



U.S. DEPARTMENT OF ENERGY

SMARTMOBILITY

Systems and Modeling for Accelerated Research in Transportation

The WholeTraveler Transportation Behavior Study

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Lawrence Berkeley National Laboratory
2019 Vehicle Technologies Office Annual Merit Review
June 11th, 2019



Overview, Relevance, Objectives, Milestones, & Approach

OVERVIEW

Timeline

- Start date: October 1, 2016
- End date: September 30, 2019
- Percent complete: 75%

Barriers

- Uncertainties associated with the energy impact of new mobility technologies arise primarily from lack of understanding of traveler behavior in the context of emerging technologies and services. Particularly:
 - Barriers and drivers of adoption and use
 - Heterogeneity in these barriers, drivers, adoption and use patterns that impact scope and timing of adoption/use

Budget

- Total project funding: \$3.2M (all partner labs) – 100% DOE
- Funding for FY 2017: \$1.15M
- Funding for FY 2018: \$1.125M
- Funding for FY 2019: \$929K

Partners

- Collaborators:
 - Berkeley Lab (project lead)
 - Idaho National Laboratory
 - National Renewable Energy Laboratory
 - UC Berkeley
 - Stanford University
 - Carnegie Mellon University
- Subcontractor
 - Resource Systems Group, INC (RSG)

RELEVANCE

- Provide vital insights to understanding the possible pathways to the vision of the EEMS Program:

“an affordable, efficient, safe, and accessible transportation future in which mobility is decoupled from energy consumption.”

- Conduct early-stage R&D at the traveler level to generate insights enabling a deeper understanding of the **individual behavioral and economic drivers of and barriers to increase mobility energy productivity** in the context of emerging and transformative transportation technologies and services.



OBJECTIVES

Overall Objectives

- Understand travel choice patterns, preferences, and decision-making processes with the advent of new mobility technologies multiple time-scales.



EV



Car-sharing



Connected and Automated Vehicles



Ride-hailing and shared mobility



E-Commerce

Understand how these patterns interrelate with **multiple dimensions of heterogeneity across the population** – characteristics that:

1. don't change over time (e.g., personality characteristics), or
2. change in predictable ways (e.g., lifecycle stage)

Provide insights and resources to **improve and accuracy and flexibility of transportation system simulation models and reduce uncertainty** associated with behavioral and human factors in transportation-as-a-system modeling and scenario analysis.

Specific Objectives this Period

1. Complete data collection and cleaning
2. Extract information and analyses from phase 2 data
3. Ready all data for anonymous sharing and storage
4. Continue data analysis
5. Write key research papers
6. Provide inputs to other SMART tasks

MILESTONES: FY 2019

Milestone Name/Description	Criteria	End Date	Type	Status
Draft of LBNL report summarizing phase 1 data	Report submitted	12/31/2018	Quarterly	SUBMITTED TO DOE AND UNDER REVIEW AT JOURNAL (entry 3 on next slide)
Progress report slide deck summarizing WholeTraveler data and insight sharing across SMART Mobility Tasks in support of Work Flow	Slide deck submitted	3/31/2019	Quarterly	SUBMITTED TO DOE
Determination of whether or not to undertake data collection in another region	Determination transmitted to DOE TM	3/31/2019	Quarterly	DETERMINATION OF NO-GO FOR ADDITIONAL FY19 DATA COLLECTION TRANSMITTED TO DOE
Draft of 1-2 journal articles/reports	Reports submitted	6/30/2019	Quarterly	(see status on next slide)
Draft of 2 journal articles/reports	Reports submitted	9/30/2019	Quarterly	(see status on next slide)

MILESTONES: PRIORITY ANALYSES

Description	Preliminary Analysis:			Refining analysis and writing up	Delivered to DOE	Final revisions/ under review at publication	Published
	starting	underway	complete				
1* Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area					Q3 2018 (Early)		Transportation Research Part D
2* Children at home: how transitions through family stages relate to mobility patterns in the San Francisco Bay Area					Q3 2018 (Early)	Being prepared for journal submission	
3* The WholeTraveler Transportation Behavior Survey: Decision-Making Data related to Transportation Energy Use in the San Francisco Bay Area					Q1 FY2019	Under review at the journal Transportation	
4* Family structure and the impact of home-delivery on household shopping trips for four purchase categories					Planned Q3 FY19		
5* Tensions and complementarities in mass transit and ride-hailing decisions through a survey-based randomization					Planned Q3 FY19		
6* Life course as a contextual system to investigate the effects of life events, gender and generation on travel mode usage					Planned Q3 FY19		
7 No title yet: relationship between personality/psychology and mode use					Planned Q4 FY19		
8 No title yet: Variability and flexibility in short-term mode choice, route choice, travel time					Planned Q4 FY19		
9 No title yet: Estimation of value of travel time					Planned Q4 FY19		
10 No title yet: Effect of uncertainty in ride-hailing prices on mode choice					Planned Q4 FY19		

* results or preliminary results summarized in this presentation

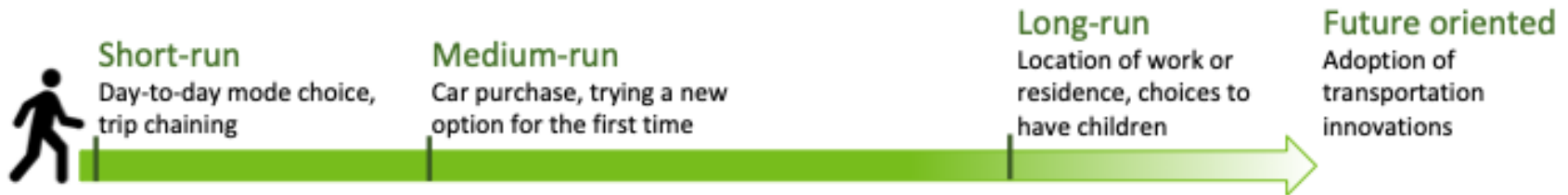
APPROACH

1. Survey-based data collection

- Develop and integrate innovative survey methods and low-cost, low-risk, low-hassle GPS data collection mechanisms
- Collect a rich array of information to study heterogeneous effects
- Collect information regarding preferences across multiple technologies/services

2. Cutting-edge analytics

- Analysis to gain insight into a number of pressing research questions
- Integrated and dynamic assessment of drivers/barriers of transportation choices across multiple time scales

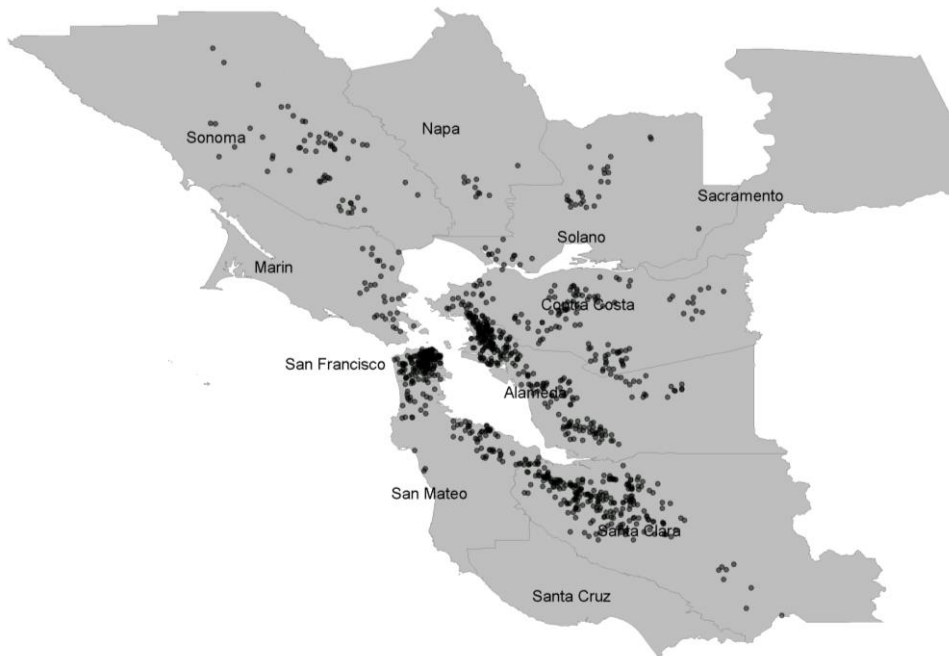


– Focus on impact of:

- Long-run lifecycle trajectory patterns;
- Psychological and personality characteristics;
- Risk and time preferences

APPROACH

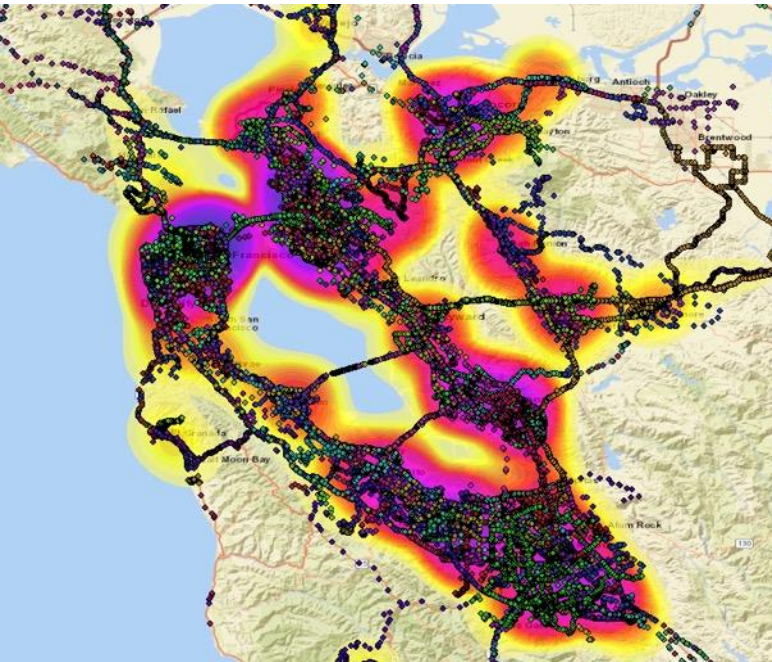
Phase 1 Survey



- Primary destination
- Mode use
- Preferences across mode characteristics
- E-commerce
 - Deliveries across different categories of goods
 - Trips replaced by these deliveries
 - Preferences for e-commerce
- Exposure to, awareness of, use of, adoption of, interest in different technologies and services
- Vehicle ownership
- TNC price sensitivity
- Personality/psychological characteristics
 - Big 5 Personality
 - Risk aversion
 - Discount rate
- Socio-demographics
- Life history calendar

APPROACH

Phase 2 GPS Data Collection



GPS Data

- One week of Google Location
 - Tracked by Google Maps
- Data attributes
 - Time-stamp
 - Lat/Long
 - Velocity
 - Altitude
 - Accuracy
 - Activity Prediction(*android only)

Phase 2 Questionnaire

- Modes used during the week
- Reason for choosing each type
- Primary purpose for each mode used.

Resolution

- Motion-based
- Approximately 3 minute interval when in motion
- Reveals general behavior and patterns versus momentary speeds and vehicle data.

GPS Analysis

- Number of daily trips
- Trip distance
- Commute time
- Average Speed
- Commute start/end
- Stops/trip chaining
- Ties to Public Transit
- Comparison to average commute time / Congestion
- Variability from day to day (Start time, location, route, trips, etc.)

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Data Collection Outcome [Objective 1 from Slide 5]

TWO PHASE DATA COLLECTION COMPLETE

Phase 1

- 9 Bay Area counties
- Address-based random sample
- Mailed invitation + Reminder postcard
- Online only (laptop or desktop)
- English only
- \$10 Amazon Gift Card

• Results

- Data collected March - June 2018
- 1,045 responses (1.7% response rate)
EXCEEDED GOAL OF 900 RESPONSES
- Median completion time 28 minutes
- Higher educated and higher income than the general population

Phase 2

- Those that completed phase 1 could opt in to phase 2
- GPS data collection using Google Location History
- Data collected over 7 days
- \$20 Amazon Gift Card

• Results

- 301 submitted data
EXCEEDED GOAL OF 200 RESPONSES

It should be noted that the resulting sample was relatively selected: higher income, better educated, and less diverse than the Bay Area population. All results from analysis of these data should be interpreted as representative of the respondent population, and not the population as a whole. Extension of the results to the broader population should be done with care and caveats.

