Latent Transition Analysis of Consumer Spending Behavior and Adaptation Across Online and In-Person Channels Through the Pandemic

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Introduction

- A tremendous growth in the adoption of tele-activities like tele-work, e-shopping, tele-health and e-learning is clearly visible as a result of the COVID-19 pandemic.
- The aspect of our lives that saw the most upheaval due to the pandemic is how our daily needs for food are fulfilled.
- The pandemic resulted in the widespread adoption of e-commerce services to meet essential needs. However, the adoption varied across socio-demographic groups and the true nature of changes in the consumer spending landscape is still unknown.

Research Objectives

To understand changes to the consumer spending landscape across the following three product category types and for different acquisition channels:

- Grocery – In-person, Pick-up and Delivery
- Cooked food – Dine-in, Take-out, Pick-up, and Delivery
- Other items – In-person, Pick-up, and Delivery

To achieve this goal, we conducted latent transition analysis (LTA) using data from a U.S. representative sample of 774 respondents across three time points: Pre-COVID, December 2020, and March 2021.

The respondents were asked whether they spent greater than $0 in the above mentioned 10 spending/acquisition categories at three different time points, and the data was subsequently used to conduct LTA.

Latent Classes and the corresponding transitions from classes across time were estimated and were also associated with socio-demographic information to understand the associated factors.

Data

- We used data from a longitudinal survey conducted amongst a U.S representative sample of respondents with 6 waves approximately 2 weeks apart (Dec 22, 2020 to Mar 08, 2021) to understand the evolution of tele-mobility adoption.
- Main sample of 450 respondents were re-invited in every wave, a 100-respondent replenishment sample added in every wave starting wave 2 to account for attrition.
- Figure 1 shows various dimensions of the data collected in the longitudinal survey.
- Primary data used in this study comes from Wave 1, 3 (pre-COVID information asked in this wave) and 6 and comprised of individuals who participated in at least one of the waves.
- Available Data:
  - Pre-COVID (Wave 3): 419 individuals; Wave 1: 450 individuals; Wave 6: 615 individuals; including data from 284 individuals who participated in all 3 waves.

