Title
PUBLIC TRANSPORTATION AT A CROSSROADS Transportation Network Companies, COVID-19, and Transit Ridership

Author
Khatun, Farzana

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IRVINE

PUBLIC TRANSPORTATION AT A CROSSROADS
Transportation Network Companies, COVID-19, and Transit Ridership

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Transportation Science

by

Farzana Khatun

Dissertation Committee:
Professor Jean-Daniel Saphores, Chair
Professor Wilfred Recker
Professor Michael G. McNally

2022

DEDICATION

To

My sisters, nephew, mother, aunt, colleagues, and friends

in recognition of their continuous love, support, guidance.

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ACKNOWLEDGEMENTS

PhD is a roller coaster ride. At one point, a student would feel things are moving slothfully. But not before they even realize the very next point would be a super bumpy turn. My journey is no different from that. Of course, I have my fair share of unevenness in this journey. But today, I like to take the opportunity to express my gratitude towards those who never left sight of me.

First and foremost, I thank my advisor, Professor Jean-Daniel Saphores. His continuous guidance, support, recommendations, and caring make me a strong individual and cultivate my intellectual appetite. There were moments when Professor Saphores kept my feet on fire, teaching me to handle pressure during a deadline. Then, there were moments when he supported me through my crisis, which one could only imagine from their parents. I always believed that a student's relationship with his advisor, especially during a six-year-long PhD program, should be dealt with delicately. Because the memories a student creates in those years have a long-lasting impact that they will cherish forever. I can proudly claim that I have had those fond memories over the last six years. Thank you so much, professor!

Second, I thank my defense committee members, Professor Michael McNally and Wilfred Recker. Overall, my experience at UCI has been overwhelming when it comes to learning from the professors. However, Professor Mike and Professor Recker undoubtedly will top my mentor's list. I had intellectual arguments with Professor McNally on several occasions, which helped me heighten my inquisitive nature. Professor Recker reminds me that age is just a number. If you are passionate about your job, you can conquer the world.

Moreover, I will never forget Professor Recker's recommendations on numerous occasions. Thank you, Professor McNally and Professor Recker!

I also like to show my gratitude to my colleagues and mentors, Dr. Suman Kumar Mitra and Dr. Rezwana Rafiq. Both these persons are less like colleagues and more like family members. Dr. Suman Kumar Mitra is the one who showed me the beauty of UCI. He was there for me to celebrate my success and to give me unconditional support during my tough time. Dr. Rezwana Rafiq showed me her care just like a sister. I am forever indebted to these two beautiful good-hearted individuals.

Next in line are my dearest friend, brother, and colleague Tanjeeb Ahmed and his lovely wife, Faiza Tabassum. Tanjeeb was always there for me for everything (till today), be it giving me a short 5-minute ride from my home to Albertson or an 8-hours long movement from one apartment to another. Tanjeeb and Faiza (and their beautiful daughter Ariana) made my PhD journey memorable when my family was thousands of miles away. Thank you Tanjeeb and Faiza.

I thank Professor Ritchie, Professor Hyland, Professor Jay, Professor Houston, and Professor Bollen for their support. I also like to acknowledge my friends from ITS – Koti, Dr. Irene, Dr. Lu, Dr. Yiqiao, Monica, Bumsub, Brian, and Nav for their continuous support and help. Special thanks to Koti for those driving lessons over the summer, which helped me to pass my driving test. Along with them, I also thank Cam and Jared for helping me get through the administrative process. Cam, thank you for tolerating all my administrative emails. Finally, I thank International Center (especially Ruth Ortega) for helping me with the legal visa process.

A special shout-out to my Bangladeshi community at Verano Place (Anagh, Wahid, Sifat, Shuvo, Naila, Manik), who love me unconditionally. I also remember my friends Ashmi, Samira, Nusrat, and Kim for their continuous support during this journey.

I acknowledge the help and support from OCTA, who helped me with data and recommended me for my scholarship.

Last but not least, I thank my elder sister Shapla, younger sister Simran, my little nephew Prottoy, my mom, and my aunt for never losing their trust in me and loving me unconditionally. That daily WhatsApp calls during the lockdown, those audio and video recordings of Simran's song, kept my sanity intact. I love you, my family!

CURRICULUM VITAE OF FARZANA KHATUN

ASSISTANT PROJECT SCIENTIST (OCT 2022 – DEC 2023)
Institute of Transportation Studies (ITS),
University of California, Irvine (UCI)

RESEARCH INTEREST

Travel Behavior, Public Transportation, Ride Hailing and Ride Share services, Econometric Modelling, and GIS Application in Transportation Planning.

EDUCATION

- **PHD IN TRANSPORTATION SCIENCE (2016-2022)**

Institute of Transportation Studies (ITS),
University of California, Irvine (UCI),
Irvine, USA.
Result: CGPA 4.00
Thesis: *"PUBLIC TRANSPORTATION AT A CROSSROADS Transportation Network Companies, COVID-19, and Transit Ridership"* under the supervision of Dr. Jean-Daniel Saphores, Professor and Chair, Civil and Environmental Engineering, University of California, Irvine, CA 92697, U.S.

- **MASTERS IN TRANSPORT PLANNING AND THE ENVIRONMENT (2014-2015)**

Institute for Transport Studies (ITS)
University of Leeds (UoL),
Leeds, UK.
Result: Obtained Merit.
Thesis: *"An automatically generated area wide walkability index for UK Cities based on existing GIS data"* under the supervision of Dr. Astrid Gühnemann, Professor of Transport for Sustainable Development, University of Natural Resources and Life Sciences, Wien.

- **MASTER OF URBAN AND REGIONAL PLANNING (MURP) (2010-2014):**

Department of Urban and Regional Planning (DURP),
Bangladesh University of Engineering and Technology (BUET),
Dhaka-1000, Bangladesh.
Result: CGPA 3.72 (on a scale of 4.00)
Thesis: *"Evaluation and Analysis of Land Use Suitability of Recent Development Plan of Cox's Bazar"*, under the supervision of Dr. Shakil Akther, Professor, Department of URP, BUET, Dhaka, Bangladesh.

- **BACHELOR OF URBAN AND REGIONAL PLANNING (BURP) (2004-2009):**

Department of Urban and Regional Planning (DURP),
Bangladesh University of Engineering and Technology (BUET),
Dhaka-1000, Bangladesh.
Result: CGPA 3.87 (on a scale of 4.00)

Thesis: *"Khas Lands (state owned lands) of Dhaka Metropolitan Area (DMA): A study on locational aspects and existing uses of khas lands and their compatibility with the DMDP (Dhaka Metropolitan Development Plan) Structure Plan (1995-2015)"* under the supervision of Dr. Ishrat Islam, Professor, Department of URP, BUET.

AWARDS/ACHIEVEMENTS/SYNERGIC ACTIVITIES

- **2022 UCI GRAD SLAM:** Participated in the UCI GRAD SLAM 2022 as one of the 10 finalists (Final: https://vimeo.com/678440946 [time: 33.46]; Semi-Final: https://www.youtube.com/watch?v=Lqu_nLglFR0)
- **2021 APTF (AMERICAN PUBLIC TRANSPORTATION FOUNDATION) SCHOLARSHIP WINNER:** Awarded during the American Public Transportation Association's TRANSform and EXPO, November 7 - 10, 2021, in Orlando, FL.
- **2021 GRADUATE DEAN'S DISSERTATION FELLOWSHIP BY UCI:** Awarded for the 2021 to 2022 academic year
- **2021 UCI GRAD SLAM:** Participated in the UCI GRAD SLAM 2021 as a semi-finalist (https://www.youtube.com/watch?v=2NlcQ7DDtEY)
- **2020 WTS TRANSPORT ACADEMY:** Interacted with a diversified group of transportation professionals, specialists, and students.
- **2019 WTS-OC SCHOLARSHIP WINNER @ GRADUATE LEVEL**: Link of the video https://www.youtube.com/watch?v=o0fNiS9FPmk
- **2014 COMMONWEALTH SHARED SCHOLARSHIP PROGRAM** for MSc in Transport Planning and Environment in ITS, University of Leeds from 2014 to 2015.
- **2011 "ABDUL HAMID AWARD" (1ST POSITION):** Awarded annually for the best theses at undergraduate level in the DURP, BUET in 2009.
- **2005 DUTCH BANGLA BANK SCHOLARSHIP**: Awarded for outstanding result in Higher Secondary School Certificate exam which financed my tuition fees during undergraduate degree (2005-2009).

PROFESSIONAL EXPERIENCE

1. **APR 2022 - JUN 2022 (PART-TIME): TEACHING ASSISTANT @ THE HENRY SAMUELI SCHOOL OF ENGINEERING, UCI**

Responsibilities

- TA for highway operation of undergraduate engineering senior students
- Conducting lab classes, teaching TransModeler & Highway Capacity Software, designing the lab projects
- Attending theory classes and maintaining office hours for students
- Grading homework, quizzes, lab reports, midterm and final

2. **OCT 2021 - DEC 2021 (PART-TIME): TEACHING ASSISTANT @ THE HENRY SAMUELI SCHOOL OF ENGINEERING, UCI**

Responsibilities

- TA for highway design lab (Civil 3D software by Autodesk) of undergraduate engineering senior students
- Conducting lab classes, designing the final lab project, and maintaining office hours for students
- Grading lab reports

3. **APR 2021 - JUN 2021 (PART-TIME): TEACHING ASSISTANT @ THE HENRY SAMUELI SCHOOL OF ENGINEERING, UCI**

Responsibilities

- TA for engineering economics course of undergraduate engineering junior students
- Conducting lab classes and maintaining office hours for students
- Grading homework, midterms, and finals

4. **APR 2020 - SEP 2021 (PART-TIME): GRADUATE STUDENT RESEARCHER @ ITS, UCI**

Project

- US DOT Pacific Southwest Region University Transportation Center (PSR UTC) funded project – "Public Transportation, Transportation Network Companies (TNCs), and Active Modes"

Responsibilities

- Applied Cross-Nested Logit Model in Biogeme to characterize transit and TNC users
- Applied Cross Nested Logit Model in Biogeme to analyze pseudo "active transport" utility of public transportation in CA
- Developed Sankey diagrams and applied generalized ordered logit (GOL) model to analyze Californians' projected mode change after the COVID19 pandemic based on the 2021 COVID19 survey (conducted by IPSOS)
- Applied binary logit models to analyze Californians' reluctance to use transit before and after the pandemic based on
- NHTS 2017 and 2021 COVID19 survey (conducted by IPSOS)

Deliverables

- Report:
  1. "Public Transportation, Transportation Network Companies (TNCs), and Active Modes" (https://www.metrans.org/assets/research/psr-19-34_to-035_saphores_final-report.pdf)
- Journal:
  1. "BEST FRENEMIES? A characterization of TNC and transit users based on the 2017 NHTS" (https://doi.org/10.1016/j.jpubtr.2022.100029)
  2. Journal accepted with correction in the Transportation Research Part A: Policy and Practice: "COVID-19, MODE CHANGES, AND TRANSIT PERCEPTION: Results from a random survey of Californians" (Under review)
- Conference/Symposium/Competition:
  1. Presented the finding at the AGS 2019 symposium
  2. Poster presented at TRBAM 2021: "BEST FRENEMIES? A characterization of TNC and transit users based on the 2017 NHTS" [Virtual]
  3. Poster presented at ICTD 2022: "THE IMPACT OF COVID-19 ON TRANSPORTATION MODES Results from a Random Survey of Californians"
  4. Podium presentation at ICTD 2022: "THEIR WAY OR THE HIGHWAY? Californians' Perception of Transit Before and During COVID-19"
  5. Presented the findings of the 2021 COVID19 survey at the UCI Grad Slam 2022 as one of the top 10 finalists (https://vimeo.com/678440946 [time: 33.46])

5. **JUL 2019 - DEC 2019 (PART-TIME): GRADUATE STUDENT RESEARCHER @ ITS, UCI**

Project

- Senate Bill (SB) 1 funded project – "Reduced transit fare programs for the California Legislature"

Responsibilities

- Conducted online and telephone surveys of transit organizations in CA
- Analyzed the impact of the free and reduced-fare program on transit ridership in CA

Deliverables

- Report: “A Review of Reduced and Free Transit Fare Programs in California” (https://escholarship.org/uc/item/74m7f3rx)

6. **JAN 2019 - MAR 2019 (PART-TIME): TEACHING ASSISTANT @ THE HENRY SAMUELI SCHOOL OF ENGINEERING, UCI**

Responsibilities
- TA for optimization course of undergraduate engineering senior students.
- Conducted discussion classes and maintained office hours for students, taking classes
- Graded homework, midterms, and finals

7. **JAN 2018 - DEC 2018 (PART-TIME): GRADUATE STUDENT RESEARCHER @ ITS, UCI**

Project
- US DOT Pacific Southwest Region University Transportation Center (PSR UTC) funded project - "Investigating the change in bus ridership of Orange County for the periods of 2014-2016"

Responsibilities
- Applied GIS and Fixed Effect Panel Regression in Stata to analyze bus ridership trends in Orange County.

Deliverables
- Conference/Symposium/Competition:
  1. Presented at the International Conference on Transport & Health (ICTH) in Melbourne, Australia [4-8 November 2019]
  2. Awarded 2nd position at Ph.D. level abstract (https://www.its.uci.edu/node/451)
  3. Presented the findings at the UCI Grad Slam 2021 semi-final (https://www.youtube.com/watch?v=Lqu_nLglFR0)

8. **OCT 2017 - DEC 2017 (PART-TIME): TEACHING ASSISTANT @ THE HENRY SAMUELI SCHOOL OF ENGINEERING, UCI**

Responsibilities
- TA for engineering math course of graduate engineering students.
- Maintained office hours for students
- Graded homework, midterms, and finals

9. **AUG 2017 - SEP 2017 (PART-TIME): SUMMER INTERN @ SPEEDFIND, INC.**

Responsibilities
- Worked as a Research Analyst for the CEO with a particular focus on Autonomous Vehicles

10. **JAN 2016 – AUG 2016 (PART-TIME): TRANSPORT CONSULTANT @ BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY**

Project
- Planning and Prioritization of rural roads in Bangladesh for LGED and funded by ReCAP, UK.

Responsibilities
- Worked directly with the team leader as a transport expert in developing the methodology based on quantitative and qualitative methods.
- Participated and presented in the stakeholder's meeting, and organized workshops with the local government people.

Deliverables
- Report:
  1. “Planning and Prioritization of Rural Roads in Bangladesh – Final Report, Volume (https://www.gov.uk/research-for-development-outputs/planning-and-prioritisation-of-rural-roads-in-bangladesh-final-report-volume-1)

2. Journal: “A Methodology for Planning and Prioritization of Rural Roads in Bangladesh” in the Sustainability (https://www.mdpi.com/2071-1050/14/4/2337)

11. JAN 2011 - DEC 2012 (PART-TIME): RESEARCH ASSOCIATES @ BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY

Project

- World Bank and University Grant Commission (UGC), BD funded project – "Higher Education Quality Enhancement Project (HEQEP) under the subproject: Modernization of Data Analysis and Simulation Laboratory of DURP, BUET"

Responsibilities

- Contacted software organizations, vendors & trainers; purchased software & hardware; attended all meetings; maintained cash book

Deliverables

- A high-tech and advanced computer lab for the Department of URP, BUET

12. MAY 2011 - NOV 2012 (PART-TIME): JUNIOR TOWN PLANNER @ BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY

Project

- "Integrated Water Supply, Sanitation and Hygiene (WASH) Planning for Local Government Institutions (LGIs)" conducted by DURP, BUET in partnership with UNICEF, DPHE, and UKAID.

13. AUG 2014 - AUG 2016 (FULL-TIME, ON LEAVE FOR PHD): ASSISTANT PROFESSOR @ BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY

Responsibilities

- Course instructor; supervised undergraduate thesis; examined master's thesis; managed administrative work.
- Served as undergraduate and graduate student board secretary.

Deliverables

1. Supervisor of the undergraduate thesis titled as: *“Factors Influencing the Noise Pollution of Dhaka City: A Study on Ramna Thana Using Noise Mapping Technique and AHP”* (February 2016), DURP, BUET, Dhaka, Bangladesh.
2. Supervisor of the undergraduate thesis titled as: *“Prospects of Upgrading the Existing Residential Buildings Green Construction: A Case Study on Ramna Thana Of Dhaka City”* (February 2016), DURP, BUET, Dhaka, Bangladesh.
3. Examiner of the master’s thesis tilted as: *“Exploring Trip Chain Behavior of The Working Population in Dhaka”* (March 2016), DURP, BUET, Dhaka, Bangladesh.
4. A Sustainable Parking Solution for Shopping Centers Through Demand Management – A Case Study on Shopping Centers of Uttara, Dhaka, Bangladesh
5. A study on selected intersections of Dhaka city

14. DEC 2009 - JUL 2014 (FULL-TIME): LECTURER @ BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY

Responsibilities

- Course instructor; managing administrative work.

15. SEP 2008 - NOV 2008 (PART-TIME): INTERN @ AQUA CONSULTANTS AND ASSOCIATES LTD.

Responsibilities

- Digitized Mouza maps using ArcView 3.2 and PC ArcInfo 3.5.1.

COURSES

Completed Courses in Undergraduate:

Theory Courses

Transportation Policy and Planning
Traffic and Transportation Study
Quantitative Techniques I and II
Mathematics I and II
Micro and Macro Economics
Surveying and Cartography
Project Evaluation and Management
Remote Sensing and GIS
Solid Mechanics and Structural Engineering
Urban Planning
Regional Planning

Sessional Courses (Workshop)

Transportation Planning workshop
Programming Techniques and Database Management
Urban Planning Studio
Regional Planning Studio
Surveying and Cartography
Participatory Local Level Planning
GIS Studio
Project Evaluation and Management Studio

Completed Courses in MSc and MURP:

Transport Data Collection & Analysis
Principles of Transport Modelling
Principles of Transport Engineering
Transport Planning and Policy
Global Issues in Transport
Transport and Urban Pollution
Choice Mode & Stated Preference
Transport Investment Appraisal
Transport Planning
GIS Applications in Urban and Regional Planning
GIS in Environmental Modeling
Urban Planning II

Completed Courses in PhD:

Travel Demand Analysis I
Travel Demand Analysis II
Planning & Forecasting
Transportation Data Analysis I
Transportation Planning Models II
Smart Cities
Writing for Publication
History of Urban Planning
Analysis Methods Plan
Land-Use Policy
Econometrics I
Econometrics II

PUBLICATIONS

- **Khatun, F.**, & Saphores, J. D. M. **(2022)**. Covid-19, Mode Changes, And Transit Perception: Results from A Random Survey of Californians. Transportation Research Part A: Transportation Research Part A: Policy and Practice (Accepted with revision)
- Hasan, M. M. U., Quium, A. A., Rahman, M., **Khatun, F**., Akther, M. S., Haque, A., ... & Shubho, T. H. **(2022)**. A Methodology for Planning and Prioritization of Rural Roads in Bangladesh. *Sustainability*, *14*(4), 2337. https://www.mdpi.com/2071-1050/14/4/2337
- Saphores, J. D., & **Khatun, F. (2022)**. Public Transportation, Transportation Network Companies (TNCs), and Active Modes. *The Pacific Southwest Region University Transportation Center,* PSR-19-34. https://www.metrans.org/assets/research/psr-19-34_to-035_saphores_final-report.pdf
- **Khatun, F.**, & Saphores, J. D. M. **(2022)**. Best frenemies? A characterization of TNC and transit users. *Journal of Public Transportation*, *24*, 100029.
- Saphores, J. D., Shah, D., & **Khatun, F. (2020)**. A Review of reduced and free transit fare programs in California.

- Rahman, M. M., Barua, U., **Khatun, F.,** Islam, I., & Rafiq, R. (**2018**). Participatory Vulnerability Reduction (PVR): an urban community-based approach for earthquake management. *Natural Hazards*, *93*(3), 1479-1505.
- Siddiq, F., Mubassirah, F., **Khatun, F.,** Sharmin, N., and Islam, I. (**2017**). Heritage Sites of Dhaka: Practice of Policies and Acts. *Journal of Cultural Heritage Management and Sustainable Development.* (Accepted with corrections)
- Kar, A., Mashraky, R., **Khatun, F.**, Huq, M. E., Mahmud, S., Islam, I. and Akther, M. S. (**2016**). Prospects of Urban Regeneration in Motijheel Commercial Area of Dhaka City. *Imperial Journal of Interdisciplinary Research,* Vol. 2 (10).
- Mahmud, S., Huq, M. E., Kar, A., Mashraky, R., **Khatun, F**, Islam, I. and Akther, M. S. (**2014**). Managing Development of Fringe Areas in Dhaka City: "Land Readjustment" as a Technique for Sustainable Future Development Ensuring Environmental and Social Justice. *International Journal of Undergraduate Research and Creative Activities*, Special edition,
- Islam, S., Haque, A. M., Shubho, M. T. H., Islam, I., **Khatun, F**. and Hossain, D. (**2013**). Addressing Community Based Problems: Exploring the Role of CBO through Participatory Approach. *European Scientific Journal*, Special Edition, Vol. 3, pp. 92–104.
- Sharmin, N., Hira, S., Ayon, B. D., Awal, M. R., Islam, I., **Khatun, F.** and Hossain, D. (**2013**). Solving Community Problems through Participatory Planning: Role of CBO (A Case Study of Monipuripara, Dhaka). *OIDA International Journal of Sustainable Development*, Vol. 6 (6), pp. 109–128.
- **Khatun, F.**, Muntasir, M. and Islam, I. (**2012**). Potential and Prospects of On- Site Slum Up-Gradation Program in Dhaka. *OIDA International Journal of Sustainable Development*, Vol. 3 (10), pp. 25–38.
- **Khatun, F.** and Muntasir, M. (**2012**). A Study on Inter-Regional Analysis of Influencing Factors on Remittance Flow in Bangladesh. *OIDA International Journal of Sustainable Development*, Vol. 3 (9), pp. 71–86.

CONFERENCE PROCEEDINGS

- **Khatun F**. and Saphores, J. D. M. (**2023**). The Impact of Covid-19 on Transit, Walking/Biking, and TNC Use in California – How Will Californians Travel after the Pandemic? Paper submitted at *100th Annual Meeting of Transportation Research Board (TRB)*, in Washington, D.C., 8-12 January 2023
- **Khatun F**. and Saphores, J. D. M. (**2022**). THE IMPACT OF COVID-19 ON TRANSPORTATION MODES Results from a Random Survey of Californians, Poster presented at *the International Conference on Transportation & Development of ASCE*, in Seattle, WA, 2nd June 2022
- **Khatun F**. and Saphores, J. D. M. (**2022**). THEIR WAY OR THE HIGHWAY? Californians' Perception of Transit Before and During COVID-19, PowerPoint presented at the *International Conference on Transportation & Development of ASCE*, in Seattle, WA, 2nd June 2022
- **Khatun F**. and Saphores, J. D. M. (**2021**). Are TNCs Eating Transit's Lunch? Evidence from the US National Household Travel Survey 2009 and 2017, PowerPoint presented at *the Emerging Scholars Transportation Research Symposium (ESTRS) 2021*, Virtual, 3rd March 2022.
- **Khatun F**. and Saphores, J. D. M. (**2021**). BEST FRENEMIES? A characterization of TNC and transit users based on the 2017 NHTS, Poster presented at the *100th Annual Meeting of Transportation Research Board (TRB)*, Virtual, 11–15 January 2021.
- **Khatun F**. and Islam I. (**2011**). A study on locational aspects and existing uses of Khas lands (state owned lands) of Dhaka Metropolitan Area (DMA), *Planning for Sustainable Asian Cities.* Paper presented at the 11th International Congress of Asian Planning Schools Association, Tokyo University, Tokyo, Japan, 19-21 September.

- Muntasir M., **Khatun F.**, Islam I. and Akther S. (**2011**). Impediments of empowering Urban Informal Industrial Communities in Bangladesh: The scenario of Jamdani weaving community in Narayanganj district. *Planning for Sustainable Asian Cities.* Paper presented at the 11th International Congress of Asian Planning Schools Association, Tokyo University, Tokyo, Japan, 19-21 September.

TRAININGS/WORKSHOPS/SEMINARS

- Trainer and lecturer of the five days long training program titled as "**Training workshop on GIS for the officials of the Bangladesh Food Security Cluster**", organized by DURP, BUET and sponsored by FAO, FSC and WFP held on November 19-23, 2015 at DURP, BUET, Dhaka, Bangladesh.
- Participated in a combination of on-line face to face training on "**Risk Sensitive Land Use Planning Blended Training Course**", organized by World Bank and Earthquake and Megacities Initiatives (EMI) held on May 18 to July 4, 2013.
- Participated in training on **"Training course on TransCAD and TransModeler"** organized by DURP, BUET, under the departmental project titled as HEQEP, held on 26-30 September 2012.
- Participated in training on **"Introductory Course on Qualitative Research Methodology"** organized by International Centre for Diarrheal Disease Research, Bangladesh (icddr,b), at icddr,b, Dhaka, Bangladesh, held on 02-13 September, 2012.
- Participated in International training on **"Urban Rain Water Harvesting"** organized by Centre for Science and Environment, New Delhi, India, in collaboration with WaterAid, Dhaka, Bangladesh, at BRAC CDM, Savar, held on 8-11 August 2011.
- Participated and presented a paper titled **"Dynamics of Urban Informal Industries in Bangladesh: The scenario of Jamdani weaving industry in Narayanganj"** with co- author at the SPP-Megacities: Dhaka Workshop on 23-24 Feb 2010, held at BUET as a joint workshop of DURP, BUET and SPP Megacities and Megachallenges.
- Participated and presented a paper titled **"Khas land (State owned lands) distribution in Dhaka Metropolitan Development Plan Area: The formal process and the informal actors"** with co- author at the SPP-Megacities: Dhaka Workshop on 23-24 Feb 2010, held at BUET as a joint workshop of DURP, BUET and SPP Megacities and Megachallenges.
- Participated in case study workshop regarding **"Post- Cyclone Spatial Redevelopment Potentials in Bangladesh"**, initiated by Urban Emergencies research program by Delft University of Technology, the Netherlands, held on 21 May 2009.
- Participated in Joint Students' Workshop of BUET and TU Dortmund, Germany on **"Dynamics in Urban Informal Settlements"** held on 5-6 March 2008

SYNERGIC ACTIVITIES

- Member of Board of Undergraduate Studies (BUGS), DURP, BUET
- Member of Board of Postgraduate Studies (BPGS), DURP, BUET
- Member of Organizing Committee of Planning Week 2009
- Member of Bangladesh Institute of Planners (BIP), Bangladesh. (http://www.bip.org.bd/)
- Member of Women Architects, Engineers, Planners Association (WAEPA), Bangladesh.
- Member of BUET Planners Association
- Member of Rain Forum, Bangladesh. (http://www.rainforum.org/)

REFERENCES

- **Dr. Jean-Daniel Saphores**

Professor and Chair,
Civil and Environmental Engineering,
University of California, Irvine, CA 92697, U.S.
E-mail: saphores@uci.edu
Phone: (949) 824-7334 Office

- **Dr. Suman Kumar Mitra**

Assistant Professor,
Department of Civil Engineering,
University of Arkansas, Fayetteville, AR 72701, U.S.
E-mail: skmitra@uark.edu
Phone: (949)-394-7049

- **Dr. Ishrat Islam**

Professor,
Department of Urban and Regional Planning (DURP),
Bangladesh University of Engineering and Technology (BUET), Dhaka, Bangladesh.
E-mail: ishratislam@urp.buet.ac.bd
Phone: 880-2-9665650-80 / Ext-7199

ABSTRACT OF THE DISSERTATION

PUBLIC TRANSPORTATION AT A CROSSROADS
Transportation Network Companies, COVID-19, and Transit Ridership

by

Farzana Khatun

Doctor of Philosophy in Transportation Science

University of California, Irvine, 2022

Professor Jean-Daniel Saphores, Chair

Public transportation in the U.S., including in California, was declining before COVID-19, and the pandemic made a bad situation much worse. In this dissertation, I analyze data from the 2009 and 2017 National Household Travel Surveys and from a California survey administered in May 2021 by IPSOS using both discrete choice (cross-nested logit and generalized ordered logit) and quasi-experimental (propensity score matching) tools first to investigate how Transportation Network Companies (TNCs, e.g., Uber and Lyft) impacted transit ridership before COVID-19, before analyzing how COVID-19 affected transit and other modes.

In Chapter 2, my results for the U.S. show that individuals/households who use either public transit or TNCs share socio-economic characteristics, reside in similar areas, and differ from individuals/households who use neither public transit nor TNCs. In addition, individuals/households who use both public transit and TNCs tend to be Millennials or belong to Generation Z, with a higher income, more education, no children, and fewer vehicles than drivers.

In Chapter 3, I quantify the impact of TNCs on household transit use by comparing travel for households from the 2017 NHTS (who had access to both transit and TNCs) matched with households from the 2009 NHTS (who only had access to transit) using propensity score matching. Overall, I find a 22% drop for weekdays (1.6 fewer daily transit trips by each household) and a 15% decrease for weekends (1.4 fewer daily transit trips by each household).

In Chapter 4, I analyze how Californians changed transportation modes due to COVID-19 and explore their intentions to use different modes after COVID-19. I find that driving but especially transit and TNCs could see substantial drops in popularity after the pandemic. Many Hispanics, African Americans, Asians, lower-income people, and people who would like to telecommute more intend to use transit less. Key obstacles to a resurgence of transit after COVID-19 are insufficient reach and frequency, shortcomings that are especially important to younger adults, people with more education, and affluent households ("choice riders").

My findings highlight the danger of public transit entering into outsourcing agreements with TNCs, neglecting captive riders, and exposing choice riders to TNCs.

Keywords: Public Transportation; Transportation Network Companies; Active Modes; COVID-19; Cross-Nested Logit; Generalized Ordered Logit; Propensity Score matching

CHAPTER 1: INTRODUCTION

Public transportation (defined herein as services that provide mass mobility to the general public, including buses, trains, and ferries, but not shared taxis and their variations) offers multiple benefits. It provides mobility services to people who cannot afford a car or cannot drive, reduces road congestion and parking demand, and thus decreases energy use, air pollution, and greenhouse gas emissions. It can also help promote health (transit users need to walk or bike to and from transit stops), fosters social connections, and allows commuters to engage in various activities (e.g., relax, read, or write) during their journey.

However, public transportation in the U.S., including in California, is under siege. Over the better part of the last two decade, ridership has been declining, possibly because of easier access to cars and the emergence of transportation network companies (TNCs, i.e., Uber and Lyft). The COVID-19 pandemic made a bad situation worse, so the challenge for public transportation officials is finding a way to restore its health so it can contribute to a more equitable and sustainable transportation system.

From the beginning of my studies, I have always been keenly interested in public transportation. Poor traffic conditions in the capital of Bangladesh, Dhaka, where I am from, contrasted with walk-friendly transit-oriented development of the UK, where I studied for my Master. Being a choice transit rider in a car heaven state like California further magnified my interest in transit (although I recently obtained my driver's license). I firmly believe that developing and developed countries alike would be better off with well-run transit systems such as those in Nordic countries (e.g., Denmark or Finland). This belief has motivated my doctoral research work, which focuses on public transit.