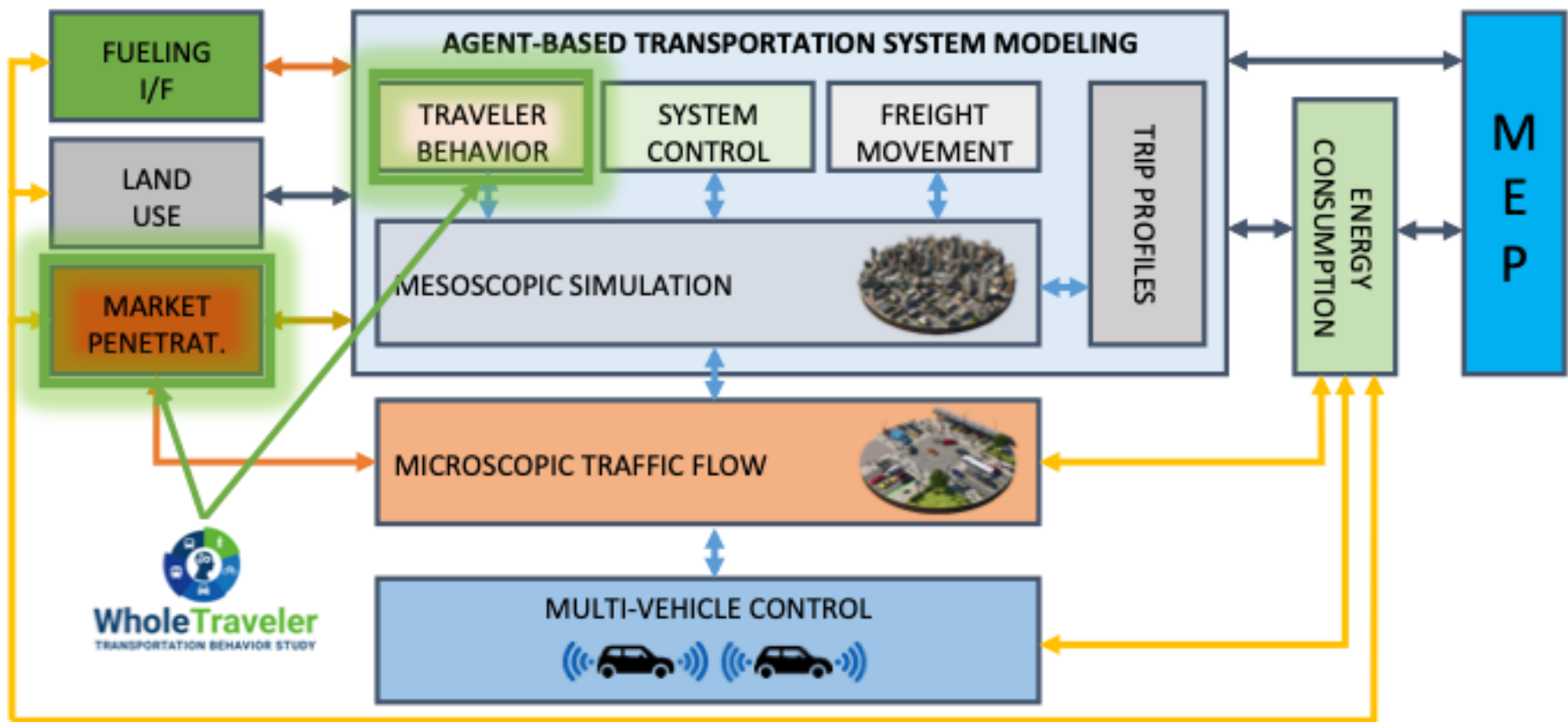
TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Overview of Data Sharing: Phase 1 Data [Objectives 2, 3 & 6 from Slide 5]

- **The de-identified Phase 1 dataset is currently shared with 21 SMART Mobility researchers**
 - Including researchers from: LBNL, ORNL, INL, ANL, NREL, and PNNL as well as academic collaborators working on SMART Mobility at a number of institutions
- **Pillars under which projects have been supported via WholeTraveler data access:**
 - Mobility Decision Science
 - Connected and Automated Vehicles
 - Workflow Task Force (for more detail see EEMS058)
 - Multimodal/Freight
 - Urban Science
- **Key thematic concentrations of interest**
 - E-commerce and shopping behavior
 - Adoption of emerging mobility technologies:
 - Automated vehicles (AVs)
 - Interest in electric vehicles (EVs)
 - General travel behavior in the context of current mobility options
- **We are in the process of preparing a de-identified version of the phase 2 GPS data**
 - Detailed GPS data; trip-level data; phase 2 questionnaire responses

WHERE WHOLETRAVELER CONTRIBUTES TO THE OVERALL WORKFLOW FOR SMART MOBILITY

END-TO-END MODELING WORKFLOW



TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Article 1 [PUBLISHED RESULTS] – [Objectives 4 & 5 from Slide 5]

Title: Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area

(Spurlock, Sears, Wong-Parodi, Walker, Jin, Taylor, Duvall, Gopal, Todd)

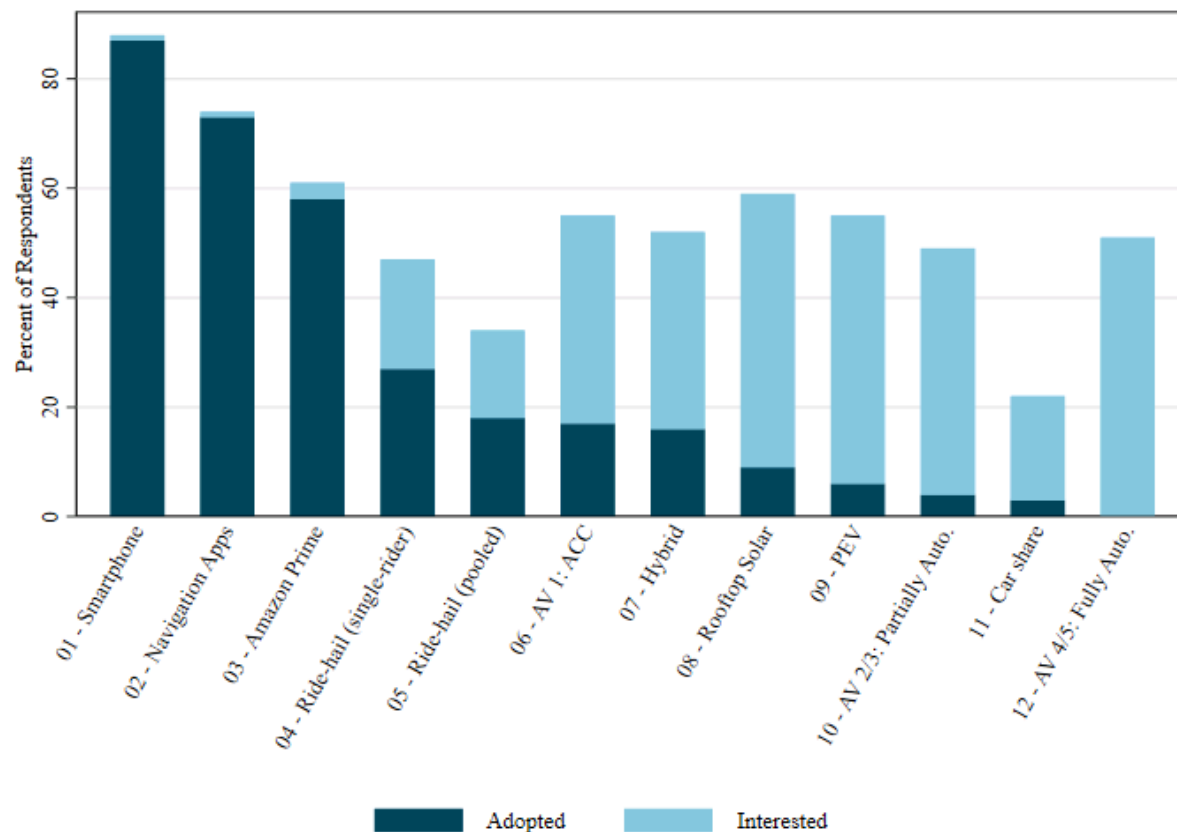
Published: *Transportation Research Part D* [DOI](#)

- We analyze adoption patterns for emerging transportation technologies and services, and relate these patterns to a variety of characteristics motivated by related literature
- We differentiate between current adoption compared to factors correlated with interest in future adoption



ADOPTION vs INTEREST

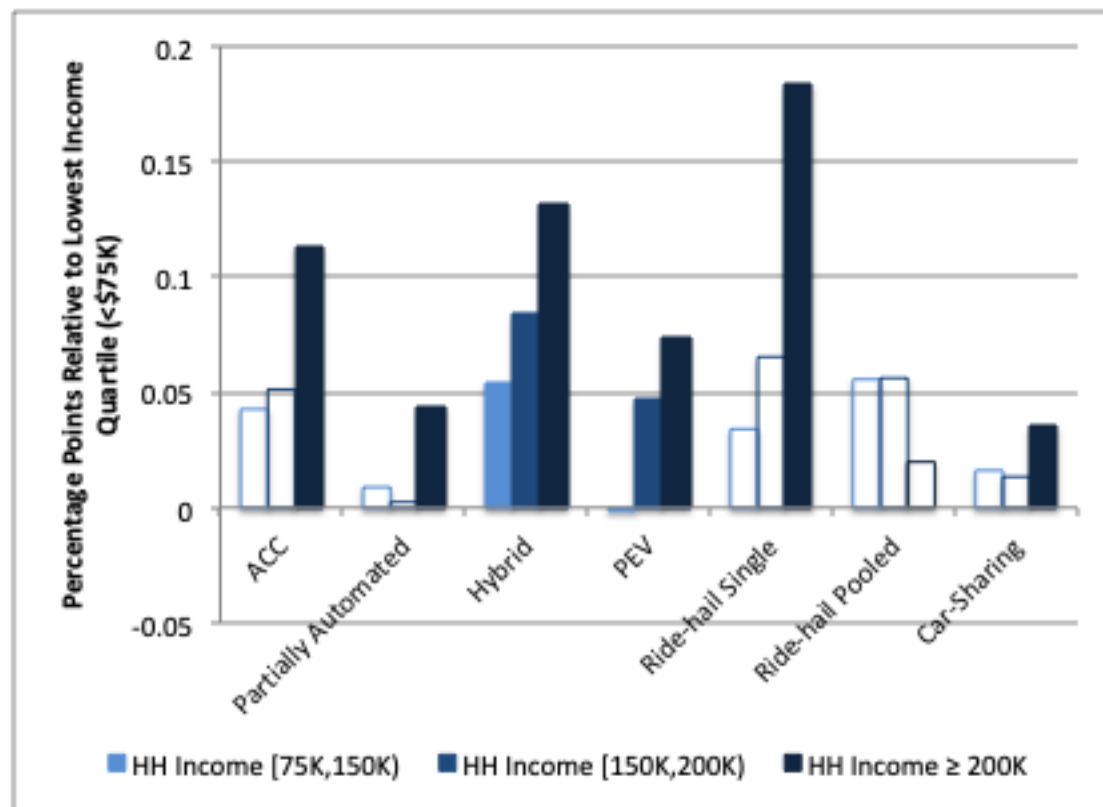
- Ride-hailing and ACC are more broadly adopted than electrified vehicles, advanced automation, or car-sharing services.
- >50% of respondents have adopted or expressed interest in adopting all levels of vehicle automation.
- Overall, there is substantial potential for market growth for the technologies and services we analyzed.



INCOME

- Highest income group is significantly more likely to have adopted almost all of the analyzed technologies and services relative to those with lower incomes
- Exception: pooled ride-hailing.
 - All income groups are similarly likely to have adopted or be interested in adopting pooled ride-hailing.
- Shared pool service may help lower- and middle-income people by giving them more flexibility and making it easier for them to engage in and access the benefits of these emerging transportation technologies and services.

Marginal adoption rates by income, all else held constant

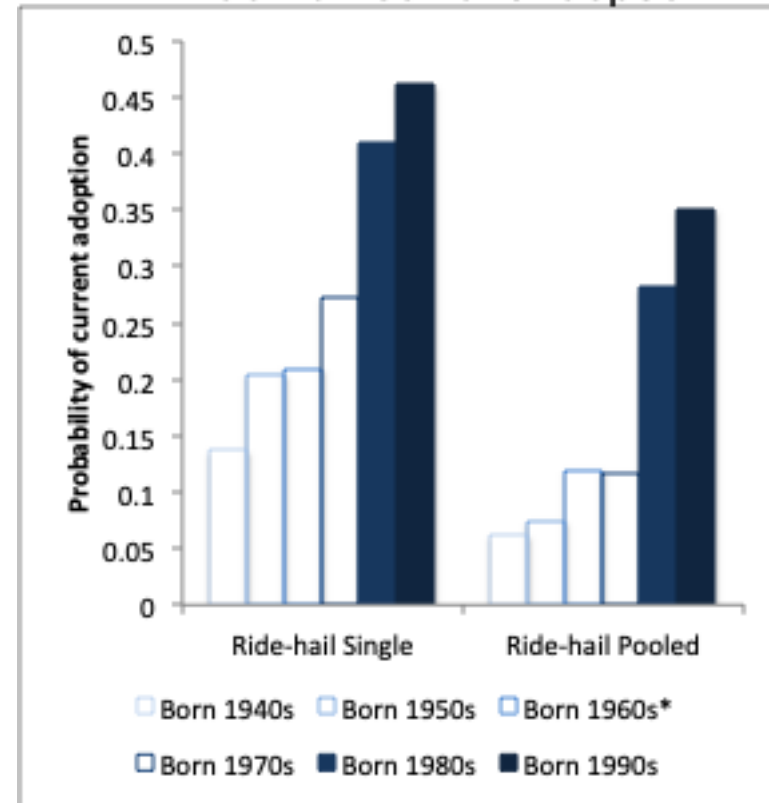


Note: filled in bars have $p < 0.10$. Hollow bars indicate no statistically significant difference relative to the omitted category

AGE

- **Ride-Hailing (see graph to right)**
 - Those born in the 1980s and 1990s are 16–25 percentage points more likely to have already adopted either single-rider or pooled ride-hailing services in comparison to those born in the 1960s, conditional on all other controls.
- **EV (not pictured)**
 - Those born in the 1980s and 1990s exhibit 6-9 percentage point lower current adoption rates for electrified vehicles
 - But they are just as likely or more likely to be interested in future adoption of electrified vehicle technologies relative to older generations.
- **Automation (not pictured)**
 - Those born in the 1990s exhibit rates of interest in future adoption of higher levels of automation that are 22–23 percentage points higher than exhibited by those born in the 1960s.

