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Triggers of behavioral change: Longitudinal analysis of travel behavior, household composition and spatial characteristics of the residence

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A B S T R A C T

Longitudinal data have the potential to reveal the causal mechanism underlying changes in observed behavior, can protect us from finding spurious relationships, study time precedence, and offer strength in helping discover association among variables. In this paper, we expand our previous analysis of the only longitudinal travel behavior database in the US that has ten waves (observation time points). The analysis here is using data from the two-day Puget Sound Transportation Panel (PSTP) travel diary and 230 households participating in all ten waves of the panel. The main objective of this analysis is to identify what triggers behavioral change in activity and travel and to quantify and compare the size of these triggering effects using different methods. Our search for triggers includes the birth of a child, child leaving the household, and the entry or exit from the labor force of a household member. In the land use changes we identify moves from high accessibility and diverse environments to lower accessibility and less diverse places and find that diversity is key in changing behavior. The method used to analyze the data is a longitudinal Mixed Markov Latent Class analysis that allows to not only account for behavioral heterogeneity at each time of observation but to also test for the existence of multiple latent trajectories of change and the role played by triggers in shaping these trajectories.

1. Introduction

Individuals may change their behavior in a variety of possible ways as a consequence of events that we name *triggers* in this paper. Behavioral change can be gradual and following a smooth trend over time or sudden. These changes can happen based on past events or in anticipation of a future event. Behavioral changes at the household level are combinations of events experienced by the individuals of households. The combination of triggers determines the choice context and should be taken into account in estimating models, particularly, when these models are about change in behavior. Goulias and Pendyala (2014), describe many different types of processes and events that can alter the individual and the choice context. These are *physiological alterations* (e.g., hormonal changes that alter physical and social selves), *transitions* (e.g., *age-graded movement* into and out of social roles such as school grades or loss of a parent), and *turning points* (e.g., events that cause reorientation of priorities and lasting alterations of a person's developmental trajectory). All types of events create barriers or offer new opportunities. They may also lead to changes in roles, self-concepts, lifestyles, worldviews, and dispositions towards other people. They are also different in their impact depending on their timing and duration, and the socio-economic characteristics of the individual such as gender and sexual orientation, and ethnic and social class. Examples of events include, and are not limited to, marriage, divorce, building a family and birth of children, entering a

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new intimate relationship, separation, entering school, choosing occupation, engaging in nonoccupational studies, graduation, continuing studies, dropping out of school, job seeking, job loss, retirement, starting first job, starting private enterprise/practice, declaring bankruptcy, moving to another community, leaving home, traveling somewhere far away, moving temporarily to another place, entering military or community service, loss due to death of close member, getting a new apartment, getting a vacation home, change in leisure activities and hobbies, drug use and abuse, committing crime(s), religious engagement, psychological crises, own illness, illness of close member, and accidents. Very few of these events are observed and/or recorded in surveys making the analysis of triggers and their rippling effects difficult to measure. Instead, we can observe a few changes such as intra-household demographic changes and built environment changes and estimate their impact on behavior using statistical models.

