UCLA
UCLA Electronic Theses and Dissertations

Title
Trajectories of Vehicle Ownership and Access in American Households

Permalink
https://escholarship.org/uc/item/95r326k9

Author
Brumbaugh, Stephen

Publication Date
2020

Peer reviewed|Thesis/dissertation

eScholarship.org
Powered by the California Digital Library
University of California

UNIVERSITY OF CALIFORNIA

Los Angeles

Trajectories of Vehicle Ownership and Access in American Households

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy in Urban Planning

by

Stephen Paul Brumbaugh

2020

© Copyright by

Stephen Paul Brumbaugh

2020

ABSTRACT OF THE DISSERTATION

Trajectories of Vehicle Ownership and Access in American Households

by

Stephen Paul Brumbaugh
Doctor of Philosophy in Urban Planning
University of California, Los Angeles, 2020
Professor Evelyn A. Blumenberg, Chair

Most American households rely on vehicles for access to employment and other opportunities, but their levels of vehicle ownership may vary over their life course. In this dissertation, I use sequence analysis techniques and longitudinal data from the Panel Study of Income Dynamics to investigate family vehicle ownership trajectories, differences in trajectories across social groups, and changes in vehicles owned by low-income households.

Chapter 1 examines trajectories of family vehicle ownership from 2001 to 2017. Many households have stable levels of vehicle ownership. "Multi-mobility," or owning more than one vehicle per adult, occurs nearly as often as owning no cars. After establishing a typology of trajectories, I construct a model to predict the likelihood that a household takes a certain trajectory type. In the model, a family's starting vehicle ratio has the most explanatory power.

Chapter 2 examines trajectories of vehicle ownership by income, race, ethnicity, and family structure from 2001 to 2017, and by birth cohort from ages 22 to 30. Most groups show stability in vehicle ownership. Vehicle ownership levels are only slightly less stable in low-income households than in other households, in part because other households sometimes experience multi-mobility.

Chapter 3 investigates changes in vehicle holdings among low-income households from 2001 to 2017. Sport utility vehicles (SUVs) account for an ever-increasing share of personal

vehicles, despite policies intended to facilitate purchases of more fuel-efficient vehicles. The average fuel economy for owned vehicles increased for all families, but at a slower rate for low-income families.

Transportation planners and policymakers may consider three types of policies to influence trajectories of vehicle ownership. The first involves policies to reduce vehicle ownership, which may have less effect on travel and pollution than expected. The second involves policies to increase ownership among low-income households, which may face political challenges. The third involves policies to maintain ownership, which may be more politically feasible if framed as efforts to help people stay employed.

The dissertation of Stephen Paul Brumbaugh is approved.

Jennie Elizabeth Brand

Paul M. Ong

Brian D. Taylor

Evelyn A. Blumenberg, Committee Chair

University of California, Los Angeles

2020

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I am indebted to Evelyn Blumenberg, my committee chair, for mentoring me through the dissertation research and writing process, for offering valuable feedback on ideas and drafts, and for offering pragmatic advice as challenges arose. Working with Evy has profoundly shaped how I think about transportation.

I am also grateful for the support of my committee members, who offered thoughtful feedback that greatly improved the quality of my work. In particular, Brian D. Taylor encouraged me to situate the work in a broader policy context, Paul Ong encouraged me to improve the statistical rigor of the work, and Jennie E. Brand encouraged me to consider the effects of place in greater depth.

At UCLA, the Department of Urban Planning and the Institute of Transportation Studies provided funding for my doctoral work. My colleagues Andre Comandon, Rebecca Crane, and Silvia González offered support, encouragement, and feedback as writing group partners.

The University of Michigan's Institute for Social Research allowed me to work with the restricted-use version of the Panel Study of Income Dynamics, and I appreciate the capable assistance of their staff. The data collection was partly supported by the National Institutes of Health with grants R01-HD069609 and R01-AG040213 and by the National Science Foundation with awards SES-1157698 and SES-1623684.

Finally, I thank my colleagues at the U.S. Department of Transportation, my friends, and my parents. Special thanks go to Sean Ford for offering comments on vehicles and fuel economy, Theresa Firestine for giving technical advice on map projections, Glenn Ellmers for being a writing partner in Washington DC, and Abel Darg, Mindy Liu, and Patrick Roberts for motivating me to keep writing. I am grateful for everyone's support through a challenging but rewarding journey, even as my transportation puns drove them mad.

VITA

2003	A.B. (East Asian Studies), Harvard University
2010	M.A. (Urban Planning), University of California, Los Angeles
2016–	Economist, U.S. Department of Transportation

Introduction

Most American households rely on vehicles for access to employment and other opportunities, but their levels of vehicle ownership may vary over their life course for social, economic, geographic, and personal reasons. Understanding trajectories of household vehicle ownership is important for transportation scholarship and policy for several reasons. First, vehicle ownership patterns may have changed for a multitude of potential reasons, including shifts in the labor market toward flexible labor, increased income volatility, and the rise of shared mobility services. Second, understanding trajectories can inform policy responses involving family vehicle ownership and access, and may suggest ways to reduce disparities in employment and wealth accumulation among social groups. Finally, planners can use information about trajectories to refine travel behavior models for long-range transportation planning.

In this dissertation, which consists of three self-contained chapters, I study vehicle ownership over a family's life course to answer three overarching research questions:

1. What are the most common trajectories of vehicle ownership in families, and what factors influence the trajectories that families take?

2. How do trajectories taken by families differ by income, race, ethnicity, family structure, and birth cohort?

3. How have low-income families changed their vehicle fleets, and what factors influence the types of vehicles they acquire?

To examine patterns of vehicle ownership, I use sequence analysis—a set of analytical methods not used in studies of vehicle ownership to date—and panel data analysis. The analysis relies on confidential geocoded data from the Panel Study of Income Dynamics

(PSID), supplemented with data on residential density from the Census and data on transit access from the National Transit-Oriented Development (TOD) Database.

In the first chapter, I examine trajectories of family vehicle ownership from 2001 to 2017. The analysis shows that many households have stable levels of vehicle ownership even if the number of vehicles in the household changes. The state of what I term “multi-mobility,” or owning more than one vehicle per adult, occurs often in households—nearly as often, in fact, as owning zero vehicles. After establishing a typology of vehicle ownership trajectories, I construct a multinomial logit model to test how a household’s baseline characteristics affect the probability it takes a given vehicle ownership trajectory. Among the characteristics tested, a family’s starting vehicle ratio has the most influence.

In the second chapter, I examine trajectories of vehicle ownership in the United States by income, race, ethnicity, family structure, and birth cohort from 2001 to 2017, and by birth cohort from ages 22 to 30. These groups have been of interest to planners and policymakers because they have shown disparities in vehicle access. While multiple scholars have examined vehicle ownership and travel behavior among members of these groups, they have not explicitly considered trajectories of vehicle ownership. I find that most population groups show a high degree of continuity in vehicle ownership. Vehicle ownership is only slightly less stable in low-income households, in part because upper-income households transition between owning one or more than one vehicle per adult.

In the third chapter, I trace changes in vehicle holdings, including vehicle type, age, and fuel economy, for low-income households. I find that sport utility vehicles (SUVs) account for an ever-increasing share of vehicles in low-income households, despite policies intended to facilitate purchases of fuel-efficient vehicles. The average fuel economy for owned vehicles increased for all families from 2001 to 2017, but at a slower rate for low-income families, although the extent to which this trend reflects consumer preferences versus constraints in the used-car market is unknown. Factors that influence the type of vehicle a family owns include family size, income, sex, and race.

I conclude the dissertation by discussing the policy implications of the research and suggest opportunities for future research. Understanding and predicting trajectories of vehicle ownership can inform three types of policy responses, with different degrees of feasibility and effectiveness. The first type involves policies to reduce vehicle ownership, which may have less influence on travel and pollution than expected given trends such as multi-mobility. The second type involves policies to increase ownership among low-income households, which may be effective but may face political challenges. The final type involves policies to maintain ownership, which may be more politically feasible if framed as efforts to help people stay employed.

CHAPTER 1

Trajectories of Family Vehicle Ownership in the United States

Abstract: Households have trajectories of vehicle ownership that vary over their life cycle. I employ sequence analysis techniques and data from the Panel Study of Income Dynamics to examine these trajectories for American families from 2001 to 2017. The analysis shows that many households have stable levels of vehicle ownership. "Multi-mobility," or owning more than one vehicle per adult, occurs frequently in households—nearly as often as owning zero cars. Many transitions in family vehicle ownership not only involve gaining vehicles instead of losing them, but also involve multi-mobility. After establishing a typology of vehicle ownership trajectories, I construct a multinomial logit model to test how a household's baseline characteristics affect the probability of taking a certain trajectory. A family's vehicle ratio has the most explanatory power in the model, given the stability of ownership over time.

1.1 Introduction

Most American households depend on automobiles for access to employment and other opportunities. Their trajectories of vehicle ownership tend to vary over their life cycle, as well as by social and economic circumstances. In this chapter, I characterize and examine these trajectories for households in the United States from 2001 to 2017 using a mobility biography approach and longitudinal data from the Panel Study of Income Dynamics (PSID).

I use sequence analysis—a set of analytical methods not used in studies of vehicle ownership to date—to describe family trajectories of vehicle ownership and identify a set of patterns that form a typology of vehicle ownership. Using these patterns, I construct a model to predict the probability of a family taking a certain trajectory given its baseline characteristics.

This chapter makes two contributions to research on household vehicle ownership. First, it uses a novel approach, sequence analysis, to explore vehicle ownership patterns. These techniques offer a holistic, complementary alternative to conventional, mostly cross-sectional statistical approaches that summarize vehicle ownership at a point in time or over a period of time. Second, the chapter quantitatively analyzes what I term "multi-mobility," or the state of having more vehicles in a household than adults. Multi-mobility has received little attention from researchers but has important implications for transportation planning and policymaking, given that higher levels of vehicle ownership may induce additional driving, traffic congestion, fuel consumption, and pollution.

1.2 Mobility biographies and vehicle ownership

Traditional studies of household vehicle ownership emphasize the relationships among household characteristics, land-use characteristics, and vehicle ownership, usually at a given time. Studies in the United States often use cross-sectional datasets such as the National Household Travel Survey; studies using panel data are rare (Klein and Smart 2017a). Cross-sectional surveys cannot capture variation *within* households, however, and cannot assess the influence of a family's past experiences without directly asking respondents about them.

Studies using a mobility biography approach, in contrast, emphasize the role of life events, life-course transitions, and learning processes in shaping a household's travel behavior (Scheiner 2017). Mobility biographies are an emerging area in travel behavior research (Müggenburg, Busch-Geertsema, and Lanzendorf 2015; Scheiner 2017). A growing number of studies examine factors that contribute to changes in household vehicle ownership, including sociodemographic factors and life events (Prillwitz, Harms, and Lanzendorf 2006;

Clark et al. 2014; Oakil et al. 2014).

Studies adopting a mobility biography approach use panel data or retrospective diaries to construct biographies for respondents with information on life events like marriage and mobility-related events like vehicle purchases. The studies typically employ descriptive statistics and regression models to look at differences between two points in time. Some studies, for example, construct regression models to test the relationship between household factors and the decision to gain or lose cars between survey waves (Oakil et al. 2014; Klein and Smart 2019). Researchers measure vehicle ownership using the number of cars owned, the ratio of vehicles to adults, or the ratio of vehicles to drivers. These studies typically focus on the number of vehicles available at the household level rather than the individual level, although research on gender and travel behavior reveals considerable intra-household variation in access to vehicles (Blumenberg, Brown, and Schouten 2018b).

Most studies using a mobility biography approach examine travel behavior in Europe (Müggenburg, Busch-Geertsema, and Lanzendorf 2015), where researchers enjoy access to several national longitudinal household studies with information on vehicle ownership and travel behavior. These studies have limited application in the American context, however, because European patterns of automobile use differ significantly from those in the United States (Buehler 2010). In the United States, only Klein and Smart (2017a, 2019) have examined vehicle ownership in families over time. Using longitudinal data from the 1999 to 2011 waves of the PSID, they study the characteristics of carless families. They find that an average of 13 percent of families in each survey wave did not have a car, but only five percent of families did not have a car for the entire period. While low-income, immigrant, and minority families were less likely to own cars than other families, carlessness was still only a temporary state even among families in these demographic groups.

Much of the research on vehicle ownership, whether it employs a traditional or mobility biography approach, focuses on distinctions between zero-vehicle households and other households, or on distinctions between having zero cars by choice or by economic circumstance (Brown 2017; Mitra and Saphores 2019). Families with at least one car but less than one car per driver are more numerous than families with zero vehicles but receive less attention in the scholarly literature. Blumenberg, Brown, and Schouten (2018b) find that low-income families in this category, which they term “car-deficit households,” use their vehicles almost as often and for almost as many miles as low-income households with at least one car per driver. That said, the authors note that drivers in car-deficit households must engage in careful negotiations around household vehicle use and that sharing vehicles can be challenging.

1.3 A case for using sequence analysis

While many mobility biography studies examine short segments of people’s lives or the influence of discrete events like marriage, fewer studies have examined relationships between longer-term life courses and travel behavior (Scheiner 2017). Sequence analysis, a collection of quantitative techniques used to analyze ordered lists of states or events (Abbott 1995), is a novel approach to examining these relationships. Sequence analysis can complement existing analytic approaches by giving researchers tools to understand complex life course processes holistically (Brzinsky-Fay and Kohler 2010). Sequence analysis emerged from computer science and information theory, offering tools to describe, classify, and compare state sequences. It also offers tools to make predictions based on a prior sequence or identify causes for different sequences (Abbott 1995). One can find sequences in many domains, including computer science (where sequence analysis techniques were developed) and bioinformatics (to classify DNA, RNA, and peptide sequences). In the social sciences, one can find sequences in life-course and career trajectories (Abbott 1995); more recently, researchers have adopted sequence analysis to examine progressions in residential location and neighborhood change (Delmelle 2015).

In the travel behavior domain, one can conceptualize a household’s vehicle ownership as a state—for example, a state of carlessness or a state of having one car per adult. That state can change for economic, residential, life-cycle, or attitudinal reasons. A low-income family whose economic fortunes vary, for example, may alternate between states of carlessness or having a single car. In another example, a couple may transition from owning one car to owning multiple cars in advance of having a child. Sequence analysis allows researchers to construct typologies of vehicle ownership patterns or to find differences in vehicle ownership trajectories among demographic groups or cohorts.

Understanding trajectories of vehicle ownership is relevant for planners and policymakers who must consider long-term patterns of vehicle ownership and usage for land use planning, transportation investments, and environmental planning. Understanding the factors that determine trajectories, such as personal characteristics or precipitating events, can help in identifying who is likely to change their vehicle ownership—and, equally importantly, who is not—and in identifying the types of policies or built environment characteristics that influence people to change. Given the key role that automobiles play in improving economic outcomes for many low-income households (Blumenberg and Pierce 2014), policymakers may wish to identify the factors that lead to stability in vehicle access.

Understanding patterns of vehicle ownership can also inform transit planning. Manville, Taylor, and Blumenberg (2018a) examine the causes of declining transit use in southern California in the 2000s. They find that increasing vehicle access—especially among low-income households who use transit most often—was the most significant factor, and more significant than commonly-cited factors like transit service, fuel prices, and ride-hailing services.

1.4 A case for studying multi-mobility

While the percentage of households owning at least one vehicle in the United States has been stable at just under 90 percent since the mid-1990s (Bureau of Labor Statistics 2018), vehicle ownership per capita continues to rise (Davis and Boundy 2019). Some households have more than one vehicle per adult, a state that I term “multi-mobility.” Multi-mobility is not exclusive to the wealthy: Klein and Smart (2017a) find that 6 percent of households living below the poverty line own more than one vehicle per adult. According to data from the 2017 National Household Travel Survey, an estimated 24.7 million households in the United States had more vehicles than members age 18 or older—more than twice the estimated 10.6 million households with zero vehicles (Federal Highway Administration 2017). Despite the prevalence of these households, a literature search revealed no studies that discussed them in detail.

A Reddit user in the "r/AskAnAmerican" group asked how common it was for American families to own more than one vehicle per person (Reddit 2017). The 66 comments offered a variety of reasons for doing so. Some families keep vehicles for children who are away at college. Others may have vehicles for business purposes. Others may have vehicles for specialized uses such as recreational travel, home improvement, hauling, or hunting. Some may have cars that are not operable but sitting somewhere until the owner can afford repairs if the cost of obtaining another car is higher than repairing it. Finally, some people may own multiple cars simply because they like cars and the status of owning certain models.

Members of the Millennial generation (born 1981 to 1996) have lower rates of licensing and vehicle ownership than earlier generations (Ralph 2017), calling into question whether multi-mobility will last. Numerous popular media articles assert that Millennials—and, recently, members of Generation Z born in 1997 or later (Roberts 2019)—have less interest in car ownership than previous generations, suggesting that multi-mobility may become less salient due to changing attitudes toward vehicle ownership. At the same time, other research has shown that economic factors are the primary explanation for lower rates of car ownership among Millennials (Blumenberg et al. 2012; Klein and Smart 2017b). Moreover, younger drivers seem to enjoy driving to the same extent as older drivers. A 2018 Gallup poll found that 76 percent of American drivers age 30 to 49—an age range overlapping Generation X and Millennials—enjoy driving "a great deal" or "a moderate amount" (Brenan 2018). The percentage is only slightly lower than the 80 percent of drivers age 50 to 64 who also enjoy driving.

Most studies of vehicle ownership look at the absolute number of cars rather than the ratio of cars to adults, and even studies that use ratios, like Blumenberg, Brown, and Schouten (2018b), create an aggregated "*one or more* vehicle per adult" category (emphasis mine). This chapter, in contrast, treats "more vehicles than adults" as a distinct analytic category from "one vehicle per adult." The difference between the two categories may seem trivial for travel behavior research, given that a person can drive only one vehicle at a time. Multi-mobility merits further examination, however, because it has implications for policies intended to alter vehicle ownership and use. Even if a person cannot drive more than one car at once, higher levels of vehicle ownership can induce additional driving and pollution. For example, someone may own a fuel-efficient compact car for the work commute and a less-efficient truck or SUV for weekend recreational travel. Multi-mobility may also mean that policies to reduce vehicle ownership may not lead to the expected reductions in daily trip-making, VMT, or vehicle emissions if people get rid of extra cars used only occasionally.

Multi-mobility also warrants examination because it may also occur outside the United States. Vehicle ownership per capita has increased with economic growth in the last several decades around the world (Dargay, Gately, and Sommer 2007). In 2017, the number of passenger cars per capita exceeded 600 vehicles per 1,000 people in six European Commission countries (Eurostat 2019), Iceland (Statistics Iceland 2018), and New Zealand (New Zealand Ministry of Transport 2019).

Outside the United States, multi-mobility has policy implications for governments that try to impose driving restrictions in attempts to reduce traffic congestion or pollution. Mexico City, Athens, and other major cities have implemented various driving restrictions—for example, by restricting driving on certain days based on license plate numbers (Zhang, Lin Lawell, and Umanskaya 2017). These restrictions prompted some households to buy more cars to skirt the restrictions. Imposing restrictions on vehicle use without considering multi-mobility thus may lead to less effective results. Multi-mobile households may respond to restrictions by using other available cars, defeating the purpose of the restrictions (Sorensen et al. 2008). Worse, many of the secondary vehicles purchased to skirt the restrictions are older and emit more pollution than primary vehicles (Sorensen et al. 2008), exacerbating the pollution issues the restrictions were intended to curb.

1.5 Data and analysis

To analyze trajectories of household vehicle ownership in the United States, I use data from the confidential geocoded version of the 2001 to 2017 waves of the PSID. The PSID is a biennial longitudinal household survey that measures employment, wealth, spending, and other social factors in American families (Institute for Social Research 2017). In 2017, 9,607 families with 26,445 individuals took part in the survey. In this analysis, family histories are the unit of analysis rather than individual observations for each family in each survey year (also called "family-year observations"). The PSID contains information on family vehicle ownership but does not contain information on daily travel behavior, save for the length of time family members spend commuting to and from work.