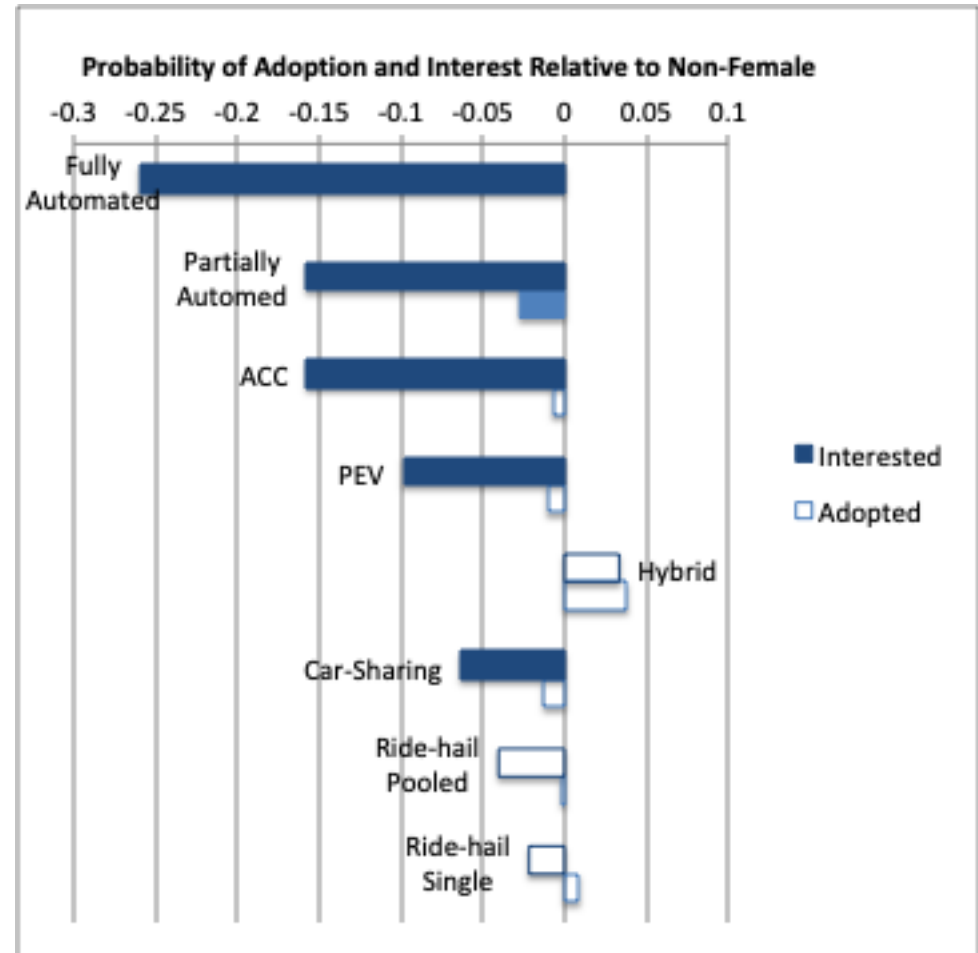
Ride-Hail Current Adoption



Note: filled in bars have $p < 0.10$. Hollow bars indicate no statistically significant difference relative to the omitted category (those born in the 1960s)

GENDER

- Female identification:
 - 3 percentage points less likely to have adopted partially automated vehicles,
 - 16–26 percentage points less likely to be interested in adopting vehicles with any level of automation,
 - 10 percentage points less likely to be interested in adopting PEVs, and
 - 6 percentage points less likely to be interested in adopting car-sharing.
- Female identification is associated with no significant difference in current or future interest in adoption of:
 - hybrid vehicles, which are a relatively mature technology.
 - ride-hailing.
- Ride-hailing may provide an opportunity to better understand what types of transportation innovations are more appealing to women.



TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Article 2 [MOSTLY FINAL RESULTS] –[Objective 4 & 5 from Slide 5]

Title: Children at home: how transitions through family stages relate to mobility patterns in the San Francisco Bay Area

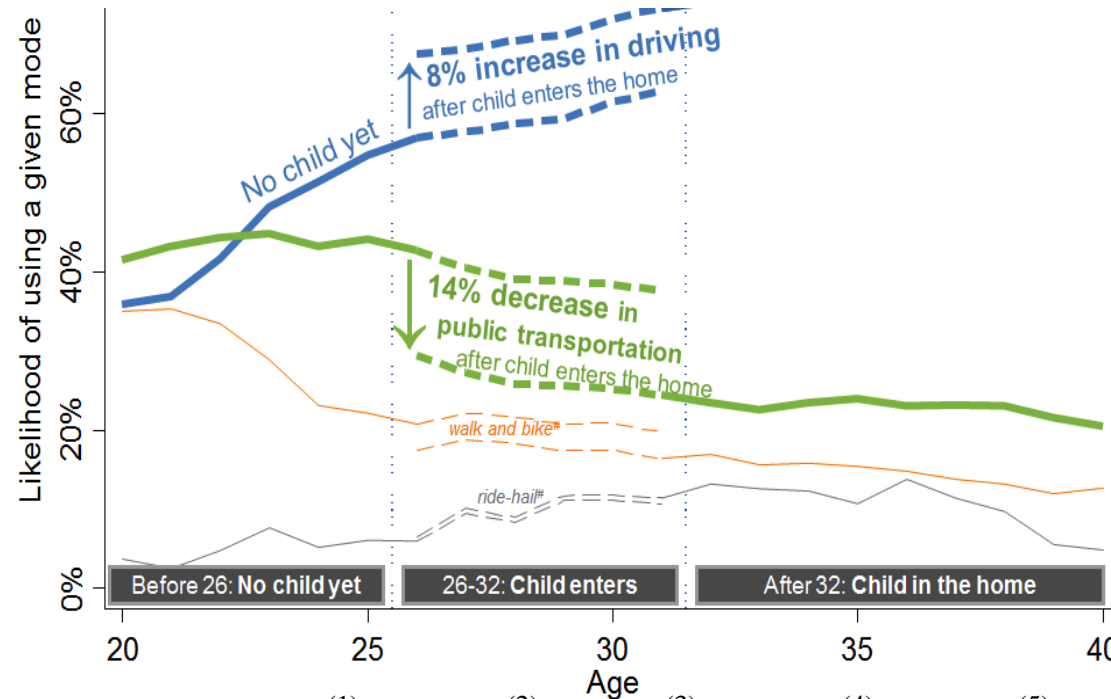
(Todd, Taylor, Jin, Wong-Parodi, Walker, Sears, Zuboy, Gopal, and Spurlock)

- Understanding the transportation choices of people with children at home (41% of the U.S. population) is critical to understanding the efficiency implications of emerging mobility options.
- We analyze the impact of children on parents' transportation choices, including how choices are tied to family development.



THE IMPACT OF CHILDREN ON TRANSPORTATION CHOICES VARIES BY THE AGE AT WHICH THE PARENT HAS THEIR FIRST CHILD

- Parents who have their first child in the middle of the age distribution (26–32 years old) show the expected correlation:
 - personal vehicle use goes up
 - public transit use goes down
 - number of modes used goes down
- Younger parents (first child at 20–25 years old) *reduce* their personal vehicle driving
- The only changes made by older parents (first child at 33–50 years old) are decreases in walking or biking and number of modes used.



	(1) Personal Vehicle	(2) Public Transit	(3) Ride- hailing	(4) Walk or Bike	(5) # of modes
<i>children * cohort 20-25yr</i>	-0.114* (0.0480)	0.0869 (0.0565)	0.0620 (0.0625)	0.0089 (0.0352)	-0.0488 (0.0618)
<i>children * cohort 26-32yr</i>	0.0838** (0.0308)	-0.139** (0.0368)	-0.0291 (0.0405)	-0.0401 (0.0280)	-0.0860* (0.0435)
<i>children * cohort 33-50yr</i>	-0.0128 (0.0308)	-0.0117 (0.0366)	-0.0232 (0.0385)	-0.0545* (0.0263)	-0.0904* (0.0424)
FE age	yes	yes	yes	yes	yes
FE person	yes	yes	yes	yes	yes
Adj. R-sq	0.585	0.510	0.412	0.532	0.550
# people	829	747	666	829	829

Standard errors in parentheses are clustered at the person level.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Article 4 [PRELIMINARY RESULTS] – [Objectives 4 & 5 from Slide 5]

Title: Family structure and the impact of home-delivery on household shopping trips for four purchase categories (Spurlock, Todd, Wong-Parodi, and Walker)

1. What is the distribution of substitution and complementarity behavior across the population for these four categories of goods?
2. Which types of shopping travel modes are being substituted for, or not, by delivery for these four categories of goods?



These results will provide valuable insights into the degree to which e-commerce delivery is increasing VMT associated with shopping overall or not, and if so, what needs are deliveries addressing in the population.

RESEARCH QUESTIONS

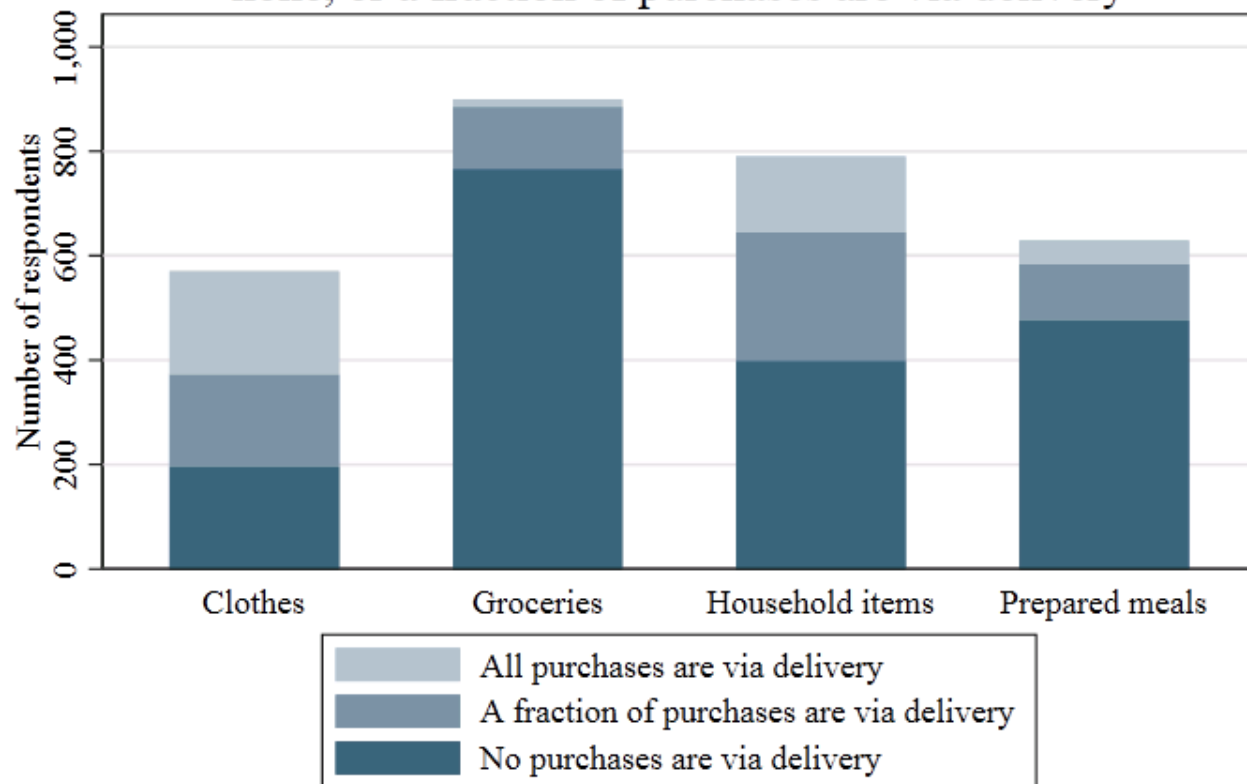


- Four categories of goods:
 - **Groceries** (e.g., cereal, meat, produce, dairy, beans)
 - **Household items** (e.g., paper towels, diapers, cleaning products, sunscreen)
 - **Prepared meals** (e.g., restaurant meals, take-out, meal delivery, cooking kit with prepared ingredients such as Blue Apron).
 - **Clothing, shoes or accessories**
- Three categories of purchase channel/mode
 - **Delivery**
 - **Vehicle** (e.g., personal vehicle, taxi, Uber, Lyft)
 - **Walk, Bike, or public transit**

