: Predicted Percentage of Departures in each Time Period for an Average Traveler

Time of Day	Commuters Without Flextime	Commuters with Flextime
Pre-peak (Before 6 AM)	16.8%	11.7%
AM Peak (6 AM- 9 AM)	72.5%	64.3%
Post-peak until midday (9 AM-12 PM)	8.0%	18.4%
After midday (After 12 PM)	2.8%	5.6%

Other Covariate Effects

Job category variables were found to be the strongest predictors of departure time choice. Workers in the industrial sector tend to depart earlier compared to those who are in managerial/professional sectors. The opposite is true for service and retail sector workers. The time-varying coefficients of industrial jobs show positive values during early morning hours starting at 5 AM, then a steep increase until 7:30 AM, following a decline afterwards (Figure 6). Early departure of industrial workers is consistent with labor economics: certain industries demand temporal agglomeration, follow rigid working hours and require their workers to arrive early in workplace. By contrast, workers in the service and retail sectors are much more likely to have departure times at later hours. The coefficients of service sector do not show significant values until 8:30 AM, but negative values afterwards suggest more departures during those hours. The same is true for retail sector, however, an important difference is that coefficients of retail sector are more spread throughout the entire day. This is expected as morning shift retail workers depart early in the morning while those who work in afternoon and evening shifts depart in later hours.

Number of daily activities can also influence departure time choice. In this study, number of trips was used as a proxy variable for the number of activities performed during the travel day. Commuters who make higher number of trips on their travel day are more likely to avoid peak hours, especially with higher probability to depart in post-peak hours. The time-varying coefficients show increasing negative values during later part of the day. This finding suggests that workers, whose daily schedule is constrained by more activities, tend to choose afternoon or evening shifts. Mandatory activities e.g. taking children to school, going to groceries, hospitals etc. usually discourage the travelers to leave before and during the rush hours.

Overall positive sign of trip duration coefficient suggests that trip duration increases hazard rate which implies that commuters with longer trip duration are more likely to depart earlier. The time varying effect shows that early morning hours have higher hazard rate which declines as the day progresses (Figure 6). This is expected because commuters try to avoid the uncertainty of longer travel and penalty of late arrival by departing in early hours.
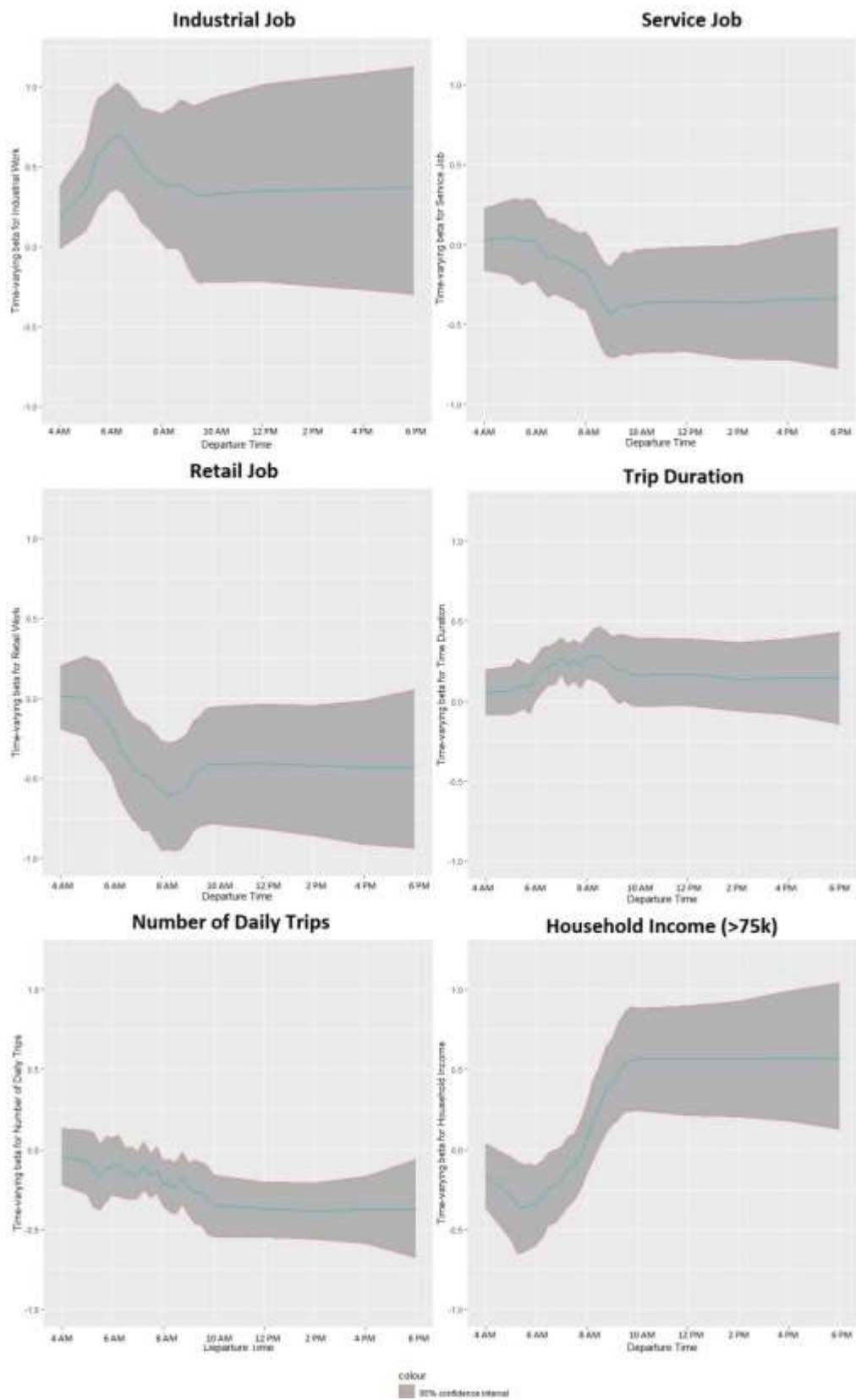
Figure 6 Time-varying effects of the covariates