Residential location also influences vehicle ownership and use. For urban residents, access to public transit reduces vehicle ownership and use (Kim and Kim 2004), although associated neighborhood factors including lower parking availability, smaller housing units, and higher accessibility may explain changes in automobile use rather than the transit access itself (Chatman 2013). Vehicle ownership may also motivate families to live near public transit, as shown in Glaeser, Kahn, and Rappaport (2008), who find that low-income households tend to make residential location decisions based on access to public transit. Rural residents, in contrast, have higher levels of car ownership than urban residents regardless of income, race, or age (Pucher and Renne 2005). The geocoded version of the PSID contains Census block groups for the residential location of respondents, allowing me to supplement the PSID with Census tract-level measures of residential density and transit access.

1.5.1 Defining families and vehicle ratios

The PSID began in 1968, and people have split off from the original survey families and formed new survey families—sometimes multiple times. This analysis focuses on families in the 2001 survey wave, which had 7,406 families. I restrict the sample to families who report vehicle information for the remaining survey years through 2017. The final sample has 3,342 family units.

Sequences may be incomplete—in this case, meaning that a family does not have information recorded for every year from 2001 to 2017—for three reasons. First, sequences may start late. In the PSID, someone may have moved and started a new family after 2001. Second, sequences may end early. Families with older members in 2001, for example, may have nobody alive in 2017. Finally, sequences may have missing data in the middle. If a family fails to respond to the PSID one year, the PSID staff tries to contact them again in later years. Ritschard, Gabadinho, and Studer (2012) note that sequences with missing states are "more the rule than the exception" in the social sciences and that there is no universal method for dealing with such sequences. In the PSID, vehicle information is almost complete, assuming that families respond to the survey: in the full dataset with 76,834 family-year observations, 23 observations have missing vehicle data. Only two families in the PSID have missing vehicle data for more than one survey year.

While data for families that respond may be complete, restricting the sample to families with sixteen years of complete data may raise questions of selection bias. The PSID has a high response rate (91 percent overall; 94 percent wave-to-wave), reducing the possibility of biased estimates. While low-income families have higher attrition rates than higher-income families in the PSID, Johnson et al. (2018) did not find that the parameter estimates were biased. Using sixteen years of complete data does reduce the number of families at the older and younger ends of the age distribution in the 2017 wave, however: some older families from 2001 will have died, and younger families in 2017 did not exist in 2001.

To measure household-level vehicle access and account for variations in household size, I construct a "vehicles per adult" ratio, following the example of Klein and Smart (2019). Klein and Smart (2019) note that using a ratio of an absolute number of vehicles has tradeoffs. Ratios may yield more insight for examining how members of households negotiate decisions about sharing cars but make it harder to interpret the effects of events like divorce that change the household structure and vehicle ownership ratios at the same time.

The PSID does not identify drivers or ask whether family members have drivers' licenses, which complicates analysis using vehicle ratios. Some families measured as having "more than one car per adult" may have one car per driver or less if they have teenagers with licenses who drive. Conversely, some families may have a higher ratio of cars to drivers than measured if not all adults have licenses and drive.

A higher percentage of families in the "more than one car per adult" group do have teenagers age 16 and 17 than families in other groups (23.0 percent versus 8.3 to 14.4 percent), although three-quarters of the group (77.0 percent) have zero teenagers. Table B.1 in Appendix B shows that the percentage of families with teenagers is highest in 2001 at 30.2 percent and declines to 18.0 percent in 2017. Not all teenagers drive, however, as illustrated with data calculated from the National Household Travel Survey in Table 1.1. The percentage has declined from 63.4 percent in 2001 to 49.9 percent in 2017. Further, given the rise of graduated driver licensing programs (Blumenberg et al. 2012), some of the teenage drivers cannot legally drive on their own until age 17 or 18. Appendix B contains supplemental tables with analysis results from this chapter recalculated using the ratio of vehicles to adults plus teenagers. The results are in line with the results presented in this chapter, in part because zero-vehicle households are unaffected by a change in the denominator and because many households have zero teenagers.

Table 1.1: Teenage drivers by year, 2001–2017 (National Household Travel Survey)

Year	Age 16	Age 17	Total
2001	59.3%	67.9%	63.4%
2009	49.8%	66.6%	58.2%
2017	40.3%	61.4%	49.9%

1.5.2 Measuring transit access

While Klein and Smart (2019) used time-invariant measures of transit access, a time-variant measure of transit access is useful in this analysis because some cities greatly expanded their transit systems during the study period. Houston, for example, extended a line at the end of 2013 and introduced two new lines in 2015. Houston also redesigned its bus network and increased the amount of high-frequency transit service offered (Kassel 2019). Charlotte offers a more extreme example: before 2007, it had no rail system at all.

To identify transit stations and the year they were constructed, I use a rail station dataset constructed from the National Transit-Oriented Development (TOD) Database (Center for Transit-Oriented Development 2012), the Transport Politic Blog (Freemark and Vance 2018), and other public sources. Planners typically define "walking distance" to a rail station as a half mile (Guerra, Cervero, and Tischler 2012); I use this threshold distance as well to measure transit access. While some residents may have gained access to multiple stations between 2001 and 2017, this analysis considers only whether a resident has access to at least one rail station within a half mile. The technical appendix contains more information on the station dataset and calculation methodology.

Because national longitudinal data for bus stops are unavailable, I examine access to fixed-rail transit only. While the lack of bus data is a drawback, rail data can cover a substantial share of public transit use. In 2017, rail accounted for almost half (48 percent) of unlinked passenger trips and slightly more than half (57 percent) of transit passenger miles in the United States (American Public Transportation Association 2019). Understanding the effects of TOD—which often involves rail stations in practice, as Chatman (2013) notes—on vehicle ownership is also a matter of research and policy interest itself.

1.6 Descriptive statistics

Table 1.2 shows descriptive statistics for the 3,342 sampled families by vehicle ratio from 2001 to 2017, making a total of 30,078 family-year observations. In this table, an observation is one family in one survey wave. Individual-level statistics like race, ethnicity, and educational attainment are for heads of families at the start of the analysis period. In a family with a male and female adult, the PSID identifies the male as the head of the household for consistency with survey waves from earlier decades.

Table 1.2: PSID family descriptive statistics

Group	Group A (0 cars)	Group B (<1 car/adult)	Group C (1 car/adult)	Group D (>1 car/adult)	All families
Household size	1.7	3.4	2.2	2.5	2.5
Children	0.3	0.6	0.5	0.6	0.5
Age (head)	55.6	54.9	54.8	53.7	54.7
Female-headed	49.0%	14.2%	24.7%	10.2%	22.1%
Median income (2017 dollars)	$18,727	$67,710	$71,709	$89,165	$69,427
White (head)	47.9%	63.9%	81.8%	83.6%	75.9%
Black (head)	38.2%	14.1%	9.1%	9.4%	12.7%
Hispanic (head)	10.6%	15.2%	5.6%	5.1%	7.7%
Asian (head)	1.0%	3.9%	2.0%	0.9%	2.0%
High school graduate (head)	65.8%	75.5%	89.6%	88.7%	84.7%
College graduate (head)	12.9%	27.1%	36.2%	31.0%	31.4%
In metropolitan area	81.8%	80.3%	77.8%	67.5%	76.6%
Near rail	19.9%	9.7%	6.7%	3.4%	7.8%
n (family-year)	3,275	6,715	14,433	5,655	30,078

Families with zero cars (group A) have much lower average annual incomes than other families, including those with less than one car per adult ($18,727 versus $67,710 in 2017 dollars). Household incomes are lower in part because family sizes are smaller: this group has an average family size of 1.7 versus 2.2 to 3.4 for other groups. More than half of families (52.1 percent) with zero vehicles are non-white, and over a third (38.2 percent) are black compared to 9.1 to 14.1 percent in other groups. Nearly half (49.0 percent) of families with zero cars are headed by a female, versus the next highest value of 24.7 percent for families with one car per adult. The head of the household is slightly older in this group than in other groups (55.6 years versus 53.7 to 54.9 years for other groups), but the difference is not substantively large. Finally, families with zero cars are more likely to live within a half mile of rail than any other group, although only one-fifth of families without cars do so (19.9 percent versus 3.4 to 9.7 percent).

Families with at least one car but less than one car per adult in the sample (group B) have more than twice the combined income of families with zero cars ($67,710 versus $18,727). They also have the largest average family size of all groups (3.4 persons versus 1.7 to 2.5 persons for other groups). The percentage of non-white families is 36.1 percent, a lower percentage than in the "zero cars" group. Asian American families in the sample account for less than 2 percent of other groups but account for 3.9 percent of families in this group. A higher percentage of families in this group are Hispanic (15.2 percent) than in the other groups (5.1 to 10.6 percent) as well. Less than a tenth of families in this group (8.1 percent) have rail station access.

Families with exactly one car per adult (group C) have the highest rates of educational attainment, as measured by the percentage of families headed by someone with a college degree (36.2 percent versus 12.9 to 31.0 percent). Families in this group also have the second-highest percentage of families headed by a female (24.7 percent). One explanation may be mathematical: a female-headed household is more likely to be a single-adult household than a male-headed household, given how the PSID identifies the head of the household, and a ratio of "at least one car but less than one car per adult" is impossible for a single-adult household. White families account for four-fifths (81.8 percent) of families in this group.

Finally, families with more than one car per adult (group D), or "multi-mobile" families, have higher incomes than all other households ($89,165). Like group C (1 car per adult), more than four-fifths (83.6 percent) of families in this group are white. Multi-mobile families are also the least likely to live near rail (3.4 percent of families).

1.6.1 Visualizing histories of household vehicle ownership

With four states of vehicle ownership and nine survey waves, one can theoretically form up to 4^9, or 262,144, unique histories or sequences. The 3,905 households in this analysis have 2,054 unique sequences. Attempting to describe more than 2,000 unique histories would be

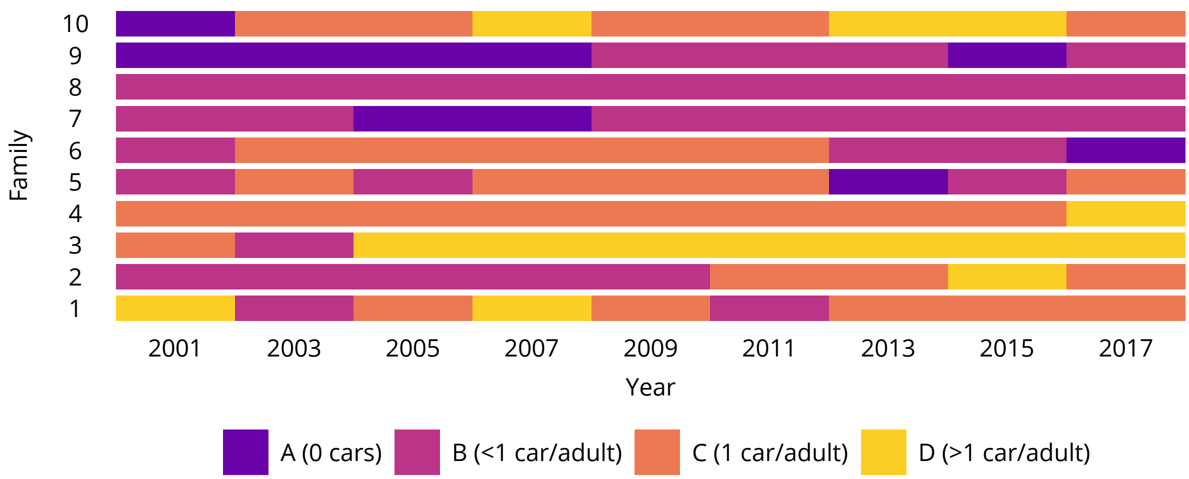

Figure 1.1: Family histories of vehicle ownership (first ten families), 2001–2017

an enormous undertaking while being unlikely to offer much insight.

A first step in understanding the histories of household vehicle ownership is finding a way to represent them visually. Textually, one can represent sequences using short notation resembling a DNA sequence: for example, a family that has zero cars (group A) for three waves and then has one car per adult (group C) for two waves would have a sequence of "AAACC." Stacking a series of sequences top of each other to view patterns naturally leads to more graphics-oriented forms of visualization. A household's history of vehicle ownership can be visualized as an index plot, which displays sequences as horizontal sets of bars; the colors in the bars correspond to states in the sequences. Figure 1.1 shows sequences of vehicle ownership from 2001 to 2017 for the first ten families in the PSID by interview ID. These ten histories show multiple states, transitions, and timings, including periods in which families have more cars than adults—a more frequent state for these ten families than having zero cars.

Some sequences occur much more often within the sampled households than others. Figure 1.2 illustrates the ten most frequent sequence patterns for household vehicle ownership, which represent nearly one fifth (18.2 percent) of families in the analysis. The results are weighted by the PSID longitudinal family weight, and the heights of the bars are proportional to the weight. Figure 1.2 shows that ratios of car ownership are remarkably

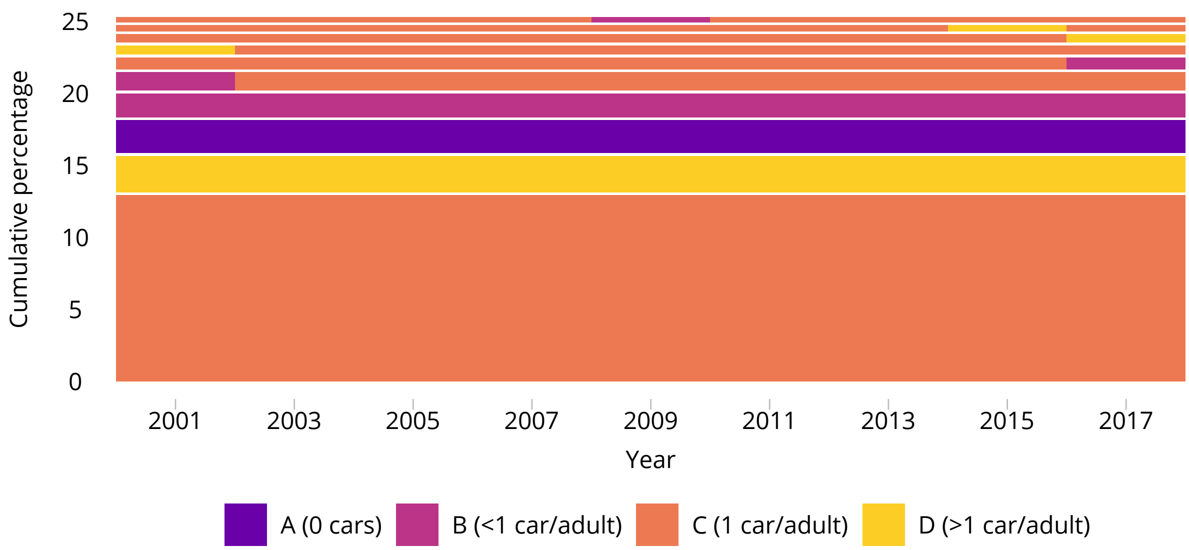

Figure 1.2: Ten most frequent sequences of vehicle ownership, 2001–2017

stable for most families: four of the top five patterns show no changes over the eighteen years, and the remaining pattern shows only one change, from "less than one car per adult" in 2001 to "one car per adult" in 2003. The most frequent pattern is keeping one car per adult for the entirety of the survey, which 10.1 percent of families did. The second most frequent pattern is having more than one car per adult for the entirety of the survey. While the third most frequent pattern is having zero cars for the entirety of the survey, none of the other nine patterns show any periods of carlessness.

A caveat to this finding is that using the PSID to derive sequences may overestimate measures of the constancy of car ownership. Because the PSID shifted from an annual survey to a biennial survey in 1997, this analysis cannot consider the cases of families changing car levels for less than two years between survey periods. Other work suggests that the degree of underreporting is not large. Klein, Smart, and Basu (2019), presenting preliminary work based on a study of families who experienced at least one period of carlessness, find that the average gap lasted 2.9 years and the median gap lasted 1.3 years.

1.6.2 Measuring complexity of ownership histories

A first step in measuring the complexity of ownership histories is calculating the average time that families spend in each of the four states over the nine survey periods. Families stay the longest in the "one car per adult" state, for 4.8 survey periods or just under 10 years. The average time spent in the "more than one car per adult" and "less than one car per adult" stages are nearly identical (1.8 and 1.7 survey periods). Finally, households spend the shortest time in the zero-car state: the average time spent in carlessness is 0.75 survey periods or approximately 18 months. This echoes the findings of Klein and Smart (2017a), who find that carlessness is only a temporary condition for most families.

Another way to assess the complexity of ownership histories is by using the transition rate, which reveals the most frequent state changes and measures the relative stability of each state. Table 1.3, which shows transition rates for the sixteen possible transitions between survey waves, shows that the most stable state is having one car per adult. The probability that a family in that state stays in the state in the next survey period is 0.76. The next most stable state is having zero cars (0.73), followed by "more than one" (0.63) and "less than one" (0.62). The probabilities of transitions where families gain cars are higher than the probabilities of transitions where families lose cars.

Table 1.3: Transition rates between vehicle ownership states

From/To	A (0 cars)	B (<1 car/adult)	C (1 car/adult)	D (>1 car/adult)
A (0 cars)	0.73	0.11	0.13	0.02
B (<1 car/adult)	0.05	0.62	0.28	0.05
C (1 car/adult)	0.02	0.1	0.76	0.11
D (>1 car/adult)	0.01	0.06	0.3	0.63

These transition rates are in line with research showing asymmetrical effects for car ownership. For example, Dargay (2001) shows asymmetrical income elasticities for ownership. The likelihood of increasing ownership after events like moving to the suburbs or gaining income is higher than the likelihood of decreasing ownership after opposite events like moving to the city or losing income. In the latter case, owning a car may become *more*

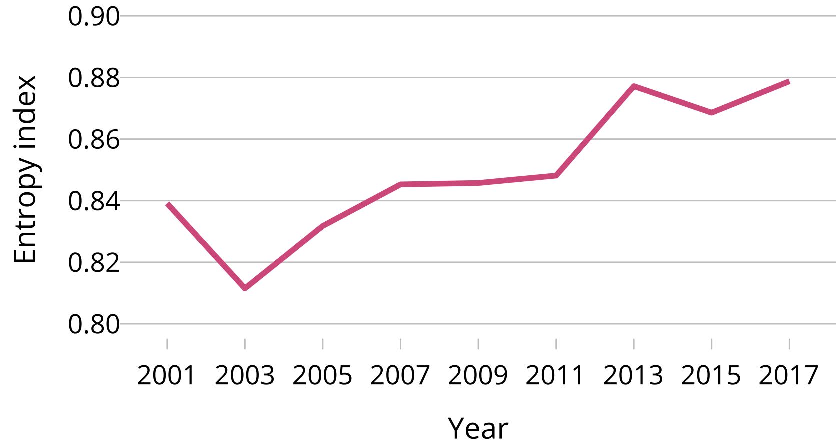

Figure 1.3: Entropy index by year, 2001–2017

important to someone seeking new employment. Because the ownership states involve ratios of vehicles to adults rather than numbers of vehicles, these transition measures account for events like marriage or divorce that change household sizes.

Household vehicle ownership is not only stable in general but also mostly stable over time. One measure of stability for a sequence is Shannon entropy, which measures the uncertainty of predicting the next states in a sequence. The entropy index has increased only slightly from 0.84 in 2001 to 0.88 in 2017 (Figure 1.3), showing that changes have not become substantially more over time, even in 2007 and 2009 during the Great Recession.

1.7 Typologies of family vehicle ownership

Life-course studies, which investigate the diversity of life trajectories (Elder 1994), often create typologies to help make sense of these trajectories (Dorsett and Lucchino 2014). Optimal matching (OM) methods are the most common techniques used to create typologies of sequences (Abbott and Tsay 2000). OM methods measure dissimilarity between sequences with algorithms accounting for sequence order and length. The resulting measures can then be used to group the sequences using standard cluster analysis techniques.