DISTRIBUTION IN THE SAMPLE OF PROPORTION OF PURCHASE EVENTS THAT ARE DELIVERIES

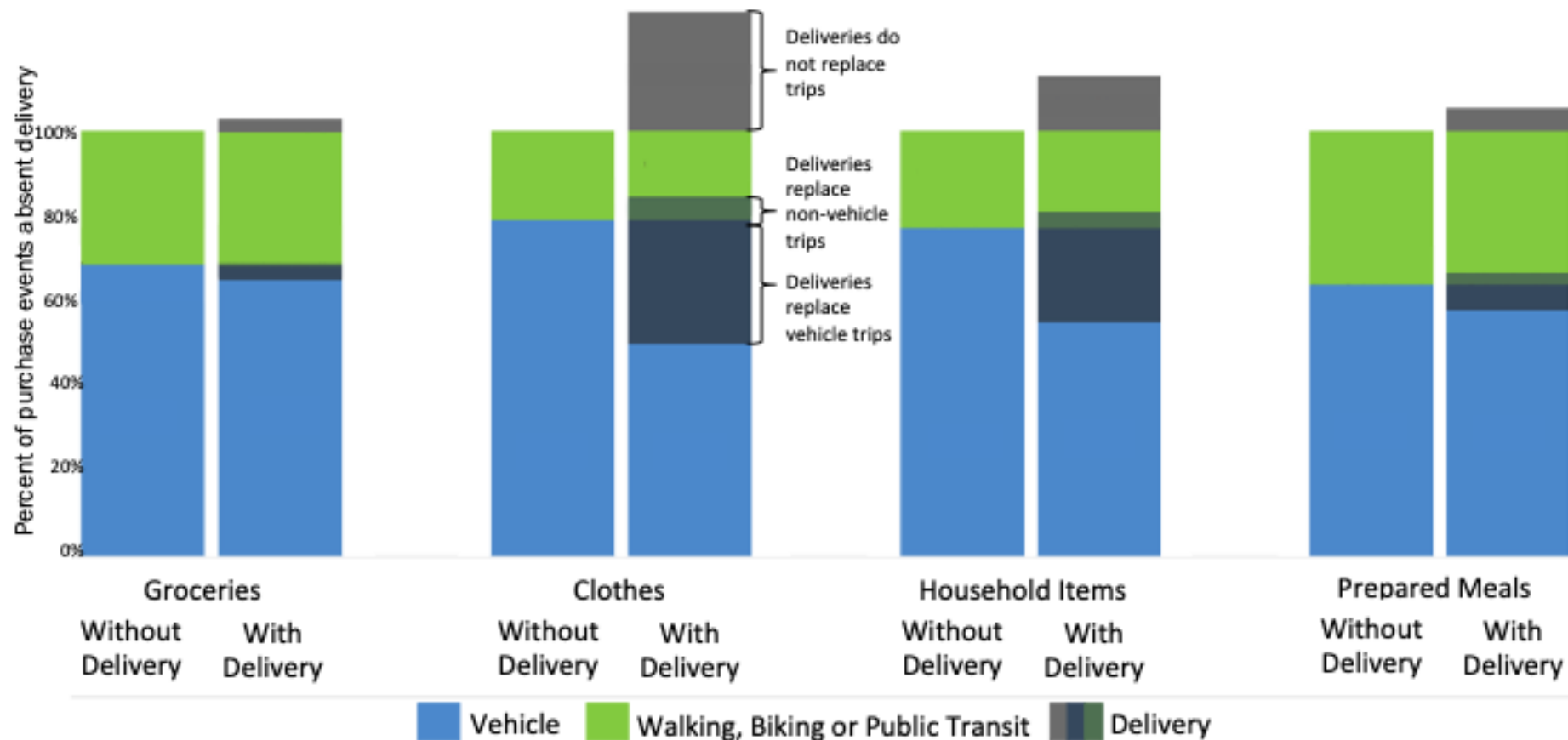
- People tend to be dichotomous in terms of delivery
 - between about 70% and 87% of people either made every purchase through delivery, or none, depending on the product.
- Groceries are purchased most and delivered least
 - ~ 80% of the sample received no deliveries of groceries
- Clothes are purchased least and delivered most
 - ~30% of the sample received all of their clothes through delivery
- Households with children receive a greater proportion of their purchases via delivery for all four categories of goods, especially household items.

The number of people for whom all, none, or a fraction of purchases are via delivery



BY PRODUCT CATEGORY, ARE DELIVERIES SUBSTITUTING FOR TRIPS, AND IF SO, WHAT KIND?

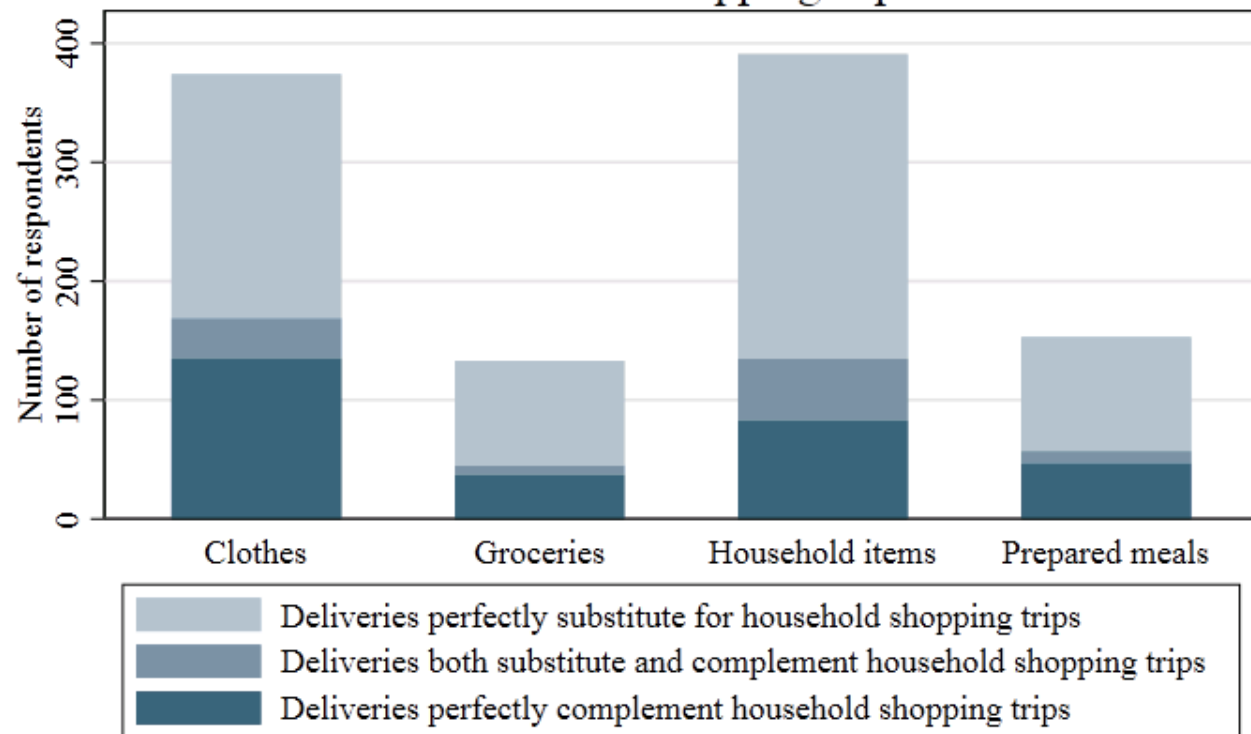
- Deliveries both supplement and substitute for household shopping trips, depending on the household.
- The proportion of vehicle shopping trips deliveries replace (substitute) is similar to the proportion of deliveries made that aren't replacing any shopping trips (supplement).
- This proportional relationship is roughly similar across product types.



DISTRIBUTION IN THE SAMPLE OF PROPORTION OF DELIVERIES THAT WOULD BE REPLACED BY ADDITIONAL TRIPS

- People are very dichotomous in terms of the degree to which deliveries supplement or substitute for shopping trips:
 - For 21-36% of people who make purchases, deliveries are fully supplemental to shopping trips
 - For 55-66% of people who make purchases, deliveries are perfect substitutes for shopping trips
- For only a small proportion of people is there a mix of supplementation and substitution
- Households with children are more likely to have deliveries supplement existing shopping trips.

The number of people for whom deliveries perfectly complement, perfect substitute for, or both, household shopping trips



TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Article 5 [PRELIMINARY RESULTS] – [Objectives 4 & 5 from Slide 5]

Title: Tensions and complementarities in mass transit and ride-hailing decisions through a survey-based randomization

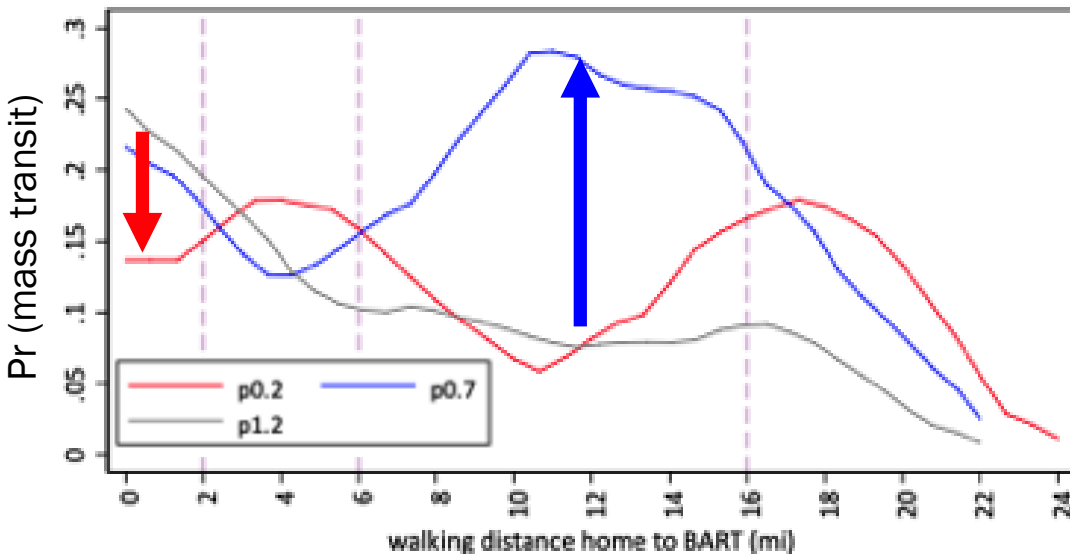
(Todd, Belal, Spurlock)

- Examine complex interaction of ride-hailing with other transportation choices in daily mode choice for primary commute trips.
- Innovation beyond current research:
 - Assesses hypothetical scenarios in which the cost of providing ride-hailing has decreased substantially (from \$1.20/mile to \$0.70 and \$0.20/mile)
 - Explores the impacts on the transportation system
- Research Questions:
 - How would a price decrease in ride-hailing impact the use of mass-transit:
 - Increase mass transit use due to first/last mile linkage?
 - Decrease mass transit use by switching to ride-hailing?
 - What is the nature of this cross-price response (linear vs non-linear)?
 - How does this cross-price response vary by
 - distance to a mass-transit station?
 - income?



ESTIMATED CHANGE IN MASS TRANSIT USE AS A RESULT OF RIDE-HAIL PRICE DECREASE, BY DISTANCE FROM TRANSIT AND INCOME

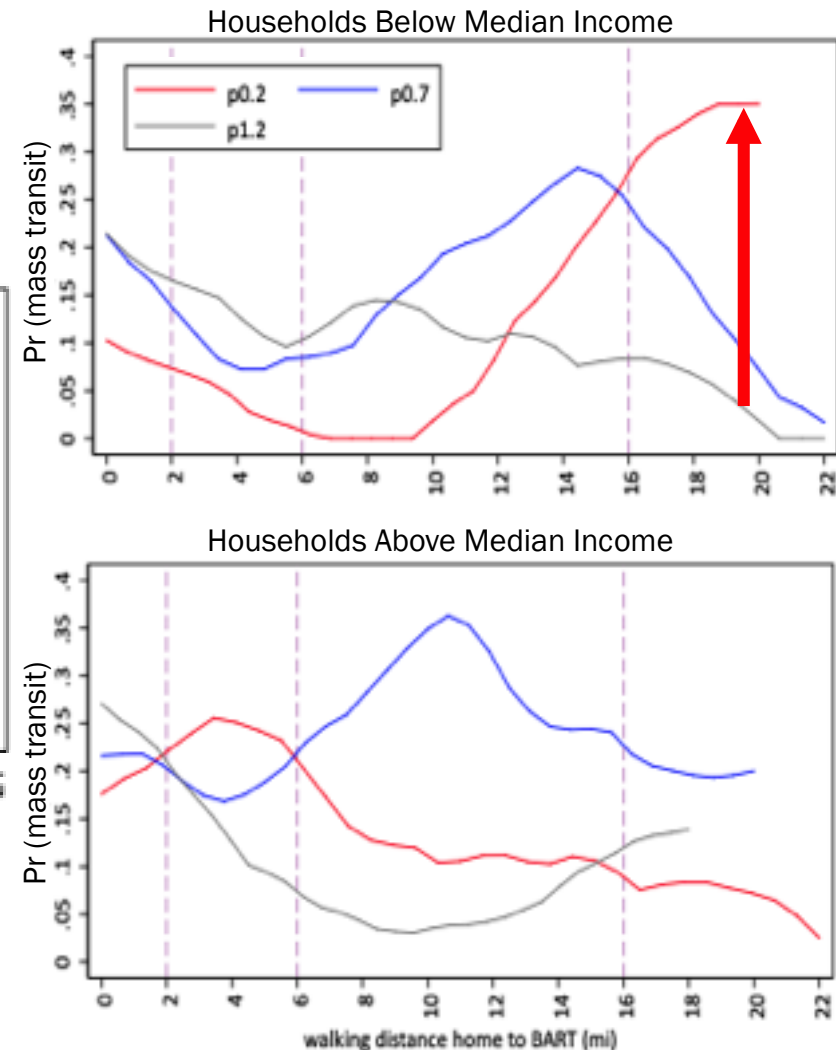
Probability of mass transit use by walking distance to BART



Statistically significant results:

- Drop in mass transit use at \$0.20/mile driven by people living close to mass transit.
- No overall change in transit use at \$0.70/mile, but significant increase in transit use for those between 6 and 17 miles to the nearest BART station.