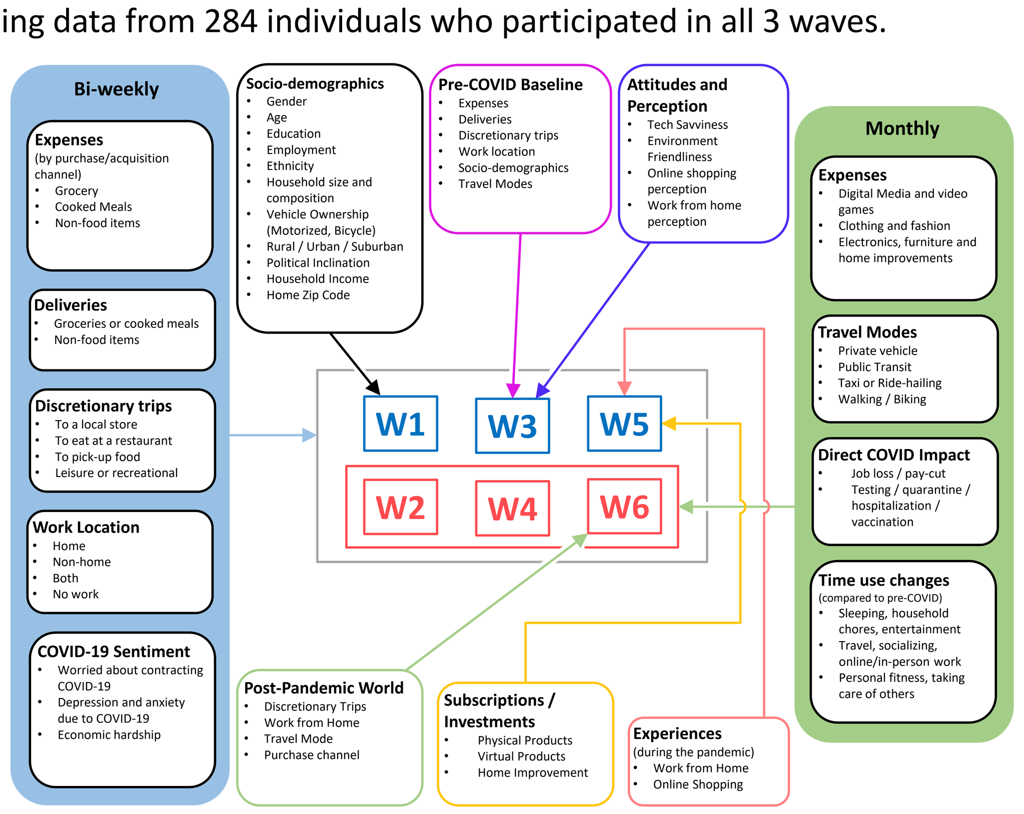


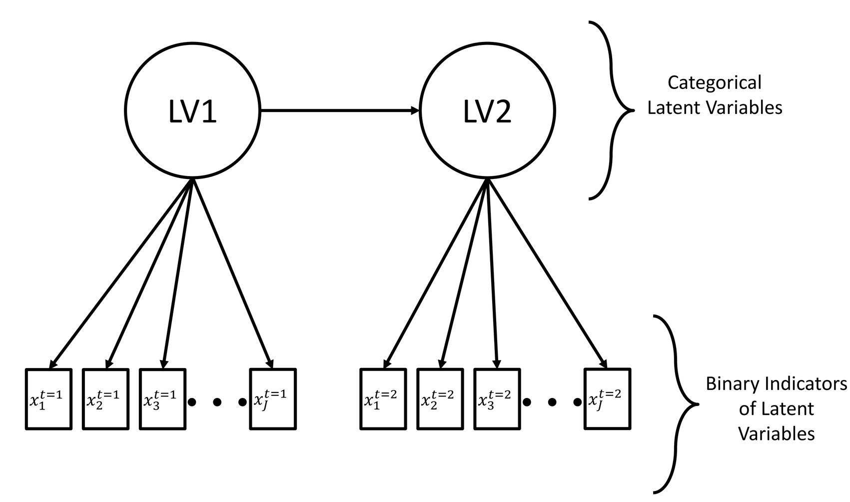
Figure 1: A snapshot of the 6-wave longitudinal survey

Methodology

- Latent Transition Analysis (LTA) is a longitudinal extension to Latent Class Analysis (LCA) and is useful to identify changes in latent classes across time.
- LTA assumes presence of a categorical latent variable at each time point measured using several categorical indicators – shown in Figure 2.
- Fundamental expression (with y being the response vector):

$$P(Y = y) = \sum_{s_1=1}^{S} \dots \sum_{S_T=1}^{S} \delta_{s_1} \tau_{s_2|s_1} \dots \tau_{s_T|s_{T-1}} \prod_{t=1}^{T} \prod_{j=1}^{J} \prod_{r_{j,t}=1}^{R_j} \rho_{j,r_j,t|s_t}^{I(y_{j,t}=r_{j,t})}$$

- We use 10 indicators related to whether an individual spent greater than $0 in a spending category (grocery, prepared food, others) via different acquisition channels (in-person, online, delivery) at various time points to measure latent classes and identify transitions.
- Main assumptions: Measurement Invariance and Local Independence
- Estimation Procedure: Full Information Maximum Likelihood (FIML) to account for missing data in the indicators.
- Bayesian Information Criteria and model interpretation used to determine number of classes.
- To associate socio-demographic information with latent classes and transitions, we use a 3-step bias correction procedure.



Three sets of parameters are estimated in LTA:

- δ_{s_t} = latent class prevalence at time t
- $\rho_{j,r_{j,t}|s_t}$ = item response probabilities conditional on latent class at time t
- $\tau_{s_{t+1}|s_t}$ = probability of transition b/w latent classes b/w consecutive time periods

Figure 2: A graphical/mathematical representation of LTA

Results

Class Percentages and Item Response Probabilities

- Our model identify five different latent classes of spending behavior in the data and changes in the percentages of individuals belonging to these classes across time (Table 1).
- Item response probabilities represent the probability of spending greater than $0 in a category conditional on the latent class.

	Class 1	Class 2	Class 3	Class 4	Class 5
Class Labels	Primarily Inperson Shoppers	In-person Shoppers with Suppressed Outside Food Demand	Multi-channel Shoppers	Delivery Dependents	Pick-up Dependents
Class Percentages					
PreCOVID	58.89%	20.96%	13.36%	3.37%	3.15%
Wave 1	10.27%	48.20%	13.18%	10.46%	17.89%
Wave 6	10.50%	52.07%	10.08%	12.95%	14.41%
Item Response Probabilities					
Grocery - In-person	0.995	0.994	0.974	0.449	0.657
Grocery - Pick-up	0.105	0.000	0.760	0.087	0.952
Grocery - Delivery	0.146	0.094	0.646	0.950	0.206
Food - Dine-In	0.837	0.093	0.639	0.070	0.056
Food - Takeout	0.696	0.430	0.932	0.186	0.424
Food - Pick-up	0.297	0.208	0.961	0.098	0.399
Food - Delivery	0.284	0.139	0.704	0.506	0.167
Others - In-person	0.928	0.556	0.908	0.181	0.381
Others - Pick-up	0.132	0.060	0.794	0.000	0.253
Others - Delivery	0.698	0.492	0.807	0.678	0.712

Table 1: Class labels, percentages and item response probabilities

- A significant decrease in size of class 1 (In-person shoppers) between pre-COVID and Wave 1 is evident and a large increase in class 2 (suppression in outside food demand) is also visible.
- An increase in the size of class 4 (delivery dependents) and class 5 (pick-up dependents) suggests a movement towards e-commerce.

Results

Class Transitions

- Figure 3 presents transition between classes across the three time points suggesting a large movement of individuals from class 1 (in-person shoppers) to class 2 (suppressed outside food demand) between pre-COVID and wave 1 time points, likely due to local restrictions or individual cautionary behavior.
- Large movement towards class 4 (delivery dependence) and class 5 (pick-up dependence) as well (b/w pre-COVID and Wave 1), suggesting an increase in delivery and pick-up services usage.
- A large stability in class proportions between Wave 1 and Wave 6 suggests at least a temporary behavioral inertia towards delivery and pick-up services and against eating out.