Cluster analysis with sequences, like any other form of cluster analysis, involves subjective judgment. Dorsett and Lucchino (2014), who use OM to construct a typology of school-to-work transitions, describe the process of identifying groups as "an empirically informed subjective decision" and warn that arbitrary decisions may lead to results that "lack sociological meaning." They caution readers that their resulting descriptions of groups are not absolute, even as they try to make informed choices in setting the parameters for measuring dissimilarity and grouping observations. Similarly, the results in this analysis involve a degree of subjectivity; other work with sequence analysis may yield a different typology of vehicle ownership trajectories.

1.7.1 Vehicle trajectory groups

After calculating OM distances for the sequences, I use Ward's method, also known as the method of minimum variance (Ward 1963), to cluster the trajectories into seven groups. Figure 1.4 shows index plots for families in each group. Although each group shows heterogeneity, the plots also show distinct patterns in vehicle ownership.

While the clusters are the same size in the visualization, families do not have an equal probability of belonging to each cluster (Table 1.4). The largest cluster is "fully equipped," to use the term from Blumenberg, Brown, and Schouten (2018b), with 40.1 percent of families (Table 1.4). More than two thirds (70.2 percent) of the families belong to one of the four clusters characterized by stability ("fully equipped," "sharing cars," "multi-mobile," and "mostly carless").

Table 1.4: Groups of vehicle ownership trajectories

Group	Percentage	Typical trajectory
Fully equipped	27.3%	Has one car per adult for most or all years
Losing access	18.9%	Starts with one car per adult then later has fewer than one car per adult
Becoming multi-mobile	17.5%	Switches between having one car per adult and having more than one car per adult
Gaining access	10.4%	Starts with fewer than one car per adult then later has one car per adult
Multi-mobile	10.0%	Has more than one car per adult for most or all years

Group	Percentage	Typical trajectory
Sharing cars	8.7%	Has at least one car but less than one car per adult for most years; includes some families that occasionally have one car per adult
Mostly carless	7.1%	Starts with one car per adult then later has fewer than one car per adult

1.7.2 Household characteristics by vehicle group

Table 1.5 shows the characteristics of families in the seven trajectory groups in 2001 and 2017. Four of the groups have stable vehicle ownership patterns, and their characteristics resemble the characteristics of families classified by vehicle group in Table 1.2. Families in the "mostly carless" group, for example, have lower median incomes in 2017 ($18,142) than those in the "sharing cars" group ($48,909), who have the second-lowest incomes. One unexpected finding is that families in the "becoming multi-modal" group, which alternates between having one car per adult and more than one car per adult, have the highest median incomes of any trajectory group, including the "multi-modal" group. A smaller share of families in the "multi-modal" and "becoming multi-modal" groups live in metropolitan areas (62.2 and 68.4 percent) than do other groups (72.4 to 79.6 percent).

Table 1.5: Characteristics of groups

Group	Fully equipped	Becoming multi-mobile	Multi-mobile	Sharing cars	Gaining access	Losing access	Mostly carless
Owns 0 cars/adult (2001)	7.2%	8.6%	5.0%	8.6%	6.3%	7.3%	13.4%
Owns <1 car/adult (2001)	15.9%	17.4%	15.8%	23.7%	18.2%	19.4%	19.0%
Owns 1 car/adult (2001)	56.7%	54.5%	55.9%	49.9%	54.9%	53.0%	45.0%
Owns >1 car/adult (2001)	20.2%	19.6%	23.3%	17.9%	20.6%	20.2%	22.6%
Household size (2001)	2.6	2.6	2.6	2.7	2.7	2.6	2.7

Group	Fully equipped	Becoming multi-mobile	Multi-mobile	Sharing cars	Gaining access	Losing access	Mostly carless
Household size (2017)	2.2	2.3	2.4	2.5	2.4	2.4	2.4
Median income (2001; 2017 dollars)	$70,705	$67,846	$73,436	$78,063	$81,692	$70,615	$70,647
Median income (2017)	$63,983	$67,161	$59,831	$72,883	$74,742	$70,739	$69,158
In metropolitan area (2001)	74.7%	76.5%	73.3%	78.5%	75.8%	73.7%	70.1%
In metropolitan area (2017)	81.3%	81.0%	78.9%	86.2%	83.9%	82.6%	83.8%
Does not own home (2001)	30.6%	31.2%	31.3%	30.9%	31.0%	32.1%	37.0%
Does not own home (2017)	25.6%	22.5%	24.1%	24.5%	22.2%	26.1%	25.3%
Near rail (2001)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Near rail (2017)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
White (head)	78.4%	77.0%	76.2%	77.0%	74.0%	77.9%	72.2%
Black (head)	13.1%	12.6%	9.6%	13.8%	12.3%	11.5%	15.8%
Hispanic (head)	3.6%	5.2%	9.6%	4.0%	6.8%	5.4%	8.1%
Asian (head)	1.6%	2.5%	1.6%	2.4%	3.4%	2.1%	1.3%
Immigrant	4.2%	7.0%	8.2%	7.2%	8.9%	6.8%	9.4%
High school graduate (2017)	89.9%	86.2%	86.6%	89.1%	87.1%	86.2%	86.5%
College graduate (2017)	35.7%	31.4%	30.7%	34.2%	38.3%	33.4%	29.3%
n (families)	854	573	314	290	363	671	277

The “losing access,” “sharing cars,” and “mostly carless” groups have larger percentages of non-white families (30.0 to 44.1 percent) than the other groups. The percentage of black families in the “mostly carless” group nearly equals the percentage of white families (42.7 versus 45.1 percent). The largest shares of Hispanic families are in the “sharing cars” group (16.1 percent) and the “mostly carless” group (9.0 percent). The largest shares of Asian families are in the “sharing cars” group (3.3 percent) and the “losing access” group (3.0 percent).

The percentage of households with immigrant household heads is higher in the “sharing cars” group (22.8 percent) and the “losing access” group (12.7 percent) than the other groups (3.0 to 8.8 percent). This result is consistent with previous research showing that

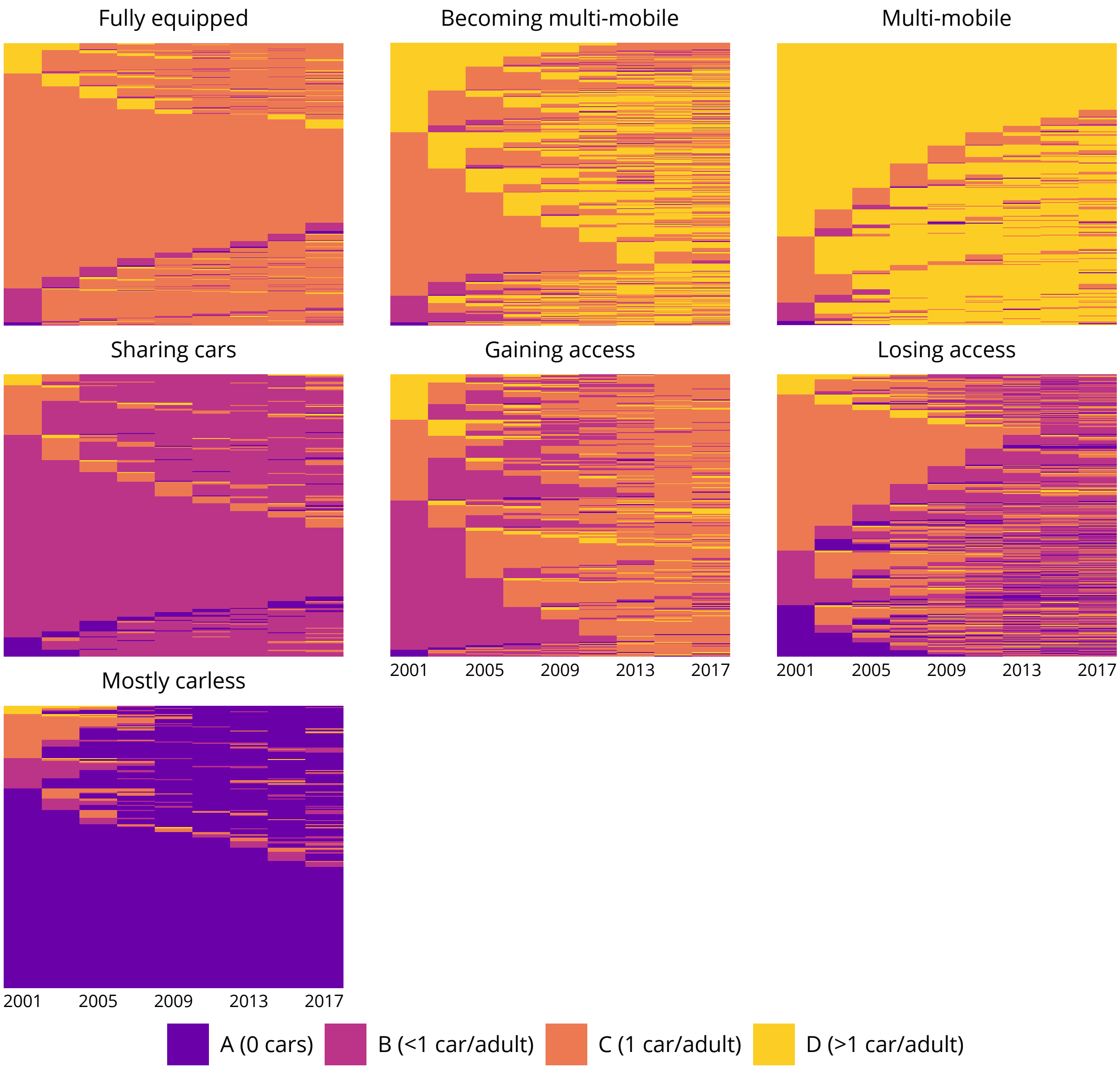

Figure 1.4: Index plots of vehicle ownership by trajectory group

immigrant families in the United States have lower levels of car ownership than native-born families (Tal and Handy 2010) and that Hispanic immigrants are more likely to use transit than non-immigrants even after staying in the United States for long periods (Blumenberg and Shiki 2007).

While lower levels of educational attainment are correlated with lower levels of vehicle ownership, higher education levels do not translate into the highest levels of vehicle ownership. Members of the "mostly carless" group have the lowest percentage of high school graduates (65.8 percent) and college graduates (12.0 percent), followed by the "sharing cars" group (72.4 percent for high school; 18.9 percent for college). The "fully equipped" group has the highest percentage of college graduates (41.2 percent) rather than a group with multi-mobility. The "losing access" group has a slightly higher percentage of college graduates than the "multi-modal" group (31.0 percent versus 30.3 percent) as well.

1.7.3 Representative sequences

Two ways to describe vehicle ownership trajectories in a group are to describe the most frequently occurring patterns or to describe patterns identified in visual representations, as done earlier. A third way is to find small sets of unique "representative" sequences showing the key features of each group (Gabadinho, Ritschard, Studer, et al. 2011). Gabadinho, Ritschard, Studer, et al. (2011) developed a heuristic to identify representative sequences that cover a minimum percentage of "nearby" sequences. Table 1.6 shows representative sequences derived using this heuristic with a 20-percent coverage threshold.

For the four sequence groups marked by stable levels of car ownership ("fully equipped," "multi-mobile," "sharing cars," "mostly carless"), only one representative sequence is necessary: a sequence with constant ownership at the given level. The representative sequences for the "gaining access" group have two to four waves of owning less than one car per adult at the start, then have waves of owning one car per adult. The representative sequences for the "losing access" group only two waves of owning less than one car per adult near the end.

Table 1.6: Representative sequences (20-percent coverage threshold)

Cluster	Representative sequence(s)
Fully equipped	C-C-C-C-C-C-C-C-C
Becoming multi-mobile	C-C-C-C-C-C-D-D-D
	C-C-C-C-C-D-D-C-C
	C-C-C-C-D-D-D-D-D
Multi-mobile	D-D-D-D-D-D-D-D-D
Sharing cars	B-B-B-B-B-B-B-B-B
Gaining access	B-B-B-B-C-C-C-C-C
	B-B-C-C-C-C-C-C-C
	C-B-B-B-B-C-C-C-C
Losing access	C-C-C-C-C-C-B-B-B
	C-C-C-C-B-B-B-B-B
	C-C-C-C-C-B-C-B-B
	C-C-C-C-C-B-B-B-C
	C-C-C-B-C-B-B-B-B
Mostly carless	A-A-A-A-A-A-A-A-A

1.8 Modeling of vehicle ownership trajectories

Having established a typology of vehicle ownership, I use statistical modeling to explore how the baseline characteristics of a household—here, the household's characteristics in 2001—affect the probability of taking a certain trajectory type. Previous literature has examined how household characteristics or life events affect the probability of adding or removing a car in the following survey wave (Klein and Smart 2019). The modeling here is more general, in that it explores the associations between a family's characteristics and its vehicle ownership trajectory.

I use multinomial logit regression to predict the probability of a household ending up in one of the trajectory groups, relative to a reference trajectory group. The model controls for a range of sociodemographic factors that research has shown to be associated with vehicle ownership, including income (Pucher and Renne 2003; Blumenberg and Pierce

2012) and race and ethnicity (Klein and Smart 2017a). The model also includes controls for residential density and access to rail stations because the built environment can influence vehicle ownership and travel behavior even after accounting for the effects of residential self-selection, although the practical effect may be limited (Cao, Mokhtarian, and Handy 2009). Finally, the model includes the initial level of vehicle ownership as an independent variable because it limits the trajectories families can take. Families with zero vehicles, for example, cannot lose automobile access; instead, they can only gain access. Similarly, although multi-mobility is possible as shown in the earlier analysis, families have practical constraints given their finances, available parking space, or ability to use multiple cars.

Inertia and lag also may influence the trajectories households take. Vehicles are durable goods and key assets for families (Bricker et al. 2017). Even if family circumstances change, families may take time to purchase vehicles or may hold off on selling them. Data from J.D. Power show that many families take weeks just to decide what car to buy: Baby Boomers spend an average of 15.7 weeks, and Millennials spend an average of 16.9 weeks (AutoGuide.com 2016). Inertia and lag may lead to households keeping the same level of vehicle ownership for longer periods than expected.

Because "fully equipped" is the most common group, I use it as the reference group. This modeling establishes correlation rather than causality (Dorsett and Lucchino 2014) but still is of potential interest to policymakers given that it may identify populations that either can be induced to reduce vehicle ownership or may need intervention to ensure a stable level of vehicle ownership.

Table 1.7 shows the results of the regression model, with odds ratios for families being in a given trajectory group relative to the "fully equipped" baseline group. All reported coefficients are significant at the $p < 0.01$ level. The model has a McFadden pseudo-R-squared value of 0.23, showing that it has considerable unexplained variation. This variation is to be expected, given that some determinants of vehicle ownership like income can change greatly for households over sixteen years.

Table 1.7: Trajectory modeling results ("fully equipped" as baseline)

Variable	Becoming multi-mobile	Multi-mobile	Sharing cars	Gaining access	Losing access	Mostly carless
Vehicle ratio (base category "1 car/adult")						
More than 1 car/adult	1.11	1.14	0.96	1.13	1.22	1.45
Less than 1 car/adult	1.10	0.97	1.55	1.03	1.52	1.72
Zero cars	0.93	0.65	1.17	0.76	1.10	1.84
Race (head; base category "white")						
Asian	1.16	0.64	1.09	1.74	1.22	0.85
Black	0.96	1.10	0.78	1.25	1.21	1.32
Hispanic	1.19	3.36	0.97	1.92	1.32	1.82
Native or other	1.03	1.17	0.59	1.51	1.15	1.38
Number of family members	1.00	0.97	1.02	0.96	0.95	0.92
Income (log)	0.99	1.10	1.01	1.10	1.11	0.95
Female-headed	1.16	1.06	0.97	0.95	0.95	0.75
High school graduate	1.05	1.05	1.04	1.04	1.04	0.98
College graduate	1.00	0.97	1.00	1.00	1.00	0.98
Within half mile of rail	1.26	0.98	1.57	1.23	1.17	0.71
Density (log)	1.02	0.97	1.06	1.04	0.99	1.05
Not a homeowner	0.98	1.05	0.92	0.82	0.93	0.90
Age	0.98	1.02	1.00	0.96	0.96	1.01
Age squared	1.00	1.00	1.00	1.00	1.00	1.00
Constant	0.84	0.10	0.29	0.39	0.95	0.55
Akaike Inf. Crit.	12,372.68	12,372.68	12,372.68	12,372.68	12,372.68	12,372.68

The variable with the greatest overall effect is the level of vehicle ownership a family has at the start of the survey. The starting ratios are highly significant predictors of probability for all trajectory groups. Starting with zero vehicles, for example, increases the odds of being in the "mostly carless" group; similarly, starting with more than one vehicle per adult increases the odds of being in the "multi-mobile" group. Higher incomes reduce the odds of being in the “losing access,” “sharing cars,” and “mostly carless” groups, as expected, yet also reduce the odds of being in the “multi-mobile” group. Education has no effect in most cases, although college graduates have lower odds of being in the “mostly carless” group.

Race and ethnicity influence vehicle ownership trajectories even after controlling for income and other socioeconomic variables. Black families have higher odds of being in the “losing access” and “mostly carless” groups. At the same time, they have higher odds of being in the “multi-mobile” and “becoming multi-mobile” groups than white families, which is difficult to explain. Asian and Hispanic families, in contrast, have lower odds of being in the “becoming multi-mobile” and “multi-mobile” groups and higher odds of being in the “losing access” and “sharing cars” groups.

Neighborhood characteristics also affect vehicle trajectories. Living within a half mile of rail increases the odds of being in the “mostly carless” and “losing access” groups and decreases the odds of being in the “becoming multi-mobile” and “multi-mobile” groups. Higher residential densities also reduce the likelihood of multi-mobility.

1.9 Discussion and conclusion

This analysis used sequence analysis techniques to describe household trajectories of vehicle ownership and create a typology of groups of households who have broadly similar ownership experiences. The analysis also used a multinomial logit model to test the extent to which a household’s starting characteristics influence the probability it takes different types of trajectories.

One of the most striking results of the analysis is the stability of car ownership levels across time for most households. As noted, Klein and Smart (2017a) have shown that carlessness is usually a temporary state at most, even in lower-income households. These results build on their research by showing that people rarely change their levels of car ownership even at other levels of vehicle access—including the “more than one vehicle per household” level. These results suggest that policies intended to reduce driving, VMT, and emissions by reducing vehicle ownership face significant challenges.

Given that vehicle access improves employment and economic outcomes for most American families (Baum 2009), including families living in major metropolitan areas, the persistently low levels of vehicle ownership observed in some households poses a policy challenge. Policymakers face a dilemma: while promoting vehicle ownership can address the needs of the most economically disadvantaged, it faces opposition on welfare policy grounds (from those who oppose expanding welfare) as well as opposition on environmental grounds (Wachs and Taylor 1998).

The persistently high levels of vehicle ownership observed in other households poses a policy challenge as well, in that high levels of vehicle ownership may contribute to excess traffic congestion and greenhouse gas emissions. In the United States, policymakers have attempted to reduce vehicle ownership by promoting carpooling and ridesharing (Shaheen, Cohen, and Roberts 2006), as well as by investing in transit and transit-oriented development in the hopes of letting people live car-free or car-light lifestyles (Dittmar and Ohland 2012). The stable levels of high vehicle ownership in this analysis show, however, that people rarely give up vehicles after acquiring them.

Given existing transportation policy, in which people travel and park for most of their trips with few direct costs for road use or vehicle storage, it is perhaps unsurprising that few people change their levels of car ownership even when their economic circumstances change. Households also keep vehicles longer now than even in the recent past, with design improvements allowing for longer operation. From 2007 to 2012, the average age of household vehicles in the United States increased from 10.1 years to 11.3 years (Pfirrmann-Powell 2014).

Future studies on vehicle ownership can use sequence analysis in multiple ways. First, researchers can examine trajectories within population subgroups of interest, especially low-income households. Second, future work can inform or serve as inputs for modeling long-range transportation plans. Data from regional household panel travel surveys would be especially useful for modeling.

