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An evaluation of part-day telecommute impacts on work trip departure times

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ABSTRACT

The primary objective of this research is to investigate the impacts of part-day telecommute arrangements on commute departure time. Part-day telecommuting occurs when the worker telecommutes while also travels to the workplace. In this case, telecommuting does not replace commute, but the workers may alter their commute departure times in order to avoid peak hour congestions. This paper intends to add empirical evidence on whether and to what extent telecommuting may lead to the temporal displacement of commute, and the actual outcomes on the network. With an interest on the departure time for commute trips, three different hazard models are developed, respectively for full-day commuters (no telecommuting episode), regular telecommuters (who telecommute on a regular basis), and non-regular telecommuters (who telecommute occasionally). Different socio-economic, demographic, and job-related attributes are used as independent variables in the model. Data were obtained from the 2010–2011 Regional Household travel Survey (RHTS) conducted in the New York Metropolitan region. This study adds to the literature by shedding light on the impacts of telecommuting on peak hour congestion relief and the underlying factors.

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1. Introduction

The impacts of telecommuting on the traffic network have been of interest to transportation researchers and planners in the past decades. It is generally assumed that telecommuting reduces travel to the work place, which contributes to congestion relief, VMT reduction, and air quality improvements, etc. Most telecommuting impact studies focused on full-day telecommuting, where commute travel was completely removed (Schintler, 2001; Choo et al., 2005; Vu and Vandebona, 2007a,b, 2008; Vu, 2007; van Lier et al., 2012; Lila and Anjaneyulu, 2013). However, not all telecommuting engagement leads to the complete replacement of commute travel. Some telecommuting may just be overworking at home, such as additional work during weekends or in the evening while some others may only lead to the temporal displacement of commute to avoid peak hour congestion.

Considering that telecommuting might be practiced in different forms, assuming telecommuters as a homogeneous group will lead to improper estimates of the impacts on the network. The importance of user Heterogeneity in travel behavior studies is well documented in the literature (Sharifi et al., 2015a,b, 2016; Jin et al., 2015, Rouphail et al., 2015a,b; Khazraeian and Xiao, 2015,; Khazraeian et al., 2016; Trask et al., 2016). Besides the differences between full-day and part-day telecommuting, another factor that is often overlooked is the regularity of telecommuting engagement. The choice of telecommuting is likely a lifestyle arrangement that involves mid-term and household level decisions. There are workers who telecommute regularly (not necessarily every day, or full-day), and those who telecommute occasionally due to specific circumstances on that specific day. Regular telecommuters have probably incorporated telecommuting into their routines, and their daily activity-travel arrangement could well reflecting the benefits/impacts of telecommuting. Non-regular telecommuters by definition just happen to telecommute on that specific day for various reasons, therefore their daily travel choices could be spontaneous and less predictable than regular telecommuters. To fully capture the impacts of telecommuting on workers' daily activity-travel pattern, both regular and non-regular telecommuting need to be accounted for.

When it comes to impact analysis, it is of the essence to identify key performance measures and quantify how and to what extent they are affected by the proposed policy (Heaslip et al., 2014; Soltani-Sobh et al., 2015, 2016). Built upon the authors' previous work on identifying various telecommuting forms, the main purpose of this study is to analyze the impacts of part-day

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telecommuting (regular and non-regular) on commute departure times. Part-day telecommuting refers to the situation where a worker telecommutes while also travels to the workplace on the same day. Although a major consequence of part-day telecommuting may be the temporal displacement of commute travel, the magnitude of such displacement and the contributing factors have not yet been explored. This study intends to add empirical evidence on whether and to what extent telecommuting may lead to the temporal displacement of commute, and provide an approach to quantify the actual outcomes of part-day telecommuting on peak-hour traffic reduction.

2. Literature review

Few research efforts have focused on part-day telecommuting and its impacts on transportation network. De Graaf and Rietveld explored the trade-off between telecommuting and out-of-home work hours using the 1995 time-use data in Netherlands through a two-level sequential hurdle model (De Graaff and Rietveld, 2004). The study identified significant contributors to work arrangement duration, and also the impact of home-working on peak period congestion. The study indicated that home-working usually took place during non-office hours (weekends and evenings), leaving peak hour commutes almost unaffected. In another effort, Wells et al., showed that full-day or part-day telecommuting had significant influences on both the timing and location choice for personal errands (Wells et al., 2001). While there are other relevant studies focusing on part-day telework, they mainly focus on telecommuting estimation rather than exploring the induced impacts (Lyons et al., 2006; Haddad et al., 2009; Lyons and Haddad, 2008; O'Keefe et al., 2016).