Demographic variables such as age, gender, ethnicity and household income were included in the model. The effects of age and ethnicity were not found significant at 95% credible interval. The effect of gender was found significant, but only in pre-peak hours, suggesting that female commuters are less likely to depart very early in the morning (before 6 AM), compared to their male counterparts. Previous studies, however, showed mixed effect of gender on departure time choice (Abkowitz, 1981; Saleh and Farrell, 2005; He, 2013). Some studies attributed the effect of gender to trip distance. Long distance commuters are more likely to be male, and therefore tend to depart earlier (Chin, 1990). Among other variables, household income (Annual income 75000+) was found significant. The coefficient values are negative until 7 AM, and positive in later hours (after 8 AM) suggesting that people of higher income are more likely to avoid early morning hours.

Among the land use variables, density and entropy were included in the model, but found insignificant. One possible explanation is that dense, diverse built environment does not necessarily mean commuters live close to their workplace. The overall congestion effect depends on the entire network, not only on the origin or destination end of the trip.

The effect of each covariate on cumulative hazard, with and without flextime option, was further compared with the baseline. In this way, the practical significance of flextime option on departure time across all the covariates can be understood. Table 2 shows the probabilities of cumulative hazards by 9 AM, averaged across all commuters. Having flextime option reduces the departure probability before 9 AM by 7.3%. Clearly, the effects of flextime on departure probability vary across the covariates. Among different job types, flextime has more significant impacts on retail and service sectors compared to industrial sector. Working in retail sector decreases the probability of departure before 9 AM by 12.51%. However, working in retail sector with flextime option further reduces this probability 22.05%. Similar effect was also observed for service sector, but less than retail. Flextime option also reduces departure probability for industrial workers, but the effect was less significant. As discussed earlier, production works usually start early in the morning, and industrial jobs demand temporal agglomeration. Therefore, the shift in departure time for industrial jobs is not as significant as other sectors.

Among other variables, trip duration and number of daily trips also show practical significance. In general, people traveling longer are less likely to depart after peak hours but if they are provided with flextime choice, then they are more likely to utilize the opportunity and depart later. An increase of trip duration by 1 standard deviation increases the probability of departure before 9 AM by 5.42%, but having flextime option reduces this probability by 0.6%. This is expected because flextime shifts the early morning departure for longer trip duration travelers but still they need to depart before 9 AM. Decreasing trip duration by 1 standard deviation, on the other hand has more significant impacts shifting the departure after 9 AM. Flextime also has significant impacts on those who need to perform more daily activities. An increase in daily activities reduces the probability of early departure, as expected. If they are provided flextime option, they can utilize the time for mandatory activities e.g. taking children to school and avoid early departure.