From a statistical modeling perspective, having a low McFadden's pseudo-R-squared (0.23) for the multinomial logit model is disappointing. From a policy perspective, however, the results are encouraging in that they suggest that there is some variation in a family's trajectory of vehicle ownership—and perhaps some ability for policy to influence that trajectory. At the same time, policymakers must be sensitive to the fact that there is considerable heterogeneity among families who alter their levels of car ownership for an extended period. Future analysis involving sequence analysis can explore this heterogeneity.

CHAPTER 2

Trajectories of Family Vehicle Ownership by Social Group

Abstract: This chapter examines trajectories of family vehicle ownership by social group using sequence analysis techniques and longitudinal data from the Panel Study of Income Dynamics. The analysis examines differences by household income, race, ethnicity, family structure, and immigrant status from 2001 to 2017, and differences by birth cohort (Baby Boomers, Generation X, and Millennials) from ages 22 to 30. Most population groups show a high degree of stability in vehicle ownership. Vehicle ownership is only marginally less stable in low-income households than in upper-income households, in part because upper-income households transition between having one car and more than one car per adult. The birth cohort analysis suggests that, after controlling for other socioeconomic factors, Millennial families have higher likelihoods relative to Generation X families of entering vehicle ownership trajectories marked by sharing cars or owning no cars.

2.1 Introduction

Disparities in vehicle access among low-income and minority groups contribute to disparities in employment and economic outcomes (Raphael and Stoll 2001; Ong 2002; Gautier and Zenou 2010; Blumenberg and Pierce 2014). Understanding differences in trajectories of vehicle access among social groups may suggest ways to reduce disparities in employment and wealth accumulation. Using sequence analysis and longitudinal data from the 2001 to 2017 waves of the Panel Study of Income Dynamics (PSID) to study vehicle ownership for a nationally representative sample of families, I investigate three research questions related to trajectories of vehicle ownership in different social groups:

1. What trajectories of vehicle ownership do different social groups tend to take?
2. How do the stability and diversity of ownership trajectories differ among social groups?
3. How do ownership trajectories in young adulthood differ by birth cohort?

This chapter contributes to several overlapping bodies of research examining vehicle ownership and travel behavior as they relate to household income, race, ethnicity, gender, and birth cohort. Researchers have explored many dimensions of these topics in depth and highlighted differences in travel behavior—differences that persist even after controlling for income—but have rarely examined differences in vehicle ownership among groups over the life course. The analysis in this chapter complements previous research by offering a holistic perspective of ownership trajectories.

2.2 Techniques for studying vehicle ownership by social group

Research on vehicle ownership by socioeconomic factors tends to employ repeated cross-sectional data to examine changes in vehicle ownership. Repeated cross-sectional surveys allow for estimates of changes at the group level for population groups of interest, but do not measure changes for individuals within the group. Typical sources of data include travel behavior datasets like the National Household Travel Survey or general social surveys like the American Community Survey. Carlessness and economic outcomes tied to vehicle ownership are of special interest to researchers, with studies examining carlessness by income (Blumenberg and Pierce 2012), race, ethnicity (Raphael and Stoll 2001; Raphael, Berube, and Deakin 2006), and birth cohort (Ralph 2017), among other factors. Researchers typically use the absolute number of vehicles as the measure of interest, although some use the share of vehicles per adult in the household.

A few scholars have employed panel datasets to examine differences in vehicle ownership by population group. For example, Klein and Smart (2017a) examine seven waves of PSID data from 1999 to 2013 and summarize carlessness across all seven waves, carlessness across "some" waves, and carlessness across no waves. They also employ descriptive statistics to examine changes in the number of vehicles from one wave to the next. Several questions outside the scope of the study arise for households with vehicle ownership for "some" waves. Do they start with carlessness and transition to car-having after some period? Do they transition in and out of car-having multiple times during the seven survey waves? How long do they remain carless on average? How often do they transition to and from other states of car ownership, like owning two vehicles?

Answering these questions with traditional statistical analysis poses several difficulties. A survey with multiple waves can quickly yield an overwhelming number of combinations for tabulation and analysis. A simple binary outcome like "owning one or more vehicles" studied over seven survey waves like in Klein and Smart (2017a) yields 2^7 or 128 potential combinations for households; adding a third outcome yields 2,187 combinations. Tabulating individual combinations would not only be unwieldy, with many combinations having insufficient sample sizes, but also would not offer many insights because some differences in combinations (for example, Yes-Yes-Yes-Yes-No-Yes-Yes versus Yes-Yes-Yes-No-Yes-Yes-Yes) may not be meaningful for the analysis.

2.3 Complexity and diversity

Employment and family life courses have become more complex for individuals over time (McMunn et al. 2015). Life courses have become more de-standardized as well, meaning that differences in life courses among individuals have increased (McMunn et al. 2015). On the one hand, vehicle ownership may have become correspondingly more complex. On the other hand, stable levels of vehicle ownership may facilitate the increase in complexity in other life domains by allowing people to change jobs and residential locations more easily.

Individuals with vehicles have much greater access to employment than people who rely on public transit, even as cities continue to increase their investments in transit (Shen 2001; Kawabata and Shen 2007; Ong and Gonzalez 2019).

Recent developments in transportation technologies and travel behavior also may affect the complexity of vehicle ownership patterns. Households may have greater complexity of travel behavior over time, for example, if they use ride-hailing services like Uber and Lyft to provide mobility in place of a private vehicle. At the same time, the effects of ride-hailing and other emerging mobility services on travel behavior should not be overstated. Three-quarters of ride-hailing adopters use the services a few times per month or less (Clewlow and Mishra 2017), and research suggests that most people who use the services have not changed their levels of vehicle ownership, especially if they do not also use transit (Clewlow and Mishra 2017). These findings suggest that ride-hailing services may not have large effects on vehicle ownership patterns.

Income volatility, or the degree to which a family's income varies, may further contribute to complexity in vehicle ownership trajectories. Income volatility from year to year has risen for families since the 1970s (Dynan, Elmendorf, and Sichel 2012), and volatility from month to month has increased as well (Hannagan and Morduch 2015). The relationship between vehicle ownership and income volatility is not immediately clear. On the one hand, vehicle ownership may insulate against income shocks by ensuring that people retain access to employment and other opportunities. In the most desperate of cases, people who cannot afford rent may live in their cars; the car offers mobility and storage (Wakin 2008; Redshaw 2017). On the other hand, vehicle ownership levels may change as income fluctuates and people need to sell their cars or end up having them repossessed if they miss a payment. Vehicle ownership may even exacerbate financial volatility if families need to pay for unexpected and expensive repairs or if vehicle ownership precludes a family from receiving public assistance due to vehicle asset limits, which vary by state (Laird and Trippe 2014).

2.4 Data and analysis

This research uses sequence analysis to examine trajectories of family vehicle ownership by social group in two parts. In the first part, I examine trajectories by income quintile, race, ethnicity, family structure, and immigration from 2001 to 2017. In the second part, I examine trajectories by birth cohort (Baby Boomer, Generation X, and Millennial) from ages 22 to 30. The analysis uses data from the confidential geocoded version of the 1969 to 2017 waves of the PSID, supplemented with measures of residential density and transit access. The PSID is a biennial longitudinal household survey that measures employment, wealth, spending, and other social factors in American families (Institute for Social Research 2017). The PSID, which emerged from an effort to assess President Lyndon Johnson's War on Poverty, has an oversampling of low-income households (McGonagle et al. 2012), making it especially useful for studying vehicle ownership in low-income groups.

To quantify the complexity of vehicle ownership for families, I compute two measures found in the literature and in the TraMineR sequence analysis package for R. These measures account for how many states and transitions a given sequence has, as well as the duration of the states (Elzinga 2010). The first measure is the complexity index, a composite measure based on the number of transitions and the longitudinal entropy of the sequence (Gabadinho, Ritschard, Müller, et al. 2011). The second measure, introduced in Elzinga and Liefbroer (2007) and developed in Elzinga (2010), is Elzinga's turbulence, based on the number of distinct subsequences, or contiguous parts within a sequence. For example, the sequence A-B-A-B-A-B has 12 distinct subsequences and is less complex than the sequence A-B-C-D-E-F, which has 22 distinct subsequences (Elzinga 2010).

2.5 Income, race, ethnicity, and family structure

In the first part of the analysis, I focus on the 2001 survey wave, which had 7,406 families, and restrict the sample to families who report vehicle information for the remaining survey years through 2017; the final sample has 3,342 family units. To measure levels of vehicle ownership, I construct a “vehicles per adult” ratio instead of using the number of vehicles. The ratio has four levels, as shown in Table 2.1. Klein and Smart (2019) note that using a ratio instead of a number has tradeoffs: ratios may better capture family decision-making about owning a car, but car ownership may stay the same even when the household structure does not change. I discuss the tradeoffs of using adults in the ratio rather than adults and teens in Chapter 1.

Table 2.1: Vehicle ownership ratios

Ratio	Description
A	Zero cars
B	More than zero but less than one car per adult
C	One car per adult
D	More than one car per adult

To classify the trajectory that a family’s vehicle ownership takes, I use the seven-group typology developed in Chapter 1 (Table 2.2). To measure transit access, I employ a dataset based on the National Transit-Oriented Development (TOD) Database (Center for Transit-Oriented Development 2012), as described in the data appendix.

Table 2.2: Groups of vehicle ownership trajectories

Group	Percentage	Typical trajectory
Fully equipped	27.3%	Has one car per adult for most or all years
Losing access	18.9%	Starts with one car per adult then later has fewer than one car per adult
Becoming multi-mobile	17.5%	Switches between having one car per adult and having more than one car per adult
Gaining access	10.4%	Starts with fewer than one car per adult then later has one car per adult
Multi-mobile	10.0%	Has more than one car per adult for most or all years
Sharing cars	8.7%	Has at least one car but less than one car per adult for most years; includes some families that occasionally have one car per adult
Mostly carless	7.1%	Starts with one car per adult then later has fewer than one car per adult

2.5.1 Income

Vehicles are the most frequently held non-financial asset in American households (Bricker et al. 2017) and play an important role in improving economic outcomes for many low-income households (Ong 2002; Blumenberg and Pierce 2014). Lower-income households own fewer vehicles and are more likely to have zero cars than higher-income households (Pucher and Renne 2003; Blumenberg and Pierce 2012). At the same time, the effects of income on vehicle ownership are asymmetric: households are more likely to purchase cars when their incomes rise than they are to shed cars when their incomes decline (Dargay 2001).

An emerging body of research explores carlessness in lower-income households (Klein and Smart 2017a), including the financial aspects of vehicle ownership. For example, subprime vehicle lenders lend disproportionately to low-income and minority households at high interest rates, which can lead to repossession as households fall behind on payments (Blumenberg, Brumbaugh, and Pollard 2018). Cross-sectional data cannot capture this instability within financially vulnerable households, however.

Table 2.3 presents descriptive statistics for PSID families by income quintile at the start of the analysis in 2001. The gap in median income between the bottom and second income quintiles decreases from $20,847 (in 2017 dollars) in 2001 ($37,739 minus $16,892) to $13,488 in 2017 ($36,202 minus $22,714), but remains relatively large. A larger percentage of families in the bottom quintile are black and Hispanic (28.4 and 11.1 percent) than in the other quintiles. The percentage of families living near rail increased to around 10 percent for the bottom, second, and top quintiles, but decreased to around 6 percent for the third and fourth quintiles. The number of vehicles per household did not change noticeably from 2001 to 2017 in any of the income quintiles, despite household sizes decreasing noticeably in the fourth and top quintiles.

Table 2.3: Descriptive statistics by 2001 family income quintile

Variable	Bottom quintile	Second quintile	Third quintile	Fourth quintile	Top quintile
Maximum income (2001; 2017 dollars)	$32,320	$55,852	$84,461	$129,808	-
Vehicles (2001)	1	1.5	1.8	2.2	2.5
Vehicles (2017)	1.1	1.5	1.9	2.1	2.4
Age (2001)	44.6	44.4	45.5	45.1	47.9
Household size (2001)	2	2.2	2.4	2.9	3.1
Household size (2017)	2.2	2.2	2.3	2.5	2.5
Children (2001)	0.7	0.6	0.6	0.8	0.8
Median income (2001; 2017 dollars)	$16,892	$37,739	$60,895	$92,769	$166,154
Median income (2017)	$22,714	$36,202	$56,000	$83,690	$132,446
White (head)	56.2%	68.8%	75.4%	83.7%	88.4%
Black (head)	28.4%	17.1%	12.6%	8.7%	4.2%
Hispanic (head)	11.1%	10.0%	6.2%	3.2%	0.9%
Asian (head)	1.0%	1.1%	2.3%	1.7%	3.6%
In metropolitan area (2001)	67.8%	69.1%	71.9%	74.7%	85.0%
In metropolitan area (2017)	78.6%	78.0%	78.9%	81.3%	90.0%
Near rail (2001)	6.8%	8.1%	8.4%	5.9%	8.8%
Near rail (2017)	9.4%	10.3%	6.0%	6.6%	9.6%
n	544	625	635	774	764

Figure 2.1 shows index plots (displays of sequences as horizontal sets of bars, with colors corresponding to states in the sequences) for families by income quintile. Carlessness (group A) is a more common state in the bottom income quintile, but persistent carlessness is not the default state even in the bottom quintile. Instead, carlessness is infrequent and often brief. For families in the bottom income quintile, the average length of a carless state is 2.4 survey periods or 4.8 years. For families in the second quintile, the average length is 1.0 periods (2.0 years); for families in the third quintile, the average length is 0.5 periods (1.0 year). Looking at the index plots shows that patterns of car ownership are similar for families in the third, fourth, and top quintiles: in fact, their index plots are almost indistinguishable, save for the third income having a few more periods of carlessness. While members of the second quintile have more episodes of carlessness, their overall pattern of vehicle access looks more like the upper three quintiles than the bottom quintile.

While low-income households are less likely to own vehicles than higher-income house-

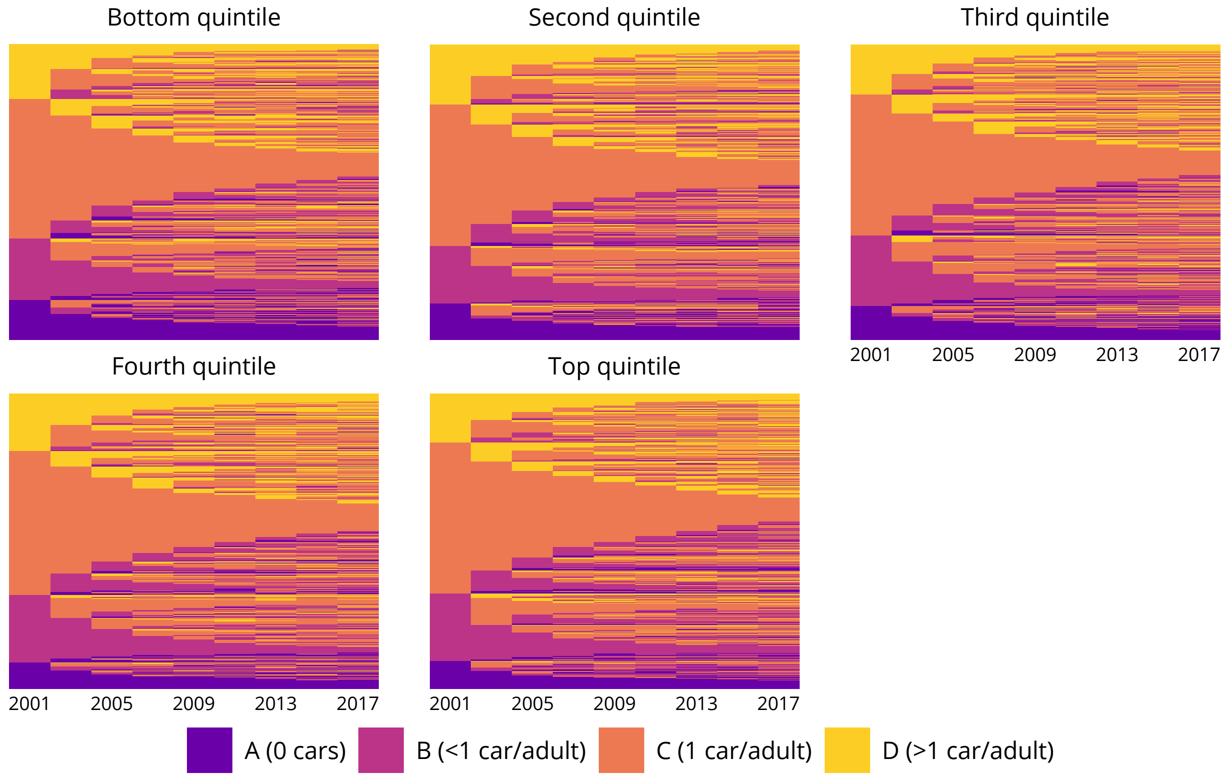

Figure 2.1: Index plots of vehicle ownership by 2001 family income quintile

holds, a small number of low-income households experience "multi-mobility," the term I use for the state of owning more than one vehicle per adult. (Chapter 1 discusses multi-mobility and its policy implications.) Low-income households are much less likely to experience multi-mobility than other households, but 32.8 percent of sampled families in the bottom income quintile experienced multi-mobility at least once during the survey period. As shown in Table 2.4, 8.2 percent of families in the bottom income quintile and 14.0 percent in the second quintile have trajectories in the "multi-mobile" or "becoming multi-mobile" groups, versus 24.4 percent in the top quintile. Multi-mobility may have different meanings in low-income and other households: while it may represent opportunities in other households for leisure or employment depending on the type of additional vehicles, it may represent burdens for low-income households in the form of financially unsustainable loans, vehicles in poor condition that are too expensive to repair, or vehicles that families have been unable to sell or retire.

Table 2.4: Trajectory groups by 2001 family income quintile

Group	Bottom quintile	Second quintile	Third quintile	Fourth quintile	Top quintile
Fully equipped	34.9%	41.8%	39.6%	37.5%	39.3%
Gaining access	5.3%	7.2%	7.9%	11.3%	14.4%
Multi-mobile	3.6%	8.0%	12.2%	14.6%	14.0%
Losing access	6.7%	9.1%	6.8%	8.5%	8.3%
Sharing cars	11.6%	12.3%	15.0%	12.7%	7.2%
Mostly carless	33.5%	12.6%	5.8%	2.4%	2.2%
Becoming multi-mobile	4.4%	9.0%	12.6%	13.1%	14.5%

The quantitative measures of complexity and turbulence (Table 2.5) do not show major differences by income quintile. The complexity index ranges from .32 for households in the bottom and third quintiles to .35 for households in the top quintile, and the turbulence ranges from .35 to .38. The similarity in index measures implies that vehicle ownership sequences are more complex in top-quintile households than in bottom-quintile households, but only slightly. One reason for the relative similarity in these measures across income groups is that levels of vehicle ownership are stable in most families. The second reason is that the measures treat all states and transitions equally. A household transitioning between "one car per adult" and "more than one car adult" each survey wave (CDCDCDCD), for example, would have the same complexity and turbulence measures as a household transitioning between carlessness and "one car per adult" (ACACACAC), despite having more stability from a travel behavior perspective in the sense that the household always has vehicle access. Both of these example households would have more complexity and turbulence than a family having "one car per adult" in every wave (CCCCCCCC). Many middle-income families consistently have one car per adult and many lower-income families consistently have zero or one cars per adult, resulting in lower measures of complexity for these groups.

Table 2.5: Complexity and diversity measures by family income quintile

Income quintile	Complexity	Turbulence
Bottom quintile	0.32	0.35
Second quintile	0.34	0.36

Income quintile	Complexity	Turbulence
Third quintile	0.32	0.35
Fourth quintile	0.34	0.38
Top quintile	0.35	0.38

2.5.2 Race and ethnicity

Minority families are more likely to own zero vehicles than other families. One key explanation is economic: minority families are more likely to be low-income and thus less likely to own vehicles than non-Hispanic white families (Klein and Smart 2017a). Another explanation is urban residence: minority families are more likely to live in urban areas, and urban residents have fewer vehicles on average than rural residents (Pucher and Renne 2005). A third explanation is that a higher percentage of Hispanic and Asian families include immigrants than black and white households, and immigrant families tend to own fewer cars than native-born families do (Tal and Handy 2010; Klein and Smart 2017a). Nonetheless, some racial and ethnic differences in vehicle ownership persist even after controlling for income and urban location (Blumenberg, Brown, and Schouten 2018b).