Probability of mass transit use by walking distance to BART



Statistically significant results:

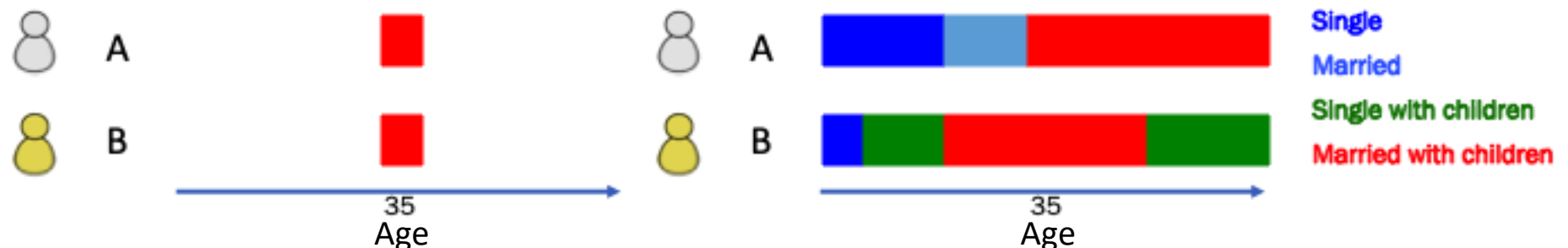
- For lower income households, large increase in transit use for those living >16 miles from nearest BART station

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Article 6 [PRELIMINARY RESULTS] – [Objectives 4 & 5 from Slide 5]

Life course as a contextual system to investigate the effects of life events, gender and generation on travel mode usage (Jin, Lazar, Sears, Todd, Sim, Wu, Spurlock)

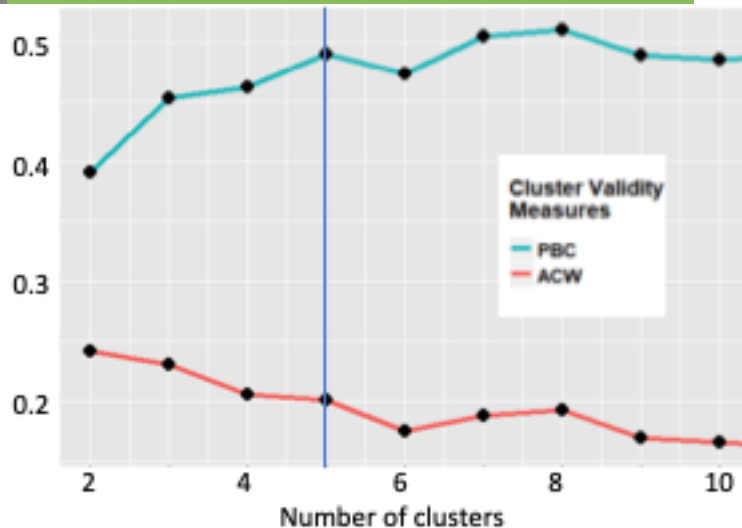
- Transitions between life events (attending school, getting employed, and having a child) can disrupt habitual travel behavior and shift choices among modes.
- Modal shift may depend on dynamically changing constraints and opportunities within individual's life context.
- Past studies used static life-cycle stages to categorize travelers without considering the dynamics present in the longer life history.
- We use different types of life course patterns/trajectories to investigate the effects of life events on travel mode usage.



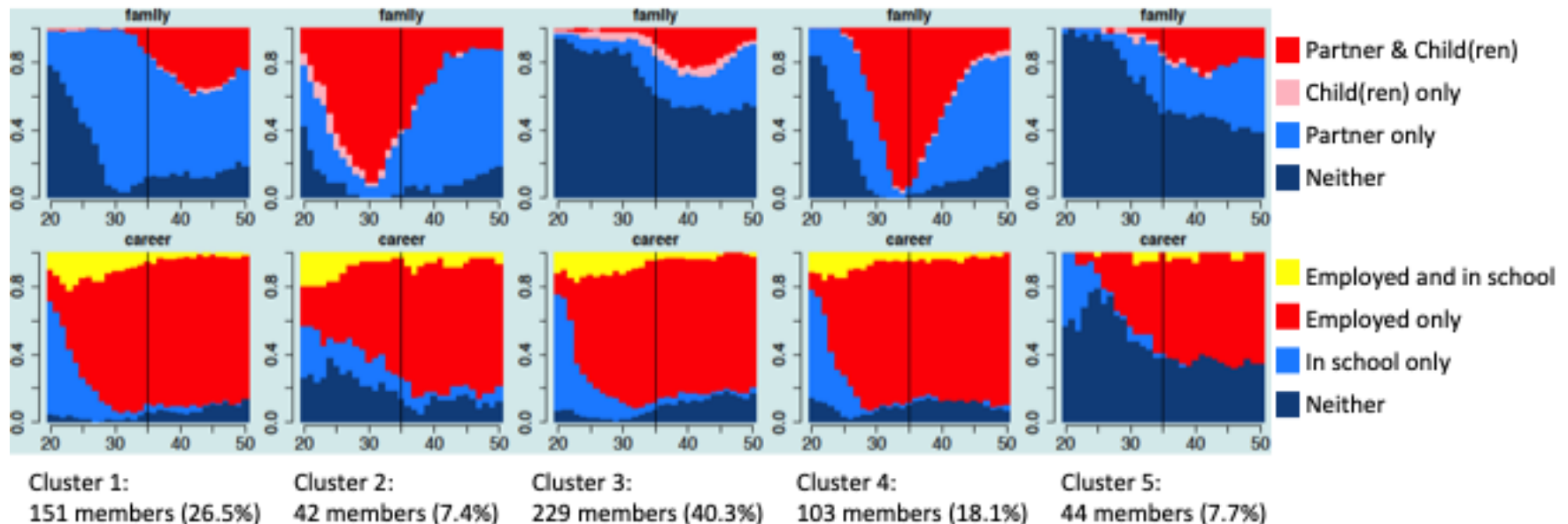
At age 35 both A and B are married with children. A static analysis of travel choices across life-cycle stages would treat them the same

Based on their life course contexts, these two have experienced different circumstances that are likely to influence their response to major life changes

CLUSTERING ANALYSIS



- Used “Edit” distance to measure the similarity between sequences, a technique used in genetics to compare gene sequences of different species.
- Clustered respondents on family/career sequences from when the respondent was between the ages of 20 and 35: (1) Living with a partner or not; (2) With young children or not; (3) working or not; (4) in school or not). Settled on 5 family/career clusters
- Each individual is assigned to one of the resulting 5 clusters:
 - Couples: school/work early, partner early, delayed children
 - Family first: partner and children early, delayed school and/or career
 - Singles: school/work early, delayed partner and children
 - Have-it-all: school, work early, couple and children only slightly later
 - Late bloomers: delayed school, work, partner and children



REGRESSION RESULTS: IMPACT OF LIFE EVENTS ON MODE USE

Clusters:

1. Couples: school/work early, partner early, delayed children
2. Family first: partner and children early, delayed school and/or career
3. Singles: school/work early, delayed partner and children
4. Have-it-all: school, work early, couple and children only slightly later
5. Late bloomers: delayed school, work, partner and children

Children

- Having child associated with lower mobility (fewer modes overall, and active modes, used - though more driving in one case).
- Clusters 3 & 4
 - Reduce walking and biking
 - Increases driving (Cluster 4)

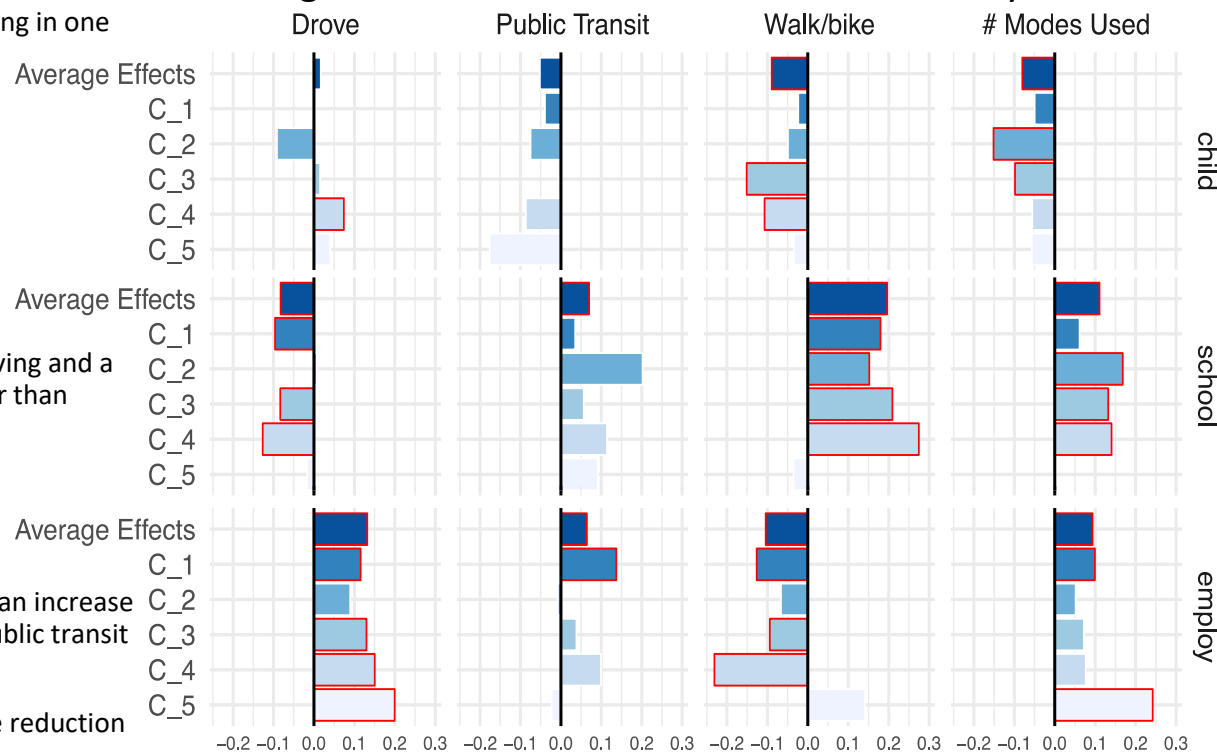
School

- Being in school is associated with a reduction in driving and a large increase in walking and biking generally (other than cluster 2).

Employment

- The transition from school to work associated with an increase in driving (significant for all except cluster 2) and public transit use for cluster 1.
- A pronounced change due to employment is a large reduction in walking and biking (clusters 1, 3 and 4).
- For most clusters the transition to employment is associated with a shifting of modes rather than an overall change in the number of modes regularly used. The exception are Clusters 1 and 5, which are associated with delayed family (1 & 5), and school/career (5).

Marginal effects of life events on mode use by cluster



Notes: Red outline indicate values statistically different from zero at the 10% level

RESPONSES TO PREVIOUS YEAR REVIEWER COMMENTS

RESPONSES TO PREVIOUS YEAR REVIEWER COMMENTS

- **“While this is good characterization of a specific urban area, it is not clear how transferable that data would be to other metropolitan regions. The project team should consider investigating how to apply the survey outcomes to other existing consumer datasets to extract EEMS-relevant information.” “Extending the data collection to another region would address one of the limitations of the work to date (single region of data collection) if time, approval processes, and budget allow.”**
 - We agree; the survey is not even fully representative of the San Francisco Bay Area, as the respondents tended to be higher income, higher educated, and whiter than the population. Given bureaucratic and timing limitations we couldn’t expand recruitment to make respondents more representative. We hope in the future to improve upon the current survey instrument and conduct collection in more diverse regions, while targeting underserved communities (low income, elderly, disabled, rural, etc.). We determined to not undertake further data collection in this fiscal year because we felt it would be preferable to use our resources to extract as much insight as possible for current data, rather than spending considerable effort and money to collect data that wouldn’t be in-hand in time to be useful for all the other SMART Mobility tasks. Further data collection will hopefully be something we can undertake in earnest in the future.
- **“‘Normalizing’ survey and GPS data for use in other DOE research projects will be a challenge. Data collection and processing for other regions may be required to achieve full usefulness.”**
 - We agree. Given that the current modeling emphasis in SMART Mobility with respect to BEAM and Polaris (the two agent-based models) tends to be concentrated in the San Francisco Bay Area and Chicago Metropolitan Area, we feel that insights from our survey are applicable to providing inputs to those models and therefore to the SMART Workflow Task Force generally. We agree that our data are not nationally representative and should therefore be used with care in SMART Mobility tasks that are undertaking national level analyses.
- **“It would have been beneficial if the team provided more detail upfront on the rationale for the approach (life history calendar, psychological/personality characteristics, and time and risk preferences), rather than in the technical backup slides.”**
 - It is a challenge to present these details in a 20-minute presentation. Each of the 10 in-depth research papers will have a full literature review and discussion of the gaps in knowledge each analysis is designed to fill.

RESPONSES TO PREVIOUS YEAR REVIEWER COMMENTS

- **“It may be good to include additional focus on economic factors as this is often the key determining factor.”**
 - We agree that economic factors are very important, and we do have some studies that focus on those factors, looking at behavioral outcomes differentiated by income for example, or explicitly in the study looking at the cross-price effects of variation in ride-hailing prices. However, the study was designed to explore a variety of behavioral barriers and drivers, not just economics, and so we hope we have balanced those objectives sufficiently.
- **“Milestones for the project are provided but given the size and scope of the project, they are somewhat thin and lacking clear definition and high impact.”**
 - More detailed milestones have been further fleshed out subsequent to data collection being completed.
- **“It may have been beneficial to include an automotive OEM on the project as it is likely they would have excellent insights and marketing analysis into traveler characteristics that define consumer behavior with regards to transportation options.”**
 - A valid point. While marketing research by OEMs is related to the technology adoption content of our survey, we focus on a broader set of behaviors as well.
- **“The stated objective of data collection in poor and underserved communities was offered in the presentation... the project team could consider if the population characteristics of Oakland could be suitable for this and if a focused data collection could be possible in FY 2018 for this sub- population... this may need to be part of the determination for the go/no-go in FY 2019, but this would allow further analysis of this component of the population while staying within the original study area... the suburban counties on the north side of the bay may also be a worthy target for additional surveys because these may represent a more common cross-section of the U.S. population.”**
 - Unfortunately the results of our collection indicated that we ended up with a pretty selected sample. As noted before, the sample was more wealthy, more highly educated, and whiter than the general population. While there are some respondents that are lower income, for example, there are few enough that we feel we have to be cautious with over-interpreting results on that score. We look at results differentiated by income, but we use the median of the sample as a cut-off in many cases, which is definitely higher than the median income in the general population.