In the years preceding the COVID-19 pandemic, the fall in transit ridership combined with the explosive growth of transportation network companies (TNCs) (i.e., companies like Lyft and Uber that provide prearranged transportation services for compensation, using an electronic platform to connect passengers with drivers) led to a rise in urban congestion, additional air pollution and emissions of greenhouse gases, and a reduction in the physical activity of people who would otherwise walk/bike to access transit. The COVID-19 pandemic has further deteriorated the health of America's transit, especially in California. As the pandemic is starting to wane, California's biggest mobility challenge is to regain people's trust in transit because the state relies on public transportation to meet its ambitious greenhouse gas reduction targets and provide mobility services to disadvantaged communities.

In this context, my dissertation focuses on two questions: 1) How did emerging technology and new mobility service (e.g., Uber and Lyft) impact transit ridership in the U.S. and California? and 2) How has COVID19 impacted California's transit ridership and mode preferences? To address these questions, I analyze data from three surveys (the 2009 and 2017 National Household Travel Surveys and a May 2021 Ipsos survey) using various analytical tools (cross-nested logit models, generalized ordered logit models, binary logit models and propensity score matching).

When Transportation Network Companies (TNCs) first appeared almost a decade ago, people applauded the added flexibility and convenience they provided, and these companies became hugely successful. However, the benefits from TNCs came at a cost. Since their inception, Uber, Lyft, and similar firms have added more vehicles on roads, increased vehicle miles traveled (VMT), fueled environmental pollution, and have likely taken away transit riders. The decline of transit and the increased use of ride-hailing services also have societal implications. For example, lower-income and people of color are the primary bus transit users (Clark, 2017), and they often do not use TNCs due to affordability issues and racial discrimination (Ge et al., 2016).

The reluctance of TNCs to share their data with researchers makes it difficult for policymakers and academics to assess the impacts of TNCs on other modes, particularly transit. To circumvent this obstacle, in Chapter 2, I analyze data from the 2017 national household travel survey (NHTS) to explore the overlap between the groups in transit and TNCs competing. While the literature focuses on TNCs or PT users, I contrast individuals/households who use only PT, only TNCs, and both in my cross-nested logit models. For consistency with most of the literature, I estimate a cross-nested logit model at the individual level. Still, to account for intrahousehold travel dependencies, I repeat my analysis with households as the basic unit of analysis. My results show that the unit of analysis (individuals vs. households) does not matter much for this dataset. I find that individuals/households who use either PT or TNCs share socio-economic characteristics, reside in similar areas, and differ from individuals/households who use neither transit nor TNCs. In addition, individuals/households who use both PT and TNCs tend to be composed of Millennials and Generation Z, with a higher income, more education, no children, and fewer vehicles than drivers. Conversely, a household with more older members, with a lower income, less education, or more children, or who have adult members with a mobility impairment, are less likely to use either transit or TNCs, and they are more likely to be "driving-only" households. Moreover, African American and Asian households are less likely to use TNCs, confirming my previous statement. My findings highlight the danger for

PT of entering into outsourcing agreements with TNCs, neglecting captive riders, and further exposing choice riders to TNCs.

In Chapter 3, I analyze the impact of TNCs on household transit use using a quasi-experimental approach. To date, published studies about the effects of TNCs on transit (and other modes) are either inconclusive (partly because of data limitations that led researchers to analyze aggregate instead of individual or household data), or they are primarily descriptive and fail to control for self-selection, which could bias results. In this context, my main contribution in Chapter 3 is to study the causal link between the emergence of TNCs and the decline of transit using propensity score matching (PSM). More specifically, I analyze data from the 2009 and 2017 National Household Travel Survey (NHTS) using PSM to cleanly isolate the impact on household travel behavior of a "treatment" (here, the availability of TNCs) while controlling for variables known to affect travel behavior. My treatment and control groups are matched households from the 2017 and 2009 NHTS, respectively. My results suggest that compared to 2009, households in 2017 made fewer daily transit trips but increased their number of walking and biking trips. 22% drop for weekdays (1.6 fewer daily transit trips by each household) and a 15% decrease for weekends (1.4 fewer daily transit trips by each household). Several transit systems have been considering contracting with TNCs to solve the "first and last mile problem" at a discounted price to make public transportation more attractive. However, these policies may create unsurmountable financial burdens over time if not carefully implemented.

Chapter 4 is concerned with the impact of the COVID-19 pandemic on different modes, with a particular interest in transit in California. California's transit ridership continues to fall despite numerous bus and rail transit investments, especially since 2014, with a few exceptions (Taylor et al., 2020). Even the Bay area, where transit is well-developed, experienced a drop of over 27 million annual boardings between 2017 and 2018 (Taylor et al., 2020). The COVID-19 pandemic compounded an already precarious situation, with San Francisco alone losing 94% of its ridership (Toussaint, 2020). As the pandemic is starting to wane, California's transit agencies need to understand public perceptions of transit if the state is to play an essential role in delivering a safe, reliable, environment-friendly, equitable, and economically inclusive transportation system. In Chapter 4, I, therefore, explore how the COVID-19 pandemic affected mode choice during the pandemic and may continue to do so after the pandemic using generalized ordered logit models estimated on data collected via a random survey of Californians conducted for UCI by Ipsos (a leading polling firm) in May 2021. I also analyze obstacles to increased transit use.

While 62% to 66% of Californians anticipate no mode change, driving, transit, and TNCs could experience substantial declines after the pandemic. A drop in driving would reduce vehicle miles traveled and help California achieve its greenhouse gas reduction target. However, it is not possible to know if the intention of 19% of Californians to reduce driving will be sufficient to offset the 15.3% who intend to drive more. Results for transit are grim: 28.9% of Californians intend to use transit less after COVID-19 versus only 7.3% who would like to use it more. This drop disproportionately affects Hispanics, African Americans, Asians, lower-income people, and people who would like to telecommute more. A silver lining is a substantial uptick in intentions to walk and bike more (25.8%), with just under 9% of Californians stating the opposite.

The main reason Californians would not take transit before the pandemic and may not take it after is their preference for driving because a personal vehicle offers more flexibility and convenience. The second and the third most popular reasons are "no stops near the destination of interest" and "service not frequent enough/service takes too long." Concerns about transit's reach and frequency are especially prevalent among younger adults, people with more education, and affluent households (the so-called "choice riders").

Finally, in Chapter 5, I summarize my main findings, outline the fundamental limitations of my analyses, and propose avenues for future work. I sincerely hope that my research will help transit agencies restore public transportation in California to health.

CHAPTER 2: BEST FRENEMIES? A CHARACTERIZATION OF TNC AND TRANSIT USERS

2.1 Background and Motivation

Since 2009, the emergence of on-demand, door-to-door ride services from Transportation Network Companies (TNCs) such as Uber and Lyft have created new and very popular mobility options that stirred competition with other modes, especially taxis and public transportation. Building on their success, Uber and Lyft launched in 2014 UberPOOL and Lyft Line in selected metropolitan areas. These new services allow travelers to share their rides with others at cheaper rates than UberX and Lyft Classic (Alemi et al., 2018a; Alemi et al., 2018b). The overall expansion of their services and these additions have further fueled the explosive growth of TNCs, which were estimated to have transported 2.61 billion passengers in 2017, up 37% from the year before (Schaller, 2018). While many have applauded the rise of TNCs, some have raised concerns about their impact on public transportation (Malalgoda and Lim, 2019), traffic congestion (Erhardt et al., 2019), air quality, and vehicle miles traveled (Alemi et al., 2018a; Schaller, 2018; Sperling, 2018), casting TNCs as a threat to the sustainability of urban transportation systems.

The reluctance of TNCs to share data publicly makes it difficult for policymakers and researchers to analyze the impacts of TNCs on other modes, particularly transit. To circumvent this obstacle, I analyze data from the 2017 National Household Travel Survey (NHTS) to examine the claim that TNCs are attracting riders who would have otherwise taken public transportation (or walked/biked, or not traveled) (Alemi et al., 2018a;

Schaller, 2018) by contrasting the characteristics of public transportation users with those of TNC users.

While several papers have examined TNC users and the possible impacts of shared mobility on transit (Blumenberg et al., 2016; Alemi et al., 2018a; Schaller, 2018), to the best of my knowledge, my study is the first to formally contrast users who take only transit, only TNCs and both using multivariate models. A better understanding of the differences between transit and TNC users should be useful to transit agencies tempted to substitute TNCs for transit in areas where transit is declining or to extend the reach of transit by contracting with TNCs. Another contribution of this study is that I perform my analyses at both the individual and the household levels. The latter accounts for intra-household dependencies of mode choice, which have often been ignored in the transportation literature.

After reviewing selected papers that characterized transit and TNC users, I motivate my model variables and summarize my modeling approach. I then discuss my results, summarize my conclusions, mention some limitations of this work, and suggest future research directions.

2.2 Literature Review

In this section, I review selected papers that characterized transit users and TNC users. I focus on studies conducted in the U.S. and Canada because of differences in context with other parts of the world. Table 2.1 summarizes the papers discussed below.

2.2.1 Characteristics of Transit Users

One strand of the literature explored the characteristics of transit riders for different forms of transit (bus, light rail, heavy rail, commuter rail) and the location of their residence (urban vs. suburban areas) (Myers, 1997; Garrett and Taylor, 1999) while another strand distinguished between captive and choice riders (Polzin et al., 2000; Krizek & El-Geneidy, 2007).

In the 1990s, researchers explored what transit service users selected based on their home location, income, gender, and race. Garrett & Taylor (1999) reported that core city dwellers, who were primarily low-income, female, non-Caucasian (predominantly African Americans), and young adults, relied more on buses and light rail transit (LRT) than other demographic groups. In contrast, suburban riders chose predominantly commuter rail, and they were primarily Caucasian, male, and members of higher-income households (Garrett and Taylor, 1999). Other studies confirmed these findings (Myers, 1997) and categorized riders into captive (i.e., people for whom transit is the only option) and choice groups (i.e., people who could use other modes, such as driving their own vehicle). For example, after analyzing data from the 1995 NPTS, Polzin et al. (2000) found that captive riders were mainly composed of the elderly and children, people with lower incomes, people with physical challenges, and families who either could not meet their travel needs by driving or did not want to own cars. Conversely, choice riders were more diversified and generally more affluent (Polzin et al., 2000).

The 2000s saw a plunge in transit ridership, especially in bus ridership, but passenger characteristics remained mostly unchanged compared to the previous decade (LaChapelle, 2009; Taylor and Morris, 2015). This fall was associated with heavy investments in rail projects, which targeted more affluent suburban choice riders, to the detriment of bus transit, which was continuing to serve primarily poorer and minority communities (Taylor & Morris, 2015). In its investigation of transit riders during the 2000s, the APTA's 2007 report characterized its main patron group as adults, predominantly women, Caucasian (for both rail and road modes but not for buses), employed, members of households with an annual income between $25,000 and $49,999, and most likely to be composed of two-members with no motor vehicles (Neff and Pham, 2007).

The profile of transit users has also received attention at the regional level (Kim et al., 2007; Krizek and El-Geneidy, 2007). For example, Krizek & El-Geneidy (2007) investigated the habit and preferences of "potential transit choice riders." Their cluster analysis for the Twin City region led them to conclude that choice riders care particularly about travel time, reliability, safety, convenience, and parking availability near transit stations. After analyzing data from an on-board passenger survey in the St. Louis Metropolitan area, Kim et al. (2007) concluded that females, African Americans, full-time students, and middle-income people are more likely to use bus transit to reach Light Rail Transit (LRT) stations. While these studies showed that the profile of transit users did not change much compared to the 90s, Brown et al. (2016) reported that adults who prefer transit in their early years tend to shift to cars when they get married and have children, which indicates a life cycle effect (Brown et al., 2016).

Clark's (2017) synthesis of passenger surveys from 163 transit systems spanning 2008 to 2015 provides a profile of transit users just before and after the emergence of TNCs: during that period, transit users were predominantly aged 25 to 54, disproportionately members of minority groups (especially for bus users), and often (71%) employed. Moreover, many (54%) had access to at least one vehicle on a regular basis, and they were slightly (55%) more likely to be female. Interestingly, households with annual incomes under $15,000 or over $100,000 or more) made up a similar percentage (21% each) of transit users. Moreover, a slight majority of transit users had a bachelor's degree or a graduate education.

Grahn et al. (2019) reported mostly similar results from their analysis of 2017 NHTS data. Their findings suggest that in 2017 transit users were younger, disproportionately Asian or African American, and less likely to own a private vehicle. Moreover, those relying primarily on buses mostly had lower incomes, while rail transit users were more likely to have higher incomes.

Although the U.S. and Canada have much in common, the profile of transit users differs in large cities on both sides of the border because large groups of middle and upper-middle-class households still reside in Canadian urban cores (Foth et al., 2013). Although Toronto has a transit system that strives to serve disadvantaged communities (Foth et al., 2013), the 1996 Canadian census shows that 22% of commuters used public transit (Kohm, 2000), partly to avoid expensive downtown parking (a feature shared with several other large Canadian cities). Moreover, unlike in the U.S., transit ridership in Canada increased between 2017 and 2018 (Hunt, 2019). One factor explaining the relatively good performance of transit in some Canadian cities is that younger people use public transit to go to school. For example, Hasnine et al. (2018) reported that female students who travel to downtown Toronto campuses use transit more than those who travel to suburban campuses, possibly because transit services are not as convenient at the outer edges of

Toronto (Hasnine et al., 2018).

2.2.2 Characteristics of TNC Users

Several recent papers have characterized TNC users and their behavior (Alemi et al., 2017; Clewlow & Mishra, 2017; Kooti et al., 2017; Leistner & Steiner, 2017; Alemi et al., 2018a-b; Grahn et al., 2019).

Some of these papers focused on TNC use among subgroups of the population. This is the case for Alemi et al. (2018a), who analyzed a panel dataset of 1,191 millennials and 964 members of Generation X in California, to understand the factors that foster and hinder the use of TNCs and the impact of TNCs on other modes. They found that millennials are more prone to using TNCs than their older counterparts because arranging rides with TNCs is more convenient and requires less waiting, although their higher cost may be a deterrent. Moreover, younger individuals, people in households without vehicles or with fewer vehicles than drivers, and multimodal users tend to replace some of their transit trips with TNC service. These findings are in line with those of other studies (Rayle et al., 2014; McDonald, 2015; Circella et al., 2017) that focused on the travel behavior of millennials and the impact of emerging technology on transportation. Alemi et al. (2017, 2018b) analyzed the same dataset to understand the circumstances under which people are more likely to use TNCs (Alemi et al., 2017) as well as factors explaining the adoption of TNC services and the frequency of their use (Alemi et al., 2018b). They reported that land use diversity and regional accessibility are associated with a greater likelihood of TNC use; moreover, individuals who make more long-distance business trips (especially by plane) are more likely to use TNCs (Alemi et al., 2018b). In addition, they found a correlation between land use diversity, density, and the frequency of TNC use, but sociodemographic variables did not seem to matter much. As expected, tech-oriented individuals who rely heavily on mobile apps are more likely to use TNCs, unlike people with a strong preference for their own private vehicle (Alemi et al., 2018a).

A few other studies have explored some potential impacts of shared mobility on vehicle ownership and mode preferences. Based on data from a survey conducted in seven major U.S. cities, Clewlow & Mishra (2017) reported that TNC adopters have a lower level of vehicle ownership than non-adopters. Moreover, they are more likely to own a private vehicle than core transit users. Overall, TNC users are comparatively younger, more educated, have a higher income, and they tend to live in denser urban environments. In addition, 9% of ride-hailing adopters disposed of their personal vehicle, and 26% reduced their personal driving. Although reported changes in transit use were minimal, Clewlow & Mishra (2017) suggested that ride-hailing can be a good substitute for bus transit and complement commuter rail. These results are consistent with other sources (Shaheen et al., 2015; Henderson, 2017) concerned with shared mobility and its impact on car ownership.

Similarly, Leistner & Steiner (2017) used descriptive statistics to explore the possibility of using Uber to mitigate the travel challenges of older adults. They found that shopping and recreational trips are three times faster on average with Uber than with transit, so they concluded that Uber may positively impact the mobility of older adults.

Kooti et al. (2017) investigated the impact of dynamic pricing on Uber users' participation and retention by analyzing 59 million rides taken by 4.1 million users between October 2015 and May 2016. They concluded that Uber riders tend to be more affluent than people who drive their own vehicles. Moreover, younger people use this service more frequently but for shorter distances than older users, and there appears to be gender parity among Uber riders.

Before the 2017 NHTS, the literature analyzed local, regional, or state data to characterize TNC users (Chen, 2015; Rayle et al., 2016; Clewlow and Mishra, 2017; Alemi et al., 2018a-b; Hampshire et al., 2019), and a nationwide understanding of these users was lacking (Sikder, 2019).

A couple of recent papers have analyzed data from the 2017 NHTS to paint a profile of TNC users (Sikder, 2019; Grahn et al., 2019). After estimating an ordered logit model, Sikder (2019) found that frequent TNC users (>= four rides over 30 days) are primarily male, younger, and have college/bachelor's degrees. They also tend to work full time but often have a flexible schedule, they have higher incomes, and their households are more likely to have fewer vehicles than drivers. Conversely, African Americans are less likely to take TNCs. Moreover, those who engage in car-sharing and bike-sharing and use public transit are more likely to use TNCs, which suggests some complementarity between transit and TNCs. Grahn et al. (2019) echoed these findings. To the best of my understanding, these two studies do not appear to have considered whether the respondents analyzed had access to TNCs (they were not as ubiquitous in 2017 as they are now), which might have impacted their results.

Another emerging strand of the literature has been exploring the impact of TNCs on public transportation, but its conclusions are not clear-cut (Rayle et al., 2016; Clewlow and Mishra, 2017; Sadowsky and Nelson, 2017; Hall et al., 2018; Malalgoda and Lim, 2019). Some studies, such as Rayle et al. (2016) or Hall et al. (2018), concluded that TNC trips replaced some transit trips. For example, based on over 2 million responses to intercept surveys, Rayle et al. (2016) found that at least half of TNC trips in San Francisco replaced transit and driving trips. Clewlow & Mishra (2017) reported similar findings: according to their analyses, TNCs are associated with a 6% drop in bus use and a 3% decrease in light rail use. By contrast, Hall et al. (2018), who investigated the effect of Uber on public transit ridership in several US metropolitan areas, reported that Uber complements transit and increased ridership by 5% after two years. Likewise, after analyzing 2007-2017 data from the top 50 US transit agencies, Malalgoda & Lim (2019) found that both bus and rail transit effectiveness (an index that measures transit service quality based on the number of employees, vehicle operating hours, and fuel consumption) declined between 2007 and 2017 and that TNC availability increased rail transit ridership in 2015. Furthermore, rail transit effectiveness limited TNC availability, so overall, TNCs are neither complements nor substitutes for bus transit. Finally, Grahn et al. (2019) reported that TNCs were primarily used for special or rare events, with ~19% of TNC trips for social and recreational events, and that TNC users use public transit at higher rates.

2.3 Data and Methodology

2.3.1 Model Variables

The 2017 National Household Travel Survey (NHTS), which was administered between April 2016 and April 2017, collected data from 129,969 households (Federal Highway Administration 2018). NHTS 2017 data were organized in four files: persons, households, vehicles, and trips.

In this study, I analyzed answers to the following two questions:

Table 2. 1 Summary of selected studies on Transit and TNC users

Study	Data source and Method	Variables	Key findings
Characteristics of Transit Users			
Garrett and Taylor (1999)	• Review of secondary sources: journals, reports, articles • National Personal Transportation Surveys (NPTS) • American Public Transportation Association	Demographic profile of transit users. Financial information about transit (e.g., subsidies).	• Core city dwellers, who are primarily low-income, female, non-Caucasian (mostly African Americans), and young adults, rely more on buses and light rail. • Suburban riders choose predominantly commuter rail; they are primarily Caucasian and male, with higher incomes.
Polzin et al. (2000)	• 1995 NPTS • Descriptive analysis	Transit captive and choice riders' transit use frequency, population density, household income, metropolitan statistical area (MSA) categories, urban classification, vehicle ownership.	• Captive riders are mainly composed of the elderly and children, lower-income groups, people with physical challenges, and families who either could not meet their travel needs using cars or do not want to own cars. • Conversely, choice riders are diverse but are generally more affluent.
Kim et al. (2007)	• St. Louis Metropolitan area, U.S. • MNL	Socio-economic: age, occupation, gender, race. Mode: pick-up and drop off option, bus, and walking	• People who take the bus to reach transit stations are more likely to live in a commercial area and to be female, African American, a full-time student, and have a middle income ($15K-$24.9)
Krizek and El-Geneidy (2007)	• Twin cities: Minneapolis and Saint Paul • Transit users survey in 2001 and non-users survey in 1999 • Factor and cluster analysis	Driver's attitude, customer service, transit service types, reliability, value of travel time, opinion about transit cleanliness, comfort, safety.	• Choice riders value travel time, reliability, safety, convenience, driver's attitude, parking availability, and other ride facilities near transit stations.
Neff and Pham (2007)	• 2007 APTA report • Onboard survey findings • Descriptive Statistics	Age, race, income, gender, education, driving license, employment status, reasons for choosing transit.	• Most likely public transportation stakeholders are adult, women, Caucasian (for both rail and road modes), households with an income between $25,000 and $49,999, employed, and predominantly two-members and zero-vehicle households.
Taylor & Morris (2015)	• 2009 NHTS, APTA, NTD and primary survey of 50 transit agencies • Descriptive analysis	Age, race, income, vehicle miles, number of unlinked passenger trips, transit subsidies.	• Lower income group, African Americans hold the highest share among bus riders. • Higher-income groups and Caucasians mostly prefer commuter rail transit.
Brown et al. (2016)	• 2001 and 2009 NHTS • Smart Location Data (SLD) from the U.S. EPA • Cohort model and logistic	Age, gender, race, ethnicity, employment status, life cycle, household size, residential density, income, transit supply index, birth cohort indicators.	• Young adults use transit services, but as they grow older, they tend to shift from transit to cars due to changes in family structure.

	regression		
Clark (2017)	• APTA report (a compilation of 211 published reports of 163 transit systems) • Descriptive statistics	Age, race, income, gender, education, driving license, employment status, reasons for choosing transit	• Transit users are primarily female, 25-54, employed, educated, minorities, and in both low and high-income groups.
Characteristics of TNC users			
Alemi et al. (2017)	• Same dataset as (Alemi *et al.*, 2018b) • One-way ANOVA and binary logit model	65 attitudinal statements related to land use, the environment, technology, government role, car ownership, and frequency of TNC use	• Land use diversity and centrality are positively associated with greater TNC adoption. • Long-distance travelers, particularly air travelers, are more likely to use TNCs.
Leistner & Steiner (2017)	• Pilot study conducted in Gainesville, FL, to facilitate the transportation needs of older adults (60+) • 40 adults completed 1,445 trips covering 8,119 miles. • Descriptive analysis	Sociodemographic: income level, marital status, age, gender, race, living arrangements; travel information: number of social, shopping, medical and service trips; trip cost, distance, & time.	• Primary use of traveling by Uber was shopping and recreation. • On average, these trips were three times faster than similar transit trips. • Uber may positively impact the mobility of older adults and may be a feasible alternative to transit.
Clewlow & Mishra (2017)	• Seven major U.S. metropolitan areas • 4,094 respondents: 2217 reside in dense, urban neighborhoods and 1877 in suburbs.	Travel attitudes, neighborhood, technology, environment; household demographics; residential location; use of shared mobility services, vehicle ownership and preferences.	• TNC adopters have a lower level of vehicle ownership than non-adopters, but they are more likely to own a private vehicle than transit users. • TNC users are younger, more educated, with a higher income, and live in denser urban areas
Alemi et al. (2018a)	• Online survey of 1,191 millennials and 964 Generation Xers. • Quota-based sampling approach of six major regions in California.	Attitudes, preferences, lifestyles, technology adoption, residential location, commute and non-commute travel, vehicle ownership, frequency of TNC use, demographic factors.	• Millennials are more likely to adopt and use TNCs. • Uber/Lyft are user-friendly (less waiting time and easy to arrange rides) • Uber/Lyft can be substitutes for transit trips and active mode trips.
Alemi et al. (2018b)	• Same dataset as (Alemi *et al.*, 2018a) • Ordered probit and zero-inflated ordered probit model	Socio-demographic characteristics. Built environment; technology adoption and use; travel behavior; vehicle ownership.	• Land use diversity and density impact frequency of TNC use. • Tech-oriented individuals more likely to use TNCs. • Individuals with a strong preference for private vehicles are less likely to use TNCs frequently.
Hall et al. (2018)	• 196 MSAs • National Transit Database, newspaper articles, press releases, social media posts.	Transit ridership, Uber entry and exit, and a variety of controls.	• Uber is complementary to transit and increases ridership by 5%

	• Difference in differences.		
Sikder (2019)	• 2017 NHTS • Descriptive statistics and ordered logit model	Personal: gender, age, student status, ethnicity, education, employment status, driver status. Household: drivers, workers, income, vehicle ownership, size. Land use: urban/rural; car share and bike share programs; transit use.	• Frequent TNC users (>= four rides over 30 days) are mostly male, younger, college degree holders, full-time workers with flexible schedules, and belong to higher income and vehicle deficit households. • African Americans are less likely to adopt TNCs. • Those who participate in shared mobility (e.g., car or bike share) and use public transit are more likely to use TNCs -> complementary effect between transit and TNCs.
Grahn et al. (2019)	• 2017 NHTS • Descriptive Statistics; weighted and unweighted linear regression	Age, education, income, number of trips (walk, bike, transit, TNC trips)	• TNC riders tend to live in urban areas; are most likely to be younger, have an advanced degree, and a higher income.
Malalgoda & Lim (2019)	• 50 U.S. transit agencies (2007-2017)	Rail transit effectiveness	• TNCs availability increased rail transit ridership in 2015 • TNCs are neither complement nor substitutes for bus transit

1. “In the past 30 days, about how many days have you used public transportation such as buses, subways, streetcars, or commuter trains?”
2. “In the past 30 days, how many times have you purchased a ride with a smartphone rideshare app (e.g., Uber, Lyft, Sidecar)?”

To select my sample, I extracted respondents who stated that they have access to both transit and TNCs if their motor vehicles are unavailable. The first question above targeted people 16 years old or older, who hold a driver’s license, and whose household could access at least one motor vehicle. This gave me 30,580 observations.

Since travel decisions routinely involve other household members, mode choices of household members may not be independent, in which case it makes sense to select the household as the basic unit of analysis. However, all the mode choice studies I found during my literature review were conducted at the individual level (Buehler and Hamre, 2015; Alemi et al., 2017; Alemi et al., 2018a-b; Sikder, 2019). Therefore, I conducted both a household-level analysis and an individual-level analysis, and I contrasted the results of both.

Dependent variables

I built my dependent variables by combining data from the two questions mentioned above. For my household-level analysis, I created four mutually exclusive groups to obtain my dependent variable based on whether any household member older than 16 took public transportation or used a TNC during the 30 days ending on their survey day:

- Group 1: at least one household member took public transportation, but none rode with a TNC.

- Group 2: at least one household member rode with a TNC, but none took transit.
- Group 3: some household members took transit, and some rode with a TNC; and
- Group 4: no household member over 16 took transit or rode with a TNC.

For my individual-level analysis, I used the same four groups to define my dependent variable except that I considered only the mode choice of each respondent.

Explanatory variables

I selected my explanatory variables based on my literature review and the variables available in the 2017 NHTS dataset. From the person file, I retrieved information about age, race, Hispanic status, educational attainment, the existence of a medical condition that could impair travel, working status (from home, full-time, or part-time), and whether a respondent was born in the U.S. After aggregating this information by household, I combined it with data from the household file: household income, lifecycle variables, the number of household drivers and vehicles, and homeownership.

Many studies (McDonald, 2015; Circella et al., 2017; Alemi et al., 2018a-b) have considered generations instead of age for exploring how different formative experiences interact with people's life-cycle and aging to shape travel behavior. I relied on definitions from the Pew Research Center (2018) to create my generation variables (birth years are in parentheses): Generation Z (1997 to 2001), who therefore were between 16 and 20 years old in 2017; Generation Y (Millennials) (1981 to 1996); Generation X (1965 to 1980); Baby Boomers (1946 to 1964); and the Silent Generation (born before 1946). For my household models, a generation variable equals one if at least one household member belongs to that category and 0 otherwise; there is no baseline. For my individual-level models, generation variables are binary and capture the generation of the respondent; the Baby Boomer category serves as a baseline.

The literature also suggests that household educational attainment plays a pivotal role in daily mode choice (Buehler and Hamre, 2015; McDonald, 2015; Alemi et al., 2017; Circella et al., 2017; Clark, 2017). To capture the level of education of a household, I created five binary variables that reflect the highest level of education of household adults based on the categories available in the 2017 NHTS.

Race and Hispanic status may matter for selecting a transportation mode (Buehler and Hamre, 2015; Clark, 2017). For my household analysis, a binary household race variable equals one if all household members identify as belonging to that race and zero otherwise. The "mixed" category captures the remaining households. Hispanic status was defined similarly. I also created binary variables for whether a respondent was born in the U.S., medical condition, and working status.

In addition, my models include common household variables such as the number of workers, household size, household structure, annual household income, and vehicle ownership, which have all been found to matter for explaining travel preferences (Buehler and Hamre, 2015; McDonald, 2015; Clark, 2017; Alemi et al., 2018a-b). To capture household structure, I retained five variables from the 2017 NHTS. To represent annual household income, I collapsed the eleven categories from the 2017 NHTS into five binary categories (see Tables 2.A.1 and 2.A.2). Homeownership is captured by a binary variable, and household size by a count variable.

As the decision to take transit or a TNC may depend on whether a household has more drivers than vehicles, I created a binary variable that equals one if a household has more drivers than vehicles and 0 otherwise.

Finally, I added five binary variables that reflect the frequency of smartphone use (daily, weekly, monthly, yearly, and never) since TNCs rely crucially on smartphone apps.

It is well-known that land use is correlated with mode choice (Buehler and Hamre, 2015; Alemi et al., 2017; Alemi et al., 2018a-b). Unfortunately, the 2017 NHTS does not provide the location of residences or places of work, but it includes some common land-use variables. I used population density (1,000 persons/sq. mile) of the home census tract of households in my sample.

To understand how the inclusion of TNCs may have impacted the patronage of different forms of transit, I created three binary variables to capture the availability of bus, light rail, and heavy rail services for the households located in a core-based statistical area (CBSA). A CBSA is a smaller geographic unit than Metropolitan Statistical Area (MSA), with at least 10,000 people and an urban center. The 2017 NHTS reports information about 53 CBSAs. For each, I gathered information about the availability of bus, light rail, and heavy rail transit from the APTA, which publishes quarterly reports on ridership by transit type for primary cities under the jurisdiction of transit organizations in the U.S. I then added this information to my dataset in the form of binary variables.

For my individual-level models, generation, race, Hispanic status, educational attainment, medical condition, working status (from home, full-time, or part-time), and the binary variable for "not born in the U.S." characterize individual respondents in my sample. Other variables (e.g., household income) are defined the same as in my household models.

Summary statistics for my model variables, which document their variability, are shown in Tables 2.A.1 and 2.A.2 in the appendix.

2.3.2 Econometric Framework

Nesting structures

For simplicity, I first estimated a Multinomial Logit (MNL) model, which is often a starting point for modeling mode choice. I tested for the Independence of Irrelevant Alternatives (IIA; see Train, 2009), but it does not hold here (see the beginning of the results section).