Table 2.6 shows descriptive statistics for families by race and ethnicity of the household head. In the PSID, any person mentioning Spanish, Latin American, or South American heritage is classified as Hispanic, regardless of race. Black and Hispanic families have lower median incomes in 2001 (around $42,000 in 2017 dollars) than other families. Asian families have the highest median incomes, but the sample size for this group is small. Black families have notably fewer vehicles on average than other families in 2017 (1.3 vehicles versus 1.8 to 2 vehicles). While Hispanic families have nearly the same number of vehicles as white families (1.8 versus 2 vehicles), Hispanic families have larger family sizes (3.4 versus 2.3 people).

Table 2.6: Descriptive statistics by race and ethnicity

Group	White	Black	Hispanic	Asian
Vehicles (2001)	2	1.2	1.6	1.8
Vehicles (2017)	2	1.3	1.8	1.8
Age (2001)	46.5	43.1	41.4	47.4
Household size (2001)	2.5	2.5	3.8	3.1
Household size (2017)	2.3	2.1	3.4	2.5
Children (2001)	0.6	0.8	1.6	1
Median income (2001; 2017 dollars)	$81,885	$41,538	$41,538	$109,481
Median income (2017)	$74,094	$35,092	$45,368	$95,774
In metropolitan area (2001)	71.4%	84.0%	89.7%	98.0%
In metropolitan area (2017)	79.5%	88.5%	98.0%	99.7%
Near rail (2001)	5.8%	14.9%	10.7%	16.2%
Near rail (2017)	7.1%	13.3%	8.4%	20.3%
n	1,986	1,022	171	62

Table 2.7 shows further evidence of racial differences in vehicle access over a family's life course. The most common trajectory for white and Asian families is "fully equipped" (43.6 and 37.7 percent of families respectively). The most common trajectory for Hispanic families is "sharing cars" (34.8 percent), and the most common for black families is "mostly carless" (31.3 percent). These findings are consistent with studies showing lower rates of vehicle ownership among black and Hispanic families (Raphael and Stoll 2001; Raphael, Berube, and Deakin 2006) and greater use of carpooling in Hispanic immigrant families (Blumenberg and Smart 2010; Liu and Painter 2012).

Consistent with the analysis by income quintile in the previous section, white families have the largest share of families in the "becoming multi-mobile" or "multi-mobile" groups (24.9 percent). Other results are less intuitive: black families have the second-largest share (18.0 percent) despite having the lowest median incomes, and Asian families have a much lower share of households experiencing multi-mobility (6.1 percent) despite having the second-highest median incomes.

Table 2.7: Trajectory groups by race and ethnicity

Group	White	Black	Hispanic	Asian
Fully equipped	43.6%	22.1%	15.4%	37.7%
Gaining access	9.5%	9.6%	13.0%	8.7%
Multi-mobile	12.5%	8.5%	4.6%	3.8%
Losing access	7.7%	6.1%	11.0%	16.1%
Sharing cars	8.9%	13.0%	34.8%	25.7%
Mostly carless	5.3%	31.3%	16.2%	5.6%
Becoming multi-mobile	12.4%	9.5%	5.1%	2.3%

Table 2.8 shows the complexity and diversity measures for families by race and ethnicity of the household head in 2001. Asian families have the lowest complexity and turbulence, and maintain the same levels of vehicle ownership longer than other groups. Hispanic families have the highest complexity and turbulence, perhaps related to immigration and changing economic fortunes over the past two decades that result in more changes in vehicle ownership.

Table 2.8: Complexity and diversity measures by race and ethnicity

Race	Complexity	Turbulence
White	0.33	0.36
Black	0.36	0.39
Hispanic	0.41	0.44
Asian	0.27	0.31

2.5.3 Immigration

The vehicle ownership trajectories of immigrants to the United States are of interest to planners because the share of immigrants in the United States has increased from 10 percent in 1998 to 14 percent in 2018 (Congressional Budget Office 2020). Vehicle ownership patterns of immigrants may change as they gain income and spatially assimilate by moving to suburbs (Blumenberg and Shiki 2007). While immigrants to the United States own fewer cars and use transit more often than native-born families do (Tal and Handy 2010), their travel behavior starts to reflect the travel behavior of native-born families after five years in the United States (Blumenberg and Shiki 2007). Nonetheless, some differences in travel behavior persist over time: Hispanic immigrants, for example, are more likely to commute by transit than native-born families even after staying in the United States for long periods (Blumenberg and Shiki 2007). One factor that explains the persistent differences is living or working in an ethnic enclave. Liu and Painter (2012) find that Hispanic immigrants living in enclaves are more likely to use transit and carpool than those who do not.

Table 2.9 shows descriptive statistics for families by immigration status for the head of the family. While immigrant families eventually have the same average number of vehicles in 2017 as native-born families (1.9 vehicles), they also have larger average family sizes (3.3 versus 2.5 people). The gap in median incomes between immigrant and native-born families narrowed from $28,141 in 2001 (in 2017 dollars) to $18,705 in 2017. Nearly all (99.7 percent) of the immigrant families lived in metropolitan counties by 2017 and were nearly twice as likely to live near rail as native-born families (15.7 versus 7.7 percent).

Table 2.9: Descriptive statistics by immigrant status

Group	Immigrant	Native-born
Vehicles (2001)	1.7	1.9
Vehicles (2017)	1.9	1.9
Age (2001)	42.7	45.9
Household size (2001)	3.8	2.5
Household size (2017)	3.3	2.3
Children (2001)	1.5	0.6
Median income (2001; 2017 dollars)	$45,692	$73,833
Median income (2017)	$51,096	$69,801
In metropolitan area (2001)	90.5%	73.7%
In metropolitan area (2017)	99.7%	80.9%
Near rail (2001)	17.8%	6.9%
Near rail (2017)	15.7%	7.8%
n	243	3,099

Figure 2.2 shows that immigrant families are less likely to own one or more vehicles per

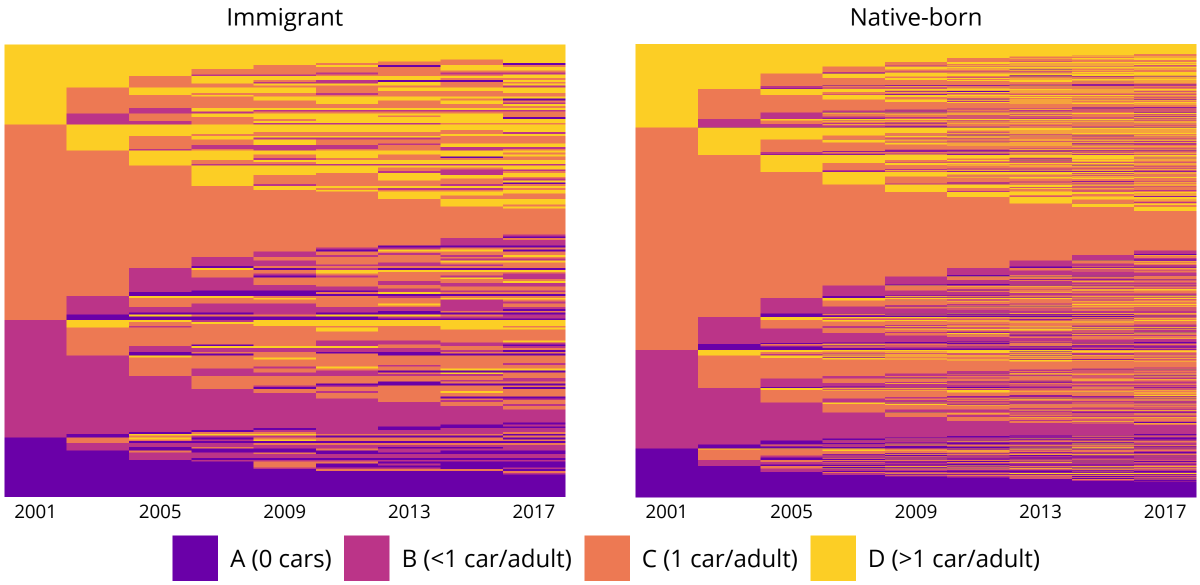

Figure 2.2: Index plots of vehicle ownership by immigrant status

adult than native-born families. Immigrant families are also more likely to change their level of vehicle ownership multiple times than native-born families. The quantitative measures of complexity and turbulence bear out this observation as well: immigrant families have higher measures of complexity and turbulence (0.38 and 0.42) than native-born families (0.33 and 0.36).

The trajectory groups in Table 2.10 highlight the extent to which immigrant families are more likely to share cars than native-born families, consistent with research showing that immigrant families carpool with other household members and people outside the household at much higher rates than native-born families (Blumenberg and Smart 2010). "Sharing cars" is the most common trajectory group for immigrant families (39.7 percent) as opposed to "fully equipped" for native-born families (40.5 percent). A slightly higher share of immigrant families than native-born families are "mostly carless" (12.8 percent versus 8.9 percent). Multi-mobility is much less prevalent in immigrant families: only 5.8 percent of immigrant families have "multi-mobile" or "becoming multi-mobile" trajectories versus 23.9 percent of native-born families.

Table 2.10: Trajectory groups by immigrant status

Group	Immigrant	Native-born
Fully equipped	15.7%	40.5%
Gaining access	15.4%	9.5%
Multi-mobile	2.1%	11.9%
Losing access	10.6%	7.8%
Sharing cars	39.7%	9.5%
Mostly carless	12.8%	8.9%
Becoming multi-mobile	3.7%	12.0%

2.5.4 Family structure

Family structure and gendered differences in labor division affect vehicle ownership in multiple ways. On the one hand, women rely on vehicles because they continue to bear a disproportionate domestic burden: women use vehicles for domestic errands and chauffeuring far more often than men do (Blumenberg, Brown, and Schouten 2018a). On the other hand, women have lower employment rates and incomes, which makes vehicle ownership more difficult to support (Blumenberg 2003). Table 2.11 shows descriptive statistics for three types of family structures: families with two or more adults, families with one male adult, and families with one female adult. Families with one female adult have fewer vehicles in 2017 than families with one male adult (0.9 vehicles versus 1.5 vehicles), despite having larger average household sizes (1.4 people versus 1.1 people). A greater percentage of families with one female adult live near rail in 2017 (14.3 percent) than families with one male adult (9.4 percent) or families with two or more adults (6.7 percent).

Table 2.11: Descriptive statistics by family structure

Group	Single female	Single male	Two or more adults
Vehicles (2001)	1	1.2	2.2
Vehicles (2017)	0.9	1.5	2.2
Age (2001)	49.7	38.8	46.4
Household size (2001)	1.4	1.1	3.2

Group	Single female	Single male	Two or more adults
Household size (2017)	1.4	2	2.6
Children (2001)	0.4	0.1	0.9
Median income (2001; 2017 dollars)	$35,566	$42,957	$92,378
Median income (2017)	$31,744	$55,538	$80,885
White (head)	66.3%	75.6%	79.5%
Black (head)	24.0%	17.6%	8.8%
Hispanic (head)	5.4%	2.4%	6.2%
Asian (head)	1.1%	2.5%	2.2%
In metropolitan area (2001)	76.7%	78.8%	73.5%
In metropolitan area (2017)	80.3%	84.3%	82.1%
Near rail (2001)	9.7%	9.9%	6.6%
Near rail (2017)	14.3%	9.4%	6.7%
n	491	364	2,487

Table 2.12 reveals differences in vehicle ownership by family structure. While single-female households are more likely to be in the "fully equipped" trajectory group (57.5 percent) than single-male and multiple-adult households (47.7 and 32.5 percent), the primary reason is that they are less likely to experience multi-mobility. One-tenth (10.5 percent) of single-female households are in the "multi-mobile" or "becoming multi-mobile" groups, versus 21.3 percent of single-male and 25.7 percent of multiple-adult households. Single-female households are more likely to be in the "mostly carless" group (23.0 percent) than single-male and multiple-adult households (16.0 and 4.0 percent). Very few single-female or single-male households (2.2 and 3.0 percent) have "sharing cars" trajectories, although the main reason is mathematical: a ratio of "at least one car but less than one car per adult" is impossible for a single adult. Some of these households change structure through cohabitation and marriage and eventually share cars, however, which is why some have the "sharing cars" trajectory.

Table 2.12: Trajectory groups by family structure

Group	Single female	Single male	Two or more adults
Fully equipped	57.5%	47.7%	32.5%
Gaining access	2.0%	3.7%	13.1%
Multi-mobile	4.9%	13.4%	12.2%
Losing access	4.7%	8.3%	8.7%

Group	Single female	Single male	Two or more adults
Sharing cars	2.2%	3.0%	15.5%
Mostly carless	23.0%	16.0%	4.5%
Becoming multi-mobile	5.6%	7.9%	13.5%

Households with two or more adults have the highest complexity and diversity measures among the three family types; single-female households have the lowest (Table 2.13). One potential reason is that families with multiple adults can choose to share or stop sharing cars, unlike families with one adult, allowing for more potential state transitions.

Table 2.13: Complexity and diversity measures by family structure

Family structure	Complexity	Turbulence
Single female	0.23	0.25
Single male	0.3	0.33
Two or more adults	0.37	0.4

2.6 Birth cohort

Members of the Millennial generation (born in 1981 to 1996) have lower rates of licensing and vehicle ownership than previous generations (Tefft, Williams, and Grabowski 2014; Ralph 2017). Numerous popular media articles assert that Millennials—and, recently, members of Generation Z (born in 1997 or later) (Roberts 2019)—have less interest in car ownership than previous generations, suggesting that multi-mobility may become less salient due to changing attitudes toward vehicle ownership. McDonald (2015) identifies online shopping and online socializing as “Millennial-specific factors” that partially explain lower rates of driving. Graduated driver licensing laws (GDLs) are another potential factor. These laws, introduced by states in the late 1990s and early 2000s, restrict driving privileges for 16- and 17-year-olds as they gain experience. Tefft, Williams, and Grabowski (2014) find, however, that few teenagers who delayed licensing did so because of GDL restrictions;

instead, their most common reasons were not having a car, not needing a car, and not being able to afford a car.

Other research has shown that economic factors, rather than generation-specific differences, are the primary explanation for lower rates of car ownership among Millennials (Blumenberg et al. 2012; Klein and Smart 2017b). Younger drivers also seem to enjoy driving to the same extent as older drivers, suggesting that attitudinal differences are less pronounced than depicted in the media—at least among Millennials who own vehicles. A 2018 Gallup poll found that 76 percent of American drivers age 30 to 49 enjoy driving "a great deal" or "a moderate amount" (Brenan 2018). The percentage is only slightly lower than the 80 percent of drivers age 50 to 64 who also enjoy driving.

Researchers studying generational differences in travel behavior in the United States typically rely on a set of cross-sectional household surveys from the last three decades to compare generations. In the United States, the most used survey is the National Household Travel Survey (formerly the Nationwide Personal Transportation Survey), conducted roughly every seven years since 1969. Klein and Smart (2017b), in one of the first studies to use American panel data, compare Millennials to earlier generations using the 1999 to 2013 waves of the PSID.

This analysis builds on existing cohort studies in two ways. First, it uses sequence analysis to study how vehicle ownership differed among generations when their members were the same age. Second, it uses PSID data from 1969 to 2017 to examine vehicle ownership among Baby Boomers when they were in their twenties. Given that many Millennials came of age during the Great Recession, which officially ended more than a decade ago in June 2009, examining vehicle ownership with a focus on trajectories can reveal the degree to which economic and social factors at the start of adulthood had a lasting effect on Millennial vehicle ownership.

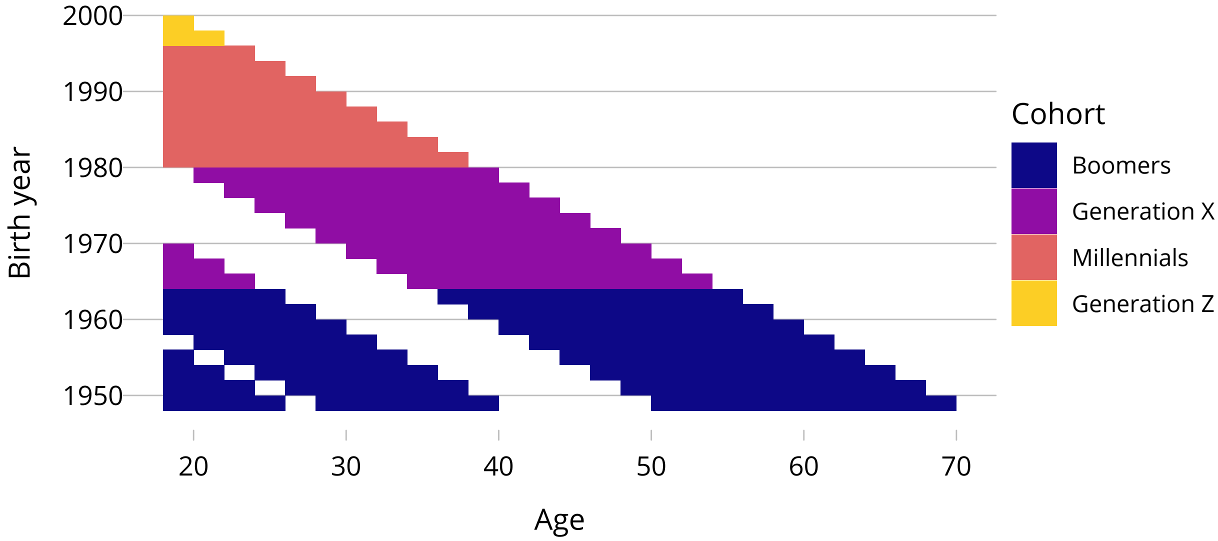

Figure 2.3: Vehicle data availability by birth year and age

2.6.1 Data availability and missing states

I compare vehicle ownership trajectories taken by families in three birth cohorts from age 22 to 30: Baby Boomers (born in 1946 to 1964), Generation X (born in 1965 to 1980), and Millennials (born in 1981 to 1996). As of 2017, the latest PSID survey wave, members of Generation Z (born after 1996) are too young to appear as household heads in the PSID for more than one or two waves. The PSID was an annual survey before 1997, but I use odd-numbered years for consistency.

One shortcoming of using the PSID is that it did not ask about vehicle ownership in 1975 and from 1989 to 1998. As a result, almost every member of Generation X has missing information for at least part of their twenties and early thirties, as does every member of the Baby Boomer generation in their forties and fifties. Members of the Baby Boomer generation have fewer missing years in their twenties than Generation X, but instead have missing information for mid-adulthood. Figure 2.3 illustrates the effects of the data issue on analysis for people by age and birth cohort. Colored blocks indicate available data.

Ritschard, Gabadinho, and Studer (2012), who developed the TraMineR software package for sequence analysis, claim that sequences with missing states are "more the rule than the exception" in the social sciences. They outline four strategies for dealing with missing states, noting that no universal method exists: deleting incomplete sequences, deleting sequences with more missing states than the researcher deems acceptable, treating missing states as a separate state, and imputing missing states. Deleting incomplete sequences wholesale would eliminate almost all observations for members of Generation X and younger Baby Boomers. Keeping as wide a range of ages as possible within each birth cohort is desirable because people born on the cusp of two generations have influences and defining events from both groups (Arsenault 2004). If generations have different attitudes toward vehicle ownership, the attitudes of people born on the cusp of two generations—and, by extension, their vehicle ownership—may reflect a blend of attitudes in the two generations.

To address the missing states, I identified an age range for the head of the household that maximizes the age range observed while maximizing the number of acceptable observations, which I define as having no more than one missing survey year. The final age range is 22 to 30 years old, which spans five survey waves. The resulting sample includes observations for 1,459 families, with 635 Baby Boomer families, 343 Generation X families, and 481 Millennial families. The supplemental appendix lists other tested age ranges for comparison.