COLLABORATIONS & REMAINING CHALLENGES AND BARRIERS

COLLABORATION AND COORDINATION WITH OTHER INSTITUTIONS



This project integrates with and supports the research of all

pillars within the **SMART Mobility Initiative**:

- We have provided the fully dataset from the phase 1 data, are about to do the same for phase 2. As noted previously, these data are already being used by a number of researchers across SMART.
- We are also in communication with a number of other SMART Mobility tasks to coordinate our analysis in such a way that some of our output can be used in the models and simulations in the Workflow Task Force.

LBNL-lead Team

• LBNL

- C. Anna Spurlock; PI; MDS Pillar Lead
- Ling Jin
- Annika Todd
- Margaret Taylor
- James Sears
- Saika Belal
- John Wu
- Alex Sim
- Yulei (Shelley) He
- Juan Caicedo

• NREL

- Andrew Duvall
- Alana Wilson
- Bingrong Sun

• INL

- Victor Walker
- Sawn Salsbury
- Tessica Gardner
- David Black
- Mindy Gerdes

• Academic Collaborators

- Gabrielle Wong-Parodi, Stanford
- Emily Wells, CMU
- Joan Walker, UCB
- Menqiao Yu, UCB
- Alina Lazar, YSU

As we work to complete the ambitious goal of producing 10 research papers plus supporting tasks across SMART Mobility, team members from across all three labs and our academic collaborators are coordinating on a number of parallel analyses and data cleaning/management efforts.

REMAINING CHALLENGES AND BARRIERS

- Our primary challenge is to complete all 10 research papers by the end of FY19. We are making significant progress and are currently on track to meet this goal, but it is ambitious.
- A number of tasks across SMART would like to incorporate results from our analyses in their models and simulations. We are prioritizing our research to provide specific results necessary for model runs in FY19; however there is a risk we won't complete those analyses in time.

PROPOSED FUTURE RESEARCH

PROPOSED FUTURE RESEARCH

- **FY 2019:**

- Continue the planned analyses outlined on slide 7. Work with collaborators across SMART Mobility to prioritize the analyses most needed for integration into other tasks and the Workflow Task Force.
- Here is a little more detail on the planned papers not summarized in this presentation:
 - **Relationship between personality/psychology and mode use:** To what extent do personality characteristics (e.g., extraversion, openness, agreeableness, neuroticism, conscientiousness) and current and historical social factors (parent example during formative years, preferences for social behavior) mediate use of transportation modes?
 - **Variability and flexibility in short-term mode choice, route choice, travel time:** Using the GPS data collected as part of Phase 2, analyze the extent to which people are variable in their departure times, arrival times, routes, etc. Generate a metric of variability that varies across people and analyze what characteristics, limitations, and travel needs correlate with variability, as well as how this variation translates through to current mode use patterns. Using insights from this analysis, conduct further exploration of implications of these patterns for micro-transit and employer-provided transportation.
 - **Estimation of value of travel time:** given that we do observe mode choices and we are able to collect data from the internet on the cost and time for each possible mode for each person, we will estimate value of travel time (VOTT) using our data. This will allow us to analyze how this estimate varies across characteristics relevant for other behavioral outcomes observed in other studies we've conducted to paint a fuller picture of transportation behavioral barriers and drivers in our sampled population.
 - **Effect of uncertainty in ride-hailing prices on mode choice:** The experimental question that randomized the cost of TNCs to explore impacts on other modes also included a treatment group where they were told there was a 50/50 chance of the price of TNCs being high or low. We will examine the extent to which uncertainty in TNC prices influences demand for TNCs and demand for other competing or complementary modes.
- In cases where analyses meet unforeseen barriers, work with DOE program managers and SMART Mobility collaborators to revise the list of planned analyses and outputs to best meet the goals of SMART Mobility.

Any proposed future work is subject to change based on funding levels.

PROPOSED FUTURE RESEARCH

- **FY 2020:**

- Address a number of important research questions not included in this project
 - How can a deeper understanding of behavior enable the future relevance of mass transit in the face of transportation innovations?
 - Is micromobility (scooter, bike share, etc.) a complement or substitute for TNCs and mass transit?
 - How does the value of travel time (VOTT) vary across individuals, and across time and activities for a given traveler?
 - What are the trade-offs between driving, micromobility, TNCs, and mass transit when it comes to safety (air quality, exposure, injury, etc.) and how are these factors impacted by the built environment?
 - What are current perceptions and preferences around owning versus using (e.g., through TNC-style services) automated vehicles (AV) and other vehicle technologies, especially for women?
 - How are the dynamics in migration between urban, suburban, and rural regions over a household's life history associated with pivotal life events (children, school, work) and transportation choices?
 - What are the more nuanced and detailed behaviors regarding e-commerce (including returns)?
 - Are there behavioral negative feedbacks that may limit the nightmare scenario of massive increasing vehicle miles traveled and increased urban sprawl because of AVs?

Any proposed future work is subject to change based on funding levels.

SUMMARY

Relevance

- Integrate with and support SMART Mobility
- Reduce model uncertainty
- Contribute to better understanding of pathways to an energy independent and efficient transportation system

Approach

- Innovative survey and data collection
- Cutting edge analytics and research agenda to pursue gaps in current knowledge
- Integrated multi-time-scale perspective across multiple emerging transportation technologies and services.

Tech accomplishments/progress

- Completion of data collection.
- Wide-spread sharing of data across SMART Mobility.
- Publication of 2 journal articles, 1 conference paper, presentation of 1 poster and 5 conference presentations.
- Analysis and/or paper development complete or close to complete for 6 of the 10 planned research papers.
- Development of valuable insights to inform research across SMART Mobility.

Proposed future research

- Complete data analyses for planned research papers.
- Work with other SMART Tasks to provide needed inputs (data and findings).
- Develop plan to build on current research to address outstanding gaps.

TECHNICAL BACKUP SLIDES

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Article 1 - Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area

- We focus on the following emerging technologies and services:

Shared-mobility: ride-hailing (single-rider and pooled); car-sharing

Electrified vehicles: hybrid electric vehicles; plug-in electric vehicles

Three different levels of AV technologies:

Adaptive Cruise Control; Partially Automated Vehicles (e.g., Tesla Autopilot); Fully Automated Vehicles

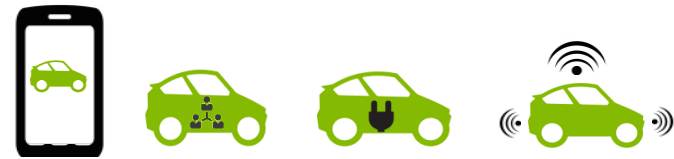
- Four types of factors that we hypothesize, based on our literature review, can explain adoption of and interest in these emerging developments:

Demographics (e.g., age, income, gender)

Location-specific factors (e.g., walkability, population density, commute distances)

Preferences for mode attributes (e.g., social interactions, convenience)

Human characteristics (e.g., risk preferences, personality)



ANALYSIS APPROACH:

$$Y_{igc} = \alpha + \mathbf{X}'_{igc}\boldsymbol{\beta} + \mathbf{P}'_i\boldsymbol{\theta} + \epsilon_i$$

Where:

Y_{igc} = Adoption or interest of individual i , in census block group g , in county c

$$\begin{aligned}\mathbf{X}'_{igc}\boldsymbol{\beta} = & \beta_1 Child_i + \beta_2 (> 4yr College)_i + \beta_3 Female_i \\ & + \beta_4 WalkScore_i + \mathbf{BirthDec}'_i\boldsymbol{\eta} + \mathbf{PopDens}'_{gc}\boldsymbol{\delta} \\ & + \mathbf{PrimaryDistance}'_i\boldsymbol{\lambda} + \mathbf{HH Inc}'_i\boldsymbol{\gamma} + C_c\end{aligned}$$

$$\mathbf{P}'_i\boldsymbol{\theta} = \mathbf{ModeAttrib}'_i\boldsymbol{\pi} + \mathbf{BigFive Personality}'_i\boldsymbol{\tau} + \mathbf{Risk Preferences}'_i\boldsymbol{\omega}$$

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Article 2 - Children at home: how transitions through family stages relate to mobility patterns in the San Francisco Bay Area

ANALYSIS APPROACH:

- Difference-in-differences (DID) ordinary least squares (OLS) multivariate panel regression model including respondent and age fixed effects.

$$Y_{igt} = \alpha_i + \beta children_{it} + \delta_g + \varepsilon_{it}$$

Where Y_{igt} is a zero-one indicator of regular use of a given mode for individual i in year t at age g

AVERAGE EFFECT OF HAVING CHILDREN ON MODE CHOICES

- Children in the home are associated with
 - A decrease in public transit use by ~5 percentage points
 - A decrease in walking or biking by ~4 percentage points
 - An overall reduction in the number of modes used regularly

	(1) Personal Vehicle	(2) Public Transit	(3) Ride-hailing	(4) Walk or Bike	(5) # Modes Used
<i>nesting/children</i>	0.0096 (0.0212)	-0.0486* (0.0255)	-0.0149 (0.0267)	-0.0380* (0.0175)	-0.0817* (0.0283)
FE age	yes	yes	yes	yes	yes
FE person	yes	yes	yes	yes	yes
Adj. R-sq	0.583	0.507	0.412	0.532	0.550
# people	829	747	666	829	829

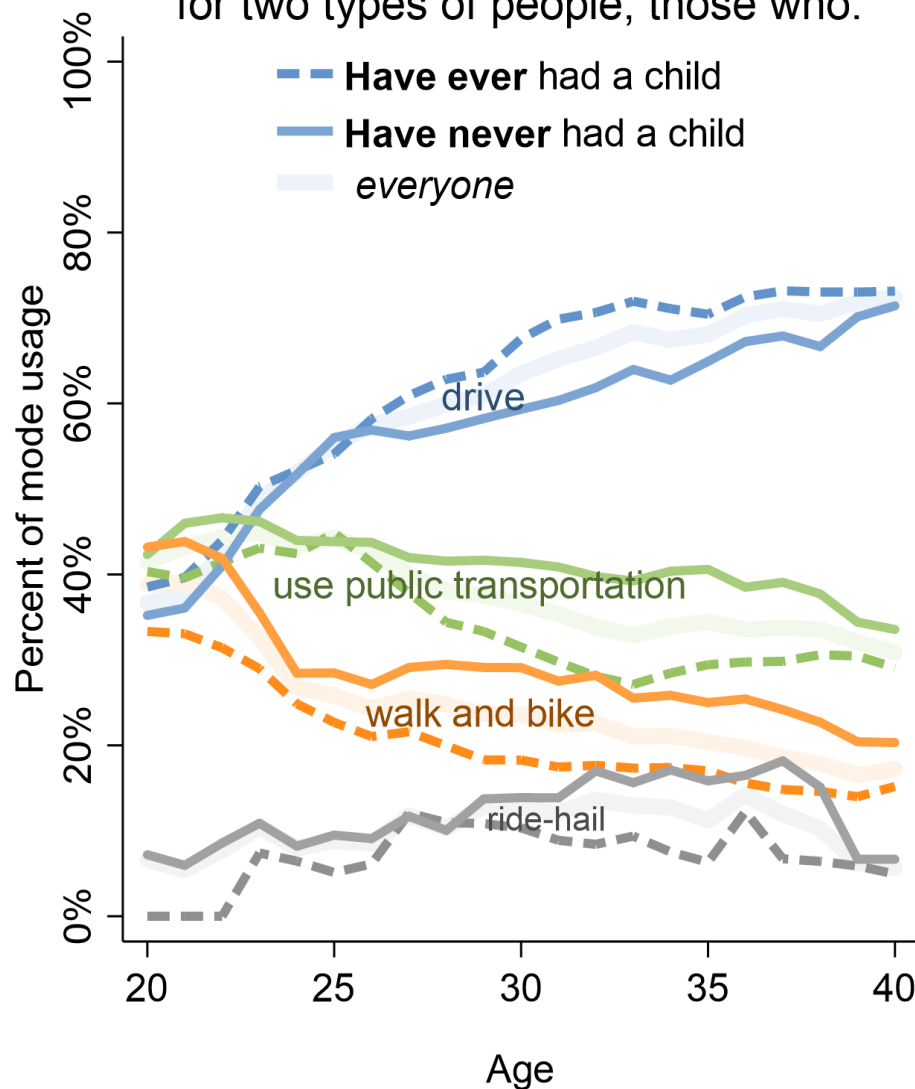
Standard errors in parentheses are clustered at the person level.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

MODE CHOICE WITH AGE

- When people have a child, on average they begin regularly driving a personal vehicle more and using some other modes (public transit, walking or biking) less.
- However, these effects are largely explained by the correlation between having a child and aging.
- When controlling for age: children in the home are associated with
 - A decrease in public transit use by ~5 percentage points
 - A decrease in walking or biking by ~4 percentage points
 - An overall reduction in the number of modes used regularly

How people's mode choices change as they get older for two types of people; those who:



NO SINGLE FAMILY LIFE EVENT TRIGGERS CHANGES ACROSS ALL MODES

- Personal vehicle driving increases at the “nesting” stage (the 2 years before people have their first child)
- persistent habit or locked-in lifestyle choices such as suburban living.
- When parents transition from nesting to having a child, their use of public transit and walking or biking declines.
- During the transition to all children being at least 5 years old, regular use of ride-hailing declines.
- This is in contrast to Dowling (2015), who found that ride-hailing use was impacted more by the need for a child safety seat, which would be more relevant for the younger-child stage.