In terms of departure time analysis, there is an extensive body of literature that focused on commute travel or other purposes (Vishnu and Srinivasan, 2013; Gadda et al., 2007; Kockelman and Lemp, 2010; Popuri et al., 2008; Saleh and Farrell, 2005; De Jong et al., 2003; Ettema and Timmermans, 2003; Bhat and Steed, 2002; Steed and Bhat, 2000; Abkowitz, 1981; Small, 1982). In general, departure time studies have explored a variety of variables including socio-economic, demographic, land use, and particularly employment/job-related attributes. Although telecommuting has not been directly incorporated into departure time studies, job-related variables have been proved to be significant contributors. Kockelman and Lemp (2010) showed that longer work durations favored early departures, and part-time workers were more likely to delay their departure times. Vovsha and Bradley (2004) inferred that full-time workers were less likely to depart during mid-day period (10 AM–12 PM). Sasic and Habib (2013) showed that occupation categories, job status, work duration, and commute distance have significant impacts on commute departure timing in morning period. According to Abkowitz (1981), flexible work schedule was reported extremely important for individuals planning for a late work arrival. The positive impacts of flexible schedules on late commute departures was further confirmed by several other studies (Vishnu and Srinivasan, 2013; Hess et al., 2004; Cambridge Systematics Inc, 2004; Guo et al., 2005). Results also indicate that specific occupation types and position titles have significant impacts on work arrival time (Abkowitz, 1981; Small, 1982). The positive impact of flexible work schedules on late departure times have been confirmed in non-US countries. Accordingly, there is a general consensus that both early departures or late arrival times are less costly for commuters with a flexible schedule (Asensio and Matas, 2008; Lizana et al., 2013; Borjesson, 2008, 2009; Kristoffersson, 2013; Thorhauge et al., 2016). As part-day telecommuting could be considered as an extended form of flexible work schedule, it is reasonable to expect that it will have a significant impact on workers' commute departure time.

Two major methods have been employed in departure time studies. One approach divides the time variable into discrete intervals, where each interval is characterized by a different utility level to the commuter. A variety of statistical structures from simple Multinomial Logit models (MNL) (Popuri et al., 2008; Saleh and Farrell, 2005; Steed and Bhat, 2000; Abkowitz, 1981; Small, 1982; McCafferty and Hall, 1982; Bhat, 1998a) to more enhanced frameworks such as Nested Logit (NL), Ordered Generalized Extreme Value (O-GEV), and Mixed Logit (ML) (Steed and Bhat, 2000; Bhat, 1998a,b; Habib, 2012; Sasic and Habib, 2013) have been explored.

While discrete time-of-day intervals were widely used by early studies, a growing body of literature starts to treat time as a continuous variable. In an effort to model departure time of shopping trips, Bhat and Steed (2002) discussed a number of disadvantages of discrete time-of-day modeling approach, including the unstable model results due to ad-hoc temporal partitioning of the day, inconsistencies of the results at interval boundaries, and impediments imposed on further applications of the model in real world time-dependent strategies. Instead, they proposed a non-parametric baseline hazard model, taking into account the unobserved heterogeneity. Komma (2008) used a similar hazard function to estimate departure times for daily commutes. Gadda et al., (2007) developed continuous departure time models for both work and non-work trips using accelerated failure time (AFT) specifications and Bayesian estimation techniques.

For the purpose of this study, the hazard function model is considered an appropriate approach to estimate commute departure time. The impacts of individual, household, job-related, and trip attributes on commute departure time are explored through the model. Two types of telecommuting behavior are considered, regular part-day telecommuting, and non-regular part-day telecommuting. By comparing the commute departure time hazard functions between full-day commuters and the two types of part-day telecommuters, one can assess and quantify the magnitudes of commute displacement when commute work are partially replaced by part-day telecommuting.

3. Data

This study uses the data obtained from the 2010–2011 **Regional Household Travel Survey (RHTS)**, which was sponsored by the New York Metropolitan Transportation Council (NYMTC) and the North Jersey Transportation Planning Authority (NJTPA). The RHTS collected 24-h travel diary information from about 18,000 households within the 28 counties of New York, New Jersey, and Connecticut. Sampling strategies were implemented to ensure representativeness of the sample and weighting factors were developed in regards to Census data. The survey collected detailed socioeconomic and demographic information, and travel-activity information, including mode, purpose, departure and arrival time, cost, and origin and destination, etc., for every member in the household.

This study focuses on workers who work for pay (excluding volunteers), and those who actually worked on the survey day (excluding weekends). A subsample of 12,593 workers was extracted from the survey data. Excluding full-day telecommuters who had no commute trips (568 observations), the dataset includes 12,025 daily commuters, which is further divided into three groups based on their work arrangement: 1) full-day commuters (non-telecommuters), 2) regular telecommuters (part-day telecommuting on a regular basis, and 3) non-regular telecommuters (part-day telecommuting on a random basis).

The classification of regular and non-regular telecommuters is based on telecommuting regularity and presence of work-related