2.6.2 Analysis results

Figure 2.4 shows vehicle ownership ratios by age across birth cohort for all families in the PSID, including households excluded from the sequence analysis. (I removed age-cohort combinations with fewer than 20 observations due to high standard errors, although some unexplained outliers remain.) Ownership ratios for Boomers, Generation X, and Millennial families increase from 0.8 to 1.0 cars per adult from ages 20 to 40, with Millennial families having slightly lower ratios than Generation X throughout. For Baby Boomers and Generation X, ratios hover around 1.0 cars per adult around age 40 to 60. For the Silent Generation (born in 1928 to 1945), ownership ratios decrease from 1.0 cars per adult around age 60 to 0.75 cars per adult around age 85.

After calculating optimal matching (OM) distances for the sequences as described in

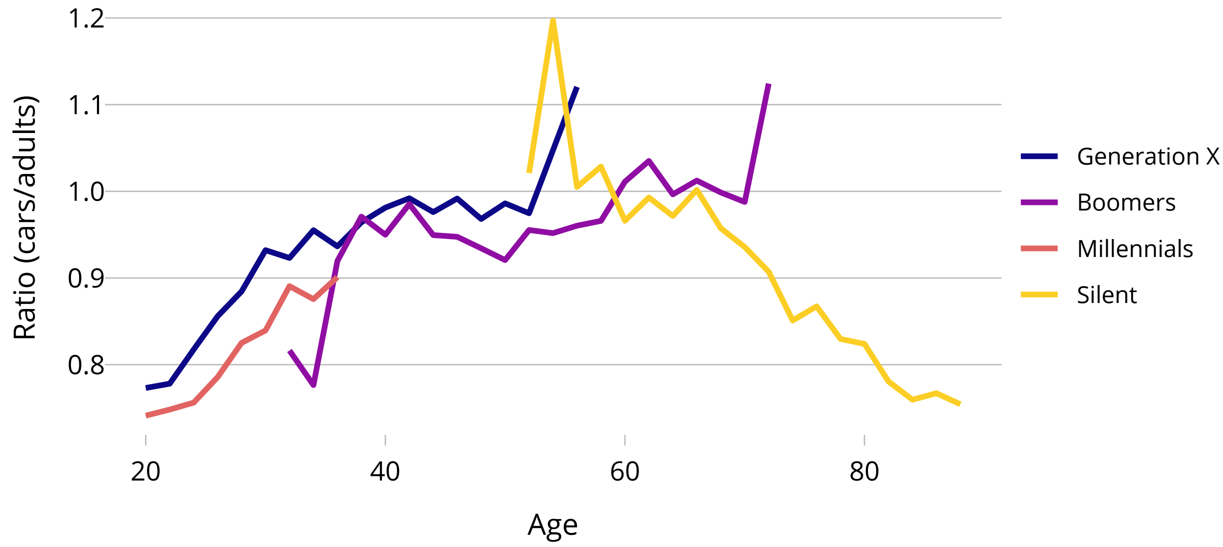

Figure 2.4: Vehicle ownership ratios by age and birth cohort

Chapter 1, I use Ward's method (Ward 1963) to cluster the trajectories into seven groups (Figure 2.5). I construct a separate typology because the analysis for birth cohorts spans an age range rather than a year range. Young adults may also have different trajectories as they start to establish themselves and their households. Three trajectory groups ("carless," "sharing cars," and "fully equipped") are marked by stable levels of vehicle ownership at zero vehicles, less than one vehicle per adult, and one vehicle per adult, respectively. Members of the "becoming multi-mobile" group have more than one vehicle per adult for most of their twenties but are more likely to switch to having one car per adult later in life. Families in the "some to full" and "none to full" groups eventually have one vehicle per adult, with families in the "none to full" group reaching that state slightly earlier than in the "some to full" group. Families in the "one to none" category start with one car per adult in their early twenties but end up having no cars by the end.

Table 2.14 shows the percentages of families in each age-based trajectory group. Generation X has the highest percentage of families in the "becoming multi-mobile" and "fully equipped" groups (59.5 percent). Millennials are more likely to be in the "carless" group than other generations (18.3 percent), but also have the second-highest percentage of families in the "becoming multi-mobile" and "fully equipped" groups (43.7 percent). Baby

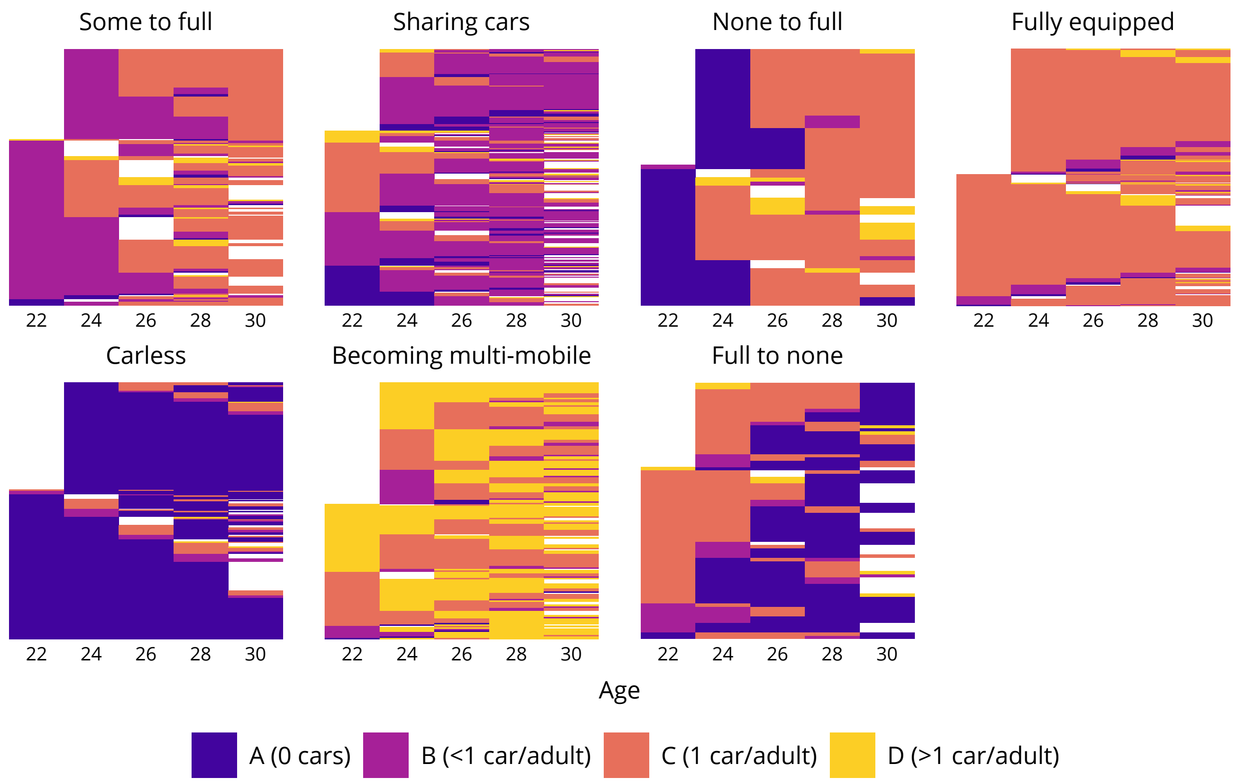

Figure 2.5: Index plots of vehicle ownership trajectories, age 22 to 30

Boomers have the lowest percentage of families in the two groups (34.7 percent) but have a greater share in the "some to full" group that gains full access to automobiles (19.1 percent).

Table 2.14: Birth cohort share by age-based trajectory group

Group	Boomers	Generation X	Millennials	Typical trajectory
Some to full	19.1%	8.5%	9.1%	Starts with fewer than one car per adult, then has one car per adult
Sharing cars	23.3%	12.2%	17.5%	Has at least one car but less than one car per adult for most years; includes some families that occasionally have one car per adult
None to full	3.5%	4.4%	5.2%	Has no cars for one or two waves, then has one car per adult
Fully equipped	26.5%	41.7%	31.6%	Has one car per adult for most or all years
Carless	14.0%	11.4%	18.3%	Rarely owns any vehicles

Group	Boomers	Generation X	Millennials	Typical trajectory
Becoming multi-mobile	8.2%	17.8%	12.1%	Switches between having one car per adult and having more than one car per adult
Full to none	5.5%	4.1%	6.2%	Starts with one car per adult then has no cars

Table 2.15 shows descriptive statistics for families in each age-based trajectory group, weighted by the family's longitudinal weight when the family first appears in the survey (at age 22 or 24). The trajectory groups show correlations between vehicle ownership, income, and race and ethnicity. Members of the "becoming multi-mobile" and "fully equipped" groups end up with the highest median household incomes at age 30 (around $70,000 in 2017 dollars). More than 80 percent of households in these groups are white. The "some to full" and "sharing cars" groups end up with the second-highest household incomes ($58,000 and $53,000 in 2017 dollars) at age 30, in part because they also have the largest household sizes (3.5 members). The "full to none," and "carless" groups have the lowest household incomes by far (around $27,000 in 2017 dollars), and the highest share of black families, consistent with the previous analysis by race. Finally, the "full to none" group presents a puzzle: while it has the highest percentage of college graduates, it also has the third-lowest median household income at age 30 ($38,000 in 2017 dollars) and a larger share of black and Hispanic households than most groups. The group may represent a mix of college graduates moving to cities and working-class urban residents.

Table 2.15: Descriptive statistics by age-based trajectory groups

Variable	Some to full	Sharing cars	None to full	Fully equipped	Carless	Becoming multi-mobile	Full to none
Birth year	1982	1983	1982	1981	1982	1980	1983
Household size (22)	2.8	1.9	1.7	1.7	2	1.9	1.4
Household size (30)	3.5	3.5	1.7	2.4	2.4	3.1	2.4
White	57.1%	55.6%	49.0%	81.4%	46.7%	88.3%	61.5%
Black	16.1%	20.0%	33.1%	12.3%	47.9%	7.2%	27.7%
Hispanic	13.9%	20.9%	5.2%	4.6%	5.2%	4.4%	10.1%
Median income (22 in 2017 dollars)	$34,529	$18,693	$13,364	$21,268	$7,644	$34,461	$18,531

Variable	Some to full	Sharing cars	None to full	Fully equipped	Carless	Becoming multi-mobile	Full to none
Median income (30 in 2017 dollars)	$58,298	$53,153	$26,503	$69,691	$27,275	$71,424	$37,580
High school graduate (30)	82.5%	79.8%	80.2%	89.8%	73.7%	78.3%	82.0%
College graduate (30)	7.2%	8.9%	0.0%	10.9%	3.7%	7.9%	10.4%
n	194	274	62	463	216	171	79

To test whether birth cohorts have different patterns of vehicle ownership after controlling for other sociodemographic factors like income, I construct a multinomial logit model. The model predicts the likelihood of a family being in a trajectory group relative to the baseline group of "fully equipped," the most common state for American households as described in Chapter 1. Independent variables include the birth cohort of the family head, the family's starting vehicle ratio (at age 22 or 24), race, and starting income. Due to issues with sample sizes that lead to separation in the logistic regression, the model incorporates fewer variables and fewer categories than the model estimated in Chapter 1. It also omits the smallest trajectory groups ("some to full" and "none to full").

Table 2.16 shows the results of the regression model. Because families have short trajectories of four or five survey waves in this analysis, a family's starting vehicle ownership level has a substantial influence on the likelihood of being in a given trajectory group. The results suggest that being a Baby Boomer household increases the likelihood of being in the "sharing cars," "carless," and "full to none" trajectory groups relative to a Generation X household, and decreases the likelihood of being in the "becoming multi-mobile" group. Being a Millennial household affects the likelihoods in the same manner relative to Generation X, albeit to a lesser extent.

Table 2.16: Cohort trajectory modeling results

Variable	Sharing cars	Carless	Becoming multi-mobile	Full to none
Vehicle ratio (base category "1 car/adult")				

Variable	Sharing cars	Carless	Becoming multi-mobile	Full to none
Zero cars	43.58***	11,536.12***	1.85	1.76**
Less than 1 car/adult	20.14***	61.43***	10.15***	3.55***
Birth cohort				
(base category "Generation X")				
Baby Boomer	2.21***	1.92***	0.50*	2.57***
Millennial	1.36***	1.12**	0.73**	1.70***
Race (base category "white")				
Black	1.35***	2.81***	1.07***	6.75***
Income (log, 2017 dollars)	0.85***	0.48**	1.99***	0.63***
High school graduate	0.60**	0.56	0.69**	0.62*
Constant	1.06	3.09	0.0002	5.08***
Akaike Inf. Crit.	1,858.46	1,858.46	1,858.46	1,858.46
* .1 ** .05 *** .01				

2.7 Discussion and conclusion

While overall vehicle ownership levels differ by income, race, ethnicity, and family structure, the analysis shows that most households experience stable vehicle ownership levels regardless of social group. The primary exceptions are Hispanic and immigrant families (most of whom are Hispanic), who have higher measures of sequence complexity and diversity than their non-Hispanic and non-immigrant counterparts. Hispanic and immigrant families may have more complex patterns of vehicle ownership as they assimilate to the United States and as their economic situation changes.

Stable levels of vehicle ownership can have different meanings and consequences for families depending on their economic circumstances. Extended periods of carlessness, for example, may represent high accessibility and freedom from the burdens of vehicle ownership for upper-income urban families. For low-income families, especially in areas poorly served by transit, carlessness may pose significant barriers to opportunity. Similarly, while multi-mobility may allow upper-income families to enjoy leisure activities like camping or recreational driving, it may represent unsellable assets and financial burdens in low-income households. Future research incorporating information on vehicle use would shed more light on multi-mobility, in particular for understanding which vehicles are secondary and how families use the secondary vehicles—if the vehicles are even usable, which may not be the case in low-income households.

Future research should also explore different techniques for measuring complexity. While the measures used in this study are quantitative, they can still be informed by qualitative research if researchers assign different values to different states and transitions. Moving from "one car per adult" to "more than one car per adult" could have a lower value assigned to it than other transitions, for example, since the transition has less effect on automobile access for families. Moving from "zero cars" to "less than one car per adult," in contrast, could have a higher value.

Finally, vehicle ownership, employment, and family structure are interrelated domains, as discussed in this chapter: vehicle ownership and employment affect each other, and family structure influences who owns and uses vehicles. While the sequence analysis in this study looks only at vehicle ownership, future sequence analysis can incorporate employment and family structure.

CHAPTER 3

Changes in Low-Income Household Vehicle Holdings

Abstract: This chapter investigates changes in vehicle holdings for low-income households in the United States from 2001 to 2017 using longitudinal data from the Panel Study of Income Dynamics. Sport utility vehicles (SUVs) account for an ever-increasing share of vehicles in low-income households, despite efforts by policymakers to facilitate purchases of smaller, more fuel-efficient vehicles. The average fuel economy for vehicles increased for all families over the period, but at a slower rate for low-income families. Factors that influence vehicle type and the decision to switch vehicle types include family size, income, sex, and race and ethnicity.

3.1 Introduction

The household vehicle fleet in the United States has undergone substantial shifts in the last two decades, with implications for the environment and urban planning. Understanding vehicle composition at the household level is important because households make decisions about buying vehicles individually, based on availability and prices in the new and used car markets. Studies of vehicle holdings in low-income households are especially important because older vehicles, which low-income households are more likely to own, account for a highly disproportionate share of emissions (Park et al. 2016). Moreover, older vehicles with lower fuel economy raise questions about affordability due to higher operating costs and potentially expensive repairs as they reach the end of their life.

This chapter investigates changes in vehicle holdings—in particular, changes in vehicle type, age, and fuel economy—for low-income households in the United States from 2001 to 2017 using longitudinal data from the Panel Study of Income Dynamics (PSID). Three research questions guide the investigation:

1. How have vehicle holdings changed within low-income households?
2. What factors determine the type of vehicles which low-income households own?
3. What factors determine whether a low-income household switches vehicle type when acquiring a new vehicle?

3.2 Background and policy significance

Transportation is the primary source of greenhouse gas emissions in the United States, and household vehicles account for a major share of those emissions. In 2018, transportation accounted for 28.2 percent of greenhouse gas emissions and 36.3 percent of carbon dioxide emissions in the United States (Environmental Protection Agency 2020). Passenger cars accounted for 41.2 percent of carbon dioxide emissions; light-duty trucks, which include SUVs (sport utility vehicles), pickup trucks, and minivans, accounted for 17.4 percent.

Policymakers seeking to reduce vehicle emissions have endorsed policies that give households incentives to retire high-polluting vehicles and replace them with cleaner vehicles. The most notable example in the United States is the 2009 Cash for Clunkers program, a $2.85-billion program administered by the U.S. Department of Transportation (USDOT) that gave dealers rebate credits for buyers trading in less fuel-efficient vehicles (Mian and Sufi 2012). California has taken a further step toward reducing vehicle emissions by subsidizing vehicle repairs or retirement for vehicles that have failed their smog check inspections (Connolly et al. 2019). Older and poorly maintained vehicles are more likely to emit disproportionately high levels of pollutants, and more likely to be owned by lower-income families (Park et al. 2016). Older model years not only have lower fuel efficiency, but also have pollution abatement devices that become less effective (Feng, Fullerton, and Gan 2013).

Keeping these devices in good operating condition improves fuel efficiency and reduces emissions from the vehicle.

Pierce et al. (2019) and other recent studies assess policies and programs that induce low-income households to buy clean vehicles or repair high-polluting vehicles. These programs are of special interest in California, which passed legislation requiring the state to reduce greenhouse gas emissions below 1990 levels by 2030 (Sheldon and Dua 2019). California and nine other states have also set targets to place a certain number of electric vehicles on the road over the next several decades (Pierce et al. 2019; Dua, White, and Lindland 2019).

Untargeted energy-subsidy programs can yield smaller environmental benefits than policymakers expect because many recipients would have made the same choices even without the subsidy (Boomhower and Davis 2014). These programs also raise policy concerns about equity: Borenstein and Davis (2016) find that households in the top income quintile have received about 90 percent of federal income tax credits for electric vehicles since 2006. Targeted subsidy programs, in contrast, induce new purchases because lower-income consumers are especially sensitive to vehicle prices and subsidy amounts (Dua, White, and Lindland 2019). Sheldon and Dua (2019) find that "Replace Your Ride," a program offering subsidies to low-income households purchasing electric vehicles in the Los Angeles region, has been more cost-effective than a former statewide subsidy program for all consumers.

Vehicle emissions in low-income households raise additional concerns about environmental justice. Many urban low-income households live in concentrated areas of poverty, where higher numbers of residents owning older vehicles result in higher neighborhood pollution levels (Park et al. 2016). Moreover, minority and low-income neighborhoods are more likely to be near freeways than higher-income households (Houston et al. 2004; Manville and Goldman 2018). Urban residents living near major roadways experience much higher levels of vehicle-related pollution and respiratory ailments than other urban residents (Houston et al. 2004).

Vehicle holdings and fuel economy are also a policy concern from a financial perspective. Transportation is the second-largest expenditure for American households after housing

(Bureau of Labor Statistics 2018). In 2017, households spent an average of $9,761 on transportation, with an average of $8,943 going to vehicle-related expenditures including $2,109 on gasoline (Bureau of Labor Statistics 2018). At the same time, the share of expenditures that households devote to transportation has steadily declined in the last two decades, from an average of 21.3 percent of total expenditures in 2000 for all households to 17.4 percent in 2017 (Bureau of Labor Statistics 2018).

Vehicles with low fuel economy increase vehicle operating costs and raise concerns about affordability for low-income households, particularly when fuel prices increase. While the United States has not recently experienced an oil crisis, fuel prices are highly volatile regardless, and fuel consumption is relatively inelastic with respect to price. Fuel economy is also relevant for emergency management, where the economically vulnerable may not be able to afford fuel prices while traveling long distances to evacuate (Fothergill and Peek 2004), even if they have access to vehicles. Public health research has implicated gasoline prices as a contributing factor to poor levels of nutrition and substance abuse treatment in rural areas, where residents need to drive to access food and healthcare (Omar, Coleman, and Hoerr 2001; Sexton et al. 2008). Older vehicles also raise concerns about durability and the potential for costly repairs. For the most economically vulnerable, having access to *reliable* transportation is as important as having access to transportation.