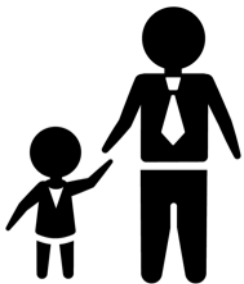
	(1) Personal Vehicle	(2) Public Transit	(3) Ride- hailing	(4) Walk or Bike	(5) # of modes used
<i>nesting</i>	0.0400 ⁺ (0.0210)	-0.0093 (0.0246)	0.0100 (0.0310)	-0.0130 (0.0189)	0.0080 (0.0309)
<i>children</i>	-0.0038 (0.0167)	-0.0637** (0.0223)	-0.0175 (0.0270)	-0.0327* (0.0161)	-0.0805** (0.0277)
<i>children (≥5yr)</i>	-0.0077 (0.0197)	-0.0062 (0.0226)	-0.0519* (0.0245)	0.0020 (0.0157)	-0.0543* (0.0269)
<i>children (>18yr)</i>	0.0404 (0.0508)	-0.0459 (0.0574)	0.0450 (0.0713)	0.0198 (0.0361)	0.0086 (0.0512)
FE age	yes	yes	yes	yes	yes
FE person	yes	yes	yes	yes	yes
Adj. R-sq	0.583	0.508	0.413	0.532	0.551
# people	829	747	666	829	829

Standard errors in parentheses are clustered at the person level.

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Article 4 - Family structure and the impact of home-delivery on household shopping trips for four purchase categories



- **Households with Children at Home:**
 - Make more purchases overall than households without children
 - Tend to be slightly younger
 - Tend to have higher incomes
 - Live in slightly less densely populated areas
 - Survey respondent is more likely to be a woman
 - Survey respondent is likely to have a higher discount factor
 - Do not appear any more or less likely to have an Amazon Prime membership



- **Analysis Approach (Purchase mode/channel choice):**
 - As a scaling parameter, based on observed patterns in the data we assumed households had 14 potential purchase events per item type per week (2 per day) for a total of 56 potential purchase events overall.
 - For each potential purchase event they have a choice across four alternatives:
 - No purchase
 - Delivery
 - Vehicle Trip
 - Non-vehicle Trip (Walk, Bike, or Public Transit)
 - We model this using multinomial Logit, both overall, and differentiating across product type.
 - Include household-level covariates for a household level analysis, and then limit the sample to households with one adult in order to include both household and individual level covariates.

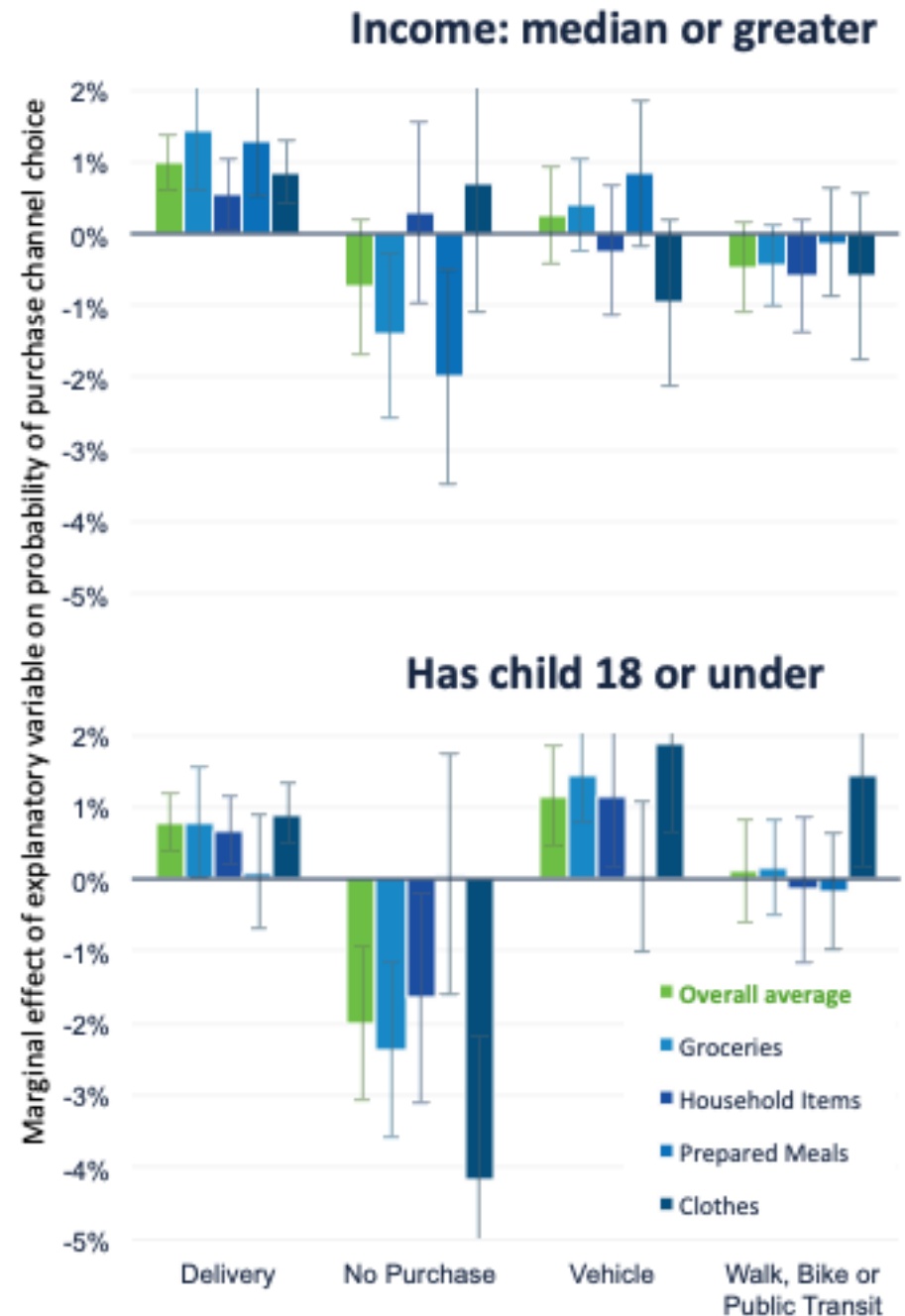


Analysis Approach (substitution vs complementarity):

- For each reported delivery there is a discrete choice across three alternatives:
 - Delivery does not replace a trip
 - Delivery replaces a vehicle trip
 - Delivery replaces a non-vehicle trip
- We model this using multinomial Logit, both overall, and differentiating across product type.

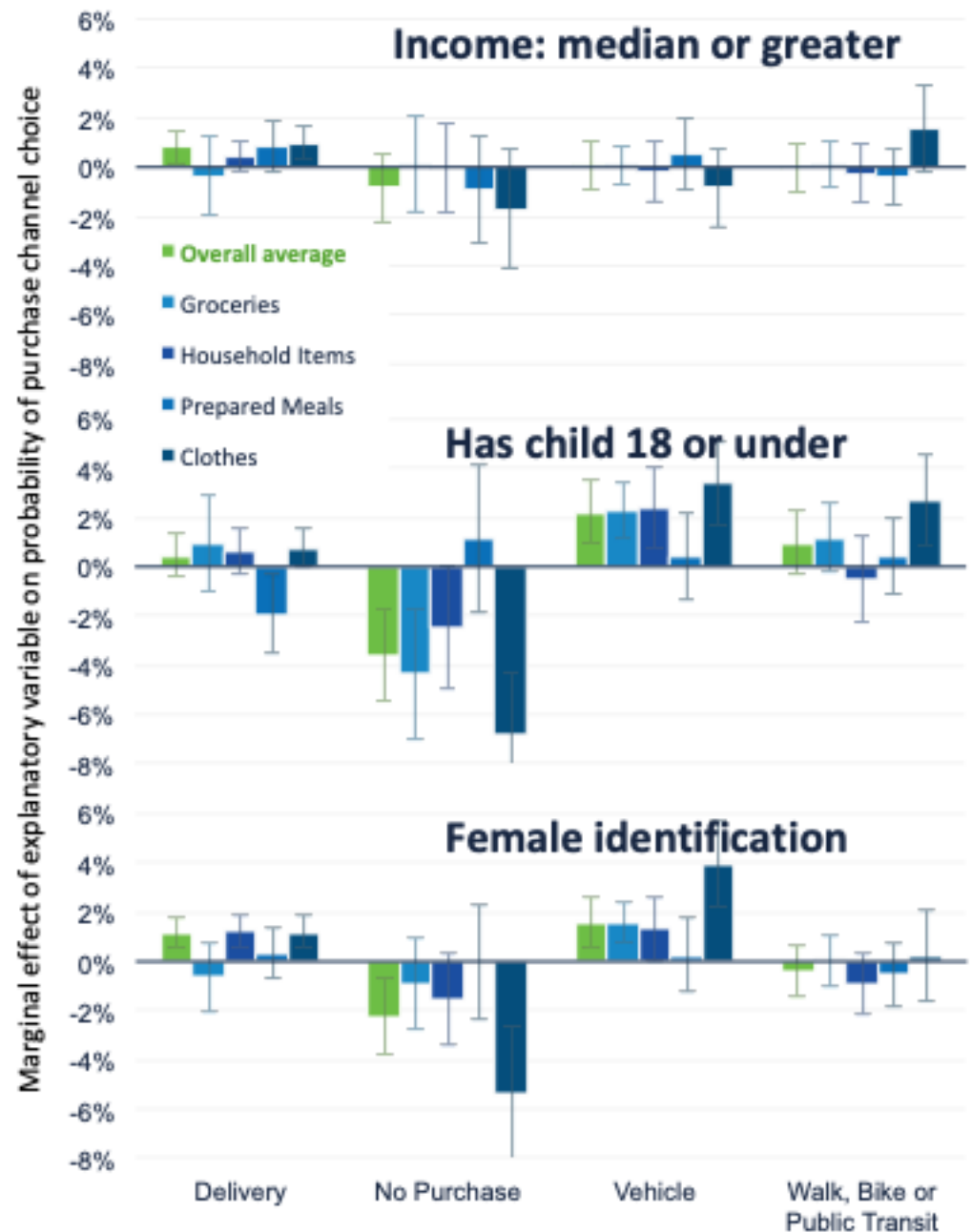
MULTINOMIAL LOGIT: SELECTED RESULTS FOR HOUSEHOLD-LEVEL ANALYSIS

- **Those with above median income**
 - Have a higher probability of making a purchase via delivery, particularly for groceries and prepared meals.
- **Households with children**
 - Are more likely to:
 - order delivery
 - make vehicle trips
 - And less likely to:
 - make fewer purchases
 - This pattern is relatively consistent across: groceries, household items, and clothes.



MULTINOMIAL LOGIT: SELECTED RESULTS FOR INDIVIDUAL-LEVEL ANALYSIS

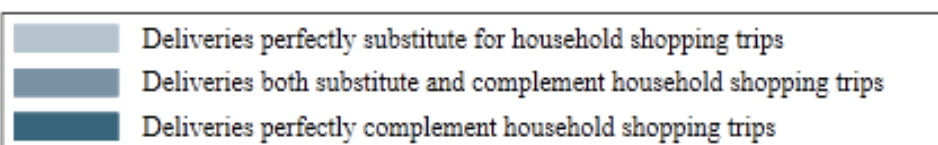
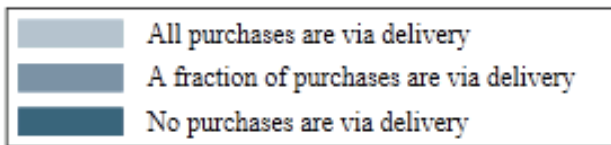
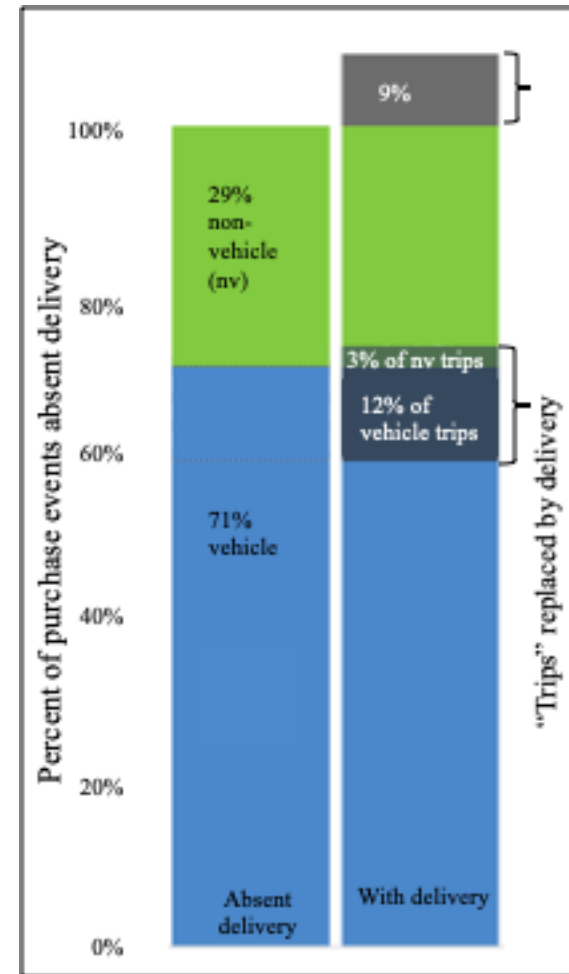
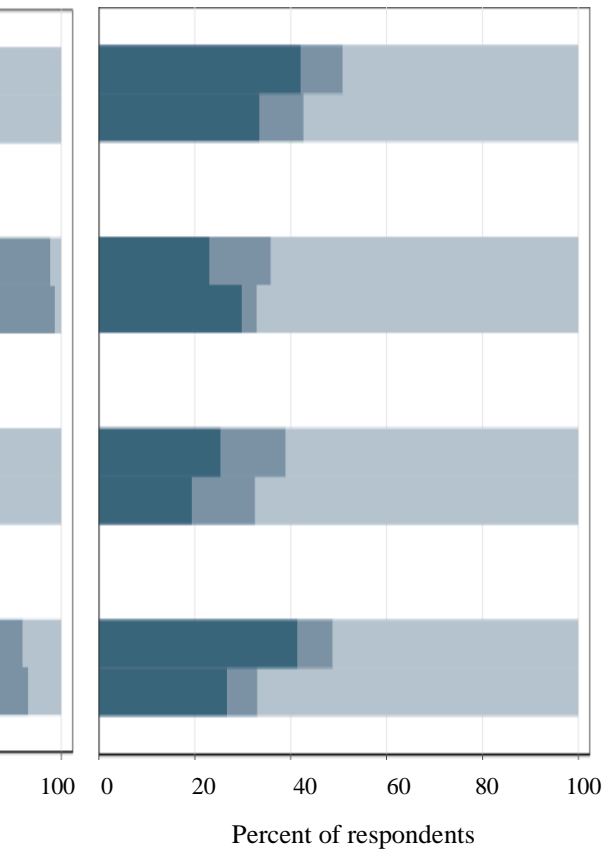
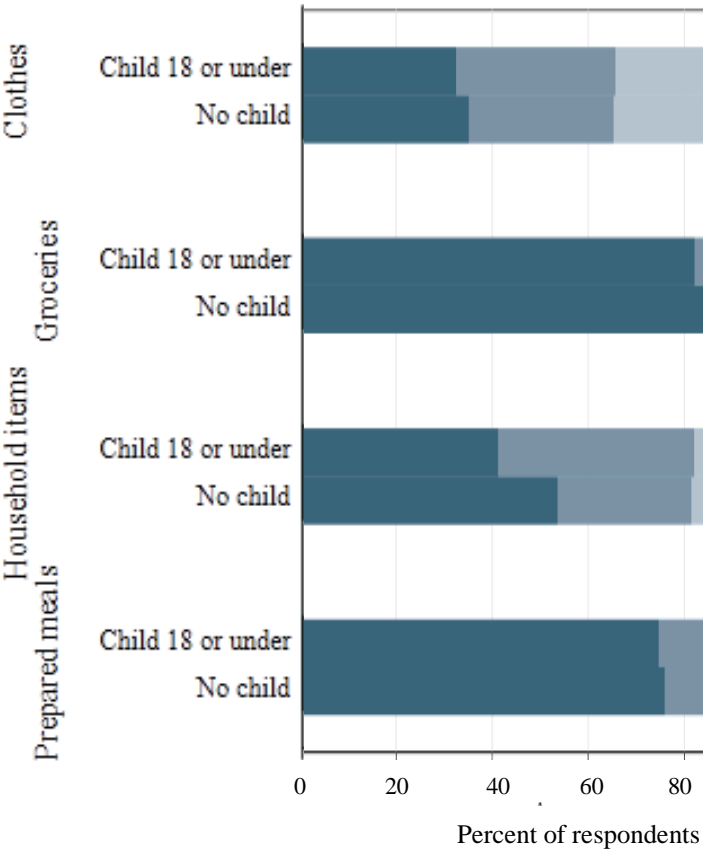
- **Income effects**
 - are less pronounced and are only significant in the case of clothing
- **Households with children**
 - Are more likely to:
 - make vehicle trips
 - And less likely to:
 - Order prepared meal delivery
 - Make fewer purchases of most product categories
- **Households with Female Individual Decision-Makers**
 - Are more likely to:
 - Order delivery of household items and clothes
 - Make vehicle trips
 - And less likely to:
 - Make fewer purchases