A nested logit (NL) model relaxes the IIA requirement for modes in different nests (Train, 2009). To select my preferred nested logit model, I experimented with several structures organized around two nests (public mobility and private mobility), where Group 1 (PT but not TNCs) is in the public mobility (PT) nest, and Group 4 (Neither PT nor TNCs) is in the private mobility nest, while Groups 2 (TNCs but not PT) and 3 (Both PT and TNCs) are allocated to either nest in different models. I selected my preferred NL structure based on AIC and BIC (lower is better) and the requirement of consistent log-sum parameters (values between 0 and 1) (Koppelman & Bhat, 2006).

A Cross-Nested Logit (CNL) model further relaxes the NL requirement that an alternative belongs to only one nest. Although uncommon, several mode choice studies have estimated CNL models (Vovsha, 1997; Ermagun and Levinson, 2017; Hasnine et al., 2018). Here, I estimated two CNL models with Group 2 ("TNCs but no PT") either in the public mobility nest with Group 1 ("PT but not TNCs"), or in the private mobility nest with Group 4 ("Neither PT nor TNCs"), and Group 3 ("both PT and TNCs") in both nests. I selected my preferred CNL model based on AIC and BIC (again, smaller is better) and suitable log-sum parameter values.

The CNL model

In a CNL model, an alternative can belong to more than one nest (Train, 2009). The extent to which alternative j belongs to nest k is given by the allocation parameter $\alpha_{jk} \geq 0$.so allocation parameters sum to one over nests for a given alternative, i.e., $\sum_k \alpha_{jk} = 1$ and $\alpha_{jk}=0$ indicates that alternative j does not belong in nest k. (Train, 2009).

A second type of parameter plays an important role here: log-sum parameters. Denoted by $\lambda_k \geq 0$, the log-sum parameter for nest k reflects the degree of independence among alternatives within nest k, where a larger value indicates greater independence and less correlation. Log-sum parameter values between 0 and 1 guarantee consistency with utility maximization, although that property may still hold for a range of alternatives when log-sum values are above one (Train, 2009).

A choice model is defined by the expression of the probability for alternative "*i*" available to decision-maker "n" (here, individual/household "n"). For the CNL, this expression is given by (Train, 2009):

$$P_{ni} = \frac{\sum_k (\alpha_{ik} e^{V_{ni}})^{1/\lambda_k} \left(\sum_{j \in B_k} (\alpha_{jk} e^{V_{nj}})^{1/\lambda_k} \right)^{\lambda_k - 1}}{\sum_{l=1}^{K} \left(\sum_{j \in B_l} (\alpha_{jl} e^{V_{nj}})^{1/\lambda_l} \right)^{\lambda_l}}, \tag{1}$$

where V_{ni} is the representative utility of alternative "*i*" for decisionmaker "*n*." For all my models,

$$\forall i \in \{1,2,3\}, V_{ni} = \beta_{i0} + \sum_{k=1}^{K-1} \beta_{ik} * x_{kn} \tag{2}$$

and V_{n4}=0 for identification since only differences in utility matter (and can be estimated). In the above, the β_{ik}s are unknown coefficients and the x_{kn}s are explanatory variables characterizing decisionmaker n (socio-economic and land use characteristics).

If each alternative enters only one nest, the α_{jk} parameters are either 0 or 1, and the CNL model simplifies to a NL model. If the log-sum parameters λ_k of a NL model all equal 1, then the NL model reduces to a MNL model.

I estimated unknown model parameters via maximum likelihood.

2.4 Results

2.4.1 Model selection

I estimated my models with Stata 15 and BisonBiogeme (Version 2.6a) (Bierlaire, 2020). A check for multicollinearity showed that it is not an issue here since the maximum VIF value is <7.1.

My final MNL, NL, and CNL structures are shown in Figure 2.1. I first estimated MNL models (Panel A). To test the Independence of Irrelevant Alternatives (IIA), I ran Hausman tests, but they returned negative values, which is at odds with their asymptotic χ^2 distribution (Vijverberg, 2011). I then ran Suest tests, which rejected the IIA for both the household and the individual MNL models.

Among the NL structures I explored, only the one shown on Panel B of Figure 2.1 gave consistent log-sum parameters (values *between 0 to 1*; Koppelman & Bhat, 2006). The NL structure with Groups 2 and 3 in the private mobility nest had inconsistent log-sum parameters (values greater than 1). The NL structure with Groups 1 and 2 in the public mobility nest and Groups 3 and 4 in the private mobility nest did not converge.

I retained the CNL structure of Figure 2.1 for its significant log-sum and allocation parameter values and lower AIC and BIC values. This CNL structure has lower values of AIC and BIC than my preferred NL and MNL models for both individual-level and household-level analyses (see Table 2.2). Likelihood ratio (LR) tests also supported my selected CNL structure over the corresponding Nested Logit structure (Panel C of Figure 2.1) with LR test values at the individual and household levels of 39,767.4 (p-values < 0.01) and 29,210.7 (p-values < 0.01), respectively.

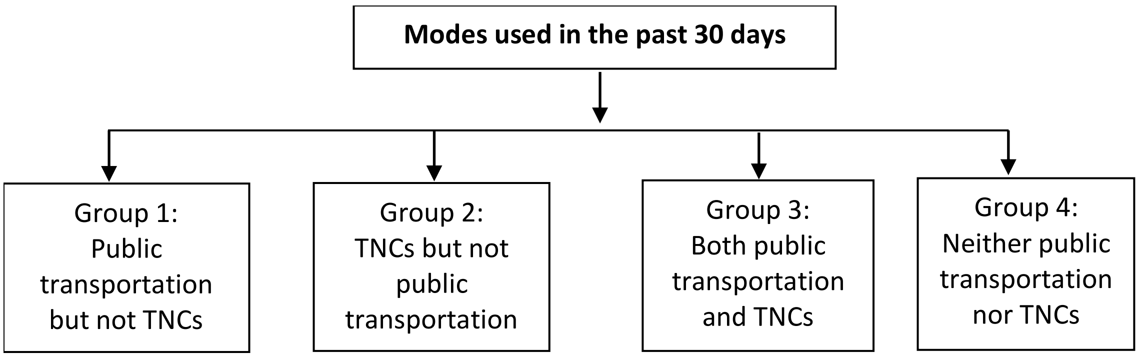
Table 2. 2 Selected Measures of Fit

		Preferred model	
	Multinomial logit	**Nested logit**	**Cross-nested logit**
Individual-level models (N= 30,580)			
Null Log-Likelihood	-27701.7	-27701.7	-27701.7
Final Log-Likelihood	-22532.5	-22,531.9	-22509.2
McFadden ρ^2	0.187	0.187	0.187
AIC	45,311.0	45,311.9	45,274.4
BIC	46,335.3	46,516.4	45,592.5
Household-level models (N=23,947)			
Null Log-Likelihood	-22,932.8	-22,932.8	-22,932.8
Final Log-Likelihood	-18,616.5	-18,615.7	-18,592.2
McFadden ρ^2	0.188	0.188	0.189
AIC	37,484.9	37,485.5	37,446.3
BIC	38,503.4	38,688.2	36,610.6

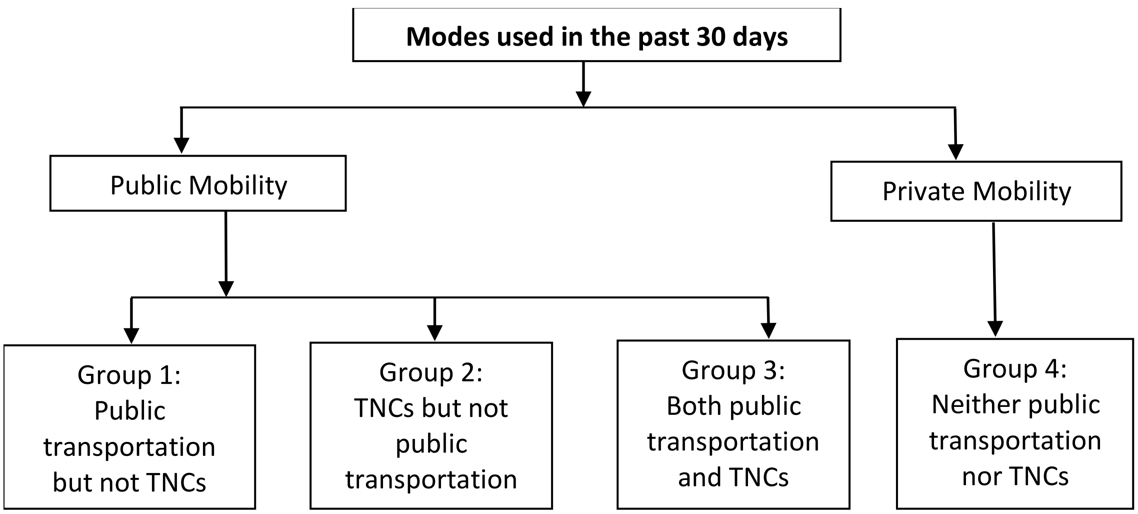
To save space, parameter estimates for my preferred MNL, and NL models are not included here. In the rest of this section, I focus on my CNL results.

2.4.2 CNL results

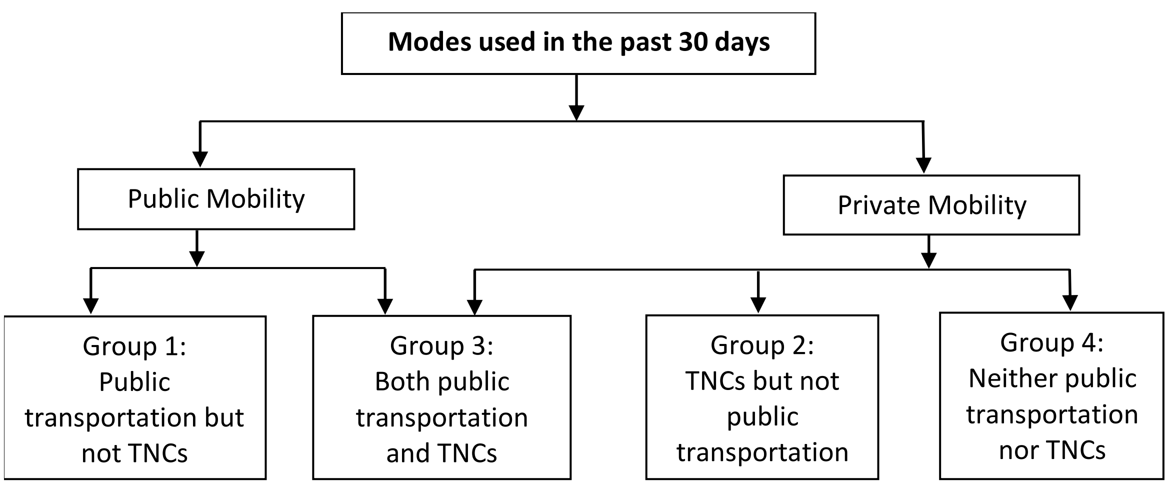
Results for my preferred CNL household-level and individual-level models are shown in Table 2.3. Except for the generation variables, which are defined differently in



Panel A: Multinomial Logit (MNL) structure



Panel B: Nested Logit (NL) structure



Panel C: Cross Nested Logit (CNL) structure

Figure 2. 1 Structure of preferred MNL, NL, and CNL models

these two models (see text below or the footnotes below Table 2.3) and therefore cannot be compared directly, my t-tests showed that only a few coefficients differ significantly (at 5%) between these two models (exceptions are "less than high school" for Groups 1 and 3, "Work for home" for Group 2, and the log of population density for Group 2), which may reflect that almost half of my respondents who took transit did so less than once a week, and nearly 60% of those who took TNCs also did so less than once a week.

Let me start with the allocation parameters for the overlapping group (Group 3: both PT and TNCs in the past 30 days). For my individual model, their values are 0.655*** and 0.345***, so 65.5% of the overlapping group utility comes from the public mobility nest and 34.5% from the private mobility nest. These values differ slightly for the household model, with values of 70.8% and 29.2%, respectively. Furthermore, the log sum parameters for both models are within the required range and significant, which suggests that the nesting structures for both analyses are valid.

In the following two sections, I discuss my results for each model.

Individual-level results

From Table 2.3, I see that compared to Baby Boomers, Generation Z respondents are more likely to use only transit (0.776***), only TNCs (0.594***), or both (0.984***) rather than drive only. Results are similar for millennials and Gen X respondents, with smaller coefficients for older respondents. Conversely, members of the Silent generation are less

Table 2. 3 Results for preferred CNL models

	Individual model (N=30,580)			Household model (N=23,947)		
	Group 1: PT but not TNCs (N_1=3052)	**Group 2: TNCs but not PT** (N_2=3004)	**Group 3: Both PT and TNCs** (N_3=2597)	**Group 1: PT but not TNCs** (N_1=2574)	**Group 2: TNCs but not PT** (N_2=2485)	**Group 3: Both PT and TNCs** (N_3=2342)
Socio-demographic and economic attributes						
Generation♣	(1 if generation of the respondent)			(1 if has at least o household member)		
Generation Z	0.776***	0.594***	0.984***	0.414***	0.188***	0.507***
Generation Y (Millennials)	0.391***	0.539***	0.582***	0.455***	0.242***	0.561***
Generation X	0.091**	0.250***	0.185***	0.089	0.011	0.101
Baby Boomers		Baseline		0.050	-0.180***	-0.020
Silent Generation	-0.242***	-0.143***	-0.265***	-0.238	-0.294***	-0.316***
Hispanic status (Hispanic =1)	-0.137**	0.032	-0.108*	-0.130	0.049*	-0.103
Ethnicity (baseline = Caucasian)						
African American	-0.117*	-0.102***	-0.145**	-0.103	-0.059*	-0.134*
Asian	-0.086	-0.087**	-0.109*	-0.116	-0.064*	-0.129*
Mixed	0.174***	0.056*	0.163***	0.072	0.052*	0.057
Educational attainment (baseline = some college or associate degree)						
Less than high school	-0.206	-0.283***	-0.266	0.216	-0.133	0.266
High school	-0.251***	-0.187***	-0.287***	-0.121	-0.160***	-0.178*
Undergraduate degree	0.460***	0.131***	0.459***	0.459***	0.106***	0.450***
Graduate or professional degree	0.675***	0.125***	0.677***	0.696***	0.114***	0.701***
Annual household income (baseline= $75,000 to $124,999)						
<$35,000	-0.063	-0.214***	-0.105*	-0.114*	-0.183***	-0.153**
$35,000 to $74,999	-0.215***	-0.155***	-0.232***	-0.239***	-0.132***	-0.260***
$125,000 to $199,999	0.312***	0.174***	0.351***	0.300***	0.142***	0.339***
>=$200,000	0.557***	0.431***	0.652***	0.549***	0.342***	0.647***
Household structure (baseline = 2+ adults with children)						
One adult, no children	0.454***	0.230***	0.465***	0.320***	0.170***	0.320***
2+ adults, no children	0.159***	0.138***	0.176***	0.136*	0.115***	0.147**
One adult, some children	0.235**	0.059	0.277***	0.134	0.041	0.167
One retired adult, no children	0.308***	0.135*	0.340***	0.140	0.077	0.152
Two+ retired adults, no children	-0.099	0.012	-0.060	-0.157*	0.033	-0.118
Household size	-0.105***	-0.063***	-0.120***	-0.089***	-0.046***	-0.108***
Household owns home	-0.208***	-0.142***	-0.263***	-0.192***	-0.102***	-0.248***
Household workers (baseline = household with no workers)						

Household with one worker	-0.018	0.033	-0.019	-0.020	0.030	-0.019
Household with two workers	0.093	0.005	0.079	0.106	0.014	0.103
Household with three or more workers	0.146	0.023	0.160	0.210*	0.070	0.246**
Works from home (Yes=1)	-0.039	0.198***	0.031	-0.016	0.131***	0.037
Works full time	0.034	0.052*	0.063	-0.005	0.024	0.025
Works part-time	-0.018	-0.020	-0.030	0.011	0.001	-0.0002
Household has fewer vehicles than drivers (Yes=1)	0.873***	0.120***	0.862***	0.903***	0.104***	0.896***
Has medical condition (Yes=1)	-0.220***	-0.160***	-0.223***	-0.19**	-0.089**	-0.208***
Not born in the U.S. (Yes=1)	0.019	-0.019	0.025	0.076	-0.020	0.069
Smartphone use (baseline = daily)						
Weekly	0.087	-0.278***	0.012	0.055	-0.204***	-0.028
Monthly	-0.004	-0.246***	-0.114	-0.024	-0.216***	-0.161
Yearly	0.055	-1.010***	-0.114	0.035	-0.756***	-0.120
Never	-0.299***	-0.621***	-0.526***	-0.316***	-0.486***	-0.528***
Land use						
Ln of population density (1,000/mi^2)	0.141***	0.087***	0.151***	0.140***	0.065***	0.152***
Availability of transit services						
Household in a CBSA with bus service	0.149**	0.120***	0.165***	0.138**	0.088***	0.161**
Household in a CBSA with light rail service	0.247***	0.086***	0.291***	0.267***	0.085***	0.302***
Household in a CBSA with heavy rail service	0.988***	0.025	0.965***	1.010***	0.012	0.996***
Constant	-2.660***	-1.130***	-2.370***	-2.540***	-0.696***	-2.240***
Log-sum parameters						
Public mobility nest	0.114***			0.111***		
Private mobility nest	0.342***			0.270***		
Allocation Parameters						
Public mobility nest	0.655***			0.708***		
Private mobility nest	0.345***			0.292***		

1. ***, **, and * indicate p-values < 0.01, < 0.05, and < 0.1, respectively.

2. For the individual-level model, generation, educational attainment, Hispanic status, worked from home, worked full-/part-time, medical condition, race, and US birth status pertain to each respondent.

3. For the household-level model, generation, educational attainment, Hispanic status, worked from home, worked full/part-time, medical condition, and immigration status indicate that at least one household member has these attributes. For race, all household members are of that race.

4. The base for both models is Group 4, where N_4 = 21,927 for the individual-level model and N_4 = 16,546 for the household-level model.

♣: generation variables are defined differently in the two models above. For the household model, a generation variable equals one if at least one household member belongs to that generation and 0 otherwise. Since the generation variables, in this case, are not mutually exclusive (a household can have members in different generations), there is no need for a baseline. For the individual model, generation variables are binary and capture the generation of the respondent; the Baby Boomer category serves as a baseline.

likely to use either only transit (-0.242***), only TNCs (-0.143***), or both (-0.265***) than to drive. These results confirm findings from McDonald (2015) and Blumenberg et al. (2016), who reported that Millennials (along with Generation Z) tend to drive less, own fewer vehicles, and rely more on other modes. These differences can be explained by their preferences, economic status, and life cycle stage (McDonald, 2015; Blumenberg et al., 2016). In contrast, Baby Boomers and Silent Generation members are less likely to use TNCs. A possible explanation is that Uber and Lyft vehicles are typically not equipped to easily serve senior citizens or people with mobility impairments. Another reason could be the digital divide, as older generations are not as comfortable as younger generations using communication technology to hail rides (Rahman et al., 2016; Jamal and Newbold, 2020).

Hispanic status and race play a (limited) role here. Hispanics appear less likely to take transit (-0.137**) or both PT and TNCs (-0.108*) than to drive only (recall that all respondents in sample have access to a motor vehicle). Compared to Caucasians, both African Americans (-0.102***) and Asians (-0.087**) are less likely to use TNCs than to drive only, possibly due to racial bias. Indeed, recent studies have shown that African Americans face higher cancellation rates from TNC drivers, suggesting racial discrimination (Ge et al., 2016). These two groups are also less likely to use both (-0.145** for African Americans and -0.109* for Asians). Conversely, members of mixed-race households are more likely than Caucasians to take transit only (0.174***), TNCs (0.056*), or both (0.163***).

Education also matters. Individuals with less than a high school education do not differ from the baseline (individuals with some college or an associate degree), except for using TNCs only (-0.283***). However, individuals with a high school degree are less likely to use either transit (-0.251***), or TNCs (-0.187***), or both (-0.287***) than to drive, compared to the baseline. Conversely, individuals with either undergraduate or graduate degrees are more likely to use either PT only (0.460*** and 0.675*** respectively), TNCs only (0.131*** and 0.125*** respectively), or both (0.459*** and 0.677*** respectively) than to drive, possibly because they live in more affluent areas that offer both services. These results are consistent with findings in Clark (2017), who reported that people with advanced degrees prefer rail transit because it is more comfortable, environment friendly, and congestion-free.

Results for household income reinforce those for education. Compared to the baseline (individuals with an annual household income ranging from $75,000 to $124,999), people in the lower-income groups are less likely to take only PT than to drive (<$35,000: -0.214***). To put this result in perspective, recall that everyone in my sample has access to a motor vehicle. Members of the lower-income groups are also less likely to use either only TNCs (<$35,000: -0.214***; $35,000 to $74,999: -0.155***) or both public transportation and TNCs (<$35,000: -0.105*; $35,000 to $74,999: -0.232***). The opposite holds in the two higher income brackets, with higher coefficient values for the highest income group. The explanation for this result is the same as for educational attainment (Clark, 2017).

As expected, family structure influences mode choice. I see that individuals with or without children are more likely to depend less on their cars and more on either public transportation only (0.454*** for one adult only, 0.159*** for two or more, 0.235** for one adult with some children), TNCs only (0.230*** for one adult, 0.138*** for two or more), or both (0.465*** for one adult, 0.176*** for two or more, and 0.277*** for one adult with some children). When families get larger and have children, they often have more constrained schedules, so they rely more on their motor vehicles to fulfill their daily travel needs (Buehler and Hamre, 2015). I also found that retired adults are more likely to use either public transportation (0.308***), TNCs (0.135*), or both (0.340***) than to drive, compared to the baseline (2+ adults with children). This is again likely due to the driving restrictions of older adults.

As household size increases, people rely increasingly less on modes other than their cars (-0.105***, -0.063***, and -0.120*** for PT only, TNCs only, and both, respectively). Households who own their home are also less likely to use PT or TNCs (-0.208***, -0.142***, and -0.263*** respectively), likely because homeowners tend to live in suburban areas where access to PT and TNCs is less convenient.

The number of workers in the household does not matter here. Moreover, individuals who worked from home are more likely to take only TNCs (0.198***) than just drive only, possibly because they may not have a driver's license. Indeed, coefficients of the variable that indicates if a household has fewer vehicles than drivers are all positive and highly significant (PT only: 0.873***; TNCs only: 0.120***; Both: 0.862***).

As expected, adults with a physical impairment that limits their mobility are less likely to depend on transit, TNCs, or both than on their own vehicles (-0.220***, -0.160***, -0.223*** for Groups 1, 2, or 3 respectively). Where people were born does not influence their mode choices in this model. Moreover, those who do not use smartphones daily are less likely to use TNCs than those who do.

Land use also plays a role here. As expected, individuals who reside in denser areas tend to use more varied modes (0.141***, 0.087*** and 0.151*** for Group 1, 2, and 3 respectively); the large positive and significant coefficient of Group 3 (individuals who used both public transportation and TNCs) reflects the overlap between PT and TNC users. Indeed, Uber and Lyft are primarily present in denser urban environments that typically also harbor well-developed public transportation networks. The availability of transit services in a CBSA area tells a similar story. Individuals who reside in a CBSA with bus, light rail, or heavy rail services use a wider variety of modes (coefficients for all three categories are positive and significant) than those who live in a CBSA without these services (Alemi et al., 2017; Alemi et al., 2018b).

Household-level results

In this sub-section, I highlight differences between my preferred CNL models at the individual level (discussed above) and at the household level. Let me start with generation variables, keeping in mind that a generation variable equals one if at least one household member belongs to that generation and 0 otherwise. First, I note that the Gen X coefficient is not significant for any household group here. Second, a negative value (-0.180***) indicates that households with Baby Boomers are less likely to use TNCs, which is even more the case (-0.294***) for households with members from the Silent generation. The latter are also less likely to use both PT and TNCs (-0.316***). These findings align with my individual-level results.

Interestingly, Hispanic households are slightly more likely to use TNCs (0.049*) than non-Hispanics, which was not the case in my preferred individual CNL model. Results are mostly unchanged for race variables, although they are typically smaller than for the individual-level model: African Americans and Asian households are less likely to belong to Group 2 (TNCs but not PT) or 3 (both PT and TNCs) than Caucasian households.

Both models have significant coefficient values for the top two education and income categories (advanced degree holders and high-income groups), with similar magnitudes and significance. For the bottom two categories, however, the household-level coefficients don't differ statistically from the baseline except for households with a high school education, who are less likely to take TNCs (-0.160***). Another difference is that households in the lower-income tier (<$35,000) are slightly less likely to use public transportation (-0.114*), which may seem surprising until I remember that all households in my sample have access to motor vehicles. That coefficient was not significant for the individual-level model. The other household income variables have the same sign, similar magnitudes, and similar significance levels.

For household structure variables, two categories (one adult with some children, and one retired adult without children) lose their significant differences with the baseline (2+ adults with children), but households with 2+ adults and no children are now less likely to belong to Group 1 (PT but not TNCs). Other household structure results are similar between the two models, and the same applies to household size and homeownership.

As for the individual model, the number of workers in the household does not matter except that households with three or more workers are more likely to use transit (0.210*) or both transit and TNCs (0.246**) than drive only, possibly because households with more adults are more likely to have at least one adult without a driver's license.

For the remaining variables, coefficient magnitude, sign, and significance are similar to those for the individual-level model.

2.5 Discussion and Conclusions

In chapter 2, I contrasted individuals/households who use public transit (PT), TNCs, and both by analyzing mode use data collected in the 2017 NHTS. I defined four mutually exclusive categories of individuals/households and estimated Cross Nested Logit models. To the best of my knowledge, this is the first nationwide study to contrast public transit and TNC users to understand the potential impact of TNCs on transit. A second contribution of my study is my comparison between individual and household-level models to account for intra-household dependencies of mode choice, which I found to have little impact here because many 2017 NHTS respondents only used TNCs and transit sparingly.

To stem the ridership decrease, transit agencies across the U.S. have been forming partnerships with Uber and Lyft to compensate for abandoned lines, address first and last-mile gaps, and offer service to night workers. For example, in 2016, San Clemente (in south Orange County, California) implemented a subsidized Lyft service to recapture some of the riders lost to the closure of two bus routes (191 and 193) (Swegles, 2016). The goal was to provide on-demand service with special considerations for shopping trips for riders 60 and over. While the COVID-19 pandemic is partly responsible for the failure of this and similar initiatives in Southern California (Pho, 2020), my results suggest that they were unlikely to succeed because Baby Boomers and Silent Generation individuals/households, as well as individuals with physical challenges or households with members with impaired mobility, are less likely to use TNCs, especially if they live in lower-density areas. Indeed, vehicles in use by TNCs typically are not equipped to accommodate customers with impaired mobility. Moreover, many older adults avoid such services because they are not comfortable using smartphones and because of discriminatory practices towards older citizens by some TNC drivers (Williams, 2021).

My results show that transit and TNCs target individuals/households who share common socio-economic characteristics and live in similar (higher density) areas. These groups are more likely to be Millennials and belong to Gen Z, with higher incomes, advanced degrees, no children, and fewer vehicles than driver's license holders. They reside in denser areas and CBSAs served by PT and now TNCs. Compared to PT, TNCs provide much more convenient and typically much faster point-to-point service, which this group of individuals/households is likely to be able to afford, so increasing the exposure of these individuals/households to TNCs may hasten their exodus to TNCs.

Instead of outsourcing to TNCs, transit agencies should consider exploring partnerships with micro-mobility operators to extend the reach of transit and take care of the first- and last-mile problem. Multimodal connectivity with bike-sharing and micro-mobility has been adopted in countries around the world, but the U.S. is lagging (Mohiuddin, 2021), even though these mobility options could potentially replace cars for up to 30% of trips under five miles, which make up more than half of all trips in the U.S. (Abduljabbar et al., 2021). Recent studies have shown that well-educated, younger adults, childless households, upper-income households, and urban dwellers with multiple mode options favor micro-mobility (Shaheen and Cohen, 2019), so partnerships with transit where micro-mobility stations are conveniently located by PT stops, and seamless payment options (such as apps integrating transit and micro-mobility) may help transit recover as it emerges from the pandemic. Embracing this approach may also enhance public health and help achieve GHG reduction goals.

Many low-income individuals/households (often belonging to disadvantaged groups) also reside in core urban areas and CBSAs served by transit. However, I found that these individuals/households are less likely than higher-income groups to take both TNCs and PT. The lower use of TNCs by less affluent individuals/households is unsurprising since it is typically not the cheapest transportation option. Extensive partnerships between transit and micro-mobility providers could prove attractive to them if pricing is right, and if micro-mobility stations are in secure areas in minority neighborhoods. I note that African American and Asian individuals/households are also less likely to use TNCs (all else being equal), which suggests racial discrimination as uncovered in other studies (e.g., see Ge et al., 2016).

My results also show that lower-income individuals/households are less likely to use PT, which seems at odds with the disproportionate use of bus transit by lower-income individuals/households. The reason for this apparent discrepancy is that all individuals/households in my sample have access to motor vehicles because the NHTS question analyzed in this chapter was restricted to motorized respondents, so none of the individuals/households in my datasets are fully captive as defined in the literature. Their disaffection for PT reflects that transit lacks the convenience and the reach of private vehicles, as recent laws have made it easier for undocumented immigrants to obtain a driver's license while some bus lines were discontinued, some bus frequencies were reduced, and investments shifted from bus transit to commuter rail.

One limitation of this study is that I do not have information about the type of public transportation that was taken by NHTS respondents in the 30 days prior to their survey day. This prevents me from distinguishing between bus and heavy rail/metro users, which is potentially problematic because the literature shows that TNCs impacts bus transit differently than heavy rail/metro systems (Rayle et al., 2016; Clewlow and Mishra, 2017; Feigon & Murphy, 2018; Hall et al., 2018; Malalgoda & Lim, 2019). A second limitation is the restriction of my dataset to individuals/households who have access to motor vehicles, as explained above. This feature explains the apparent contradiction between my finding that low-income people are reluctant to take transit and the literature, which reports that low-income people are prime users of bus transit in the U.S. (Myers, 1997; Garrett & Taylor, 1999; Polzin et al., 2000; Kim et al., 2007; Krizek and El-Geneidy, 2007; Taylor and Morris, 2015). A third limitation is the absence in the 2017 NHTS of detailed location data and mode-specific cost and travel time, which would have helped me better understand mode choice. A fourth limitation is that Groups 1-3 contain infrequent and frequent users of a given mode. However, accounting for the frequency of use of transit or TNCs would likely have required a more complex model that would have been more difficult to interpret.

Future work could explore whether TNCs are complements or substitutes for different types of public transportation (e.g., heavy rail or light rail versus buses). It would also be of interest to compare the travel behavior of individuals/households before and after the emergence of TNCs (using, for example, matching methods such as propensity score matching), and analyze the potential opportunities and obstacles for transit to partner with micro-mobility providers.