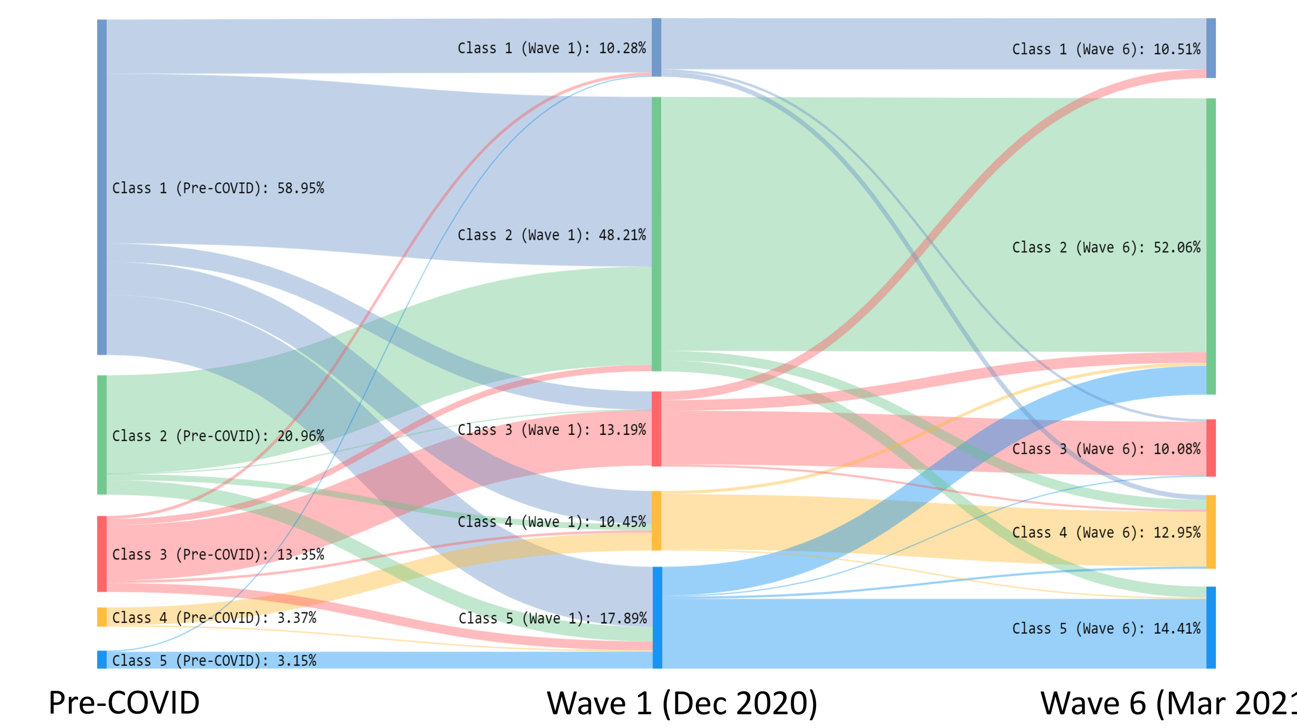


Figure 3: Sankey visualization of transition across classes across three time points

- Our results suggest that only 15 pathways (out of 125 possible) account for 88.3% individuals in the data with the following paths being the top 5: 1-2-2 (27.56%), 2-2-2 (15.99%), 1-1-1 (8.31%), 1-5-5 (7.22%), 3-3-3 (7.10%)

Membership model

- Results from the membership/transition models identify various socio-demographic factors associated with latent classes and transition between classes.

With respect to the latent class membership for pre-COVID time point, following factors were found to be statistically significant (with the direction of association in parentheses):

- Class 1: Graduate Education (+), Income > $100k (+)
- Class 2: Household with child (-), Age 35-55 yrs (-), Income < $50k (+)
- Class 3: Graduate education (+), Household with child (+), Urban household (+), Income > $100k (+)
- Class 4: Household without vehicle (+), Age > 55 yrs (+)

Following factors were found to have statistically significant impact on the probability of transition between different classes between time points:

- Class 1 (Pre-COVID) to – Class 1: Worried about contracting COVID (-); Class 2: Urban household (+); Class 3: Worried about contracting COVID (-); Class 4: Worried about contracting COVID (+)
- Class 5 (Wave 1) to – Class 5: Worried about contracting COVID (+), Received at least one dose of COVID vaccine (+)

Conclusions and Discussion

- Results suggest a shift (at least temporary) towards delivery and pick-up services due to COVID-19 and a behavioral stability between two waves during the pandemic.
- Pandemic resulted in strong suppression of food spending, especially for dine-in, however, in-person shopping remains a significant channel for groceries.
- Socio-demographic variables reveal important factors associated with the behavioral shifts like income, vehicle ownership, household location, worry about contracting COVID-19.
- Understanding changes to spending landscape as vaccine rates increase and as we approach normalcy is an avenue for future research.

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