Despite substantial recent investments in public transit systems (Manville, Taylor, and Blumenberg 2018b), access to a vehicle remains one of the most important determinants of employment for low-income individuals in the United States—and for individuals of all income levels, for that matter (Blumenberg and Pierce 2014). Accordingly, the percentage of households owning at least one vehicle in the United States has reached a steady level of just under 90 percent since the mid-1990s (Bureau of Labor Statistics 2018). While vehicle ownership rates are lower in low-income households, most still own vehicles: in 2018, 66 percent of households in the bottom income quintile and 89 percent in the second-bottom quintile owned one or more vehicles (Bureau of Labor Statistics 2018).

3.3 Vehicle ownership in low-income households

Most research on vehicle ownership in low-income households focuses on the number of vehicles they have rather than the kinds of vehicles they own. Research has examined the influence of socioeconomic factors and the built environment on vehicle ownership (Brown 2017; Ong and Gonzalez 2019), the effects of vehicle ownership on employment and economic outcomes (Blumenberg and Pierce 2014), and availability in households with fewer vehicles than drivers (Blumenberg, Brown, and Schouten 2018b). Ong and Gonzalez (2019) also examine the influence of neighborhood-level structural barriers—disparities in vehicle financing, insurance premiums, and policing—and find that they have negative effects on vehicle ownership rates and on owning vehicles less than ten years old.

One study, Pierce et al. (2019), describes household vehicle fleets for Californians as a secondary analysis for a study of programs to encourage low- and moderate-incomes to purchase electric vehicles. The authors conduct a choice experiment with 1,600 households planning to buy a vehicle in the next three years to determine what type of vehicle they intended to buy. Even with fuel economy measures prominently displayed, respondents preferred SUVs to cars and preferred trucks to SUVs; in both cases, respondents preferred vehicle types with lower fuel efficiency. While the survey had many low-income respondents, the results may not have been nationally representative: the authors note that they could not find comparable studies or data. The authors call for future research to examine household vehicle holdings (or “fleet packages”) and the effects of household structure and socioeconomic factors on these holdings.

To use an electric vehicle, one must also have a place to charge it and equipment to do so. Even with subsidies, low-income households are less likely to own electric vehicles because they are more likely to rent (and thus less likely to have access to the needed infrastructure) than to own property. Davis (2019) finds that homeowners in the United States are three times more likely than renters to own electric vehicles, even after controlling for income, but also questions whether this gap reflects an actual market failure for policymakers to address.

A related strand of research involving vehicle characteristics investigates the effects of fuel economy on incomes and spending. Greene and Welch (2018) estimate the effects of fuel efficiency gains on incomes and find that lower-income households experienced greater relative gains than higher-income households. This finding is intuitive, given that lower-income households have smaller household budgets and given that low-income households have lower fuel price elasticity than higher-income households with respect to vehicle miles traveled (VMT), meaning that low-income households reduce their driving less when fuel prices increase (Wang and Chen 2014).

3.4 American vehicle manufacturing and fuel efficiency trends

National vehicle manufacturing and fuel efficiency data from the Environmental Protection Agency (EPA) offers context for the household-level analysis. Figure 3.1, adapted from Environmental Protection Agency (2019), illustrates changes in the composition and fuel economy of vehicles manufactured in the United States from 1975 to 2017. In 1980, following the oil crises of the 1970s that made fuel efficiency a highly salient issue for consumers, sedans and station wagons experienced their peak market share, accounting for 80 percent of new vehicles. Over time, however, their share has steadily declined to 45 percent of vehicles, with a temporary increase during the Great Recession from December 2007 to June 2009, which once again brought fuel efficiency to the forefront of consumers' minds—this time in terms of affordability. Station wagons have nearly disappeared from the market: in 2018, only 200,000 were sold, with one model (the Subaru Outback, designed to look "rugged" like a sport utility vehicle) accounting for more than four-fifths of the sales (Joseph 2020).

Despite considerable scholarly attention paid to hybrid and electric vehicles, the larger car market is shifting toward SUVs. In 2017, SUVs accounted for a record 43 percent of market share for new vehicles (Environmental Protection Agency 2019). Car and truck SUVs were nearly non-existent in 1980, but their market share has grown to 43 percent in 2017.

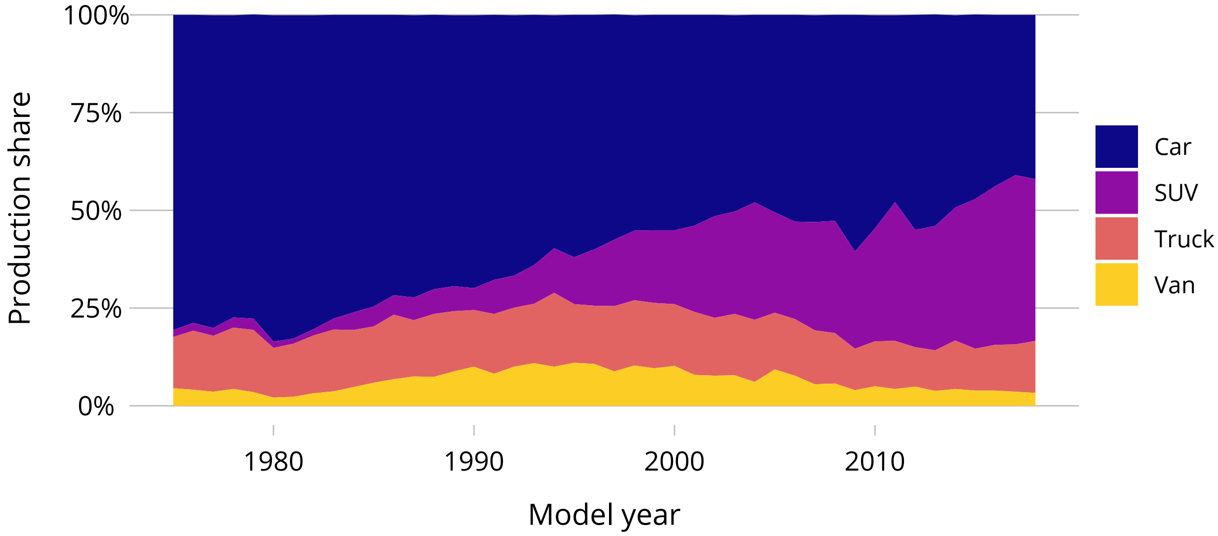

Figure 3.1: Production share by vehicle type, 2001–2017 (EPA data)

Because SUVs have lower average fuel efficiency than cars, the market shift from cars to SUVs has offset some of the vehicle fuel efficiency gains at the aggregate level. Hybrid SUV and electric SUV models have started to appear in the market, with new models expected to appear shortly (Foldy 2020).

While most of the increase in market share for SUVs has come at the expense of cars, a smaller share has come at the expense of minivans and vans, which serve household needs which cars cannot, especially for larger families. Minivans and vans had their largest market share in the 1990s, with a peak of 10 percent in 1994, but their market share has dwindled to 2 percent as of 2017. Pickup trucks, in contrast, have held a steady market share of 12 to 15 percent over the last three decades, most likely because they fill a niche for people hauling large items, including items used in employment, that SUVs do not.

Fuel economy has increased for all vehicle types since 1975, but the rate of improvement varies by vehicle type, as shown in Figure 3.2, adapted from Environmental Protection Agency (2019). (Fuel efficiency for SUVs, which EPA split into "truck SUV" and "car SUV" categories, is an average for car and truck SUVs weighted by production share.) In 1975, vehicles of all types had fuel economy below 14 miles per gallon (MPG). In the aftermath

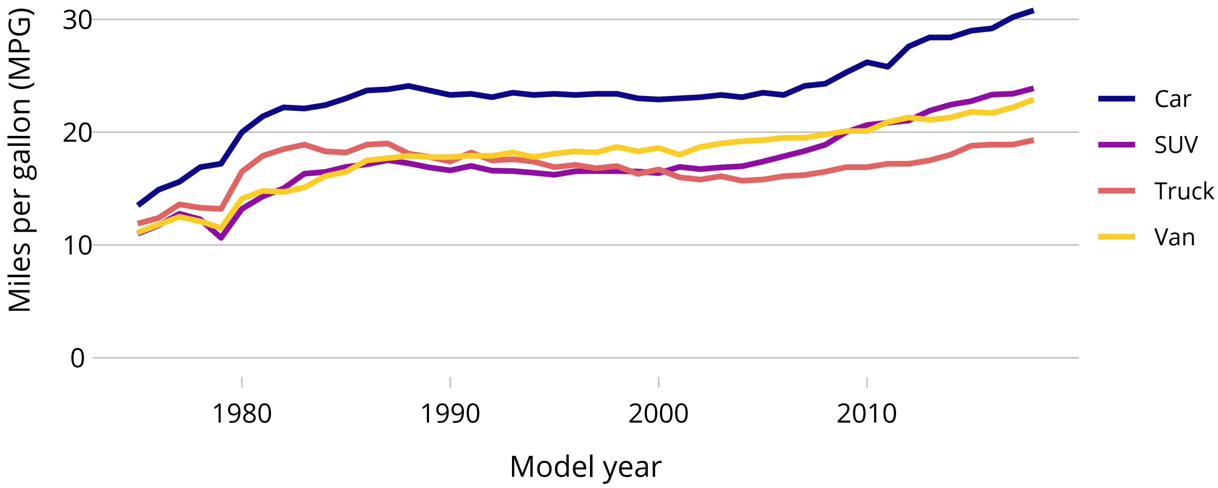

Figure 3.2: Fuel economy by vehicle type, 2001–2017 (EPA data)

of the oil crises of the 1970s, manufacturers increased fuel efficiency for vehicles; by 1985, new cars had an average of 23 MPG. From the mid-1980s to the mid-2000s, however, fuel efficiency gains stagnated: for trucks, fuel efficiency *declined* from 18.2 MPG in 1985 to 15.8 MPG in 2005. While a variety of new vehicle technologies made engines more efficient, manufacturers added weight to their vehicles and features that collectively canceled out the gains derived from the vehicle technologies (Lutsey and Sperling 2005). Since 2005, cars and SUVs have experienced notable gains in fuel efficiency, and minivans have gained to a lesser extent. While the average fuel efficiency of trucks has also increased, it has only made up for losses over the last two decades and has barely changed from 1985 (18.9 MPG in 2017; 18.2 MPG in 1985).

Federal regulation plays a key role in fuel economy and vehicle manufacturing trends. In 1975, following the 1973 oil crisis, Congress enacted corporate average fuel economy (CAFE) standards to improve vehicle fuel economy for passenger vehicles starting in 1978 (Yacobucci and Bamberger 2010). In 2012, the Obama administration enacted more stringent CAFE standards with a target of 54.5 MPG for vehicles manufactured in model year 2025 (Office of the Press Secretary 2012), although vehicles have lower effective fuel economy in real-world conditions than in federal laboratory tests for CAFE standards (Webster 2011). Future regulatory developments, such as the Trump administration's current effort to relax CAFE standards, will affect fuel economy and vehicle prices in low-income households when vehicles filter into the used car market (Keith, Houston, and Naumov 2019). Jacobsen (2013), evaluating the long-run effects of CAFE standards in the used-car market, finds that wealthier households bore the initial burden of higher vehicle prices as manufacturers added fuel-saving technologies, but also finds that lower-income households incurred welfare losses once the vehicles entered the used car market. The CAFE standards also affect the type of vehicles entering the used car market. Whitefoot and Skerlos (2012) find that the standards, which set fuel-economy targets based on vehicle size, created incentives for manufacturers to produce larger vehicles.

3.5 Analysis

National trends in vehicle manufacturing alone do not tell the full story of trends in vehicle holdings in low-income households. Low-income households buy most of their vehicles used, not new (Paszkiewicz 2003). While the supply of new vehicles affects the supply of used vehicles, the ways in which consumers of new vehicles purchase, use, and sell the vehicles also affect supply and price, as does demand from higher-income consumers of used vehicles. Finally, vehicles age differently depending on their type, make and model, and maintenance.

When making used vehicle purchases, low-income consumers may also have different considerations from higher-income consumers. For example, reliability and repairability over the long term may be more relevant factors to low-income consumers. Low-income households also may be more likely to purchase trucks if they are more likely to work in jobs requiring them. Manufacturer, make, and model preferences may differ as well: low-income households living in dense urban areas with limited free parking may prefer smaller vehicles, and may avoid certain popular vehicles if they fear theft.

3.5.1 Data and measures

I use data from the confidential geocoded version of the 2001 to 2017 waves of the PSID to examine trends in vehicle holdings, supplemented with measures of residential density and transit access. The PSID is a biennial longitudinal household survey that has measured employment, wealth, spending, and other social factors in American families (Institute for Social Research 2017) since 1968. In 2017, 9,607 families with 26,445 individuals took part in the survey. The PSID, which emerged from an effort to assess President Lyndon Johnson's War on Poverty, includes an oversampling of low-income households (McGonagle et al. 2012), making it useful for studying vehicle ownership in low-income groups.

To identify transit stations, I employ a dataset constructed from the National Transit-Oriented Development (TOD) Database (Center for Transit-Oriented Development 2012), Wikipedia station lists, and a list of transit stations produced by The Transport Politic Blog (Freemark and Vance 2018), as described in the data appendix.

I define "low-income" as having a household income under 200 percent of the federal poverty guideline levels in a given year. The federal poverty guidelines, issued annually by U.S. Health and Human Services and used by government agencies to decide eligibility for various aid programs, account for family size but not for geographic location or ages of family members. Using this threshold, the number of families in the analysis that are low-income each year ranges from 2,153 (2001) to 3,292 (2015). I use a broad definition of poverty to minimize issues with sample size when grouping families by the number of vehicles and types of vehicles owned.

The PSID has information on the three newest vehicles a family owns by model year and the total number of vehicles owned. The model year is bottom-coded at 19 to 40 years before the survey year depending on the year, as described in the data appendix. The PSID has information on a vehicle's year, manufacturer, make, type (car, pickup, van, or SUV), how it was acquired (bought, leased, or given), and whether the vehicle is used for business. The PSID also has information on hybrid and electric vehicles starting in 2011. A restricted-use version of the PSID also includes vehicle models.

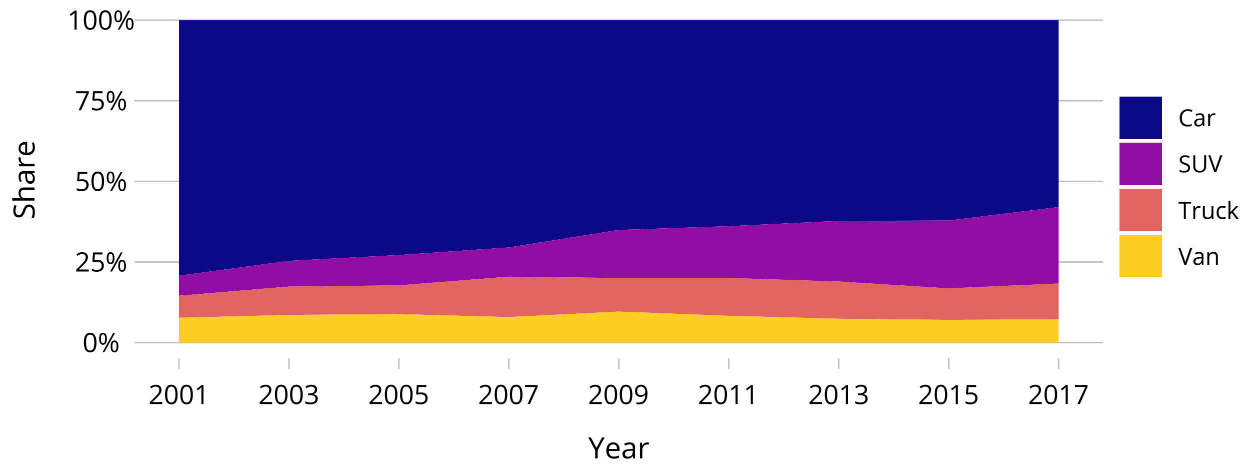

Figure 3.3: Vehicle share by type and year, low-income households with one vehicle

To derive initial estimates of fuel economy, I incorporate data from Environmental Protection Agency (2020), as described in the data appendix, matching the model year, manufacturer, and vehicle type. These estimates should be understood as rough estimates to identify trends, given that an individual family's driving patterns and vehicle maintenance have substantial effects on actual fuel economy [@].

3.5.2 Vehicle fleet packages in low-income households

For low-income households owning one vehicle, the share of SUVs has increased from 6.2 percent in 2001 to 23.7 percent in 2017 (Figure 3.3). Most of this increase comes from cars, whose share decreased from 79.3 percent to 58.0 percent. (For other households, the share of SUVs increased from 15.3 percent in 2001 to 34.2 percent in 2017.) The share of trucks in low-income households increased from 6.8 percent in 2001 to a peak of 12.5 percent in 2007 but decreased to 11.1 percent by 2017. The share of vans increased from 7.7 percent in 2001 to a peak of 9.6 percent in 2009, and then declined to 7.2 percent in 2017. This trend is likely to continue as new minivan sales also continue to decline (Foldy 2019). In contrast, the share of pickup trucks may not decline, given their steady manufacturing share.

A small but growing share of low-income families with vehicles owns a hybrid, plug-in hybrid, electric, or alternative-fuel vehicle with compressed natural gas or liquefied petroleum gas (Table 3.1). The percentage of low-income families with vehicles that owned at least one of these types is low but increased from 2.1 percent in 2011 to 4.5 percent in 2017. These rates are only slightly lower than rates for other families, which increased from 2.6 percent to 6.2 percent over the same period.

Table 3.1: Families with hybrid, plug-in hybrid, electric, or alternative-fuel vehicles

Year	Low-income	Not low-income
2011	2.1%	2.6%
2013	3.2%	4.6%
2015	3.2%	5.7%
2017	4.5%	6.2%

Table 3.2 shows vehicle holdings in low-income households owning two vehicles by year. The most common combination of vehicles overall for families owning two vehicles was owning two cars (26.7 percent of households), followed by owning a car and a truck (23.2 percent). Owning a car and an SUV has become much more common—and became the most common holding combination in 2017, with 24.2 percent of households owning a car and an SUV that year. The fourth most common combination, a car and van, has declined in share from 15.5 percent to 8.1 percent as the "car and SUV" combination became more common.

Table 3.2: Vehicle share by type and year, low-income households with two vehicles

Year	Car, car	Car, SUV	Car, truck	Car, van	SUV, SUV	SUV, truck	SUV, van	Truck, truck	Truck, van	Van, van
2001	31.2%	7.5%	28.2%	15.5%	1.3%	4.7%	1.5%	2.1%	6.4%	1.7%
2003	34.2%	9.8%	28.1%	12.2%	1.1%	5.3%	0.8%	2.2%	5.5%	0.9%
2005	28.7%	9.8%	31.6%	11.1%	1.7%	6.8%	1.9%	1.3%	6.0%	1.2%
2007	27.0%	12.8%	23.5%	11.9%	2.3%	6.2%	4.8%	3.4%	6.6%	1.5%
2009	26.5%	16.9%	24.9%	10.6%	1.5%	9.5%	2.2%	2.5%	4.5%	0.8%
2011	26.7%	18.7%	22.6%	8.6%	1.3%	9.3%	2.9%	3.8%	5.4%	0.9%
2013	24.7%	22.5%	23.1%	7.8%	3.0%	8.5%	2.1%	2.3%	5.5%	0.4%
2015	24.0%	21.7%	20.2%	10.5%	5.5%	9.3%	2.1%	2.8%	3.8%	0.1%
2017	19.6%	24.2%	20.1%	8.1%	6.2%	9.8%	2.1%	4.6%	3.6%	1.8%

The PSID has information for the newest three vehicles a family owns. A small percentage of low-income families in the sample (5.4 percent) own three or more vehicles. The four most common combinations of three vehicles for these households were two cars and a truck (17.1 percent of households); a car, an SUV, and a truck (13.4 percent); three cars (12.6 percent); and a car and two trucks (9.9 percent) (Table 3.3). While the sample size is too small to produce annual estimates by vehicle type, combinations with SUVs are likely to have become much more common in recent years, given trends in vehicle ownership for one- and two-car households.