2.6 References

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2.7 Appendix

Table 2.A. 1 Descriptive statistics for individual-level analysis (N = 30,580)

Variables	Group 1: PT but not TNCs (N_1 = 3,052)	Group 2: TNCs but not PT (N_2 = 3,004)	Group 3: Both PT and TNCs (N_3 = 2,597)	Group 4: Neither PT nor TNCs (N_4 = 21,927)	Overall Sample (N = 30,580)
Socio-demographic and economic attributes					
Generation					
Generation Z	1.87%	1.83%	2.19%	1.82%	1.86%
Generation Y (Millennials)	19.92%	47.40%	48.40%	18.28%	23.87%
Generation X	26.21%	28.53%	28.38%	23.30%	24.54%
Baby Boomers	43.28%	20.24%	18.83%	43.84%	39.34%
Silent Generation	8.72%	2.00%	2.19%	12.75%	10.39%
Hispanic Status (Hispanic =1)	5.73%	8.95%	7.86%	6.50%	6.78%
Ethnicity					
Caucasian	81.65%	83.06%	81.32%	85.61%	84.60%
African American	5.96%	3.89%	4.00%	5.50%	5.26%
Asian	6.55%	6.19%	7.93%	4.06%	4.85%
Mixed	5.83%	6.86%	6.74%	4.83%	5.29%
Educational attainment					
Less than high school	1.21%	0.60%	0.73%	1.60%	1.39%
High school degree	5.21%	2.80%	2.23%	11.48%	9.22%
Some college or associated degree	16.97%	16.38%	11.74%	28.72%	24.90%
Undergraduate degree	33.09%	42.41%	38.24%	29.86%	32.13%
Graduate or professional degree	43.51%	37.82%	47.05%	28.34%	32.37%
Annual household income					
<$35,000	13.79%	9.02%	9.09%	18.11%	16.02%
$35,000-$74,999	21.00%	20.31%	16.63%	30.82%	27.60%
$75,000 to $124,999	27.88%	27.53%	24.10%	28.85%	28.22%
$125,000 to $199,999	21.66%	22.14%	24.99%	14.81%	17.08%
>=$200,000	15.66%	21.01%	25.18%	7.38%	11.06%
Household structure					
One adult, no children	16.68%	23.77%	21.02%	13.01%	15.11%
2+ adults, no children	31.49%	41.41%	43.43%	25.06%	28.87%
One adult, some children	2.33%	2.46%	2.81%	2.80%	2.72%
2+ adults with children	23.69%	22.90%	22.53%	23.38%	23.29%
One retired adult, no children	7.37%	1.80%	1.81%	8.94%	7.48%

2+ retired adults, no children	18.45%	7.66%	8.39%	26.80%	22.52%
Household owns home	74.48%	61.68%	56.10%	78.09%	74.25%
Household workers					
Household with no workers	20.54%	7.19%	7.97%	27.80%	23.36%
Household with one worker	35.32%	40.81%	36.73%	34.73%	35.56%
Household with two workers	37.91%	46.30%	48.63%	31.81%	35.27%
Household with three or more workers	6.23%	5.69%	6.66%	5.67%	5.81%
Works from home (Yes=1)	9.17%	15.75%	13.52%	8.26%	9.54%
Works full time	51.77%	70.47%	71.01%	44.29%	49.88%
Works part-time	12.78%	10.95%	9.74%	12.58%	12.20%
Household has fewer vehicles than drivers (Yes=1)	18.58%	9.35%	22.53%	8.63%	10.87%
Has medical condition (Yes=1)	4.29%	1.53%	1.89%	6.56%	5.44%
Not born in the US (Yes=1)	11.89%	10.79%	13.90%	8.26%	9.35%
Smartphone use					
Daily	81.23%	97.04%	96.96%	76.28%	80.57%
Weekly	5.54%	1.50%	1.85%	5.39%	4.72%
Monthly	2.33%	0.57%	0.39%	2.28%	1.96%
Yearly	1.18%	0.03%	0.15%	1.20%	0.99%
Never	9.73%	0.87%	0.65%	14.85%	11.76%
Land use					
Availability of transit services					
Household in a CBSA with bus service	67.86%	68.94%	81.94%	43.24%	51.51%
Household in a CBSA with light rail service	59.99%	59.45%	75.47%	34.89%	43.25%
Household in a CBSA with heavy rail service	41.38%	23.50%	52.14%	13.78%	20.75%

Notes:
1. All explanatory variables in my models are binary, except for “**Number of household members** (Mean: 2.32; S.D: 1.16; Min: 1; Max: 11)” and “**Ln of population density** (measured in 1,000/mi^2)” (Mean: 1.11; S.D: 1.30; Min: -3.00; Max: 3.40), which are count and continuous variables, respectively. These two variables are not shown in Table 2.A.1.
2. CBSA stands for Core Based Statistical Area.

Table 2.A. 2 Descriptive statistics for household-level analysis (N = 23,947)

Variables	**Group 1: PT but not TNCs** (N1 = 2,574)	**Group 2: TNCs but not PT** (N2 = 2,485)	**Group 3: Both PT and TNCs** (N3 = 2,342)	**Group 4: Neither PT nor TNCs** (N4 = 16,546)	**Overall Sample** (N = 23,947)
Socio-demographic and economic attributes					
Generation					
Generation Z	2.53%	2.70%	3.33%	1.89%	2.18%
Generation Y (Millenials)	21.87%	48.09%	50.26%	18.56%	25.08%
Generation X	28.40%	32.60%	32.41%	24.80%	26.74%
Baby Boomers	47.16%	23.34%	23.23%	47.09%	42.30%
Silent Generation	10.06%	2.37%	2.73%	15.33%	12.19%
Hispanic Status (Hispanic =1)	5.59%	8.93%	7.47%	6.21%	6.55%
Ethnicity					
Caucasian	82.05%	82.90%	82.11%	85.74%	84.70%
African American	6.33%	4.35%	4.06%	5.89%	5.60%
Asian	6.14%	6.04%	7.81%	3.67%	4.59%
Mixed	5.48%	6.72%	6.02%	4.69%	5.12%
Educational attainment					
Less than high school	0.62%	0.20%	0.38%	0.93%	0.77%
High school degree	4.74%	1.81%	1.45%	9.89%	7.68%
Some college or associated degree	15.38%	14.21%	9.82%	27.61%	23.17%
Undergraduate degree	32.40%	40.48%	34.97%	29.96%	31.81%
Graduate or professional degree	46.85%	43.30%	53.37%	31.60%	36.58%
Annual household income					
<$35,000	15.35%	9.86%	9.44%	21.19%	18.24%
$35,000-$74,999	22.96%	22.05%	17.46%	32.63%	29.01%
$75,000 to $124,999	28.09%	27.81%	24.81%	27.09%	27.05%
$125,000 to $199,999	20.05%	21.29%	24.34%	12.93%	15.68%
>=$200,000	13.56%	18.99%	23.95%	6.16%	10.03%
Household structure					
One adult, no children	19.77%	28.73%	23.31%	17.24%	19.30%
2+ adults, no children	28.67%	36.78%	40.31%	21.91%	25.98%
One adult, some children	2.64%	2.90%	3.03%	3.38%	3.22%
2+ adults with children	22.26%	21.69%	22.93%	20.00%	20.71%
One retired adult, no children	8.74%	2.17%	2.01%	11.85%	9.55%
2+ retired adults, no children	17.91%	7.73%	8.41%	25.61%	21.25%
Household owns home	73.74%	60.93%	56.75%	76.26%	72.49%
Household workers					

Household with no workers	22.22%	7.89%	8.20%	30.80%	25.29%
Household with one worker	38.07%	45.39%	39.07%	37.58%	38.59%
Household with two workers	34.69%	41.73%	46.33%	27.81%	31.80%
Household with three or more workers	5.01%	4.99%	6.40%	3.81%	4.32%
Works from home (Yes=1)	12.04%	18.23%	17.21%	9.80%	11.64%
Works Full time	56.02%	75.37%	76.56%	48.21%	54.64%
Works Part-time	16.55%	14.69%	13.83%	14.71%	14.82%
Household has fewer vehicles than drivers (Yes=1)	16.16%	7.69%	20.20%	7.14%	9.45%
Has medical condition (Yes=1)	5.67%	2.25%	2.52%	8.21%	6.76%
Not born in the U.S. (Yes=1)	14.02%	12.19%	16.48%	9.02%	10.62%
Smartphone use					
Daily	80.07%	96.74%	96.88%	74.24%	79.41%
Weekly	5.71%	1.69%	1.75%	5.58%	4.82%
Monthly	2.41%	0.56%	0.43%	2.36%	1.99%
Yearly	1.20%	0.04%	0.17%	1.21%	0.99%
Never	10.61%	0.97%	0.77%	16.60%	12.79%
Land use					
Availability of transit services					
Household in a CBSA with bus service	66.39%	68.09%	81.04%	42.20%	51.28%
Household in a CBSA with light rail service	58.66%	58.75%	74.30%	33.86%	43.06%
Household in a CBSA with heavy rail service	39.28%	21.93%	50.51%	13.13%	20.51%

Notes:

1. All explanatory variables in my models are binary, except for “**Number of household members** (Mean: 2.19; S.D: 1.15; Min:1; Max:11)” and “**Ln of population density** (measured in 1,000/mi^2)” (Mean: 1.11; S.D: 1.31; Min: -3.00; Max: 3.40), which are count and continuous variables, respectively. These two variables are not shown in Table 2.A.2.

2. CBSA stands for Core Based Statistical Area.

CHAPTER 3: ARE TNCS EATING TRANSIT'S LUNCH? EVIDENCE FROM THE U.S. NATIONAL HOUSEHOLD TRAVEL SURVEY 2009 AND 2017

3.1 Introduction

The popularity of door-to-door on-demand mobility services (e.g., Uber, or Lyft), which emerged around 2010 (Blystone, 2021), has soared over the last decade. Transportation Network Companies (TNCs)[1] were made possible by advances in smartphone technologies and their widespread success, software innovations, a compelling vision for selling mobility as a service, and a willingness to challenge local regulations. By January 2016, TNCs were available in around 175 metropolitan areas across the U.S. (Shaheen and Cohen, 2018). A 2018 report estimated that TNCs transported 2.61 billion passengers in 2017, up 37% from the year before, with 75 million trips in San Francisco alone, the highest per person number of trips among all other U.S. cities (Schaller, 2018). However, this did not help alleviate congestion as San Francisco is now the third most congested city in the U.S. (Bliss, 2018).

While the popularity of TNCs is undeniable, their impact on public transportation and other modes has been of increasing concern to policymakers and transit operators because transit patronage has continued to decrease in many parts of the U.S. over the past decade despite increasing investments (Dickens and Neff, 2011; Hughes-Cromwick and Dickens, 2018). For example, in California, public investments in transit increased by 50% between 2000 and 2015, yet California lost 62.2 million annual transit rides between 2012

[1] In 2013, the California Public Utilities Commission declared that Uber, Lyft and other ride-hailing services should be called transportation network companies (TNC) (Clewlow & Mishra, 2017). They are also known as ride-sourcing and ride-sharing services.

and 2016 (Manville et al., 2018). This decline has been attributed to increasing access to private vehicles (Manville et al., 2018) and to the emergence of TNCs such as Uber and Lyft (Schaller, 2018). The decline of transit and the increasing popularity of TNCs had a number of adverse consequences, including likely increases in congestion and vehicle miles traveled (VMT) in urban areas, additional air pollution and greenhouse gas emissions, and a reduction in walking and biking linked to transit use (Alemi et al., 2018; Schaller, 2018; Sperling, 2018).

My review of the literature identified a couple of gaps. First, published studies concerned with the impact of TNCs on other modes rely either on descriptive statistics (Rayle et al., 2016) or analyze observed data using econometric methods that characterize association but not causality (Jin et al., 2019). Traditional models such as linear/logistic regression or fixed effect panel regression applied to observational data can result in biased estimates of the impact of a treatment (here the availability of TNCs) because they do not account for self-selection (Li, 2013). Some studies (Hall et al., 2018; Pan and Qiu, 2018; Ward et al., 2021) used quasi-experimental methods like Difference-in-Difference (DID) to tackle the self-selection bias, but they analyzed aggregate data. Second, I could not find a micro-level (i.e., household-level) analysis of the impact of TNCs on transit use (and on other modes) as published studies analyze data aggregated over various geographies (Hall et al., 2018).

In this context, the main contribution of this study is to apply propensity score matching (PSM) – a quasi-experimental method which has been widely used in medicine, public health, and to a lesser extent economics – to selected household data from the 2009 (my control year) NHTS and the 2017 (my treatment year) NHTS to tease out the causal impacts of the appearance of TNCs on transit ridership in the United States, while controlling for a broad range of variables known to potentially impact household travel (Mishra et al., 2015). Using households as my unit of analysis allows me to understand how TNCs impacted the travel of different socio-economic groups while accounting for intra-household travel dependencies.

Understanding the impact of TNCs on transit is critical for guiding transit policy. A number of transit systems are considering contracting with TNCs to solve the “first and last mile problem” and make public transportation more attractive. If not carefully implemented, these policies may create unsurmountable financial burdens over time (Mallett, 2018). Moreover, as argued by Erhardt et al. (2019), TNCs increase VMT and urban congestion, policies and/or regulations may be needed to both improve transit and curb the growth of TNCs to foster urban sustainability.

After reviewing selected papers dealing with the impact of TNCs on transit and other modes, I motivate my model’s variables and my modelling approach. I then discuss my results, summarize my conclusions, mention some limitations of my work, and suggest future research directions.

3.2 Literature Review

TNCs provide convenient and secure travel by matching passengers to drivers through an online mobile app. Although TNCs have attracted much attention from scholars, a comprehensive understanding of their impacts on household travel is still missing. While many have applauded the rise of TNCs, some scholars have raised concerns about their potential impact on transit, urban congestion, and household VMT (Circella et al., 2017; Grahn et al., 2020; Malalgoda & Lim, 2019; McDonald, 2015; Rayle et al., 2014, 2016).

A number of papers have explored the characteristics of TNC users (Alemi et al., 2017; Circella & Alemi, 2017; McDonald, 2015; Rayle et al., 2014). They report that TNC users are mostly younger, well-educated, belong to higher income groups, and either do not own private vehicles or have fewer vehicles than drivers in their households. They concluded that they also tend to replace some of their transit trips with TNC service. However, these results were often obtained locally using restricted data, so they are not easy to replicate.

The impact of TNC on other travel modes, especially on taxis and transit, has also received a lot of attention. Although the increased popularity of TNCs has clearly been detrimental to taxis (Cramer & Krueger, 2016; Schaller, 2018), their influence on transit is still ambiguous. Indeed, some studies claim that TNCs complement transit while others argue they are taking away ridership (Rayle et al., 2016). TNCs have also been criticized for reducing walk and bike, as people who would have walked or biked are now preferring the convenience of TNCs. In the rest of this section, I review selected papers that analyzed the impacts of TNCs on other modes, with a particular interest for transit. Table 3.1 summarizes the papers discussed below.

3.2.1 TNCs and transit

While TNC patronage has been booming, transit has been losing ridership: between 2011 to 2017, In the U.S., bus transit lost almost 9.4% of its passenger miles traveled (Dickens and Neff, 2011; Hughes-Cromwick and Dickens, 2018). Given the role that transit could play in reducing congestion and decreasing air pollution and emissions of greenhouse gases, the impact of TNCs on transit has been receiving increasing attention from academics (Clewlow & Mishra, 2017; Grahn et al., 2020; Malalgoda & Lim, 2019; Mallett, 2018; Rayle et al., 2016).

Some studies have shown that depending on the transit mode (i.e., bus vs. train), TNCs are either substitutes or complements for transit. For example, working with comprehensive travel and residential survey data collected in seven U.S. major cities between 2014 to 2016, Clewlow & Mishra (2017) concluded that TNCs took respectively 6% and 3% of bus and light rail passengers, but increased commuter rail passengers by 3%. Rayle et al. (2016 also reported that TNCs both compete with and complement public transit. Based on an intercept survey of 380 people in San Francisco in 2014, their findings suggest that TNC trips are mostly social and leisure trips, meet the demand for convenience thanks to point-to-point service, and transport people twice as fast as public transit. While insightful, I note that both studies are explorative in nature and cannot make causation claims. Moreover, Rayle et al. (2016) oversampled social and leisure trips, which were collected from only three neighborhoods, they did not consider trip purposes, and they acknowledge that their results are not representative of general TNC users.

Other studies, however, argue that TNCs complement but do not compete with transit. This is the conclusion reached by the Shared Use Mobility Center based on the fact that TNCs are mostly in demand between 10 pm and 4 am, when public transportation is either unavailable or provides only reduced service (Feigon and Murphy, 2018). Hall et al. (2018) reported similar findings based on their investigation of 196 U.S. metropolitan statistical areas (MSA). After analyzing 2004 to 2015 data from the national transit database (NTD), they concluded that Uber complements transit as it increased ridership by 5% (Hall et al., 2018). Malalgoda & Lim (2019) reached slightly different conclusions after analyzing 2007-2017 NTD data of the top 50 U.S. transit agencies. They found that rail transit effectiveness limited TNCs availability and that TNCs are neither complements nor substitutes for bus transit. Their also reported that both bus and rail transit effectiveness declined over their study period and that TNC availability increased rail transit ridership in 2015 (Malalgoda and Lim, 2019). Hall et al. (2018) (who also used DiD) and Malalgoda & Lim (2019) both analyzed annual unlinked passenger trips data, which may not accurately reflect door-to-door travel behavior by transit (Taylor and Fink, 2013).

My study is not the first to analyze data from the 2017 NHTS to investigate the impact of TNCs on transit. Grahn et al. (2020) reported that TNC services were primarily used for special or rare events instead of for regular use. Their findings suggest that approximately 19% of TNC trips were social and recreational, and that TNC users use public transit at higher rates. However, they did not conduct a multivariate analysis.

A few studies have relied on difference-in-differences (DiD) to analyze the aggregate impact on transit of the emergence of TNCs (Hall et al., 2018; Pan and Qiu, 2018; Ward et al., 2021). As mentioned above, Hall et al. (2018) showed that the overall positive of TNCS on transit masks substantial spatial heterogeneity. Pan and Qiu (2018) reported that U.S. bus ridership dropped significantly after the emergence of Uber, but in areas with more physically challenged people. Ward et al. (2021) found that urban areas with affluent and childless families experienced a larger decrease in transit ridership compared to other areas. I also note DiD's requirement that the difference between the treatment and control groups be constant over time in the absence of a treatment is tough to prove, and it does not allow understanding how different groups may be affected by the emergence of TNCs.

In their 2022 study, Erhardt et al. concluded that TNCs are responsible for a 10% decline in San Francisco's bus ridership between 2010 and 2015, which resulted in a net economic loss. More insights about TNC's impact on transit can be found in (Baker, 2020; Diao et al., 2021; Doppelt, 2018; Graehler et al., 2018; Ngo et al., 2021; Ward et al., 2021; Young et al., 2020).

3.2.2 The impact of TNCs on other travel modes

In addition to transit, TNCs also affected other modes such as taxis, and possibly walking, and biking (Rayle et al., 2016; Schaller, 2018). TNCs were not regulated when they started operating but that changed over time after protests and political pressure. Except for Vermont and Oregon, where TNCs are still free to operate on their own terms, 48 U.S. states and Washington, D.C. had regulated their operation by the end of 2017 (Malalgoda and Lim, 2019). Studies showed that TNCs did replace taxis in several major U.S. cities (Schaller, 2018) but their impact on active modes such as walk and bike has so far received little attention (Young and Farber, 2019).

Rayle et al. (2016) found that TNCs and taxis in San Francisco target the same population, and have similar trip lengths. In fact, TNCs replaced many taxi trips and most TNC users confirmed that many would have used taxis if TNCS were not available. TNCs also replaced many walk, bike, and transit trips (Rayle et al., 2016).

Schaller (2018) confirmed that taxis are losing ridership to TNCs. A 30% ridership surge between 2000 to 2012 was followed by an almost 50% crash in the five years after

2012, a drop that overlapped with a TNC surge. According to Schaller (2018), approximately 60% of TNC users might have used public transportation (or walked/biked, or not traveled) if TNCs had not been available in the first place. In Toronto, Young & Farber (2019) reported that ride hailing services brought down taxi ridership significantly but interestingly, TNCs increased the use of active modes. Both studies (Schaller, 2018; Young and Farber, 2019), however, relied on descriptive statistics to reach their conclusions and they did not account for self-selection.

This brief review shows that a rigorous household level analysis of the impacts of TNCs on transit use is still missing. Second, none of the papers I reviewed makes a causal claim about the impact of TNCs on other modes (except Hall et al., 2018; Pan & Qiu, 2018; Ward et al., 2021; but these studies analyzed aggregate data) and particularly transit (Jin et al., 2019; Rayle et al., 2016) because the methods they used analyze observational data for correlations and do not control for self-selection (Li, 2013).

3.3 Methodology

To understand the impact of TNCs on transit use, I jointly analyzed data from the 2009 and the 2017 National Household Travel Surveys (NHTS), which respectively information about household travel before and after the emergence of TNCs.

Since travel decisions routinely involve other household members (e.g., when a household member uses a household vehicle, it is not available to others or some household members may travel together), mode choices of household members are not independent. I, therefore, chose the household as my unit of analysis.

Table 3. 1 Selected studies on the impact of TNCs on transit and other modes (2016-2021)

Study (Year)	Data source and Methodology	Variables	Key findings
Rayle et al. (2016)	• San Francisco, CA • 2014 • 380 respondents from intercept survey • Descriptive statistics	*Socio-economic:* age, gender, vehicle availability, education, driver's license *Travel:* trip purpose, trips origins, and destinations, wait times	• At least half of ride sourcing trips replaced modes like public transit and driving • Impacts on overall vehicle travel are unclear
Clewlow & Mishra (2017)	• 7 major cities of the U.S. • 2014 to 2016 • Descriptive statistics	*Socio-economic:* age, gender, race, education, vehicle ownership, urban and suburban *Travel:* trip purpose.	• 6% average net drop in transit use among Americans in major cities • Ride hailing draws 6% Americans away from bus services and 3% from light rail services
Hall et al. (2018)	• 196 MSAs • 2004 to 2015 • National Transit Database (NTD), newspaper articles, Uber press releases, blog and social media posts • Difference in differences	*Travel:* transit ridership, Uber entry and exit.	• Uber is complementary for transit and increased ridership by 5%
Pan and Qiu (2018)	• Over 300 urban areas in the U.S. • Between 2002 and 2017 • National Transit Database (NTD), U.S. Energy Information Administration, Bureau of Economic Analysis, United States Census Bureau • Difference in difference	*Socio-economic:* age, disability and language ability, unemployment, poverty rate, GDP, population, income *Travel:* unlinked bus passenger trips, VRH, average diesel and gasoline cost	• Bus ridership dropped significantly after Uber's entry, but impact is spatially heterogeneous • Urban areas with more older people saw lower drop; areas with more physically challenged people, individuals a with language barrier, and unemployment saw a sharper drop in bus trips
Schaller (2018)	• U.S. • 2018 • 2017 NHTS and secondary studies • Descriptive Statistics	*Travel:* Number of trips (transit, walk, bike, taxi and TNC), VMT.	• 60% of TNC users would have used public transportation (or walked/biked, or not travelled) • 40% of them would have driven private vehicles if TNCs had not been available
Grahn et al. (2020)	• U.S. • 2017 NHTS • Descriptive Statistics	*Socio-economic:* age, education, income *Travel:* number of trips (walk, bike, transit, TNC trips).	• TNC services were primarily used for special or rare events. • 19% of the TNC trips were social and recreational • TNC users used public transit at higher rates

Jin et al. (2019)	• New York City (NYC), U.S. • 17th (weekday) and 20th (weekend) of September of 2014 • NYC Taxi and Limousine Commission, Metropolitan Transportation Authority, U.S. Census Bureau, William and Anita Newman Library of Baruch College, ACS (2010–2014) • Buffer and spatial correlation analysis, Gini coefficient.	*Socio-economic:* total population, median household income, race *Travel:* Uber pickups (time, longitude, latitude, and base name), transit stops locations and vehicle arrival time, taxi pickup and drop-off dates/times/locations, bus/subway/rail routes GIS shapefiles	• In NYC, Uber's competitive role is more prominent with public transit especially in areas where PT has good spatial and temporal coverage. Uber complements public transit at night and early morning when these services are running • Uber and taxis are not equally distributed among different boroughs of NYC
Malalgoda & Lim (2019)	• Data of 50 U.S. transit agencies • 2007-2017 • National Transit Database • Fixed effect Panel Regression & data envelopment analysis	*Socio-economic:* Aggregate level socio-economic factors; *Travel:* Transit Effectiveness, TNCs availability, transit supply.	• TNCs availability increased rail transit ridership in 2015 • TNCs are neither complementary nor supplementary for bus transit
Young & Farber (2019)	• Toronto, Canada • In 2016, two years after the widespread adoption of ride hailing services • 2016 Transportation Tomorrow Survey • Descriptive Statistics	*Socio-economic:* Age, education, income; *Travel:* Number of trips (private vehicle, walk, bike, transit, TNC).	• Ride hailing services had brought down taxi ridership but increased use of active modes.
Baker (2020)	• Census tracts of San Francisco (SF), California • Fall of 2016 • SF County Transportation Authority, SF Municipal Transportation Agency, SF Bay Area Rapid Transit District, ACS 5-year estimates (2016), SF Police Department, Longitudinal Employer- Household Dynamics, Origin-Destination Employment Statistics • GWR and OLS	*Socio-economic:* choice rider & transit dependent neighbourhood; land use and housing variables; income, age, education, race, vehicle ownership, % of commuters, daily average police incidents *Travel:* TNC pickups/drop-offs, total daily public transit ridership & stops.	• TNC use and transit ridership are positively correlated in parts of SF • A positive relationship between TNCs and public transit ridership in the choice riders' neighbourhoods is prominent in the southeaster census tracts of the San Francisco.
Young et al. (2020)	• Toronto, Canada • In 2016, two years after the widespread adoption of ride hailing services • 2016 Transportation Tomorrow Survey • OLS and ordered logistic regressions	*Socio-economic:* Age, income, gender, driver's license, vehicle ownership; *Travel:* Transit pass, trip's start time, purpose, location, duration, in-vehicle/wait/walk times (PT+RH)	• TNCs competes more with PT when time saving from TNCs is <15 min • TNC trip location, timing, purpose, and the features of the fastest transit alternative matter more than individual characteristics

Clark et al. (2021)	• Cities in Lane County, Oregon • January and December (2012–2017) • Lane Transit District • Negative binomial regression	*Travel:* total number of bus passengers at a given stop, time, & date; dummy variables to capture Uber's availability in the cities of Lane County (before, during & after)	• Uber's penetration in the treatment cities (Eugene and Springfield) reduced bus transit ridership by 5.4% compared to the control cities of Lane County. Even after Uber left the cities, the reduction still persisted.
Diao et al. (2021)	• All U.S. metropolitan statistical areas where Uber and/or Lyft operated in 2016 • 2005 to 2016 • National Transit Database, Federal Highway Administration, Bureau of Economic Analysis, ACS • Fixed effect panel & IV regression, 2SLS	*Socio-economic:* household vehicle ownership, GDP, population, median household income and unemployment rate; *Travel:* Travel time index (TTI) & congested hours (CH), monthly transit ridership	• TNCs reduced monthly public transit ridership by 8.9% in the 174 MSAs • TNCs increased congestion in terms of travel time index by 0.9% and congested hours by 4.5% • TNCs has an insignificant influence in vehicle ownership
Ward et al. (2021)	• Urban areas of the U.S. • 2010 to 2017 • Polk/his Markit, U.S. Census Bureau • Difference-in-difference propensity score-weighted regression	*Socio-economic:* ZIP code-level population, income, unemployment 7 childless households' rates; *Travel:* annual individual vehicle registration, transit commuters, gasoline price.	• TNCs impact on transit use is heterogeneous among different urban areas. • Urban areas with higher income and childless households tend to experience larger decrease in transit ridership
Erhardt et al. (2022)	• San Francisco (SF), CA, U.S. • 2010 to 2015 • Automated Passenger Counters (APC) & Automated Vehicle Location (AVL) of SFMTA, ACS, Metropolitan Transportation Commission, GTFS, SFCTA, TNC API data-scraping • Fixed-effect panel regression	*Socio-economic:* number of households, people, workers; income *Travel:* bus & transit ridership, # of bus/rail routes/stops, vehicles service mile, average speed, on-time performance, fare, gasoline price, TNCs pick-ups & drop offs	• TNCs caused 10% drop in bus ridership in SF despite transit service expansions. • Locations with more TNC pick-ups and drop-offs experienced more decrease in bus ridership

After motivating my choice of explanatory and control variables, I describe propensity score matching (PSM), which I relied on to carry out my analyses.

3.3.1 Conceptual Framework

To tease out the impact of a new mode on travel (in this case, the emergence of TNCs), it is necessary to understand how people would have acted if that mode had not been available in the first place. Traditional cross-sectional approaches (such as χ^2 tests or regressions) would provide biased estimates when analyzing causal inferences in this context because they fail to remove the self-selection bias (Angrist and Pischke, 2008; Shi et al., 2021). Observed effects may therefore arise from impacts other than the treatment (Lanza et al., 2013). Since experimental methods (such as the random assignment technique, which is common in medicine Heinrich et al., 2010) are impossible in this context, I relied on a quasi-experimental alternative: Propensity Score Matching (PSM) (Angrist and Pischke, 2008; Rosenbaum and Rubin, 1983).

PSM has gained in popularity in transportation recently (e.g., see Dai et al., 2020; Nasri et al., 2020; Park et al., 2018; Shi et al., 2021; Wetwitoo & Kato, 2019) partly thanks to advances in computing power (Heinrich et al., 2010), but mostly because of its relative simplicity when dealing with multidimensional covariates (Angrist and Pischke, 2008), and its reliance on fewer assumptions than alternative approaches (Nasri et al., 2020). Moreover, with finite samples, PSM provides more precise estimates (Angrist and Pischke, 2008) and it is more efficient than the Heckman selection model or Difference-in-Difference (Angrist and Pischke, 2008; Dehejia and Wahba, 1999; Li, 2013; Nasri et al., 2020; Wetwitoo and Kato, 2019). Although Heckman's (1979) selection model can reconstruct counterfactuals using observational data, it deals with the probability of treatment assignment indirectly using instrumental variables whereas PSM directly adjusts the covariates between the control and treatment groups (Li, 2013).

To obtain an unbiased estimate of the impact of a "treatment" (here, the availability of TNCs), PSM matches a sample that has been subjected to that "treatment" with a control group constructed to have very similar characteristics that has not received “the treatment”. The matching is done based on characteristics known to influence the outcome of the treatment to remove any self-selection bias (Heinrich et al., 2010). PSM is thus similar in spirit to evaluating the impact of a treatment (here, the effect is various travel attributes such as the number of household trips or daily household VMT) on a set of twins (here pairs of identical households), where for each pair one received the treatment and the other did not (and is, therefore, in the control group). Averaging differences in the outcome between the treatment and the control groups then gives an unbiased estimate of the impact of the treatment (Heinrich et al., 2010). Here, I explored the impact of TNCs on transit use both in the U.S. and in California. Figure 3.1 shows my conceptual framework.

To apply PSM to assess the impact of TNCs on household transit use, I need to create treatment and control groups. These groups are defined by variables (“control variables”) that are known to impact household travel. Here, my treatment group comes from 2017 NHTS households who had access to both TNCs and transit, and my control group was selected using PSM from households who participated in the 2009 NHTS and had access to transit. Control group households did not have access to TNCs since Uber officially launched in May of 2010 (Blystone, 2021).