ADDITIONAL FIGURES

Percent of the people for whom all, none, or a fraction of purchases are via delivery

Percent of the people that get deliveries for whom deliveries perfectly complement, perfectly substitute, or both, household shopping trips



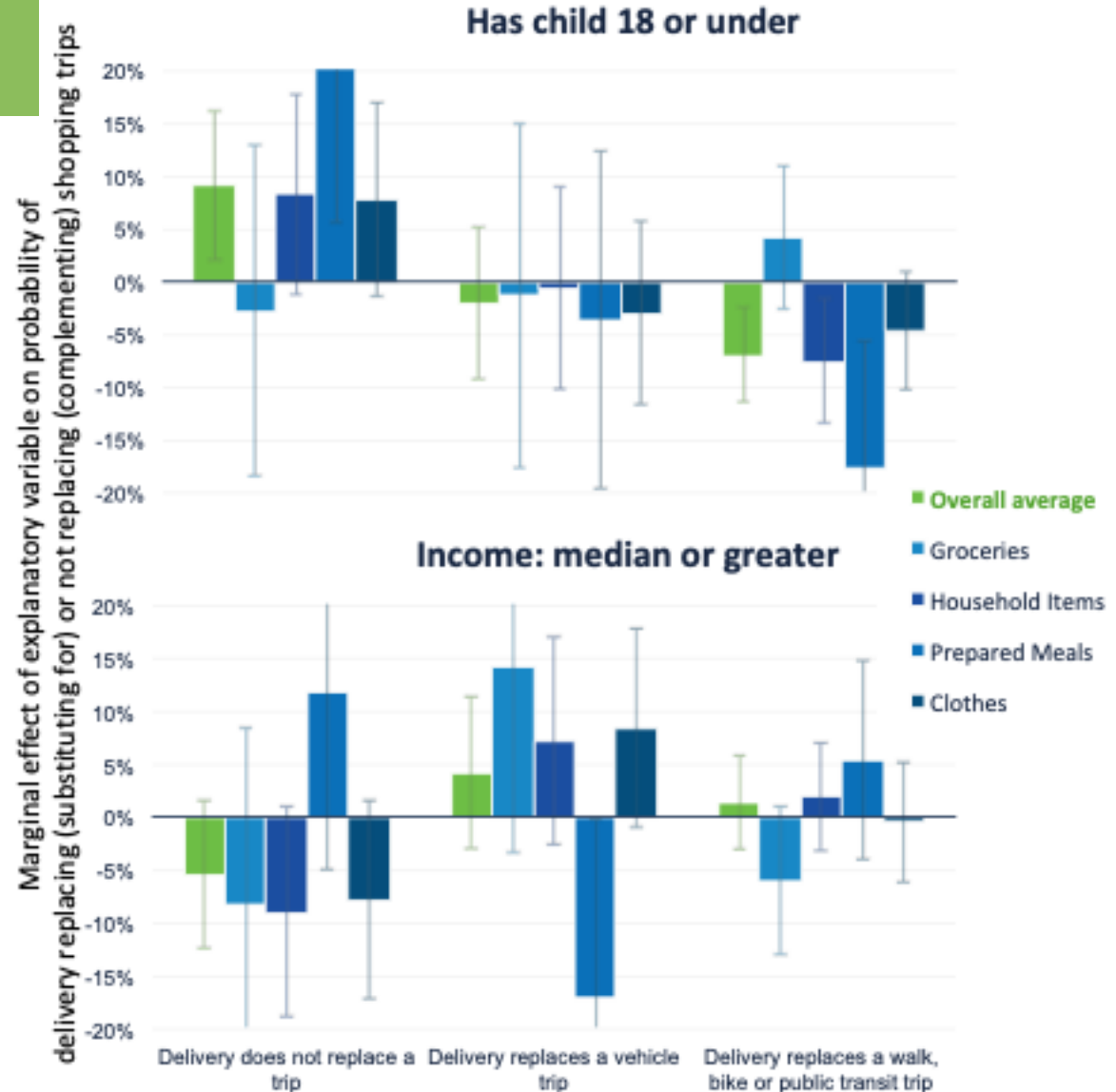
MULTINOMIAL LOGIT: SELECTED RESULTS

Those with above median income

- Are less likely to have deliveries supplement trips in general and in particular more likely to have deliveries substitute for vehicle trips for all item categories except prepared meals.
- Those with higher incomes are more likely to have prepared meal delivery supplement trips and less likely to have them replace vehicle trips.

Households with children

- Are more likely to have deliveries supplement trips in general and in particular less likely to have deliveries substitute for non-vehicle trips for all item categories except groceries.
- This is particularly true for prepared meals. This suggests that households with children who order meals are likely to cook at home rather than travel to a restaurant if they couldn't receive delivery.



TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Article 5 - Tensions and complementarities in mass transit and ride-hailing decisions through a survey-based randomization

ANALYSIS APPROACH:

- Randomize across respondents the hypothetical price of ride-hailing:
 - \$1.20 per mile (close to today's prices)
 - \$0.70 per mile
 - \$0.20 per mile
- Calculate cost, given these prices, of their full commute via ride-hailing.
- Given these costs, ask then what modes they'd use, including multi-modal combinations.
- Estimate effects using Logit discrete choice model

AVERAGE TREATMENT EFFECT OF RIDE-HAIL PRICES ON MASS TRANSIT USE

- Relative to a price of \$1.20 per mile:
 - There is no statistically significant change in the odds of using mass transit for those assigned \$0.70/mile
 - Those assigned \$0.20/mile significantly decrease their odds of using mass transit

Dependent Variable:

Choose a trip that includes mass transit

\$0.20/mile	0.610* (0.044)
-------------	-------------------

\$0.70/mile	1.171 (0.481)
-------------	------------------

Obs	742
pseudo R-squared	0.0106

Table reports odds ratios and p-values

Significance levels

+ for $p < 0.10$; * for $p < 0.05$; ** for $p < 0.01$; *** for $p < 0.001$

RELATIONSHIP BETWEEN PRICE RESPONSE AND DISTANCE

Dependent Variable: Choose a trip that includes mass transit	(1)		(2)	
	Odds ratio	p-value	Odds ratio	p-value
DistanceHomeBART 0-2mi	0.552+	(0.056)	0.875	(0.689)
DistanceHomeBART 2-6mi	0.218**	(0.002)	0.438	(0.114)
DistanceHomeBART 6-16mi	0.0690***	0.000	0.186*	(0.027)
DistanceHomeBART >16mi	0.269**	(0.002)	0.939	(0.897)
DistanceHomeBART 0-2mi*Low Inc	0.605	(0.252)	0.621	(0.301)
DistanceHomeBART 2-6mi*Low Inc	1.150	(0.851)	0.895	(0.886)
DistanceHomeBART 6-16mi*Low Inc	1.322	(0.789)	1.848	(0.564)
DistanceHomeBART >16mi*Low Inc	0.276	(0.129)	0.341	(0.212)
\$0.20/mi*DistanceHomeBART 0-2mi	0.352+	(0.055)	0.281*	(0.024)
\$0.20/mi*DistanceHomeBART 2-6mi	0.743	(0.555)	0.683	(0.470)
\$0.20/mi*DistanceHomeBART 6-16mi	1.352	(0.671)	1.852	(0.410)
\$0.20/mi*DistanceHomeBART >16mi	0.839	(0.812)	0.730	(0.681)
\$0.70/mi*DistanceHomeBART 0-2mi	1.814	(0.570)	1.885	(0.556)
\$0.70/mi*DistanceHomeBART 2-6mi	6.459*	(0.028)	9.208*	(0.011)
\$0.70/mi*DistanceHomeBART 6-16mi	0.275	(0.128)	0.260	(0.122)
\$0.70/mi*DistanceHomeBART >16mi	0.937	(0.934)	1.080	(0.924)
\$0.20/mi*DistanceHomeBART 0-2mi*Low Inc	1.484	(0.591)	1.507	(0.587)
\$0.20/mi*DistanceHomeBART 2-6mi*Low Inc	0.123	(0.124)	0.119	(0.128)
\$0.20/mi*DistanceHomeBART 6-16mi*Low Inc	0.380	(0.556)	0.384	(0.568)
\$0.20/mi*DistanceHomeBART >16mi*Low Inc	10.88*	(0.048)	8.569+	(0.082)
\$0.70/mi*DistanceHomeBART 0-2mi*Low Inc	1.948	(0.327)	1.679	(0.464)
\$0.70/mi*DistanceHomeBART 2-6mi*Low Inc	0.476	(0.531)	0.877	(0.915)
\$0.70/mi*DistanceHomeBART 6-16mi*Low Inc	0.447	(0.514)	0.279	(0.314)
\$0.70/mi*DistanceHomeBART >16mi*Low Inc	2.503	(0.446)	1.852	(0.617)
DistanceBARTDestination < 1.5mi			0.208***	(0.000)
Obs	712		712	

Significance levels + for p<0.10; * for p<0.05; ** for p<0.01; *** for

Dependent Variable:

Choose a trip that includes mass transit

	(1)	(2)
DistanceHomeBART 0-2mi	0.423***	0.677+
	0.000	(0.098)
DistanceHomeBART 2-6mi	0.231***	0.414*
	0.000	(0.024)
DistanceHomeBART 6-16mi	0.0785***	0.241**
	0.000	(0.010)
DistanceHomeBART >16mi	0.170***	0.635
	0.000	(0.281)
\$0.20/mi*DistanceHomeBART 0-2mi	0.431*	0.348**
	(0.020)	(0.005)
\$0.20/mi*DistanceHomeBART 2-6mi	0.634	0.827
	(0.426)	(0.750)
\$0.20/mi*DistanceHomeBART 6-16mi	1.196	1.260
	(0.822)	(0.777)
\$0.20/mi*DistanceHomeBART >16mi	0.872	0.748
	(0.794)	(0.591)
\$0.70/mi*DistanceHomeBART 0-2mi	1.064	0.900
	(0.855)	(0.765)
\$0.70/mi*DistanceHomeBART 2-6mi	0.619	0.700
	(0.403)	(0.548)
\$0.70/mi*DistanceHomeBART 6-16mi	4.480*	5.207**
	(0.014)	(0.009)
\$0.70/mi*DistanceHomeBART >16mi	1.180	1.181
	(0.764)	(0.769)
DistanceBARTDestination < 1.5mi		0.212***
		0.000
Obs	712	712

Table reports odds ratios and p-values

Significance levels

+ for p<0.10; * for p<0.05; ** for p<0.01; *** for p<0.001