Table 2: Practical Significance of Flextime on Covariates

Variable(s)-Specific Sensitivity	Cumulative Departure By 9AM	% Change (Effect – Baseline)
Flextime	74.06%	-7.30%
Sex (Female)	81.20%	-0.16%
Flextime + Sex (Female)	73.87%	-7.49%
Income<50K	80.65%	-0.71%
Flextime + Income<50K	73.08%	-8.28%
Income(50K-75K)	83.17%	1.81%
Flextime + Income(50K-75K)	76.43%	-4.93%
Income 75K+	82.38%	1.02%
Flextime+ Income 75K+	75.59%	-5.77%
Industrial Job	92.45%	11.09%
Flextime+ Industrial Job	87.90%	6.54%
Retail Job	68.85%	-12.51%
Flextime + Retail Job	59.31%	**-22.05%**
Service Job	78.66%	-2.70%
Flextime + Service Job	70.54%	**-10.82%**
Trip Duration (+ 1 SD)	86.78%	5.42%
Flextime +Trip Duration(+ 1 SD)	80.76%	-0.60%
Trip Duration(- 1 SD)	75.00%	-6.36%
Flextime + Trip Duration(- 1 SD)	66.71%	**-14.65%**
Number Of Daily Trips (+1 SD)	76.85%	-4.51%
Flextime + Number Of Daily Trips (+1SD)	68.65%	**-12.71%**

The bolded percentages show practical significance of flextime

CONCLUSIONS

This paper examines the choice of departure time by using trip data from the Austin Household Travel Survey conducted in 2017 and 2018. A Bayesian proportional hazards model is established to evaluate the effectiveness of flextime on commuters' travel outcomes. By using a continuous-time approach, the model overcomes the limitation of discrete time structure, and offers precise prediction of departure times. Another improvement of this model from the commonly used proportional hazard model formulation is that it includes the time varying effects of covariates on departure time choice.

The results show that flextime has a significant impact on departure time choice among Austin commuters. The time-varying effect shows that effect of flextime on departure time is not constant but significantly varies throughout the day. Workers with flextime tend to depart later than those without such option with stronger probability to avoid AM peak hours. The predicted probabilities calculated from the hazard function shows that flextime decreases the share or peak hour departure

from 72.5% to 64.3%. The difference is more evident in post-peak hours: having flextime option increases the probability of post-peak departure from 8% to 18.4%. The proportional hazard model controlled significant variables affecting departure time choice such as workers' job type, trip duration, number of trips during the travel day and household income. Job category variables were found to be have the strongest effect on departure time choice among the covariates. Industrial workers show higher probability to depart in early morning hours while those in service and retail sector tend to depart later. The results also show that effects of flextime vary across covariates. Flextime option have more practical significance shifting the departure time for retail and service sector employees, those who travel longer and whose daily schedule is constrained by more activities.

The findings of this study have substantial implications in transportation policy analysis, particularly at the time when employment characteristics, working arrangements and communication technologies are changing rapidly, and alternative work schedule (AWS) programs are becoming more prevalent. The continuous departure time model developed in this paper can be used to evaluate the impacts of flexible working schedule at any level of temporal resolution.

The significant positive impact from this paper reconfirms the theoretical underpinnings that implementing such policies would ease congestion by staggering travel demand from peak to off-peak hours. As found by previous research, careful implementation of flextime programs can provide multi-level benefits including reducing congestion and pollution, enhancing productivity, and maximizing personal wellbeing. Constructing new infrastructure is expensive and time intensive. Alternative work schedule (AWS) programs can effectively manage the demand by encouraging more off-peak hour departures. AWS policy implementation is a potential research direction in future studies.

AUTHOR CONTRIBUTION
The authors confirm contribution to the paper as follows: writing-original draft preparation: M. Rahman, K.M. Gurumurthy; conceptualization and design: M. Rahman, K.M. Gurumurthy, K. M. Kockelman; methodology: K.M. Gurumurthy, M. Rahman; supervision: K. M. Kockelman; data assemble and analysis: M. Rahman, K.M. Gurumurthy; writing-reviewing and editing: K. M. Kockelman. All authors have reviewed the results and approved the final version of the manuscript.

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