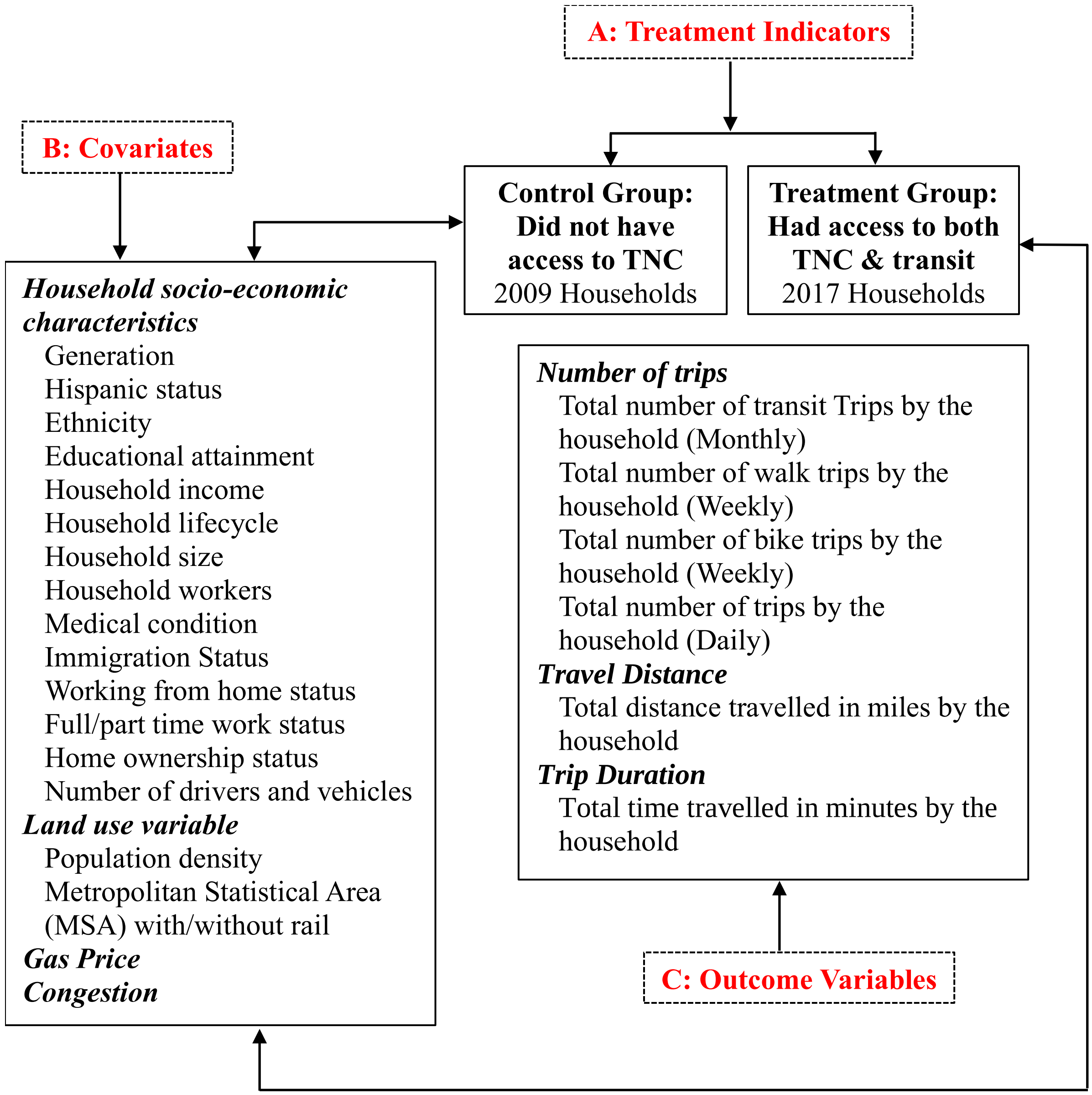


Figure 3. 1 Conceptual framework of TNCs impact on transit

To create my control and treatment groups, I relied on four types of covariates, which were selected based on my literature review: household socio-economic characteristics, land use variables, gasoline price, and road congestion. They are discussed below.

My outcome variables, which characterize monthly household travel, include the number of transit trips, the number of walk/bike trips, total distance traveled, and total travel time.

3.3.2 Modelling approach

There are two steps for applying PSM: in the first step I used a matching method to obtain my control group from a treatment group. In the second step, I estimate the impact of the treatment on an outcome variable.

Matching Method

A naive way of matching participants from the control and treatment groups would be to directly consider observed covariates. However, this process quickly becomes complex with multiple covariates (Heinrich et al., 2010). Instead, PSM matches based on the probability (also called the propensity score) of being treated (having access to both TNC and transit) among potential control households (Heinrich et al., 2010). In this study, first, I calculated the propensity score (probability) of all observations using a simple logit model where the dependent variable D equals 1 for the treated (the 2017 households who had access to both TNC & transit), and 0 otherwise for the untreated, i.e., the 2009 households who had access to only transit. Next, I used a "one to one matching with replacement" algorithm to match households in the control and treatment groups (Heinrich et al., 2010).

One to one matching can take two forms: with replacement or without. The former first creates a pair where a treated household is compared to a control household which is similar based on its propensity score, but the control household can only be used only once for matching. However, matching without replacement can perform poorly if the overlapping area of the propensity scores is small between the control and treatment group (Dehejia and Wahba, 2002). Therefore, the most common way to match is with replacement (Dehejia and Wahba, 2002).

Estimating impacts

There are several ways to estimate the coefficients of the outcome variables. I used the Average Treatment Effect (ATE), which calculates the difference in mean value between control and treatment households. A precondition for applying this technique is that the matched group should be statistically equivalent to the treated group (Heinrich et al., 2010).

Let Δ_i if the effect of the treatment for household *i*. It is defined by the difference between the potential outcomes in presence (Y_{1i}) and absence (Y_{0i}) of the treatment (availability of TNCs). It can be written:

$$\Delta = Y_{1i} - Y_0 \tag{1}$$

I can capture the treatment effect in three ways: Average Treatment Effect (ATE), Average Treatment Effect on the Treated (ATT) and Average Treatment Effect on the Untreated (ATU). ATE is the difference in mean outcomes between the treatment and control group whereas ATT and ATU measure the impact of the treatment (availability of TNCs) on those assigned to the treatment group, and what the intervention would have been on those who did not have access to the intervention (Angrist and Pischke, 2008; Heinrich et al., 2010). In this study I useATT which measures the impact of the treatment (availability of TNCs) on various household travel outcomes:

$$ATT = E(Y_1 \mid D=1) - E(Y_0 \mid D=1) \tag{2}$$

Here, E(.) is the expected value operator, and $E(Y_0|D=1)$ is the expected outcome that treatment group households would have obtained in absence of treatment. This is not observed but I do observe the term $E(Y_1|D=1)$ which is the value of Y_0 for the control group households. Therefore, I can write:

$$\Delta = E(Y_1 \mid D=1) - E(Y_0 \mid D=0) \tag{3}$$

Now to calculate the difference between Δ and the ATT, I add and deduct $E(Y_0|D=1)$ term from both sides of Equation 3:

$$\begin{aligned} &\Delta = E(Y_1 \mid D=1) - E(Y_0 \mid D=1) + E(Y_0 \mid D=1) - E(Y_0 \mid D=0) \\ &\text{or, } \Delta = ATT + E(Y_0 \mid D=1) - E(Y_0 \mid D=0) \end{aligned} \tag{4}$$

In Equation 4, $E(Y_0 \mid D=1) - E(Y_0 \mid D=0)$ is the selection bias, which means the difference between the counterfactual for treated households and the observed outcome for the untreated households. If there is no selection bias, i.e., if this term is equal to 0, then ATT can be estimated by the difference between the mean observed outcomes for treatment and control group households:

$$ATE = E(Y_1 \mid D=1) - E(Y_0 \mid D=0) \tag{5}$$

PSM requires the Conditional Independence Assumption (CIA) which asserts that after controlling for covariates (control variables), the treatment assignment is “as good as random” (Angrist and Pischke, 2008; Heinrich et al., 2010). CIA ensures that I accounted for the differences between control and treatment groups to reduce the selection bias and, consequently, addressed the correct impact of the treatment (Angrist and Pischke, 2008; Heinrich et al., 2010).

3.4. Data

3.4.1 The 2009 and 2017 NHTS

The 2009 NHTS collected socio-economic and travel data from 150,147 households using the random digit dial (RDD) telephone sampling method and the Computer-Assisted Telephone Interview (CATI) approach to retrieve data (Federal Highway Administration, 2011).

The 2017 NHTS collected data from 129,969 households. Unlike the 2009 NHTS, it relied on address-based sampling with mail-back as the primary response mode and phone/web as the secondary response (Federal Highway Administration, 2018).

Both of these surveys were conducted in two phases: a household recruitment survey and a person-level retrieval survey (Federal Highway Administration, 2011, 2018). The resulting datasets of both surveys are organized into four files: person, household, vehicle, and trip files (Federal Highway Administration, 2011, 2018). I used information from all these files to create my dependent and explanatory variables.

3.4.2 Covariates (Control Variables)

Socio-Economic Characteristics

I selected the covariates used to match households in the control and treatment groups based on my literature review and the variables available in both NHTS datasets. I gathered the following information from the person file: age, educational attainment, race/ethnicity, working status (from home, full-time, or part-time), medical condition, and born abroad status. After aggregating this information to the household level, I combined it with household Hispanic status, income, lifecycle variables, number of household members and workers, home ownership, and number of household drivers and vehicles from the household file.

A number of studies have considered generations instead of age for explaining household travel preferences (Alemi et al., 2018; Circella & Alemi, 2017; McDonald, 2015). I therefore relied on definitions from the PEW Research (2018) to create the following generation variables: 1) Generation Y (Millennials), for people born between 1981 and 1996, who therefore were between 21 and 36 years old in 2017. For the 2009 NHTS, I considered people born between 1981 and 1993, so that in 2009, their age would be between 16 and 28 years. 2) Generation X, which captures people born between 1965 and 1980; 3) Baby Boomers, for people born between 1946 and 1964; and 4) The Silent Generation, for people born before 1946. These are included as binary variables in my models. I excluded Generation Z from my sample because, even though I could get adults (aged between 16 to 20 years old) from the 2017 NHTS, for 2009 database, this group of people were still children in 2009.

Ethnicity and Hispanic status may matter for selecting a mode (Buehler and Hamre, 2015; Clark, 2017). Based on the frequency of responses in the 2009 and 2017 NHTS, I defined four binary ethnicity variables: "White," "African American," "Asian," and "Mixed". In my dataset, an ethnicity variable equals one for a household if that household identifies as belonging to that ethnicity, and zero otherwise. The "mixed" category captures the remaining households. Hispanic status was defined similarly.

The literature also suggests that household educational attainment plays a pivotal role in daily mode choice (Alemi et al., 2018; Buehler & Hamre, 2015; Circella et al., 2017; Clark, 2017; McDonald, 2015). To capture the level of education of a household, I extracted the maximum level of education among household members. Following the classification used in both NHTS, I created four binary variables: GED or less (to have enough observations for this category, I merged “less than high school” with “high school degree”), some college or associate degree, BS/BA, and graduate or professional degree.

My model also includes common household variables such as annual household income and family structure, household size, number of workers, home and vehicle ownership, which have been found to matter for explaining household travel preferences (Alemi et al., 2018; Buehler & Hamre, 2015; H. M. Clark, 2017; McDonald, 2015).

To capture annual household income, I collapsed eighteen categories in the 2009 NHTS, and eleven 2017 NHTS into five quintile (20% strata) binary variables.

I created six binary variables to capture the impact of household structure on the use of transit or TNCs: one adult with no children, two or more adults with no children, one adult with some children, two or more adults with some children, one retiree with no children, and two or more retirees without children (my baseline here). Because of collinearity with the household structure variables, my models do not include a variable for the number of household members.

I created two binary variables for the number of the workers (households with zero, and >=1 workers), and a binary variable to code home ownership status. As the decision to take transit or a TNC should not depend directly on the number of household vehicles or on the number of driver’s license holders, but rather on whether a household has more drivers than vehicles, I created a binary variable that equals 1 if a household has more drivers than vehicles and 0 otherwise. Finally, I included binary variables for working from home, working fulltime or part time, the presence of a medical condition that impairs mobility, and born abroad.

Land Use

Land use also influences mode choice (Alemi et al., 2017, 2018; Buehler & Hamre, 2015). Neither the 2009 NHTS nor the 2017 NHTS provide location information for their respondents, but they include a few land use variables.

First, I used the population density (persons/sq. mile) of the census tract of the household home location. I created four binary variables by taking quartiles (25% strata) for both 2009 and 2017 NHTS. For California, instead of four, I created three categories as I do not have enough observations.

To understand how the emergence of TNCs may have impacted the patronage of different forms of transit, I created three binary variables to capture the availability of bus, light rail, and heavy rail services for the households located in a core-based statistical area (CBSA). A CBSA is a smaller geographic unit than Metropolitan Statistical Area (MSA), with at least 10,000 people and an urban center. The 2009 and 2017 NHTS report information about 52 and 53 CBSAs, respectively. For each, I gathered information about the availability of bus, light rail, and heavy rail transit from the APTA. I then added this information to my dataset in the form of binary variables.

Gasoline Price

Several papers have shown that gasoline prices can substantially impact mode choice (Iseki & Ali, 2015; Taylor et al., 2003). NHTS captured gasoline prices in the trip file. As I analyze data from two different NHTS datasets, I created binary variables for the quintiles of gas prices for each corresponding year as a simple way to normalize gasoline prices.

Congestion

TNCs usually competes with transit in congested urban areas where travelers have the choice between alternative travel options, so I added a variable to control for congestion in my model. The Urban Mobility Report, published by the Texas A&M Transportation Institute (TTI), records a wide range of traffic condition related data for 494 urban areas across the United States. As my congestion variable, I used the total annual hours of delay per auto commuter for each of 2009 and 2017. There are 101 records for 2009 and 494 records for 2017. I also extracted the population of these 595 urban areas from this report and normalized it using quintiles for both 2009 and 2017. As both the 2009 and the 2017 NHTS reports categorical values for MSA size, I created similar categories for the population extracted from the Urban Mobility Report (population less than 250,000; 250,000 to 499,999; 500,000 - 999,999; 1,000,000 - 2,999,999 and 3,000,000 or more). Unfortunately, the Urban Mobility Report does not provide data for non-MSA areas, so I assumed that households who reside in those areas experience low congestion and allocated them in the first quintiles for both 2009 and 2017. I could not use this variable for California because there were not enough data to create these categories.

Table 3.2 provides summary statistics of the 2009 and 2017 households, respectively for both the U.S. and CA.

Table 3. 2 Descriptive Statistics

Variables	**U.S.** Control group: (N = 66,139)	Treatment group: (N = 19,861)	**California** Control group: (N = 14,334)	Treatment group: (N = 6,204)
Household socio-demographic and economic attributes				
Generation				
At least one adult from Generation Y	11.82%	24.88%	14.46%	23.29%
At least one adult from Generation X	24.80%	27.33%	27.09%	28.56%
At least one adult is a Baby Boomers	50.19%	42.60%	53.11%	42.91%
At least one adult is from the Silent Generation	35.56%	11.76%	34.10%	12.04%
Household Hispanic Status (Hispanic =1)	8.54%	6.86%	14.65%	9.24%
Household ethnicity				
All household members are WhiteWhite	85.34%	84.40%	78.05%	80.59%
All household members are African American	5.88%	5.85%	3.63%	2.72%
All household members are Asian	2.69%	4.55%	6.68%	8.40%
All household members are of mixed ethnicity	6.09%	5.21%	11.64%	8.28%
Household educational attainment				
Less than high school or high school degree	22.77%	8.57%	17.41%	5.87%
Some college or associated degree	28.12%	23.74%	29.71%	23.82%
Undergraduate degree	25.80%	31.77%	26.88%	32.08%
Graduate or professional degree	23.31%	35.92%	26.00%	38.23%
Household annual income				
First Quintile	14.93%	28.60%	12.87%	23.65%
Second Quintile	19.54%	18.19%	14.62%	15.97%
Third Quintile	22.97%	14.83%	18.71%	28.68%
Fourth Quintile	17.87%	20.36%	22.57%	18.54%
Fifth quintile	24.69%	18.03%	31.23%	13.17%
Household structure				
One adult, no children	8.42%	17.84%	8.68%	16.47%
Two or more adults, no children	22.94%	26.41%	22.05%	26.87%
One adult, some children	2.41%	3.28%	2.79%	3.05%
Two or more adults, some children	30.49%	22.04%	33.05%	22.02%
One retired adult, no children	8.24%	8.76%	8.27%	8.46%
Two or more retired adults, no children	27.49%	21.67%	25.16%	23.13%

Household workers				
No worker	28.30%	23.81%	27.40%	23.68%
At least one worker	71.70%	76.19%	72.60%	76.32%
Household home ownership (Yes=1)	88.89%	73.44%	82.83%	70.23%
Household has fewer vehicles than driver	10.18%	8.77%	8.85%	8.91%
At least one member worked from home	7.84%	11.63%	9.36%	13.39%
Work full time/part time				
At least one adult works Full time	57.20%	55.64%	59.49%	53.11%
At least one adult works Part time	18.81%	15.48%	21.51%	16.94%
At least one member has medical condition	14.52%	6.22%	15.18%	6.72%
At least one adult was not born in the U.S.	13.92%	10.72%	23.55%	15.67%
Land use				
Population density (persons/sq. mile) of the census tract				
First Quartile	32.16%	31.18%	42.10%	40.55%
Second Quartile	35.96%	25.42%	42.35%	41.68%
Third Quartile	25.97%	33.45%	15.55%	17.76%
Fourth Quartile	5.91%	9.95%	NA	NA
Availability of transit services				
Household in a CBSA with bus service (Yes=1)	51.60%	50.36%	79.85%	64.20%
Household in a CBSA with light rail service (Yes=1)	27.53%	42.50%	50.18%	61.33%
Household in a CBSA with heavy rail service (Yes=1)	12.30%	19.03%	11.14%	28.34%
Gasoline price (in cents per gallon)				
First Quintile	18.96%	20.83%	18.40%	20.23%
Second Quintile	19.86%	18.51%	18.03%	15.49%
Third Quintile	20.81%	18.01%	17.42%	22.89%
Fourth Quintile	18.36%	19.67%	18.53%	13.31%
Fifth quintile	18.80%	21.26%	15.00%	16.76%
Congestion (total annual hours of delay per auto commuter)				
First Quintile	26.58%	11.42%	NA	NA
Second Quintile	6.51%	10.25%	NA	NA
Third Quintile	12.06%	3.22%	NA	NA
Fourth Quintile	13.53%	10.97%	NA	NA
Fifth quintile	41.32%	64.15%	NA	NA

Notes: All variables summarized in this table are binary, so values displayed represent percentages.

3.4.3 Treatment indicators

I created two groups of households for the PSM: 1) a control group: households from the 2009 NHTS who had access to transit (but not to TNCs since TNCs were not available in 2009) and 2) a treatment group: households from the 2017 NHTS who had access to both TNCs and transit. My data process followed three steps:

- *Step 1:* First, I created two datasets for the year 2009 and 2017 that consists of socio-economic, trip data, and gasoline price information,
- *Step 2:* Second, I appended the 2009 and 2017 data where households from 2009 serve as a control group, and
- Step 3: Third, I merged the congestion variable (annual hours of delay per auto commuter) with the data from Step two.

Step 1: Extract socio-economic, trip, and gasoline price information

I first extracted socio-economic and land use date from the 308,901 observations in the 2009 NHTS person file. After collapsing these observations to the household level, I had data on 94,843 households. Next, I gathered trip distance, trip duration, and gas price information from the trip file and collapsed these variables by household. I merged these variables with socio-economic variables, which gave me a control group of 79,059 households for 2009.

To select my treatment group from the 2017 NHTS, I extracted respondents who stated that they have access to transit and rideshare services if their motor vehicles are unavailable. This question was targeted at people over 16 years old, who have a driver's license and access to at least one vehicle. After collapsing these 30,905 observations to the household level, I obtained a sample of 24,220 households. I then extracted trip data (distance, duration, and gas price) from the trip file, collapsed these attributes to the household level, and merged those data with the socio-economic variables. This gave me a treatment group of 21,453 households.

Step 2: Appending 2009 and 2017 data

In my second step, I appended 2009 and 2017 database and created a binary variable that segregated the control group households (value 0) from the treatment group households (value 1). At this stage, my sample size is 100,512 households.

Step 3: Merging with congestion variable

In Step 3, I added the congestion variable (annual hours of delay per auto commuter) to data from Step 2. I lost many observations due to the unavailability of congestion data from non-MSA areas, leaving me with a final sample of 86,000 households, where 66,139 (43,389 for weekdays and 22,750 for weekends) are from the 2009 NHTS (control group) and 19,861 (13,823 for weekdays and 6,038 for weekends) are from the 2017 NHTS (treatment group).

For California, I followed the same process, which gave me a final sample of 20,538 households (14,334 for 2009, and 6,204 for 2017).

3.4.4 Outcome variables (trip related attributes)

My study purpose is to understand TNCs' impact on transit use, to be more specific, how household travel behavior has changed between years 2009 and 2017 due to the intervention of TNC. I captured these changes with three outcome variables:

- *Number of trips.* I considered three travel modes, 1) transit (monthly total number of transit trips), 2) walk (weekly total number of walk trips), and 3) bike (weekly total number of bike trips).
- *Travel distance*: total distance traveled in miles
- *Travel duration*: total travel duration in minutes

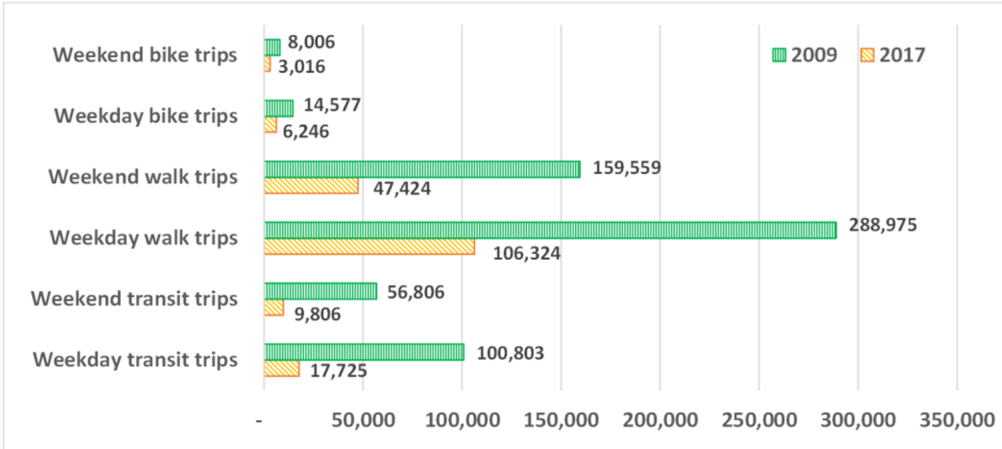
Household travel and mode preferences may change on weekends compared to weekdays. I developed separate models to capture these differences. Figure 3.2 (a-c) and Figure 3.3 (a-c) represent the distribution of these variables.

3.5 Results and Discussion

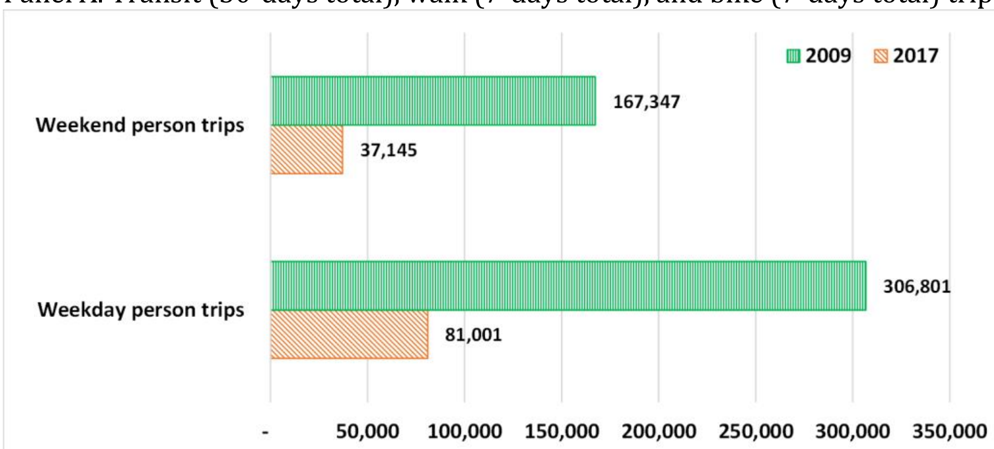
My results were estimated using Stata 17. Multicollinearity is not an issue here as the maximum VIF is 4.87 (3.28 for California).

3.5.1 Balancing test

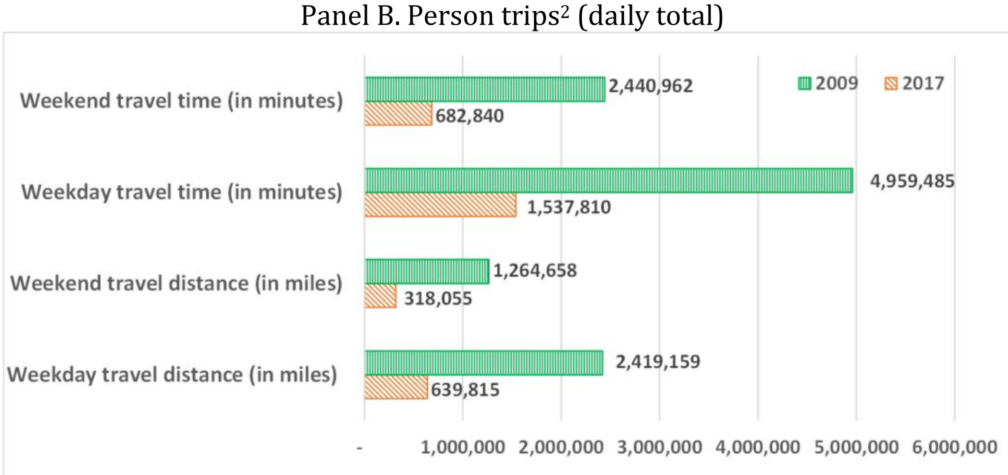
In an experimental design, randomization deals with self-selection so that observations between the treated and control groups are balanced and on average a difference in outcome comes from the treatment. For non-experimental data, however, treatment indicators (control and treatment groups) may vary based on the values of the control



Panel A. Transit (30-days total), walk (7-days total), and bike (7-days total) trips



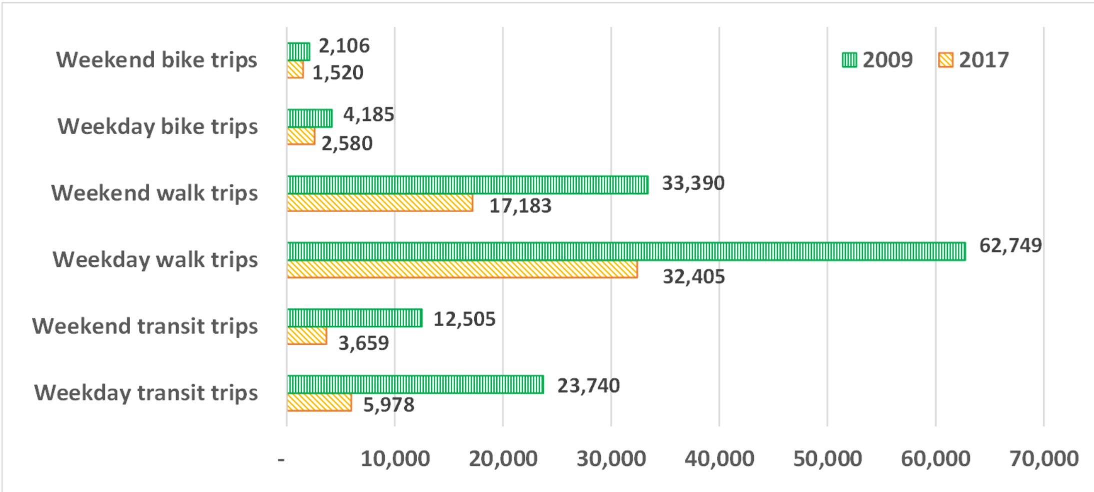
Panel B. Person trips[2] (daily total)



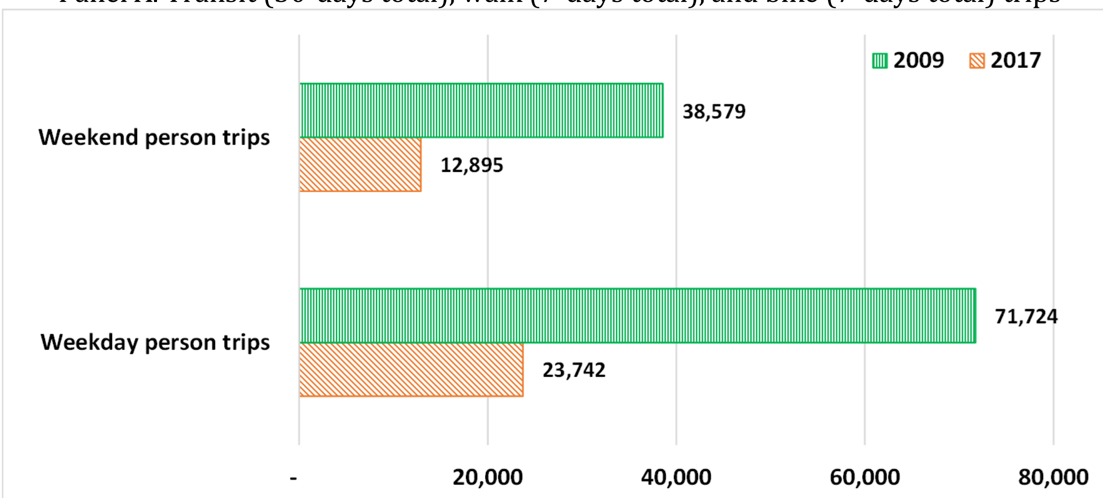
Panel C Distance traveled (daily total in miles) and time traveled (daily total in minutes)

Figure 3. 2 Distribution of U.S. households trip-related attributes in 2009 and 2017

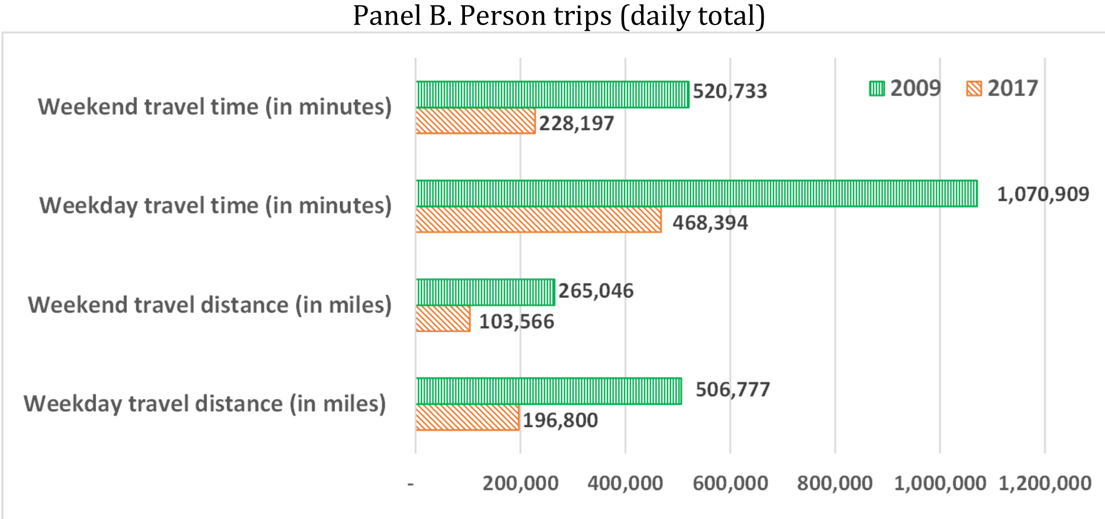
[2] A person trip is a trip from one address to another by one person using any mode of transportation (2017 NHTS).