Van Acker et al. (2010) in their overview article about land use, activity-travel, and attitudes/perception argue persuasively that one should analyze the relationships among behavior, social- demographic changes, and the built environment jointly to account for complex relationships. In a similar vein of development, Mokhtarian and Cao (2008) acknowledge the significant relationships between land use characteristics and travel behavior and caution us to be aware of potential pitfalls in data analysis techniques that are not designed to discover causality. In fact, they conclude that a longitudinal data collection design has the potential to reveal the causal mechanism underlying the observed behavior, can protect us from finding spurious relationships, this type of design has (of course) information to study time precedence, and offers strength in helping discover association among variables. In order to investigate the causal relationship from land use and household characteristics to travel behavior with longitudinal data analysis, the life cycle stage should be also considered because persons or households in different life cycle stages experience different events, for example, young households experience birth of children, children going to school, and older households experience children leaving the nest and retirements. In light of this, many travel behavior models have considered the effect of life cycle stages on daily activity travel time investments, and activity travel choices for a long time. Clarke et al. (1982) claimed that life cycle stages play critical roles in capturing travel behavior dynamics because the processes from birth to death, and their moderation effects from their society are dealt with the concept of life cycle. Therefore, the following components should be considered when the life cycle approach is used: aging processes, staging processes (from one to another life cycle stage), exposure to historical episodes, and cohort membership. Kitamura (1989) considered life cycle as a component of life style, and measured and used it as individual characteristics that explain travel behavior. He used both a longitudinal (1953–1983) and a cross-sectional analysis (comparison of population categorized by income, life-cycle stage, and age) to explore the relationship between life cycle and monetary expenditure. He also summarized important factors of travel behavior along with the life cycle stages including gender, employment status, the elderly, income, and car ownership. Recent examples on the relationship between life cycle and travel behavior includes: cohort effect on travel behavior (e.g., Miranda-Moreno and Lee-Gosselin, 2008; Goulias et al., 2008), presence of children in the household (e.g., Yarlagadda and Srinivasan, 2008; Vovsha and Petersen, 2005), the elderly effect on travel behavior (e.g., Hildebrand, 2003; Okola, 2003; Srinivasan and Bhat, 2006), explicitly accounting for the behavioral differences across life cycle stages (e.g., Sun et al. 2009; Yoon and Goulias, 2010; Lee and Goulias, 2014), and the study of key events in behavioral patterns (Scheiner et al., 2016). A key idea that supports causality analysis is the *latent variable* because this variable captures unobserved longitudinal changes and is a reflection of trigger variables and the rippling effects of these variables on predispositions not recorded in the data.

Latent variables in the context of regression methods are particularly useful in pattern analysis because they offer a statistical way to account for unobserved factors that explain the variation of observed variables jointly. For example, latent variables are used to represent latent propensities to choose a specific behavioral pattern (Kroesen, 2015), unobserved character traits (Hess and Stathopoulos, 2013), identification of market segments with different decision weights (Tang and Mokhtarian, 2009), heterogeneity in preferences of train ticket purchases (Hetrakul and Cirilo, 2013), latent plans in the context of driving (Choudhury et al., 2010), risk aversion in switching behaviors (Tsirimpa et al., 2010), and in their more traditional form of correlated unobserved factors (Rungie et al., 2011, 2012). In this context, latent variables are used here to identify distinct behavioral groups based on correlations among many observed behavioral variables. This allows to group people in behavioral profiles representing different ways of time allocation and travel in a day. This is a parsimonious representation of behaviors that accounts for correlation among different types of variables (nominal, continuous, counts). The groups of people identified through a search of patterns represent different segments with distinctly different daily behavioral patterns. This is called the *latent class analysis* in which the categories of a latent variable represent membership to groups and they are identified through a search for a well-fitting model. Then, the temporal trajectory of membership in these behavioral groups is modeled by another latent variable that represents a temporal profile of behavior for each observation. The combination of these two latent variables maps unobserved heterogeneity as a combination of cross-sectional and longitudinal variation. In addition, these latent variables are functions of observed sample characteristics to account for observed differences among the units of our sample. Moreover, transitions from one pattern to another are also functions of changes in each observed household and land use surrounding its dwelling unit. In this way we can test which changes in and outside the household are significantly associated with a change in behavior. As mentioned earlier these are the changes that we name *triggers* in this paper to signify their role in transitions among different pattern of behavior. Latent variables in this paper are used to perform a pattern recognition exercise with the methods described in Vermunt and Magidson (2002) combined with the Mixed Markov models of Langeheine and van de Pol (1990). The method has many similarities with Goulias (1999) and is closer to the applications in Kroesen (2014) and Kroesen and van Cranenburgh (2016).

The longitudinal database to perform this type of analysis exists in the United States and it is called the Puget Sound Transportation Panel (PSTP). PSTP spans a long period from 1989 to 2002 with data that are harmonized and suitable for longitudinal analysis (Goulias et. al., 2003). This enabled the use of multi-equation multivariate statistical techniques to unravel causality in behavioral variables at multiple levels (Goulias, 2002) as suggested later by Mokhtarian and Cao (2008). More recently the PSTP database was enriched with longitudinal land use information that allows examination of residential relocation jointly with