Panel A. Transit (30-days total), walk (7-days total), and bike (7-days total) trips



Panel B. Person trips (daily total)



Panel C. Distance traveled (daily total in mi) and time traveled (daily total in min)

Figure 3. 3 Distribution of California households trip related attributes in 2009 and 2017

covariates (Heinrich et al., 2010). Therefore, I need to check that the conditional independence assumption (CIA) of PSM holds.

To check the CIA, I used the psmatch2 command of Stata 15. Results for the U.S. show that, after matching, the mean bias values are 3.7% for weekdays, and 4% for weekends. A range under 10% indicates that the CIA assumption is verified (Caliendo and Kopeinig, 2005). For California, the mean bias values are also below 10%, so the CIA assumption is verified: 3.6% for weekdays, and 5.5% for weekends.

3.5.2 Impact of TNC on household travel in the U.S.

To facilitate the discussion of my results, I present my estimates with the same time unit, i.e., the number of trips per day per household. Results are presented in Table 3.3, where control group households who did not have access to TNC in 2009 serve as the baseline. I also present the percentage change of the outcome variables with respect to 2009 households in the same table.

Let me now discuss individual parameters. Table 3.3 shows that for weekdays, compared to control group households (from the 2009 NHTS), households who had access to TNC (from the 2017 NHTS), made ~22% fewer transit trips per day (~1.6 fewer trips per day per household). Similarly for weekends, household trips decreased by 15% (~1.5 fewer trips per day per household). This is one of the main findings of this study.

While households reduced their transit trips in 2017, they made more weekly walk and bike trips. Household weekdays walk trips increased by 5.4%, with a higher increase (10.4%) for bike trips. It is also interesting to observe that households made fewer person trips per day in 2017 compared to 2009, with a larger decline for weekdays (-2.1%).

Table 3. 3 Treatment Effect Results for the U.S.

	Number of obs.	Transit Trips	Walk Trips	Bike Trips	Person Trips	Distance traveled (miles)	Time traveled (minutes)
U.S. and weekdays	13,823	-1.59*** (-21.8%)	1.13*** (5.4%)	0.11*** (10.4%)	-0.47*** (-2.1%)	-6.53*** (-3.7%)	4.70** (1.3%)
U.S. and weekends	6,038	-1.43*** (-15.2%)	1.53*** (5.8%)	0.17*** (12.8%)	-0.36*** (-1.3%)	•	15.94*** (3.9%)

Notes:
1) My control group households are the households from the 2009 NHTS who did not have access to TNCs, and it serves as the baseline. The coefficient values in the table associated with households from the 2017 NHTS who had access to both TNCs and transit. For example, the underlined value in the table represents that compared to 2009, households in 2017 made fewer transit trips and it was reduced by 1.59 trips per day per household.
2) The values in the bracket represent percentage change of the outcome variables with respect to control group households from the 2009 NHTS.
3) Insignificant coefficients are replaced by "•".
4) ****, **, and * indicate p-values < 0.01, < 0.05, and < 0.1, respectively.

Households in 2017 traveled fewer miles on weekdays compared to 2009 when TNCs were not available. One possible explanation could be associated with my findings of households making fewer transit trips on weekdays. People travel a longer distance through transit for several reasons; first, transit routes are usually fixed, so they are unlikely to provide the shortest route between origins and destinations. Another reason is a switch from transit to TNCs on weekdays (-1.59***) in 2017, which means more point-to-point travel. Even though these findings suggest that households traveled fewer miles and made fewer transit and person trips in 2017, household total travel duration increased in 2017. One possible explanation could be an increase in congestion during the last decades in the U.S. reflected by the increase in annual delay per auto commuter between 2009 and 2017 for four types of urban areas in the U.S. (Figure 3.4). The increase in travel time is higher on weekends, possibly because people are traveling longer for recreational purposes.

3.5.3 Impact of TNC on household travel in California

Table 3.4 shows results for California, treatment effect estimates, and percentage changes with respect to 2009 households. Results for California are similar to those for the U.S., which means that in California, households are making fewer transit trips in 2017 due to the availability of TNC compared to 2009.

Interestingly, for weekdays, California lost more transit riders to Uber and Lyft than the U.S. as whole: -44% for California versus -22% for the U.S. (daily around 2.5 trips for each household in California versus 1.6 trips in the U.S.). This decline is comparatively higher on positive coefficient values for walk trips are higher for weekends in California. As for the U.S. results, California households had more bike trips in 2017 compared to 2009. I also found that weekdays. The total number of person trips in California decreased on weekdays and on weekends. Travel duration values tell a different story: Californians spent more time on the road in 2017 than in 2009. Again, these coefficient values are higher for weekdays.

3.6 Conclusions

In this chapter, I analyzed the impact of TNCs on household transit use. After extracting household data from the 2009 and 2017 National Household Travel Survey (NHTS), I

Figure 3. 4 Box plots of annual delay per auto commuter for years 2009 and 2017

Source: Urban Mobility Report, 2009 and 2017

Table 3. 4 Treatment Effect Results for CA

	Number of obs.	Transit Trips	Walk Trips	Bike Trips	Person Trips	Distance traveled (miles)	Time traveled (minutes)
CA and weekdays	4,077	-2.54** (-43.6%)	0.94* (6.1%)	•	-0.98*** (-5.6%)	•	14.48*** (5.5%)
CA and weekends	2,127	-1.59*** (-27%)	2.04*** (13%)	0.31*** (31%)	-1.09*** (-6%)	•	•

Notes:
1) My control group households are the households from the 2009 NHTS who did not have access to TNCs, and it serves as the baseline. The coefficient values in the table associated with households from the 2017 NHTS who had access to both TNCs and transit. For example, the underlined value in the table represents that compared to 2009, households in 2017 made fewer transit trips and it was reduced by 2.54 trips per day per household.
2) The values in the bracket represent percentage change of the outcome variables with respect to control group households from the 2009 NHTS.
3) Insignificant coefficients are replaced by “•".
4) ****, **, and * indicate p-values < 0.01, < 0.05, and < 0.1, respectively.

applied propensity score matching, a quasi-experimental method, to isolate the impact on household travel of a "treatment" (here, the availability of TNCs) while controlling for variables known to affect travel behavior. My treatment and control groups are matched households from the 2017 and 2009 NHTS, respectively. My findings suggest the emergence of TNCs in the U.S. decreased household transit trips so that on an average weekday, households in 2017 made 22% fewer transit trips (1.6 fewer daily transit trips) compared to 2009. This drop is steeper in California with 2.54 fewer daily trips per household (a 44% decrease). A silver lining, however, is that as transit was losing ridership to TNCs, walking and biking increased in the U.S., by 5.4% on weekdays and 10.4% on weekends. This increase was even higher in California.

Several transit systems have been contracting with TNCs to solve the "first and last mile problem" by subsidizing them to make public transportation more attractive. However, these policies may create unsurmountable financial burdens over time if not carefully implemented. Except in cases where continuing transit service cannot be justified, these policies may be risky for transit. Most importantly, if as indicated in Schaller (2018) , TNCs contribute to VMT and to urban congestion, policies and/or regulations are needed to both improve transit and curb the growth of TNCs in order to foster urban sustainability.

My study is not without limitations. Studies of the decline of transit in the U.S. pointed out that other than negative impact from outside (for example, TNCs in this case), transit's internal service effectiveness plays a vital role in determining its success. Transit supply variables, convenience and safety to riders are some of the vital factors. Deteriorating condition of these factors might decline transit ridership. For example, in recent years, Washington DC and New York city have lost transit ridership due to operational deficiencies and safety issues (Malalgoda and Lim, 2019). Modeling these issues is beyond the scope of this study but I acknowledge that customers perceptions of transit service attributes (e.g., service reliability, safety, or comfort of the transit infrastructure) play an important role in patronage (Wan, Kamga, Liu, et al., 2016) . Unfortunately, these data were not readily available in the NHTS, another limitation of this chapter.

Future work could capture the effect of transit supply variables with more fine-tuned data on transit ridership. It would also be of interest to consider capturing the impact of transit supply side factors, for example employment size, bus schedules, fleet size. Publicly available data for these variables are at a more aggregate level, such as at the

Metropolitan Statistical level (MSA). Another area of interest would be to explore the geographical impact of TNCs on transit depending on population density. Finally, I suggest exploring how the travel behavior of households without cars differs from the travel of motorized households in the presence of TNCs.

3.7 Acknowledgements

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CHAPTER 4: COVID-19, MODE CHANGES, AND TRANSIT PERCEPTION RESULTS FROM A RANDOM SURVEY OF CALIFORNIANS

4.1 Background and Motivation

COVID-19 has reshaped people's mobility patterns and their use of various transportation modes, both globally (Arellana et al., 2020; Park, J. 2020; Jenelius & Cebecauer, 2020; Orro et al., 2020) and in the U.S. (Liu et al., 2020; Brough et al., 2021; Ehsani et al., 2021; Hu et al., 2021; Hu & Chen, 2021; Kim & Kwan, 2021). Public transportation and transportation network companies (TNCs) have been hit particularly hard (Du & Rakha, 2020; Hu & Chen, 2021; Kim & Kwan, 2021). As transportation planners and transit operators start planning the after-pandemic, they may wonder if the pre-COVID-19 trends observed in California will continue, with transit losing ridership while TNCs recover and car use soars to new heights, adding to urban congestion and preventing California from reaching its greenhouse gas reduction target.

Transit in the United States has been especially hard hit by the pandemic. A June 2020 national survey of 2,011 adults shows that transit trips decreased by over 23% (Ehsani et al., 2021). Some areas were more affected than others. For instance, between mid-February and mid-May 2020, high-tech cities in the Bay Area and university cities such as Ithaca (NY), Ann Arbor (MI), and Madison (WI) experienced a steeper decline than cities in the South and the Midwest (Liu et al., 2020). In California, the impact of COVID-19 on transit has been brutal: San Francisco alone lost 94% of its transit ridership during the lockdown (Toussaint, 2020).

Several studies have quantified the impact of COVID-19 on public transit and TNCs (Du & Rakha, 2020; Islam, 2020; Liu et al., 2020; Brough et al., 2021; Ehsani et al., 2021; Hu & Chen, 2021; Kim & Kwan, 2021). Most of these predict that the pandemic will trigger a paradigm shift in travel behavior due to health concerns and a broader use of telecommuting (Morshed et al., 2021). However, except for Ehsani et al. (2021), who conducted a nationally representative survey of U.S. adults, and Conway et al. (2020), who relied on a convenience survey of U.S. households, none of these studies have explored the potential use of transit after the pandemic. Ehsani et al. (2021) relied on descriptive statistics to elicit U.S. adults' potential interest in transit, driving, and walking/biking, but they did not provide a socio-economic profile of mode users. Conway et al. (2020) were concerned with likely long-term behavioral changes in telecommuting, traveling, shopping, and meal deliveries in the U.S., but their sample is limited to highly educated American adults, and they did not conduct multivariate econometric modeling.

In this context, the purpose of this chapter is twofold. First, I explore how the COVID-19 pandemic will likely affect transit use (along with driving, walking/biking, and TNCs) in California after the pandemic is over, based on a random survey of Californians conducted for me by Ipsos (a global top 5 market research firm) in the second half of May 2021. Second, I examine Californians' perception of the obstacles that stand in the way of increasing transit use before and during the pandemic because listening to feedback from transit users is essential for transit agencies to stem the ridership decline and gain new users (Eboli & Mazzulla, 2011; Machado-León et al., 2016; Wan et al., 2016). To the best of my knowledge, my investigation is the first to inquire about Californians' willingness to take transit after the pandemic and to explore obstacles that need to be overcome for transit to recover.

In the next section, I review selected papers dealing with the impact of COVID-19 on transit use. I then present my data and motivate my modeling framework. After discussing my results, I summarize my findings, explore some policy implications, mention some limitations, and suggest some ideas for future work.

4.2 Literature review

4.2.1 COVID-19 and transit

Soon after the start of the COVID-19 pandemic, researchers started investigating its impact on transit (Islam, 2020; Liu et al., 2020; Brough et al., 2021; Ehsani et al., 2021; Hu & Chen, 2021; Qi et al., 2021).

Liu et al. (2020) analyzed mobility patterns in 113 U.S. counties (63 metro areas in 28 states) between mid-February and mid-May 2020. They reported that communities with higher proportions of essential workers, vulnerable populations, and more coronavirus Google searches maintained higher demand levels during COVID-19. High-tech cities in the San Francisco Bay Area and university towns lost more riders than transit systems in the Midwest. Moreover, cities with more jobs that do not require a physical presence, more young adults, and a higher percentage of Whites saw larger drops in transit use. Qi et al. (2021) also showed that more affluent metropolitan areas with more advanced degree holders, higher employment rates, and more Asians experienced steeper transit reductions than less affluent areas with a higher percentage of Hispanics.

Several studies investigated the decline of transit ridership in the U.S. at different spatial scales: county (Parker et al., 2021), census tract (Wilbur et al., 2020), block group (Brough et al., 2021), and transit station (Hu & Chen, 2021).

Parker et al. (2021) argued that the observed decline in transit at the county level is correlated with transit service changes, concerns with COVID-19 infections, and stay-at-home orders. After surveying 97 metropolitan and rural counties in 26 states, they found that, since the pandemic, 75% of transit riders were taking transit less frequently, although lower-income riders did not change their travel behavior much.

Wilbur et al. (2020) explored spatial and temporal variations in transit decline at the census tract level in Nashville County and the Chattanooga area. Their results show that, compared to January-February 2020, morning and evening peaks in May-June 2020 lost more riders due to stay-at-home orders and remote work options. This decline persisted even after lockdown restrictions were lifted, which suggests that alternative work arrangements impacted transit use. Moreover, high-income tracts lost up to 19% more riders than low-income tracts.

In King County, Washington, Brough et al. (2021) showed that between February and April 2020, when overall mobility declined by 57%, public transit use dropped by 74%. As in Tennessee, transit decline was steeper in areas with more highly educated and affluent residents.

At the station level, Hu & Chen (2021) found that COVID-19 impacted at least 95% of the stations in Chicago, Illinois, pulling down ridership by 72.4% on average. Moreover, areas with more Whites, more educated and more affluent households, and a larger percentage of commercial land use lost more riders. Conversely, areas with more land use dedicated to trade, transportation, and utilities experienced a smaller decline (Hu & Chen, 2021).

Table 4.A.1 summarizes selected transit-related studies. Although I found two studies that investigated perceptions and intentions about the future use of different modes (Conway et al., 2020; Ehsani et al., 2021), an investigation for California that analyzes a random sample using rigorous statistical modeling is still missing.

4.2.2 COVID-19 and other modes

Other modes were also affected. COVID-19 lockdowns resulted in a massive loss of riders and revenues for TNCs. In 2020, for example, Uber trips shrank by 27% compared to 2019, although UberEats revenues jumped 200% thanks to online food deliveries (Iqbal, 2021).

After conducting a comparative analysis between 2019 and 2020 (for a six-months interval: January to June), Du & Rakha (2020) found that in Chicago, UberPool trips dropped by almost 71% during early March 2020 and vanished by mid-March. They also reported that Uber's popularity for shorter trips decreased by 40%.

Loa et al. (2021) explored TNC passenger characteristics in the greater Toronto area during the pandemic. Their analysis of data collected via a web-based survey showed that 54% of frequent TNC users decreased their use while 17.7% increased it. Moreover, students and transit pass owners frequently used TNCs during the pandemic to avoid transit due to health concerns. In their conclusions, they emphasized the importance of attitudes (particularly risk-perception) toward ride-sourcing during unprecedented times.

Collaborative ventures between TNCs and transit agencies designed to serve first and last miles and senior citizens also collapsed during lockdowns (Pho, 2020). At the beginning of the Spring 2020 lockdown, Conway et al. (2020) found that 20% of highly educated U.S. adults expected to use transit and ride-hailing services less than before the pandemic.

While Americans reduced their driving during the lockdown (Ehsani et al., 2021), many walked and biked more (Doubleday et al., 2021). For instance, people in Houston and Seattle walked and biked more than people in New York during the lockdown (Doubleday et al., 2021). Fewer outbreaks and restrictions in Houston than in New York, and walk and bike-friendly trails in Seattle are the prime reasons for these differences among the three cities (Doubleday et al., 2021). More insights on the pandemic's impact on active transportation can be found in Conway et al. (2020), Kurkcu et al. (2020), Buehler & Pucher (2021), and Hu et al. (2021).

4.2.3 Perceptions of transit

It is well known that transit service attributes play a pivotal role in customer satisfaction. These attributes range from service reliability to the safety and comfort of transit infrastructure.

An investigation of 1,700 Bus Rapid Transit (BRT) riders in New York City showed that service frequency, vehicle speed, and on-time performance have a significant and positive impact on customer satisfaction (Wan et al., 2016). Other factors impacting customer satisfaction with BRT are the fare payment system, hours of operations, and how concerns are handled. Wu et al. (2018) also reported that the preferences of local bus users differ from those of BRT users. For the former, reliability, travel time, and personal safety at stops are critical.

Moreover, some passengers value more on-board performance, while others prefer good physical infrastructure when they wait for a bus or a train (Fan et al., 2016; Lagune-Reutler et al., 2016; Park et al., 2021). A user satisfaction survey in Minneapolis, MN, showed that transit stops with shelters, benches, and trees make waiting more acceptable (Fan et al., 2016). In Utah, a survey designed to explore the relationship between first- and last-mile experience with user satisfaction revealed that riders are concerned about traffic and crime safety at transit stops (Park et al., 2021). Moreover, improvements in out-of-vehicle environments such as safety and transfer experiences weigh more than improvements of in-vehicle factors.

Transit satisfaction can also be tied to geographical location and rider type. By spatially segmenting transit riders in the greater Hamilton area, Canada, Grisé & El-Geneidy (2018) showed that frequent transit riders who live in the proximity of a train station ("connected choice riders") are frustrated with station crowding during morning peak hours. Conversely, infrequent users - primarily students who live relatively far from the central station – would like more off-peak services and better internet connectivity (Grisé & El-Geneidy, 2018).

4.3 Data and methods

4.3.1 Survey

My data were collected during a survey of Californians conducted by Ipsos in late May 2021 for a study of how the COVID-19 pandemic affected the way Californians travel and buy food. The survey was administered to a random sample of California members of

KnowledgePanel© (KP), the largest (~60,000 members) and oldest probability-based online U.S. panel. KP is large enough that its California members are representative of the California population.

To overcome limitations from phone-based sampling (since most American households no longer have a landline; see Blumberg and Luke, 2018), KP members are recruited using address-based sampling based on the Delivery Sequence File of the U.S. Postal Service. Special efforts are made to include harder-to-reach populations, such as African Americans, Latinos, Veterans, Americans with disabilities, LGBTQ and non-binary people, rural residents, and non-internet and cellphone-only households. Ipsos provides new panel members who do not have internet access with a tablet and a mobile data plan (connecting them to the internet).

Conducting a survey with KnowledgePanel offers several advantages. First, it allows overcoming the self-selection bias of online surveys since respondents are chosen based on their characteristics, which are recorded when they enroll and updated annually. Second, participant fatigue is minimized because panelists take only two to three KP surveys per month on average. Third, surveying KP members helps address mode bias since all questions are asked online. Finally, it helps address non-response bias thanks to high (~70% on average) survey cooperation rates (ratios of the number of respondents to the number of KP members contacted).

Survey questionnaire was first written in English and tested on graduate students. It has two parts. Part I inquiries about commuting, telework, and travel before, during, and potentially after the COVID-19 pandemic. Part II explores how Californians shopped for groceries and prepared meals before and during the pandemic, and what they may do after.

A pilot study was fielded by Ipsos in May 2021 on 25 California members of KnowledgePanel. I modified my survey instrument based on their feedback. To include Californians who prefer communicating in Spanish, the survey was also translated into Spanish and pre-tested it with native speakers. Both versions of the survey were administered starting May 22, 2021. By the end of May 2021, data collection stopped with 1,026 respondents.

Figure 4.1 shows the location of the residential zip codes of the respondents to my survey. These locations overlap reasonably well with the distribution of Californians, with more respondents in large urban centers in northern, central, and southern California and fewer respondents in rural and less populated areas.

I also used the 2017 NHTS (National Household Travel Survey) to find out why Californians shied away from using transit before the pandemic. The 2017 NHTS, which was administered between April 2016 and April 2017, collected data from 129,969 households (Federal Highway Administration, 2018).

Accessibility to transit stops is essential for transit users. I therefore restricted my analyses to respondents in both surveys who live close to the transit stops. For my 2021

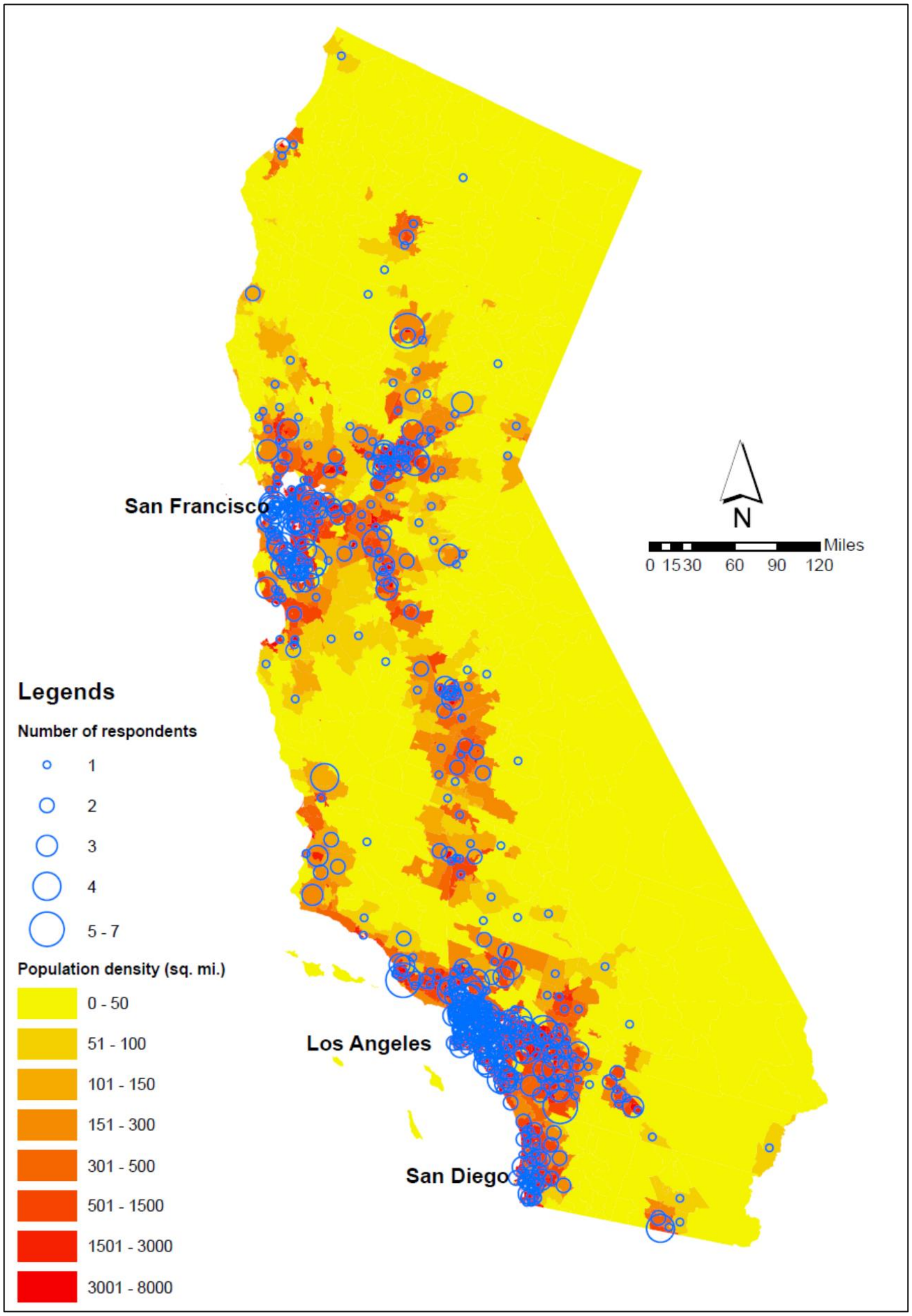


Figure 4. 1 Zip code location of respondents to the 2021 COVID-19 survey

COVID-19 survey, I kept only respondents whose ZIP code centroids are within 1000[3] m of a transit stop, which gave me a total of 575 observations. For the 2017 NHTS, I know the exact location of respondents' homes and workplaces, so I analyzed only respondents who live and work within 1000 m of a transit stop, which gave me a sample with 13,142 observations.

4.3.2 Dependent variables

Impact of COVID-19 on different travel modes in California

In this chapter, I analyze responses to the question "After the COVID-19 pandemic is over, how often do you think you will be using the following modes for any travel purpose compared to before the COVID-19 pandemic?" To answer this question, respondents had three options: 1) Less than before COVID-19; 2) Same as before COVID-19; and 3) More than before COVID-19. As explained below, I analyzed their answers using generalized ordered logit models.

Dependent variables for transit use reluctance in California

To understand how reasons for not taking transit may have changed due to the pandemic, I analyzed responses to the 2017 NHTS question (which was asked only to Californians 16 years or older): "What keeps you from taking transit (or taking transit more often) to your destination(s)? Please select the top three reasons."

To explore how much Californians may rely on transit once the pandemic is over, I also analyzed responses to the following question from my May 2021 Ipsos survey: "After

[3] Typical walking distance between home and the nearest stop is 0.5 mile (Durand et al., 2016). However, Durand et al. (2016) showed that, for Californians this distance could extend up to 2 to 3 miles. Therefore, I selected 1000 m as this standard provided me a reasonable sample size to analyze the GOL and BL results.

the COVID-19 pandemic is over and assuming pre-COVID-19 transit schedules and prices, what would prevent you from taking transit more (local buses, commuter trains, subway, trams, or ferries) for any travel purpose? Please rank your top three reasons (from 1=most important overall to 3=3rd most important)."

For my May 2021 Ipsos survey and the 2017 NHTS, I analyzed the top three reasons for not taking transit (more) using logit models (Train, 2009). For each reason, my dependent variable equals one if a respondent selected that reason in his/her top three, and 0 otherwise. For each model, I included a rich set of explanatory variables known to impact transit use (see below). In addition, I estimated logit models to understand which Californians have health or personal safety concerns about taking transit once the pandemic is over.

4.3.3 Explanatory variables

I selected my explanatory variables based on my literature review, and the available data. I divided my explanatory variables into four categories: individual-specific attributes, household-specific attributes, land use characteristics, and a COVID-19 severity variable.

Individual-specific attributes

I gathered the following information for each respondent in my sample: age, gender, race, Hispanic status, educational attainment, occupation, telecommuting patterns (for the May 2021 COVID-19 survey) and whether a respondent was born in the U.S. (only for the 2017 NHTS).

Many studies have considered age and gender for explaining mode use (e.g., see Buehler & Hamre, 2015; Brown et al., 2016; Alemi et al., 2017; Circella et al., 2017). Age and gender also affect transit use preferences (de Oña et al., 2016; Wan et al., 2016; Zhen et al., 2018). To capture how generation-specific experiences may shape attitudes toward transit, I included age as generation variables using definitions from the Pew Research Center (2018). To have adequate observation for each generation category, I combined Millennials (born 1981-1996) with members of Generation Z (born after 1996), and members of the Silent generation (born 1928-1945) with those of the GI generations (born before 1928). The other two generation variables are Generation X (born 1965-1980) and Baby Boomers (born 1946-1964), the latter serving as baseline. I included gender as a binary variable in my models.

The literature also suggests that individual educational attainment and occupation play a pivotal role in transit and TNC ridership (e.g., see Buehler & Hamre, 2015; Brown et al., 2016; Alemi et al., 2017; Clark, 2017; Alemi et al., 2018; Grahn et al., 2020), and in transit choice preferences (de Oña et al., 2016; Zhen et al., 2018). To capture the level of education of a respondent, I created four binary variables: high school or less, some college or associate degree, undergraduate degree (my baseline), and graduate or professional degree.

Similarly, I combined occupations into five categories: 1) sales and service; 2) clerical or administrative support; 3) manufacturing, construction, maintenance, or farming; 4) professional, managerial, or technical; and 5) others (only for the COVID-19 survey).

Race and Hispanic status play an important role in transit and TNC use (Buehler & Hamre, 2015; Brown et al., 2016; Alemi et al., 2017; Circella et al., 2017; Grahn et al., 2020). I thus created a binary variable for Hispanic status and four binary variables for race: White, African American, Asian, and Other. I also created a binary variable to indicate if a respondent was born in the U.S. (for the 2017 NHTS).

Several studies have shown that telecommuting played a significant role in explaining changing travel patterns during this pandemic (Wilbur et al., 2020; Parker et al., 2021). Therefore, I added three binary variables to capture the impact of telecommuting on Californians' projected mode use change after the pandemic is over: weekly working days from home will decrease, remain the same, or increase.

Household- specific attributes

My models include standard household variables such as annual household income, household size, vehicle ownership, and homeownership, which have been found to matter for explaining household travel preferences (Clark, 2017).

I collapsed the seven income categories Ipsos uses for KnowledgePanel members and the eleven categories in the 2017 NHTS into six binary categories (see Table 4.2), with $50,000-$74,999 as my baseline. In addition, for my May 2021 Ipsos survey questions, I added four variables designed to capture changes in household income during the pandemic (household income increased, decreased, remained changed, or the respondent did not know).

Homeownership is reflected by a binary variable, and the number of household members by a count variable. As the decision to take transit should not depend directly on the number of household vehicles or the number of household drivers, but rather on whether a household has more drivers than vehicles, I created a binary variable that equals one if a household has more drivers than vehicles (for the 2017 NHTS only). Since my May 2021 Ipsos survey did not ask for the number of household drivers, I created binary variables to indirectly capture changes in mobility restrictions associated with car ownership: the number of household vehicles increased, decreased, or remained unchanged during the pandemic compared to before.

Land use characteristics

My review of the literature showed the importance of capturing geography in evaluating perceptions of transit and TNC use (Buehler & Hamre, 2015; Clark, 2017; Alemi et al., 2018; Eboli et al., 2018; Grisé & El-Geneidy, 2018; Jaafar Sidek et al., 2020). The 2017 NHTS includes some land-use variables commonly used to explain transit ridership. I included two of them in my models: population density (1,000 persons/sq. mile) in the home census tract and characteristics of the metropolitan statistical area (MSA) where a household resides (MSA with and without rail service). For my May 2021 Ipsos survey, I defined population density (people/acres) by ZIP code.

It is well-known that places with more transit facilities, such as transit stops within walking distance, increase people's tendency to walk and take public transit (Turrell et al., 2013; Renne et al., 2016). Therefore, for the 2017 NHTS California sub-sample, I used GIS to create a variable that counts the number of transit stops within 1000 m (Durand et al., 2016) of a respondent's home and another one for their workplace (if they were employed). For my May 2021 Ipsos survey, I included a variable that captures the number of transit stops in home zip codes.

COVID-19 severity

To capture the impact of the pandemic on different travel modes and Californian's perception of transit, I retrieved the total number of COVID-19 cases in each California county between the start of the pandemic and mid-May 2021 (just before my survey) and divided it by county population. I then allocated the resulting numbers to my respondents based on the zip code.

4.3.4 Sample size

For models gaging the impact of the pandemic on different modes with my May 2021 Ipsos survey, I lost thirty observations to non-response for each mode, as discussed in the results. For my analysis of reasons why Californians are reluctant to take transit, my final sample size is 539 for my May 2021 Ipsos survey, and 12,635 for the 2017 NHTS.

4.4 Econometric modelling framework

4.4.1 Generalized ordered logit models for projected mode changes

To explain ordered limited dependent variables such as answers to a survey question collected on a Likert scale, the starting point model is often an ordered logit model (Long & Freese, 2014). Assuming there are M possible choices (1 to M), the probability that respondent i chooses an answer higher than $m \in \{1, \ldots, M\text{-}1\}$ is given by

$$\Pr(Y_i > m) = \frac{\exp(\boldsymbol{X}_i \boldsymbol{\beta}' - \tau_m)}{1 + \exp(\boldsymbol{X}_i \boldsymbol{\beta}' - \tau_m)}, \tag{1}$$

where $\boldsymbol{X}_i$ is a vector of observed explanatory variables, $\boldsymbol{\beta}$ is a vector of unknown parameters, and the τ_ms (m=1, …, M-1) are unknown thresholds to estimate jointly with $\boldsymbol{\beta}$.

For respondent *i* and answer $m \in \{1, …, M-1\}$, the odds Ω_{im}, is defined by

$$\Omega_{im} = \frac{\Pr(Y_i > m)}{\Pr(Y_i \leq m)} = \exp(\boldsymbol{X}_i\boldsymbol{\beta}' - \tau_m), \tag{2}$$

so, the ratios of the odds for two different respondents and the same alternative can be shown to be independent of that alternative. This property, which is called the proportional odds assumption (or the parallel line assumption), is an implication of the ordered logit model. In practice, it often does not hold (Long & Freese, 2014). An alternative is the generalized ordered logit (GOL) model (e.g., see (Peterson & Harrell, 1990), where the βs can depend on the answer considered, so that

$$\Pr(Y_i > m) = \frac{\exp(\boldsymbol{X}_i\boldsymbol{\beta}'_m - \tau_m)}{1 + \exp(\boldsymbol{X}_i\boldsymbol{\beta}'_m - \tau_m)}. \tag{3}$$

For parsimony, the GOL model tests the parallel line assumption for all explanatory variables. If it holds for a given explanatory variable for two different answers, it reports the same coefficient.

For *M* answers, a GOL model estimates *M-1* equations (a series of cumulative logistics regression) (Williams, 2016), so the results can be interpreted via odds ratio. For respondent *i* and answer $m \in \{1, …, M-1\}$, the odds Ω_{im} are given by:

$$\Omega_{im}(\boldsymbol{X}_i) = \frac{\Pr(Y_i > m)}{\Pr(Y_i \leq m)} = \exp(\boldsymbol{X}_i\boldsymbol{\beta}'_m - \tau_m), \tag{4}$$

If $\Omega_{im}(\boldsymbol{X}_i, x_l + 1)$ denotes the odds obtained by increasing variable *l* by one unit, then:

$$\Omega_{im}(\boldsymbol{X}_i, x_l + 1) = \exp\left(\boldsymbol{X}_i\boldsymbol{\beta}'_m + \beta_{lm} - \tau_m\right) \tag{5}$$

Combining Equations (5) & (6) gives the odds ratio for variable *l:*

$$OR_{lm} = \frac{\Omega_{im}(\boldsymbol{X}_i, x_l + 1)}{\Omega_{im}(\boldsymbol{X}_i)} = \exp\left(\beta_{lm}\right). \tag{6}$$

A positive β_{lm} (an odds ratio >1) indicates that an increase in the corresponding explanatory variable raises the probability that a respondent selects an answer greater than *M* versus an answer lower than or equal to *M* (here using a mode more frequently after the pandemic) (Williams, 2016). Conversely, a negative β_{lm} (an odds ratio <1) indicates that an increase in value of the corresponding explanatory variable decreases the probability that a respondent selects an answer greater than *M* versus an answer lower than or equal to *M*. Using maximum likelihood, I estimated GOL models for each of the following modes: driving, transit, walking/biking, and TNCs.

4.4.2 Binary logit models for transit reluctance in California

I estimated logit models to analyze the reasons why Californians are reluctant to take transit. As is usual for logit models, I present results (obtained by maximum likelihood) in terms of odds ratios, which for explanatory variable *k* can be written (Long, 1997):

$$\Omega_{ik} = \frac{\left(\frac{\Pr\left(Y_i = 1 | X_{i(k+1)}\right)}{\Pr\left(Y_i = 0 | X_{i(k+1)}\right)}\right)}{\left(\frac{\Pr(Y_i = 1 | X_i)}{\Pr(Y_i = 0 | X_i)}\right)} = \exp(\beta_k). \tag{7}$$

In Equation (7), $X_{i(k+1)}$ is the vector of explanatory variables for respondent *i* modified by adding 1 to the k^{th} explanatory variable. An odds ratio (OR) allows comparing whether the probability of an event (here selecting a reason for not taking transit more) is the same for two groups. The odd of an event is the ratio of the probability that the event will happen (here that a respondent picked a specific reason for not taking transit more) divided by the probability that it will not happen. If OR∼1 for explanatory variable *j*, then explanatory variable *j* has no impact on whether a respondent will not take transit more for that reason; if OR>1, a respondent is more likely to give that reason for not taking transit more; the reverse holds if OR<1.

4.5 RESULTS

4.5.1 Impacts of COVID-19 on different travel modes

Overall results

My econometric work was performed using Stata 17. Before interpreting the results from my multivariate models, it is helpful to graph my explanatory variables, which were weighted to match my respondents to the California population. Ipsos calculated these weights based on the 2019 American Community Survey distributions of the following variables for Californians aged 18 and over: gender by age, race and Hispanic status, education, household income, and language proficiency (for English and Spanish). Results are shown in Figure 4.2 and in Figures 4.3 to 4.6.

Figure 4.2 shows that almost two-thirds of Californians intend to use transportation modes at their disposal as often after the pandemic as before. However, the remaining third intends to make substantial mode changes. Three modes could come down on the losing side: driving (19% less vs. 15.3% more), and particularly transit (28.9% less vs. 7.3% more), and TNCs (34.1% less and 3.9% more). Having 19% of Californians drive less would be good news for the state's efforts to reduce VMT as part of its strategy to reduce greenhouse gas emissions, although I do not know how much less these respondents will

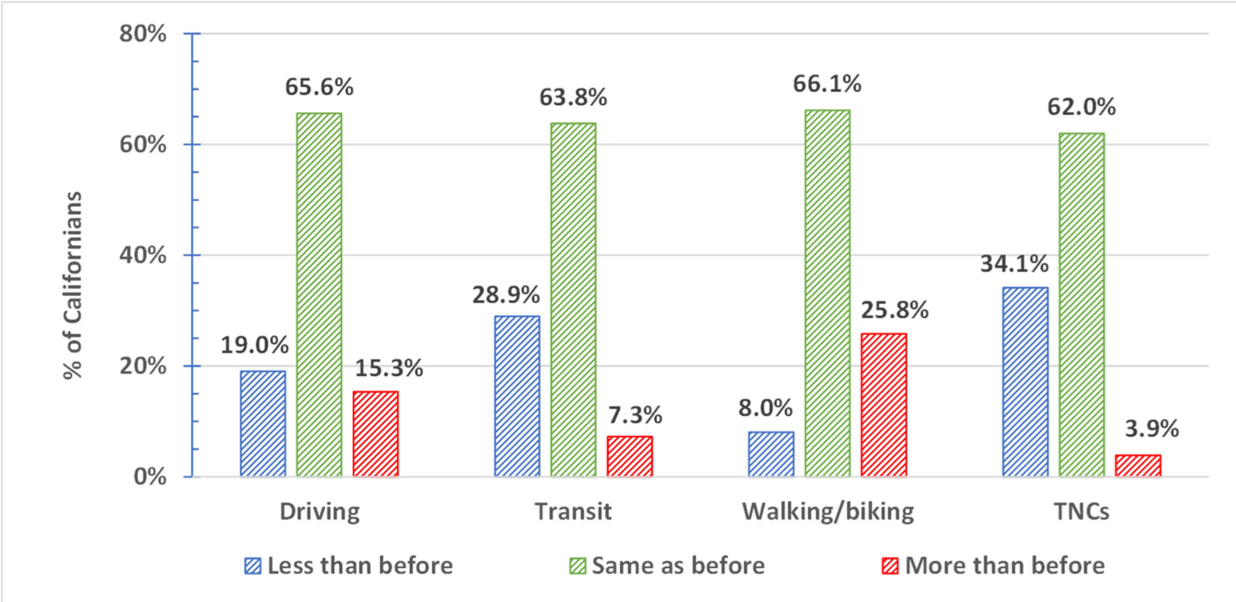


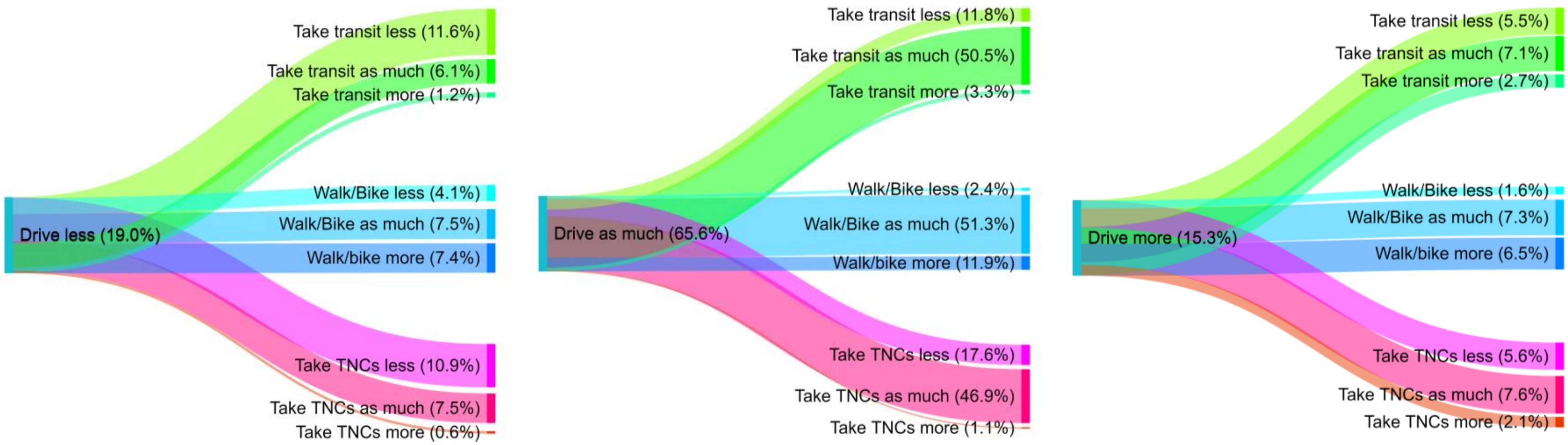
Figure 4. 2 Projected mode use changes (post- vs. pre-pandemic)

drive and how much more the 15.3% of Californians who intend to drive more will actually drive. Moreover, my survey does not capture how driving may change due to population and economic growth, or the continued expansion of online shopping and the growth of the logistics sector in California. Conversely, many more Californians (25.8%) plan on walking and biking more after the pandemic than before, than plan on walking and biking less (8%), which is encouraging.

Californians' intentions to change modes post-pandemic

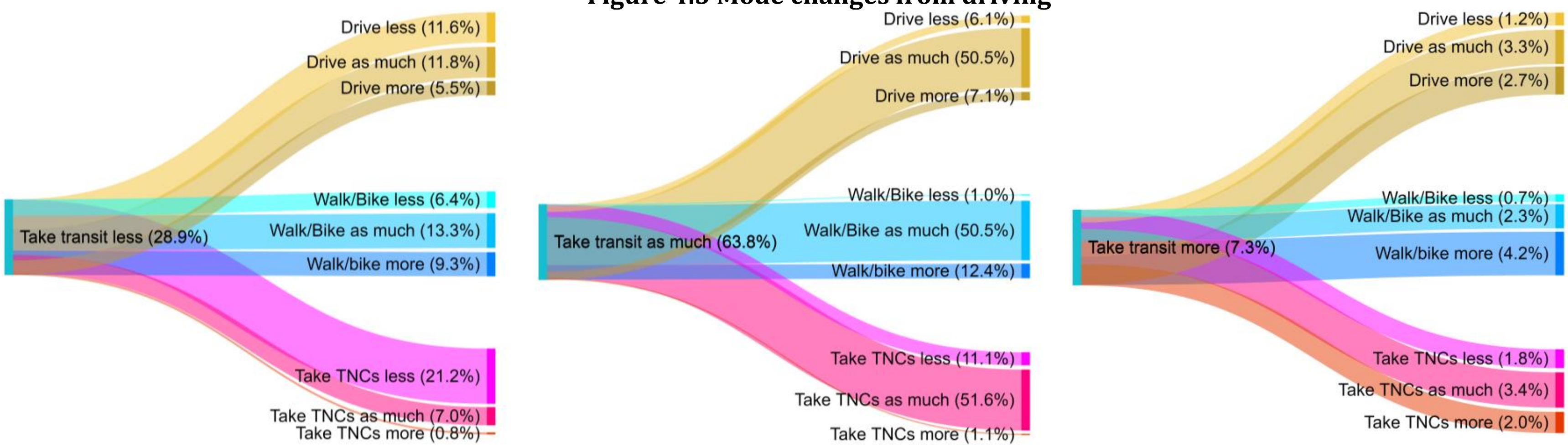
Figures 4.3 to 4.6 show Californians' projected changes in their travel modes after the pandemic compared to before. As for Figure 4.2, percentages for these Sankey diagrams were calculated by weighting my respondents' answers to scale my sample to the California population.

Let me start with Panel A of Figure 4.3, which shows how the 19% of Californians



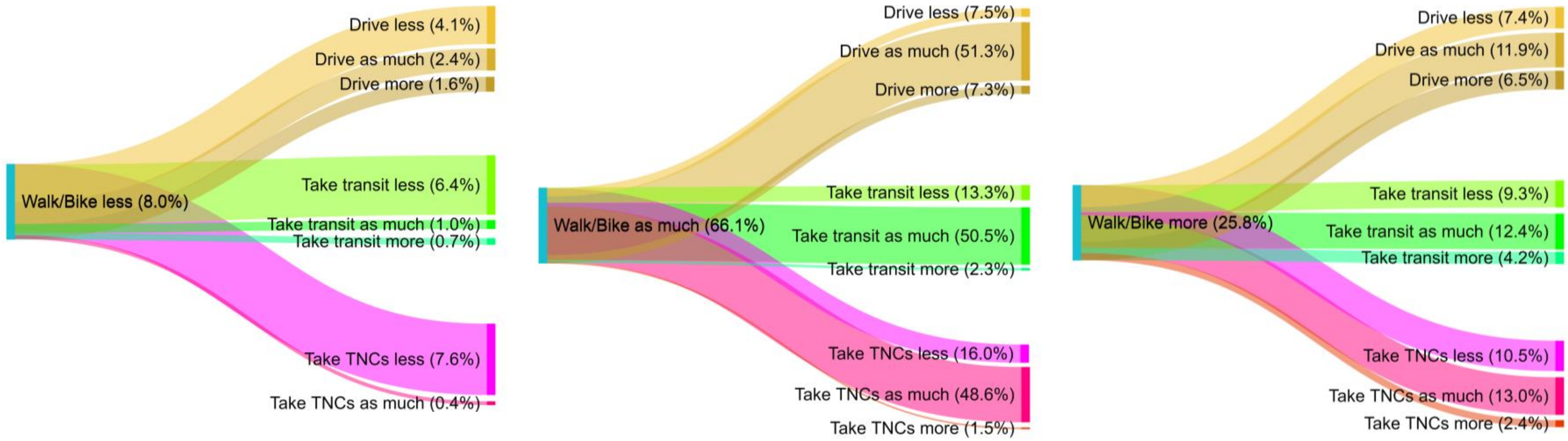
Panel A. Drive Less **Panel B. Drive as much** **Panel C. Drive more**

Figure 4.3 Mode changes from driving



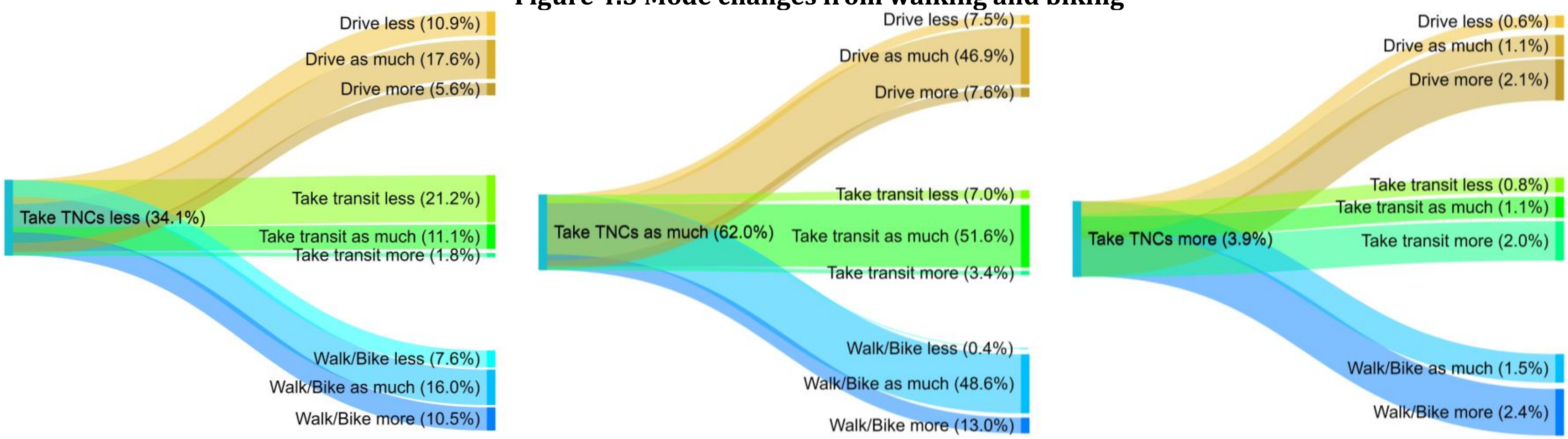
Panel A. Take transit less **Panel B. Take transit as much** **Panel C. Take transit more**

Figure 4.4 Mode changes from transit



Panel A. Walk/bike Less **Panel B. Walk/bike as much** **Panel C. Walk/bike more**

Figure 4.5 Mode changes from walking and biking



Panel A. Take TNCs less **Panel B. Take TNCs as much** **Panel C. Take TNCs more**

Figure 4.6 Mode changes from TNCs

set on driving less are considering using other modes. Most of them (11.6%) intend to take transit less, with only 1.2% stating that they may take transit more. The percentage of Californians who intend to reduce their use of TNCs is also substantial (10.9%), with only 0.6% planning on using TNCs more. On the bright side, walking/biking is expected to see a boost from that group (7.4%), although 4.1% are thinking about walking and biking less. Most Californians (65.6%) plan on driving as much after the pandemic as before (Panel B of Figure 4.3). Although the projected use of other modes is unchanged for half of Californians, I note that 11.8% and 17.6% plan to take transit and TNCs less, respectively.

Only 15.3% of Californians intend to drive more (Panel C of Figure 4.3). Among these, 5.5% consider taking transit less and only 2.7% more. For TNCs, the projected increase is 2.1%, with a larger decrease of 5.6%. Conversely, Californians who consider driving more are more likely to increase how much they walk/bike (6.5%) than to decrease it (1.6%).

Figure 4.4 shows mode shifts from transit. Panel A shows that many Californians who are considering taking transit less are also planning on driving less (11.6%) and taking TNCs less (21.2%). They are also considering walking and biking more (9.3%), although 6.4% want to walk/bike less, reinforcing findings from Figure 4.3. I observe a shift from transit to driving more (5.5%) with only a tiny gain for TNCs (0.8%), which is far from compensating expected losses, possibly because of lingering health concerns. On Panel B of Figure 4.4, I observe a lot of stability among Californians who want to continue using transit as much after as before the pandemic, with small losses for driving (6.1% compensated by a 7.1% increase), and gains for walking and biking (12.4%). Only 7.3% of Californians intend to take transit more after the pandemic (Panel C of Figure 4.4). Of these, a tiny fraction (1.2%) wants to drive less, but 2.7% intend to drive more. For TNCs, 1.8% want to use them less, and 2% want to take them more.

Figure 4.5 shows potential mode shifts from walking and biking. Only 8% of Californians are considering walking/biking less post-pandemic (Panel A), and they intend to decrease their mobility across all other modes: 4.1% want to drive less, 6.4% intend to take transit less, and 7.6% want to use TNCs less. There is much more stability among the 66.1% of Californians who intend to walk and bike as much as before (Panel B). In this group, the percentage of those who plan to drive less (7.5%) is almost balanced by those who plan to drive more (7.3%). However, transit (13.3% for less vs. 2.3% for more) and TNCs (16% for less vs. 1.5% for more) should see losses. Of the 25.8% of Californians who intend to walk and bike more (Panel C), 7.4% plan to drive less, 9.3% want to take transit less, and 10.5% intend to take TNCs less.

Finally, Figure 4.6 relates intentions about taking TNCs to other modes. Starting with the relatively large percentage (34.1%) of Californians who plan on taking TNCs less (Panel A), I see that one-third of these (10.9%) wants to decrease how much they drive, and two-thirds (21.2%) want to reduce how much they take transit. The percentage of those who also plan to walk/bike more (10.5%) slightly exceeds those who wish to walk and bike less (7.6%). Among the 62% of Californians who support the status quo for TNCs (Panel B), 7.5% want to drive less, and 7% to take transit less. As in Figures 4.3 and 4.4, those who want to walk and bike more (13%) outnumber those who want to walk and bike less (only 0.4% here). Finally, among the small group who wants to take TNCs more (3.9%), driving more edges driving less (2.1% vs. 0.6%), taking transit more (2%) outgains taking it less (0.8%), and walking and biking more comes up ahead (2.4% vs. 0%). However, these Californians are clearly in the minority.

Results from Generalized Ordered Logit models

Let me now characterize Californians based on their intentions to alter or not their use of various transportation modes after the pandemic compared to before. Results are presented in Table 4.1. I replaced non-significant coefficients with "•" to help focus on statistically significant values. For a given mode, Table 4.1 shows odds ratios for two equations: (0 = Less than before) vs. (1 = Same as before or more); and (0 = Less than or as much as before) vs. (1 = More than before). For cells with only one coefficient, both equations have the same coefficient. As discussed above, models were estimated on the sample of Californians who reside "close" to transit stops.

Driving (Column I of Table 4.1)

First, I see that only a few explanatory variables are statistically significant for driving. Hispanics (2.00*), Asians (3.22‡) compared to Whites, workers in sales and services (1.72*) compared to others, intend to drive more post-pandemic. The same applies to people whose household income decreased (1.87*) and whose number of household vehicles increased (3.82*) during the pandemic. As expected, respondents who think that they will work more from home post pandemic (0.37‡) intend to drive less.

Transit (Column II of Table 4.1)

From Figure 4.1, I know that many Californians plan to use transit less (28.9%) after the

Table 4. 1 GOL odds ratios for projected mode changes (N=545)

	Driving	Transit	Walk/bike	TNCs
Column number	*I*	*II*	*III*	*IV*
Individual specific variables				
Generation (base=Baby Boomer)				
Generations Z & Y	•	•	•	•
Generation X	•	•	•	•
Silent and GI Generations	•	•	•	•
Gender (Male = 1)	•	•	•	0.67*
Hispanic (Yes =1)	•/2.00*	0.37‡	0.44*/1.77*	0.36‡
Race (base=Whites)				
African American	•	•	•	0.33†
Asian	•/3.22‡	•	•	0.50*
Other	•	•/4.33†	•	0.45*
Educational attainment (base=Undergraduate degree)				
Less than high school & high school	•	•	0.50*	0.44*
Some college or associate degree	•	•/0.31*	•	•
Graduate or professional degree	•	•/0.25*	•	•
Occupation (base=Others)				
Sales and service	1.72*	•	•	•
Telecommuting pattern (base=No change)				
Working from home days/week decreased	•	•	•	•
Working from home days/week increased	0.37‡/•	0.37‡/•	0.42*/•	•
Household specific variables				
Annual household income (base=$50,000-$74,999)				
<$25,000	•	•	•	•
$25,000-$49,999	•	•	•	•
$75,000-$99,999	•	•	•	•
$100,000-$149,999	•	•	•	•
>=$150,000	•	•	•	•
Changes in household income during COVID-19 (base=No change)				
HH income decreased	•/1.87*	•/2.70*	•/1.82*	•
HH income increased	•		•	•
Does not know about HH income change	•	•	•	•
Household owns a home (Yes=1)	•	•/0.26‡	•	•/0.22†
Number of people in the household	•	•	•	•/1.56‡
Changes in # of household vehicles during COVID-19 (base=No change)				
It decreased	•	•/4.62*	•	•/6.68†
It increased	3.82*	0.18†/•	•	0.36*/•
Land use				
Population density (persons/acres)	•	•	•	•
Number of transit stops in ZIP codes	•	•	•	•
COVID-19 cases				
Percentage of COVID-19 cases	•	•	•	•

Notes:
1. * p<0.05, † p<0.01, ‡ p<0.001.
2. A "•" indicates that a coefficient was not statistically significant
3. The first coefficient in a cell corresponds to the logistic regression: 0 = Less than before vs. 1 = Same as before or more. The second coefficient corresponds to: 0 = Less than or as much as before vs. 1 = More than before. For cells with only one coefficient, both logistic regressions have the same value.

pandemic. Column II of Table 4.1 shows that Californians who are less likely to use transit as much or more include Hispanics (0.37‡), people with an associate (0.31*) and graduate degree (0.25*), people who intend to telecommute more (0.37‡), and who own a home (0.26‡). Conversely, respondents who identify as "other race" compared to Whites (4.33†) and respondents whose household's income decreased during the pandemic (2.70*), intend to use public transit more once the pandemic will be over. Changes in vehicle holdings also impact intention to take transit. Californians who reduced their number of vehicles during the pandemic intend to take transit strictly more (4.62*). The reverse holds for those in households who gained vehicles (0.18†).

Walking/biking (Column III of Table 4.1)

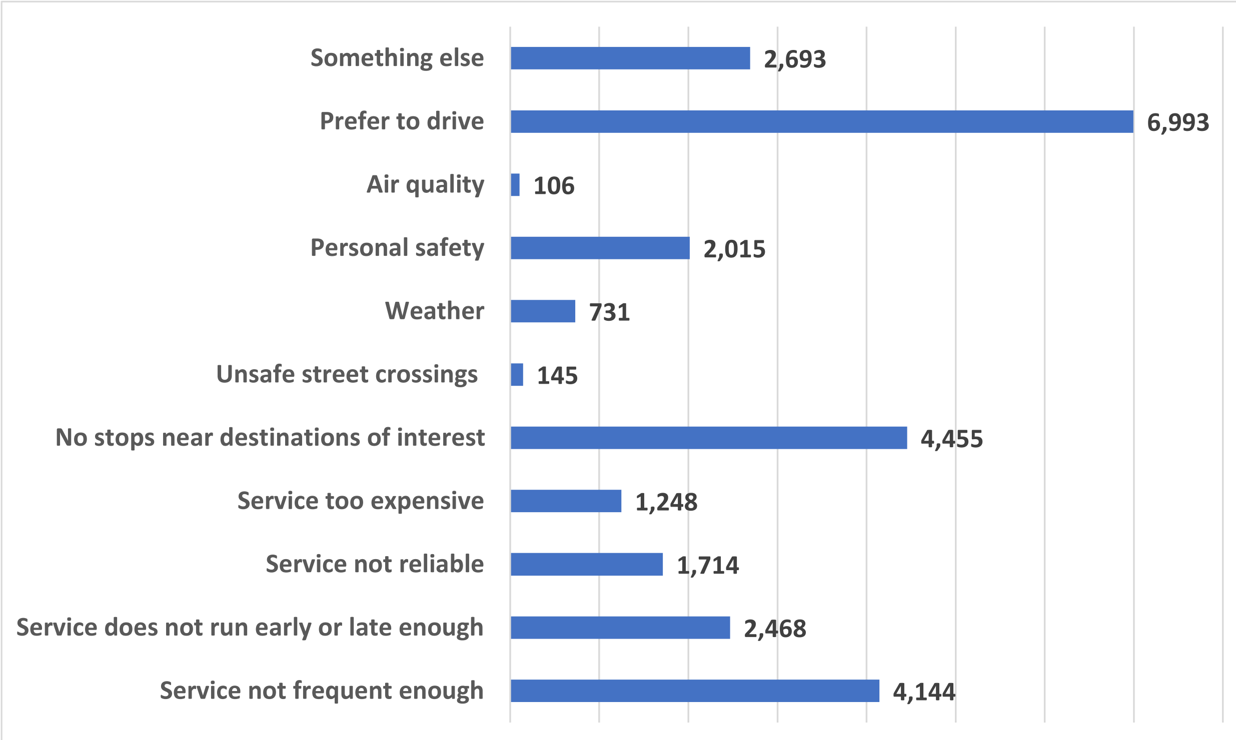
The situation is brighter for walking and biking (also recall Figure 4.5), although not all Californians intend to walk and bike more. For Hispanics, the picture is mixed. Some do not want to walk or bike as much or more after the pandemic (0.44*), while others (1.77*) intend to walk or bike more. This suggests some heterogeneity within Hispanics, and possibly some different circumstances (related for example to safety and the presence of walking/biking infrastructure) that are not reflected in my explanatory variables. Respondents with only a high school education or less are less likely to walk as much or more, or strictly more (0.50*) after the pandemic. Income also matters here as households whose income decreased during the pandemic plan on walking more (1.82*), while those who will work more from home after the pandemic are less likely to walk or bike at least as much (0.42*).

TNCs (Column IV of Table 4.1)

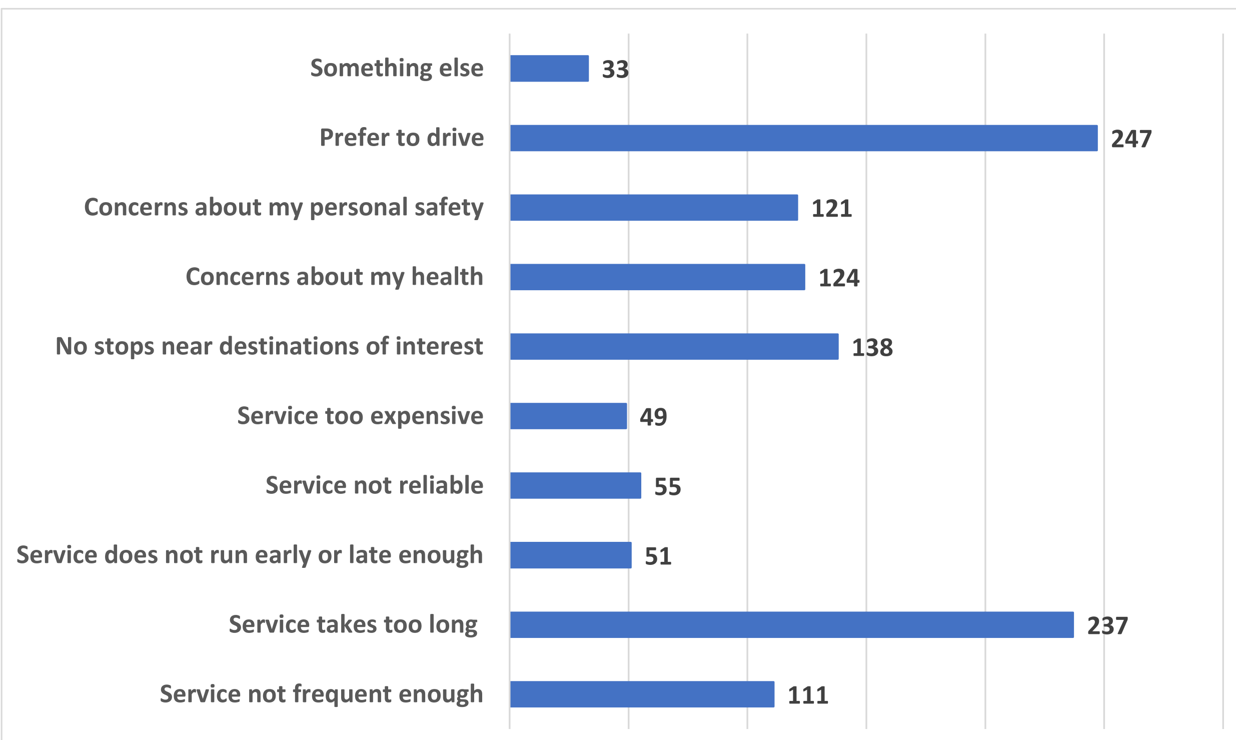
Intentions towards using TNCs after the pandemic seem even less favorable than for transit (Figure 4.5). Males (0.67*) compared to females, Hispanics (0.36‡) compared to non-Hispanics, African Americans (0.33†), Asians (OR 0.50*) and others (0.45*) compared to Whites, and those with a high school education or less (0.44*) compared to college graduates, are less likely to take TNCs as much or more, or strictly more, after the pandemic. In addition, respondents whose household's own a home (0.22†) are less likely to use TNCs strictly more after the pandemic. Conversely, Californians with a larger household (1.56‡) are more likely to take TNCs more. Changes in household's vehicle possession during the pandemic have a mixed impact on TNCs. For instance, Californians, who decreased their number of vehicles during the pandemic (6.68†), intend to use TNCs more whereas those who increased their vehicle holding (0.36*) differ.

4.5.2 Reasons for not taking transit

Overall responses for transit use reluctance from the two surveys I analyzed are summarized on Figure 4.7. From Panel A (2017 NHTS), I see that the main reason for not taking transit is "Prefer to drive" (26.18%), followed by "No stops near destination of interest" (16.68%) and "Service not frequent enough" (15.51%). Results are similar for my May 2021 Ipsos survey. Again, "Prefer to drive" comes first (21.18%), with "Service takes too long" (20.33%) a close second, followed by "No stops near destination of interest" (11.84%), which was also third in the 2017 NHTS. Three other reasons were mentioned by roughly a quarter of respondents each: "Concerns about my health" (11%), "Concerns about my personal safety" (10%), and "Service not frequent enough" (10%).



Panel A. Reasons for not taking transit more before the pandemic (2017 NHTS, N=12,635)



Panel B. Reasons for not taking transit more after the pandemic (2021 Ipsos survey, N=539)

Figure 4.7 Reasons for not taking transit

Findings from the 2017 NHTS (Table 4. 2)

Odds ratios for my logit models that analyze reasons for not taking transit more are presented in Tables 4.2 (2017 NHTS data) and 4.3 (May 2021 Ipsos survey).

First reason for not using transit more: I prefer to drive (Column I of Table 4.2)

From Column I of Table 4.2, I see that only a few explanatory variables are statistically significant. Larger families tend to prefer driving over taking transit (1.07‡). Conversely, respondents with a graduate or professional education (0.80‡), who were not born in the U.S. (0.74‡), and whose household has fewer vehicles than drivers (0.60‡), are less likely to state that they simply prefer driving. Finally, I note that the odds ratios for my land use variables are close to 1, so they have no practical impact on Californians' preferences for driving over transit. These results illustrate one important point - a large fraction of mass transit users are highly educated, and their driving preferences do not detract them from using transit (but I know that they are more likely to use rail transit than buses to commute) (Clark, 2017).

Second reason: No stops near destinations of interest (Column II of Table 4.2)

From Column II of Table 4.2, I see that Gen Z & Y respondents are more likely to invoke the lack of transit stops for not taking transit (1.20‡), and so do respondents with graduate and professional degrees (1.11*), a higher household income (1.16† for ≥$150,000), and those who live in an MSA with rail (1.43‡). Some of these results echo findings from the transit literature, which reported that students and office workers prefer more frequent, on-time,

Table 4. 2 Binary logit results for not taking transit in California (NHTS 2017) (N=12,635)

	Y=I prefer to drive	Y=No stops near destinations of interest	Y=Service not frequent enough
Column number	***I***	***II***	***III***
Individual specific variables			
Generation (baseline=Baby Boomer)			
Generation Z & Y	•	1.20‡	1.29‡
Generation X	•	•	1.12*
Silent and GI Generation	•	•	0.59*
Gender (Male = 1)	•	•	•
Hispanic status (Hispanic =1)	•	0.81‡	0.81‡
Race (baseline=Whites)			
African American	•	0.66‡	0.71**
Asian	•	•	1.14*
Other	•	•	•
Educational attainment (baseline=Undergraduate degree)			
Less than high school & high school	•	0.70‡	0.55‡
Some college or associated degree	•	0.78‡	0.71‡
Graduate or professional degree	0.80‡	1.11*	1.16†
Occupation (Professional, managerial, or technical = baseline)			
Sales and service	•	0.77‡	0.85†
Clerical or administrative support	•	0.87*	•
Manuf., constr., maintenance, or farming	•	•	0.72‡
Not born in the U.S.	0.74‡	•	1.28‡
Household specific variables			
Annual household income (baseline=$100,000-$149,999)			
<=$49,000	•	0.71‡	•
$50,000-$99,999	•	0.85†	•
>=$150,000	•	1.16†	•
Number of people in the household	1.07‡	0.95‡	0.95†
Household owns home	•	•	•
Fewer vehicles than drivers	0.60‡	•	•
Land use			
Household in an MSA with rail (Yes=1)	•	1.43‡	•
Population density (1000 persons/ mi^2)	•	0.99*	0.99†
Number of stops within 1000 m of residence	0.99‡	•	•
Number of stops within 1000 m of workplace	1.00‡	1.00‡	•

Notes:
1. * p<0.05, † p<0.01, ‡ p<0.001
2. The table shows the odds ratio (OR) of each explanatory variable. An odds ratio greater (lower) than 1 indicates the increased (decreased) likelihood of choosing a particular reason corresponding to "transit use reluctance".
3. A "•" indicates that a coefficient was not statistically significant

service and easily accessible transit facilities (de Oña et al., 2016; Grisé & El-Geneidy, 2018). Conversely, Hispanics (0.81‡), African Americans (0.95‡), respondents with a college degree (0.78‡) or less (0.70‡), who are in sales (0.77‡) and administrative jobs (0.87*), whose annual household income is ≤$49k (0.71‡) or between $50k and $99k (0.85†), and who live in a larger household (0.95‡) are less likely to invoke a dearth of transit stops for not taking transit more, possibly because some of them live in urban cores are typically served by bus transit.

Finally, I note that except for "households who reside in an MSA with rail service," 1.43‡), land use variables have odds ratio close to 1, so they do not play a role here.

Third reason: Insufficient service frequency (Column III of Table 4.2)

Many of the explanatory variables that are significant for "lack of transit stops" are also significant for "insufficient service frequency" and they have roughly similar odds ratios (compare Columns II and III of Table 4.2). Indeed, younger (1.29‡ for Gen Z & Y) and middle-aged respondents (1.12* for Generation X) are more likely to mention insufficient transit frequency as a reason for not taking transit, and so do Asians (1.14*), respondents with graduate and professional degrees (1.16†), and those not born in the U.S. (1.28‡).

Conversely, older adults (0.59*), Hispanics (0.81‡), African Americans (0.71**), respondents with some college (0.71‡) or less (0.55‡), who work in sales (0.85†), or construction (0.72‡), who are part of a larger household (0.95†) are less likely to invoke insufficient service frequency for not taking transit more. One possible explanation is that older adults may have fewer time constraints. In addition, Hispanics and African Americans may live disproportionately in core urban areas where buses run relatively frequently.

Findings from the May 2021 Ipsos survey (Table 4.3)

First reason for not using transit more: I prefer to drive (Column I of Table 4.3)

As before, people with graduate and professional degrees (0.54*) are less likely to state that they prefer driving, possibly because of the flexibility, comfort, and safety that this mode provides. Conversely, people who reside in a ZIP code with a large number of COVID-19 cases (1.08*) are more likely to invoke that reason for not considering taking transit after the pandemic. Most other variables are not significant, which suggests that the pandemic has solidified the preference for driving versus taking transit among many Californians.

Second reason: Service takes too long compared to driving (Column II of Table4. 3)

The second most popular answer for not taking transit after the pandemic in the COVID-19 survey was "Service takes too long compared to driving." This reason was not available in the 2017 NHTS. Again, only a handful of variables are statistically significant. Hispanics (0.53*), and respondents who live in a more densely populated areas (0.98*) are less likely to mention service time as a reason for not taking transit.

Third reason: No stops near destinations of interest (Column III of Table 4.3)

As expected, the lack of transit stops near destinations of interest (Column III of Table 4.3) is a common reason for not taking transit and it is shared across a wide spectrum of respondents. The only groups less likely to mention this reason are people who are in sales and service (0.52*), members of households with an annual income below $25,000 (0.18†), and respondents in more densely populated areas (0.97*).

Table 4. 3 Transit use reluctance in California (N=539)

Variable	I prefer to drive	Service takes too long compared to driving	No stops near destinations of interest	Concerns about my health due to the proximity of many people	Concerns about my personal safety at a transit station or in a transit vehicle
Column number	*I*	*II*	*III*	*IV*	*V*
Individual specific variables					
Generation (base=Baby Boomer)					
Generations Z & Y	•	•	•	•	•
Generation X	•	•	•	•	•
Silent and GI Generations	•	•	•	•	•
Gender (Male=1)	•	•	•	•	•
Hispanic status (Hispanic=1)	•	0.52*	•	•	•
Ethnicity (base=White)					
African American	•	•	•	3.06†	•
Asian	•	•	•	•	•
Other	•	•	•	•	•
Educational attainment (base=Undergraduate degree)					
High school or less	•	•	•	•	•
Some college / associate degree	•	•	•	•	•
Graduate or professional	0.54*	•	•	•	•
Occupation (base=Professional, managerial, or technical)					
Sales and service	•	•	0.49*	•	•
Clerical or administrative	•	•	•	•	•
Manufacturing, construction, maintenance, or farming	2.42*	•	•	•	•
Other	•	•	0.34*	•	•
Telecommuting pattern (base=No change)					
Working from home decreased	•	•	•	•	•
Working from home increased	•	•	•	•	•
Household specific variables	•	•	•	•	•
Annual household income (base=$50,000-$74,999)					
<$25,000	•	•	0.18†	•	•
$25,000-$49,999	•	•	•	•	•
$75,000-$99,999	•	•	•	•	•
$100,000-$149,999	•	•	•	•	•
>=$150,000	•	•	•	•	•
Changes in household income during COVID-19 (base=No change)					
HH income decreased	•	•	•	•	•
HH income increased	•	•	•	1.88*	•
Does not know	•	•	•	•	•
Household owns a home (Yes=1)	•	•	•	•	•
Number of people in the	•	•	•	•	•

household					
Changes in # of household vehicles during COVID-19 (base=No change)					
It decreased	•	•	•	•	•
It increased	•	•	•	•	•
Land use					
Population density (persons/acres)	•	0.98*	0.98*	•	1.02*
Number of transit stops in ZIP code	•	•	•	•	•
COVID-19 cases	•	•	•	•	•
Percentage of COVID-19 cases	1.08*	•	•	•	•

Notes:
1. * p<0.05, † p<0.01, ‡ p<0.001
2. The table shows the odds ratio (OR) of each explanatory variable. An odds ratio greater (lower) than 1 indicates the increased (decreased) likelihood of choosing a particular reason corresponding to "transit use reluctance".
3. A "•" indicates that a coefficient was not statistically significant

Fourth reason: Health concerns due to the proximity of many people (Column IV of Table 4.3)

Since health concerns have been dominating my lives since the start of the pandemic, this question examines if Californians have lingering health concerns that will stop them from taking transit when the pandemic is over. From Column IV in Table 4.3, I see that, after controlling for other socio-economic variables, African Americans (3.07†) are more likely than Whites (my baseline) to harbor health concerns when taking transit after the pandemic. This result confirms a recent survey (Johnson & Funk, 2021), which found that this group see COVID-19 as more of a threat to public health than Hispanics and Whites, combined with the fact that African Americans have been disproportionately affected by the pandemic. I also note that those who intend to work less from home after the pandemic are less likely (0.43*) to pick this reason for not taking transit.

Fifth reason: Concerns about my personal safety at a transit station or in a transit vehicle (Column V of Table 4.3)

Finally, Column V of Table 4.3 characterizes Californians concerned about their personal safety when taking transit. Only one variable is statistically significant and that is population density.

4.6 Conclusions

In Chapter 4, I explored Californian's intentions about using different modes (driving, transit, walking and biking, and TNCs) for any travel purpose after the pandemic is over based on results from a random survey of Californians conducted for me by Ipsos in late May 2021. I also examined the main reasons why Californians were reluctant to use transit in 2017, and why they may not use transit once the COVID-19 pandemic is over.

While for each mode between 62% and 66% of respondents anticipated no change, three modes could experience substantial drops in popularity: driving, transit, and TNCs. A drop in driving would reduce VMT and help the state achieve its greenhouse gas reduction target, although nobody can say at this point if the intentions by 19% of Californians to reduce driving will be sufficient to substantially offset the 15.3% of Californians who intend to drive more, partly as they decrease their use of transit.

Results for transit are grim: over 28.9% of Californians intend to use transit less after COVID-19, and only 7.3% would like to use transit more post pandemic. While this drop affects a broad range of Californians, it appears to disproportionately affect Hispanics, African Americans, Asians, lower income households, and people who would telecommute more, many of which had been sustaining transit ridership until before the pandemic.

Likewise, over 34% of Californians intend to use TNCs less after the pandemic.

A silver lining to these results is a substantial uptick in intentions to walk and bike more (25.8%), although 8% of Californians stated opposite intentions. Surprisingly, results were mixed among Hispanics.

The main reason why Californians would not take transit before the pandemic and why they likely will not take it after is well-known: Californians prefer to drive, which I interpret as saying that driving a personal vehicle offers more flexibility (e.g., to drive someone, to carry shopping, to leave at any time) and is perceived as safer than taking transit. The second and the third most popular reasons in the 2017 NHTS (“no stops near destinations of interest” and “service not frequent enough”) and in my 2021 COVID-19 survey (“no stops near destination of interest,” and “service takes too long”) reinforce that point.

My results indicate that limitations of transit’s reach and frequency are especially of concerns for younger adults (Gen Z and Gen Y), people with more education, and especially members of more affluent households (the so-called “choice riders”; see (Polzin et al., 2000; Krizek & El-Geneidy, 2007). A key priority for transit agencies should therefore be to increase (as much as possible and appropriate) the frequency of their service, develop their network and extend their reach by addressing the first- and last-mile problems.

To attract younger riders in urban areas, one possibility would be to either offer micro-mobility services (e.g., shared e-scooters, bikes, or e-bikes) or create a partnership with one or several providers. Other measures include enhancing transfers between different transit modes or different transit providers, streamlining payment via smartphone apps (and including micro mobility payments), and providing internet service in areas with blank spots.

A more decisive approach would be to change the way transit is financed. As argued elsewhere (e.g., see Nuworsoo (2004), or Saphores et al. (2020), and the references therein), free or reduced-fare transit pass programs structured like insurance programs (where a large group of potential transit riders - such as all students at a college or all employees in a large firm - periodically pays a lump sum to a transit agency while only a subset of that group actually uses transit) could bring transit agencies back to fiscal health while enhancing the mobility of students, workers, and disadvantaged groups.

To address health concerns of African American and Asian riders after the COVID-19 pandemic finally subsides, transit operators should adopt best practices to promote health (many have already done so in California; see (Bernstein et al., (2021), for example) and publicize their efforts using both more traditional (e.g., radio and TV ads) and more modern (e.g., social media) approaches. It is also essential to address public safety concerns, which tend to be voiced by women (Loukaitou-Sideris, 2014, 2015; Lubitow et al., 2020) but that are likely shared by many people who are not taking transit. Possible measures include providing adequate lighting at transit stations (especially bus stops), providing a clean and comfortable environment, and possibly installing CCTV cameras. Public acceptance should also be gauged for installing monitoring cameras in transit vehicles, coupled with patrols by public safety officers (considering that policing is a very sensitive issue, especially in disadvantaged communities and communities of color, that have long been singled out by local police officers). Overall, however, transit policy needs to be integrated into comprehensive policies designed to achieve California's transportation, social, and environmental goals. These policies should consider the generalized costs and the characteristics of all the transportation options available to residents of specific communities. This includes better pricing urban spaces (i.e., parking), and the externalities of private motor vehicles (e.g., air pollution and greenhouse gas emissions), and fostering new mobility options to achieve more equitable mobility.

My study analyzes intentions of using various modes post-pandemic and I am aware that people's intentions may vary more than their actual actions. This shortcoming could be overcome by combining perception-related surveys with other survey methods, for example, participant observation (asking to keep a travel diary) and in-depth interviews (Northcote & Macbeth, 2005; Herbert, 2013), but it is beyond the scope of this study, and left for future work.

Future research on the impact of COVID-19 on various modes could also analyze the heterogeneity of intentions to use various transportation modes after the pandemic among Hispanics, African Americans, and Asians to gage, for example the quality of their access to transit, biking, and walking infrastructure. Finally, I would like to underscore the need for rigorous research on transit issues, especially for small transit agencies in California.

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4.9 Appendix

Table 4.A. 1 Summary of selected studies on the impact of COVID-19 on transit and transit perceptions (2020-2021)

Study (Year)	Data source and methodology	Variables	Key findings
Impact of COVID-19 on transit			
Islam (2020)	• U.S. • January 2012 and June 2020 • National Transit Database (NTD) • Difference-in-differences (DID)	• *Dependent:* Unlinked passenger trips (UPT), vehicle revenue hours (VRH), vehicle revenue miles (VRM); *Explanatory:* mode and service-specific dummy variables for each transit agency, state-specific indicator for stay-at-home order	• Due to the pandemic, ridership fell by 67 to 71%, VRH by 43 to 45% and, VRM by 46 to 48% • Implementation of safer-at-home policies did not cause a statistically significant fall in public transit ridership and vehicle usage.
Liu et al. (2020)	• 113 counties, 63 metro areas & 28 U.S. states • 2020: 02/15 to 05/17 for monthly and 03/16 to 05/10 for hourly data • Transitapp.com, U.S. Facts, ACS 5-year estimates (2014–2018) • Logistic regression, Ordinary Procrustes	• *Dependent:* Monthly and hourly demand data; *Explanatory:* non-physical occupations, African American, population over 45, people commuting to work, households with no vehicles, Google search trend index	• Cities in the deep South and Midwest lost more demand than the high-tech areas of the Bay Area (CA) & university cities (Ithaca, Ann Arbor, and Madison.) • Unlike younger adults and Whites, older people, African Americans & essential workers continued to use transit during the pandemic
Wilbur et al. (2020)	• Nashville and Chattanooga, TN, U.S. • 01/01/19-07/01/20 • Metropolitan Government of Nashville and Davidson County, Chattanooga Area Regional Transportation Agency, U.S. Census Bureau and Proximity One • Descriptive analysis	• *Dependent*: Average weekly ridership; *Explanatory:* median income, median housing value, median rent, race.	• By late April 2020, ridership declined by 66.9% and 65.1%, respectively, in Nashville and Chattanooga. Morning and evening peaks on weekdays saw more decline due to stay-at-home orders and telework • Affluent census tracts in Nashville lost more riders than less affluent tracts
Brough et al. (2021)	• King County, Washington, U.S. • February 2020 and April 2020 • SafeGraph Inc. • Descriptive statistics and OLS	• Bus boarding data, education, income	• Between February and April 2020, transit boardings dropped by 74%; CBGs with 10% of bachelor's degree holders saw a 45% decline in travel, whereas CBGs with 90% of bachelor's degree holders saw a 69% decline.

Hu & Chen (2021)	• Chicago, Illinois, U.S. • January 2001 to April 2020 • General Transit Feed Specification, Chicago Transit Authority, Chicago Metropolitan Agency for Planning, ACS 5-year estimates (2017), Chicago Data Portal, LEHD, National Climatic Data Center • Bayesian Structural Time Series (BSTS), Partial Least Squares (PLS)	• BSTS - *Dependent:* daily average ridership (station); *Explanatory:* holiday, max. T° & precipitation • PLS - *Dependent:* station-level change in ridership due to COVID-19. *Explanatory:* age, race, median income, education, job and population density, % of jobs by sector, land use, COVID-19 cases and deaths; # of trips and average frequency	• COVID-19 impacted 95% of stations, reducing transit ridership by 72.4%. • Regions with more Whites, more educated people, high-income, & commercial land use lost more riders than regions with more trade, transportation, and utility sectors jobs. • Regions with more severe cases/deaths saw smaller transit decline
Parker et al. (2021)	• U.S.: 97 metropolitan and rural counties and 26 states • January to December 2020 • Primary survey data from Embee Mobile • Descriptive statistics, negative binomial regression, and Tobit regression	• Travel behavior (weekly total # of trips, total and average distance traveled by transit and non-transit riders), economic factors, household dynamics, physical and mental health, personality characteristics, political views, adherence to COVID-19 related measures, demographics	• COVID-19 impacted travel for transit riders more than for non-transit riders. • Due to service change, concerns about infections, and stay-at-home orders, 74.5% reported taking transit less • During the pandemic, lower-income transit riders neither reduced their transit trips nor traveled shorter distances
Studies on rider's satisfaction and perceptions of transit			
Wan et al. (2016)	• New York City, U.S. • 2014 • 1,700 (BRT) riders survey on 4 routes • 5 points Likert scale survey, t-tests, χ^2 tests and ordinary least squares (OLS)	• 13 key service attributes • OLS - *Dependent*: total satisfaction; *Explanatory*: age, gender, weather condition, weekday vs. weekend service, trip purpose, and satisfaction for 13 SA	• Top attributes for BRT: frequency, on-time performance, and speed • BRT-dependent riders are more satisfied with service quality • Young people, males, commuters prioritize schedule info. at bus stops and real-time information on the internet
Grisé & El-Geneidy (2018)	• Greater Toronto and Hamilton Area, • Between 2011 and 2016. • 4,750 customers survey satisfaction data on the GO rail transit • Principal component analysis and k means cluster	• 6 broad service attributes: service and train stations, loyalty and overall GO Train satisfaction, accessibility and commuting behavior, level of service, financial status, personal travel behavior, satisfaction with parking and parking occupancy	• Loyal underserved users have a positive perception of station cleanliness, staff, and safety at train stations, but are unhappy with on-time performance, seat availability, & communication of delays • Spatially captive users highly satisfied

		with the availability of parking and seats

CHAPTER 5: CONCLUSIONS

For my dissertation, I considered two questions: 1) How did Transportation Network Companies (e.g., Uber and Lyft) impact transit ridership in the U.S. and California? and 2) How did the COVID19 pandemic impact transit ridership and mode preferences in California? To address these questions, I analyzed data from three surveys (the 2009 and 2017 National Household Travel Surveys and a May 2021 Ipsos survey) using various analytical tools (cross-nested logit models, generalized ordered logit models, binary logit models, and propensity score matching).

Chapters 2 and 3 dealt with the first question. In Chapter 2, I contrasted individuals/households who use public transit (PT), TNCs, and both by analyzing mode use data collected in the 2017 NHTS. I defined four mutually exclusive categories of individuals/households and estimated Cross Nested Logit models. My results show that transit and TNCs target individuals/households who share common socio-economic characteristics and live in similar (higher density) areas. These groups are more likely to be Millennials and belong to Gen Z, with higher incomes, advanced degrees, no children, and fewer vehicles than driver's license holders. In addition, they reside in denser areas, and CBSAs are served by PT and TNCs.

In Chapter 3, I quantified the impact of TNCs on household travel, particularly on transit use, walking and biking. I analyzed data from the 2009 and 2017 National Household Travel Survey (NHTS) using propensity score matching (PSM) to cleanly isolate the impact on household travel behavior of a "treatment" (here, the emergence of TNCs) while controlling for variables known to affect travel behavior. My treatment and control groups are matched households from the 2017 and 2009 NHTS, respectively. My findings suggest that households made fewer transit trips due to TNCs' penetration of the U.S. transportation market. For example, on an average weekday, a household in 2017 made 1.6 fewer transit trips (a 22% drop) compared to 2009. For a weekend, this rate is a 15% decrease (1.4 fewer daily transit trips per household). For California, this rate is higher for weekdays and weekends, approximately 44% and 27%, respectively.

Chapter 4 dealt with the second question. In Chapter 4, I explored Californian's intentions to use different modes (driving, transit, walking and biking, and TNCs) for any travel purpose after the pandemic is over based on a random survey of Californians conducted by Ipsos in late May 2021. I also examined why Californians were reluctant to use transit in 2017 and why they may not use it once the COVID-19 pandemic is over. While 62% and 66% of respondents for each mode anticipated no change, three modes could experience substantial drops in popularity: driving, transit, and TNCs. A decrease in driving would reduce VMT and help the state achieve its greenhouse gas reduction target. However, nobody can say at this point if the intentions of 19% of Californians to reduce driving will be sufficient to substantially offset the 15.3% of Californians who intend to drive more, partly as they decrease their use of transit. Results for transit are grim: over 28.9% of Californians intend to use transit less after COVID-19, and only 7.3% would like to use transit more post-pandemic. While this drop affects a broad range of Californians, it disproportionately affects Hispanics, African Americans, Asians, lower-income households, and people who would telecommute more, many of which had been sustaining transit ridership until before the pandemic. A silver lining to these results is a substantial uptick in intentions to walk and bike more (25.8%), although 8% of Californians stated opposite intentions. The main reason why Californians would not take transit before the pandemic and why they likely will not take it after is well-known: Californians prefer to drive, which I interpret as saying that driving a personal vehicle offers more flexibility (e.g., to drive someone, to carry shopping, to leave at any time) and is perceived as safer than taking transit. The second and the third most common reasons in the 2017 NHTS ("no stops near destinations of interest" and "service not frequent enough") and in my 2021 COVID-19 survey ("no stops near the destination of interest," and "service takes too long") reinforce that point.

My dissertation makes several contributions. To the best of my knowledge, Chapter 2 is the first nationwide study to contrast public transit and TNC users that rely on cross-nested logit structures. The second contribution of Chapter 2 is a comparison between individual and household-level models to account for intra-household dependencies of mode choice. The main contribution of Chapter 3 is to tease out the causal link between the emergence of TNCs and the decline of transit at the household level using propensity score matching, as previous studies relied either on descriptive statistics, correlation analyses, or considered aggregate ridership changes. Finally, my investigation in Chapter 4 is the first to inquire about Californians' willingness to take transit after the pandemic and to explore obstacles that need to be overcome for transit to recover.

Overall, my findings highlight the danger of public transit entering into outsourcing agreements with TNCs, neglecting captive riders (people with no alternatives to transit), and exposing choice riders to TNCs. My results also indicate that limitations of transit's reach and frequency are especially of concern for younger adults (Gen Z and Gen Y), people with more education, and especially members of more affluent households (the so-called "choice riders."

A key priority for transit agencies should therefore be to increase (as much as possible and appropriately) the frequency of their service, develop their network and extend their reach by addressing the first- and last-mile problems, possibly by creating partnerships with micro-mobility (e.g., shared e-scooters, bikes, or e-bikes) providers. A more decisive approach would be to change the way transit is financed through free or reduced-fare transit pass programs, which could bring transit agencies back to fiscal health while enhancing the mobility of students, workers, and disadvantaged groups. Finally, transit policy needs to be integrated into comprehensive policies designed to achieve U.S. and California's transportation, social, and environmental goals.

My dissertation is not without limitations. The main limitation of Chapter 2 is that I do not have information about the type of public transportation (e.g., bus versus light rail or heavy rail) that NHTS respondents took 30 days before their survey day. This prevents me from distinguishing between bus and heavy rail/metro users, potentially problematic because TNCs impact bus transit differently than heavy rail/metro systems. A second limitation is the restriction of my data to individuals/households who have access to motor vehicles, as explained above. An important limitation of Chapter 3 is not including transit supply variables, convenience, and safety in my models. Finally, in Chapter 4, I analyzed intentions such as people's intention to drive more post-pandemic, which can be considered a limitation because people's preferences may be at odds with their actual actions. These shortcomings could be overcome by combining perception-related surveys with other survey methods, for example, participant observation (by keeping a travel diary) and in-depth interviews.

Future work (related to Chapter 2) could explore whether TNCs are complements or substitutes for different types of public transportation (e.g., heavy rail or light rail versus buses). For Chapter 3, it would be of interest to capture the effect of transit supply variables with more fine-tuned data. Transit supply side factors could include, for example, employment size, bus schedules, or fleet size. For Chapter 4, future research related to the impact of COVID-19 on various modes could investigate the effects of additional land use variables (especially as they relate to transit and the walking/biking infrastructure). Finally, it would also be interesting to understand the heterogeneity of intentions to use various transportation modes after the pandemic among Hispanics, African Americans, and Asians to gauge the quality of their access to transit, biking, and walking infrastructure.

Despite considerable investment over the last decade, public transportation is losing ridership, both in U.S. and California. Emerging technologies and COVID-19 are two key reasons behind this decline. I hope my dissertation will help policymakers and transit agencies make better-informed decisions to help transit get back to health after the dawn of the CVOID-19 pandemic.