Table 3.3: Vehicle share by type, low-income households with three vehicles

Group	Share
Car, car, truck	17.1%
Car, SUV, truck	13.4%
Car, car, car	12.6%
Car, truck, truck	9.9%
Car, car, SUV	9.8%
Car, car, van	8.1%
Car, truck, van	6.2%
SUV, truck, truck	4.0%
Car, SUV, SUV	3.6%
Car, SUV, van	2.7%

3.5.3 Vehicle ages in low-income households

The average age of a family's vehicle has increased for households of all income levels, consistent with other research showing that families are holding on to cars longer (Pfirrmann-Powell 2014). For low-income households, the average age of their newest vehicle has increased from 8.3 years in 2001 to 10.6 years in 2017 (Table 3.4). For other households, the average age has increased from 4.7 to 6.1 years. On the one hand, holding vehicles longer can be positive for low-income households if improvements in vehicle technology allow them to drive vehicles longer without needing major repairs. With improvements in vehicle technology, well-maintained cars can last 200,000 miles or more (Consumer Reports 2018). On the other hand, the average age for vehicles in low-income households suggests that many of the vehicles they own do not have the increased fuel efficiency of vehicles produced in the last decade, resulting in higher operating costs than if they had more recently manufactured vehicles.

Table 3.4: First vehicle age by year and income status

Income	2001	2003	2005	2007	2009	2011	2013	2015	2017
Not low-income	4.7	4.8	4.8	4.9	5.5	6.1	6.2	6.2	6.1
Low-income	8.3	8.8	9.3	9.3	9.3	10.2	10.6	10.7	10.6

While the average age of all vehicle types has increased, the increase was largest for vehicles other than cars. In 2001, cars had the highest average age of all first vehicle types owned by low-income households (8.6 years), while SUVs had the lowest ages (6.0 years) (Table 3.5). By 2017, the average age of SUVs increased to 9.9 years, almost the same as the average age of cars (10.2 years). The average age of trucks and vans also increased noticeably. For trucks, the average age increased from 8.1 years in 2001 to 12.8 years in 2017; for vans, the average increased from 8.2 to 12.1 years.

Table 3.5: First vehicle age by year and type, low-income families

Year	Car	SUV	Truck	Van
2001	8.6	6	8.1	8.2
2003	9.1	6.6	8.3	9.2
2005	9.8	7.2	8.5	8.7
2007	9.5	8.1	9	9.1
2009	9.7	7.6	9.5	10.2
2011	10.2	9.5	11.2	10.7
2013	10.4	10.3	11.8	11.1
2015	10.7	9.4	13	11.3
2017	10.1	9.9	12.8	12.1

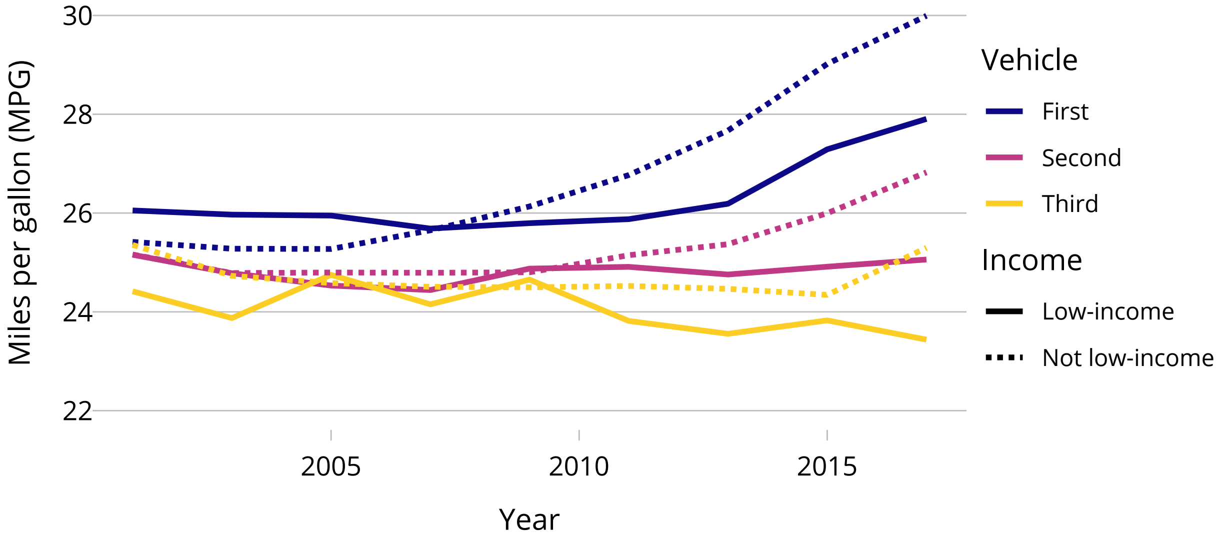

Figure 3.4: Average fuel economy for vehicles by family income, 2001–2017

3.5.4 Fuel economy

Figure 3.4 shows estimates of average MPG for vehicles in low-income and higher-income families by year. In 2001, vehicles in low-income families—few of which were SUVs—had slightly higher MPG than vehicles in higher-income families (26.1 MPG versus 25.4 MPG). Fuel economy increased for higher-income households but not lower-income households until 2007, at which point the two groups had equal MPG. After 2007, fuel economy increased for both groups, but at a faster rate for higher-income households. In 2017, the average fuel economy for vehicles in low-income families was 27.9 MPG versus 30.0 MPG for higher-income families.

Fuel economy is lower for second and third vehicles than for first vehicles, as expected given that second and third vehicles have older model years. Unlike with first vehicles, however, low-income families consistently had lower average MPG than higher-income families over the two decades; the gap also widened slightly even as fuel economy increased for vehicles in both groups. In 2001, the average fuel economy for second vehicles was 25.2 MPG for both low-income and higher-income households. In 2017, low-income households had an average of 26.8 MPG for second vehicles versus 25.1 MPG for higher-income households. Third vehicles had the lowest average MPG and, unlike first and second vehicles, have shown little change in fuel economy. For low-income families, fuel economy for third vehicles declined slightly from 24.4 MPG in 2001 to 23.4 MPG in 2017.

3.5.5 Characteristics of low-income households and vehicle ownership

Table 3.6 shows the characteristics of low-income households by the type of the newest vehicle they own. Owners of vans and SUVs have higher numbers of children on average (1.6 and 1.1 children) and higher median incomes ($24,000 and $22,000 in 2017 dollars) than other families. Families with trucks are much less likely to be female-headed households (19 percent) than families with other vehicle types (36 to 53 percent). Families with SUVs have slightly younger heads of household than other families (45.8 years old versus 47.9 to 50.6 years old). Owners of cars, in contrast, are slightly older (50.6 years old) and slightly more likely to be retired. About one-fifth of families with trucks (17.4 percent) use them for business purposes besides commuting, a higher percentage than for families with other vehicles (9.8 to 13.2 percent).

Some differences in family income by vehicle type may stem from differences in prices for used vehicles by type. Data from CarGurus, an online automotive marketplace that compiles vehicle listings from dealers across the country, illustrate relative differences in used vehicle prices by vehicle type. As of January 2020, average prices for used SUVs and pickup trucks (around $26,000) are higher than for used sedans and wagons (around $15,000); average prices for used vans and minivans (around $19,000 and $16,000) are in between (CarGurus 2020). Because these average prices are for all vehicle listings in the United States, relative prices may differ slightly in the set of used vehicles that low-income households typically consider.

Table 3.6: Low-income household characteristics by first vehicle type

Group	Car	SUV	Truck	Van	All vehicles
Household size	2.3	2.9	2.5	3.6	2.3
Children	0.6	1.1	0.7	1.6	0.7

Group	Car	SUV	Truck	Van	All vehicles
Age (head)	50.7	45.7	49	47.8	50.7
Female-headed	53.0%	44.8%	18.8%	35.5%	50.7%
Income (median, 2017 dollars)	$19,627	$22,200	$19,776	$24,001	$17,740
White (head)	62.9%	60.5%	65.2%	60.1%	58.2%
Black (head)	22.0%	18.6%	11.3%	15.8%	24.9%
Hispanic (head)	11.5%	17.5%	20.1%	19.6%	13.2%
Asian (head)	1.2%	0.5%	1.0%	1.4%	1.2%
High school graduate (head)	74.5%	74.0%	64.4%	62.6%	68.5%
College graduate (head)	12.4%	11.6%	6.2%	8.7%	9.2%
In metropolitan area	69.6%	67.5%	60.8%	69.5%	70.8%
Near rail	6.9%	5.7%	3.9%	5.1%	8.3%
Vehicle used for business	10.4%	13.1%	17.8%	11.5%	11.8%
n (family-year)	10,333	2,884	1,585	1,526	25,324

To test the relative influence of social, demographic, and geographic characteristics on the type of vehicle low-income families own, I perform a multinomial logit regression using the low-income households identified the PSID. The regression models the odds of owning an SUV, truck, or van relative to the odds of owning a car, the baseline outcome. Independent variables include a range of sociodemographic and geographic factors that may influence the vehicle a family buys, taken from the earlier discussion as well as from Zhao and Kockelman (2002), who model household vehicle ownership using national data from 1995:

- Income: Higher-income consumers are more likely to own SUVs than lower-income families; Zhao and Kockelman (2002) found that lower-income families were more likely to own pickup trucks. These relative probabilities may hold even within lower-income families.

- Use of vehicles: Families using vehicles for business purposes (apart from commuting) may be more likely to own trucks, which can accommodate business needs like hauling objects.

- Residential location: Households in dense urban areas may be more likely to own cars than larger vehicles given limited space for driving and parking. Households in rural areas may be more likely to own pickup trucks to accommodate outdoor activities.

One limitation of the modeling is that it does not account for the simultaneity of employment and vehicle ownership (Baum 2009; Gurley and Bruce 2005; Ong 2002). Having a vehicle makes finding employment easier; at the same time, having a job makes owning a vehicle easier. Without data on exogenous factors that may influence vehicle ownership without influencing employment (or vice versa), accounting for simultaneity is difficult (Ong and Gonzalez 2019).

Table 3.7 shows the results of the regression model. All reported coefficients are significant at the $p < 0.01$ level. The odds of owning a van or SUV as the primary vehicle increase with the number of children in the household, but the odds of owning a truck, van, or SUV are lower for female-headed households. Higher incomes are associated with higher odds of owning an SUV, as expected. Living within a half mile of rail, living in denser areas, and not being a homeowner all decrease the odds of owning a non-car vehicle. Using the primary vehicle for business purposes increases the odds that the vehicle is a truck or, to a lesser extent, an SUV. Finally, owning additional vehicles increases the likelihood that the primary vehicle is a truck or an SUV, but decreases the likelihood that the primary vehicle is a van. Racial differences in primary vehicle ownership persist even after controlling for other factors: black households have lower odds of owning trucks, vans, or SUVs, while Hispanic families have higher odds of owning trucks.

Table 3.7: Vehicle type modeling results (“car” as baseline)

Variable	SUV	Truck	Van
Race (head; base category “white”)			
Black	0.75	0.50	0.53
Hispanic	0.99	1.94	0.89
Asian	0.40	1.04	0.57
Employment (head; base category “employed”)			
Retired	1.64	1.08	0.78
Unemployed or disabled	0.97	1.02	0.93
Keeping house	0.96	1.21	0.91
Student	1.47	1.11	1.13
Adults	0.95	0.92	1.01

Variable	SUV	Truck	Van
Children	1.27	0.92	1.68
Female-headed	0.84	0.22	0.60
Age (head)	1.10	1.09	1.14
Age squared	1.00	1.00	1.00
High school graduate	0.93	0.98	1.00
College graduate	1.00	0.99	1.00
Income (log)	1.14	0.91	0.97
Vehicle used for work	1.28	1.72	1.15
Number of vehicles	1.06	1.00	0.86
Within half-mile of rail	0.93	0.86	0.91
Density (log)	1.01	0.84	1.01
Not homeowner	0.85	0.67	0.79
Constant	0.01	0.55	0.01
Akaike Inf. Crit.	29,424.58	29,424.58	29,424.58

3.5.6 Changes in vehicle type within households

The PSID does not directly ask if or how families changed vehicle ownership—by buying, selling, trading in, or disposing of vehicles—since the last survey. I use the make, model year, and type of vehicles to identify households that have acquired vehicles between survey waves. Assuming that the newest model-year vehicle in the household is the household's primary vehicle, I examine whether households change the type of their vehicle when they acquire a new primary vehicle. (The households may still own the previous vehicle.) Table 3.8 shows that most families keep the same vehicle type. Owners of cars are the most likely to stay with the same type of vehicle (81.6 percent), followed by owners of SUVs (70.4 percent). If car owners switch vehicle types, they are most likely to switch to SUVs. If owners of SUVs, trucks, and vans switch vehicle types, they are most likely to switch to cars.

Table 3.8: Vehicle types for low-income families acquiring a new vehicle

Previous vehicle	Car	SUV	Truck	Van
Car	84.6%	7.4%	4.5%	3.6%

Previous vehicle	Car	SUV	Truck	Van
SUV	20.1%	70.7%	6.6%	2.6%
Truck	18.9%	8.5%	67.6%	5.0%
Van	22.5%	8.2%	9.4%	59.9%

To determine what factors influence families to switch from owning a car as their primary vehicle to owning an SUV, truck, or van, I construct a multinomial logit model. The sample consists of families who had a car as the primary vehicle in one year and acquired a new vehicle the following survey year. Table 3.9 shows the odds of switching relative to the odds of acquiring another car as the primary vehicle. One unexpected result is that living within half a mile of rail increases the odds of switching to an SUV, truck, or van. One potential explanation is that, because these families have transit access, they switch to vehicles that fulfill more specialized needs. Other relationships are more expected. For example, families with more children are more likely to switch to SUVs and vans, and wealthier families are more likely to switch to SUVs and less likely to switch to trucks and vans. Residential density decreases the odds of switching to trucks. Using the vehicle for employment increases the odds of switching to a truck and, to a lesser extent, an SUV.

Table 3.9: Vehicle switching modeling results ("keep car" as baseline)

Variable	Car to SUV	Car to truck	Car to van
Race (head; base category "white")			
Black	0.71	0.58	0.44
Hispanic	0.87	1.65	0.59
Asian	0.44	1.63	0.40
Employment (head; base category "employed")			
Retired	1.64	1.14	0.90
Unemployed or disabled	0.88	0.93	0.91
Keeping house	1.00	2.22	1.01
Student	1.56	0.53	1.63
Adults	0.97	0.95	1.09
Children	1.29	0.93	1.76
Female-headed	1.00	0.20	0.62
Age (head)	1.07	1.10	1.08

Variable	Car to SUV	Car to truck	Car to van
Age squared	1.00	1.00	1.00
High school graduate (head)	0.97	1.11	0.97
College graduate (head)	1.00	1.00	1.00
Income (log)	1.16	0.92	0.98
Vehicle used for work	1.16	1.73	0.84
Number of vehicles	1.07	1.11	0.86
Within half-mile of rail	1.10	1.35	1.03
Density (log)	0.98	0.88	0.99
Not homeowner	0.89	0.64	1.28
Constant	0.02	0.14	0.02
Akaike Inf. Crit.	6,625.50	6,625.50	6,625.50

3.6 Discussion and conclusion

SUVs account for an ever-increasing share of vehicles in low-income households, despite efforts by policymakers to facilitate purchases of smaller, more fuel-efficient vehicles. The average fuel economy for vehicles increased for all families over the period, but at a slower rate for low-income families. To what extent do these two trends reflect disparities in access to fuel-efficient vehicles? To what extent do the trends reflect consumer preferences for other vehicle features besides fuel efficiency?

One unanswered question in this research and a key area of interest for future research is whether the rise in SUV ownership among low-income households reflects consumer preferences versus a shift in vehicle availability in the used car market that creates disparities in access to fuel-efficient vehicles. Despite the "sport" in "sport utility vehicle," most purchasers of SUVs have more mundane uses for the vehicles, like running household errands. Many vehicles typically described as SUVs, like the Toyota RAV4, are more precisely known as crossover vehicles (Consumer Reports 2019). These vehicles, built on car platforms, offer more passenger and cargo space than cars while offering better fuel economy than trucks.

Regardless of SUV designations, low-income families may use them because they have many of the same passenger-transporting and errand-running needs as other families in this area—and may have more needs since they cannot afford to pay others to perform services as many higher-income households do. Many SUV drivers also perceive driving in larger vehicles as safer (Thomas and Walton 2008); low-income drivers have similar concerns about driving and safety. Finally, SUVs—and vehicles in general—operate as status symbols as well as means of transportation, even as they receive fierce criticism from environmentalists and anti-consumerist groups (Vanderheiden 2006). Focusing on ways to reduce the negative effects of SUVs, like removing them from fuel-economy exemptions and promoting the manufacturing of electric or hybrid SUVs, can benefit lower-income households who buy them used as well as the upper-income households who buy them new.

Empirical evidence further demonstrates that, while vehicle affordability is an important policy concern, it is far from the only factor motivating vehicle purchases in low-income households. Surveying low- and moderate-income households in California, Pierce et al. (2019) asked households who were considering disposing of their vehicle what their primary reason was. While 19 percent reported that the vehicle was too expensive to maintain and 4 percent reported that they could no longer afford the vehicle, twice as many respondents (41 percent) wanted a different or newer make or model—twice the percentage citing financial reasons. The authors note that "vehicle aesthetics, style, and personal preferences are extremely salient" even for low-income households. Indeed, low-income families, like all families, have consumer preferences. The PSID lacks information to judge the degree to which the increase in SUV ownership reflects changing consumer preferences versus supply constraints. While discussions of affordability center on vehicle purchases and operation, resale may be an issue as well.

Finally, this chapter offered an initial analysis of fuel economy for vehicles owned by low-income households. Future studies can incorporate information about daily trip-making patterns, which can have substantial effects on fuel economy: mileage is much lower in cities than on highways due to frequent stopping, starting, and idling.

Conclusion

American households have taken fewer daily trips over the last two decades, and their average vehicle miles traveled (VMT) have declined as well (McGuckin and Fucci 2018). Forecasted growth rates in national VMT for future decades have also decreased (Federal Highway Administration 2019). Public transit and many environmental advocates have seized upon these trends to declare that the developed world has reached "peak car" (Goodwin and Dender 2013) and to lobby for more money to expand transit and less money to expand and maintain highways (Dutzik and Baxandall 2013).

The analysis in the first two chapters shows that family trajectories of car ownership do not show declining levels of vehicle ownership, even as daily trip-making and VMT decline. On the contrary, most families show stable or even increasing levels of vehicle ownership over the last two decades. As the analysis in Chapter 3 shows, an increasing number of these families—including low-income families—now own sport utility vehicles (SUVs) as well.

How can researchers and policymakers reconcile these differing trends, and what implications might the trends have for transportation planning and policy? While the data used in this dissertation do not permit a quantitative analysis of household VMT or daily travel patterns, some instances of increased vehicle ownership and multi-mobility may be related to social and recreational travel. While increases in online activities correspond with declines in vehicle trips for social purposes overall (McGuckin and Fucci 2018), families may have more time and resources for different types of social travel with extra vehicles. Owning an additional truck or SUV may allow families to take camping trips, for example; owning a sports car or vintage model may allow people to take recreational drives.

One of the most striking results of the analysis is the overall stability of car ownership levels across time for most of the surveyed households, even as they experience major life events like moving, marriage, and having children over the analysis period. One explanation is that trends in moving to areas that allow for car-light or car-free lifestyles, particularly among Millennials, may be overstated. Some Millennials moved into central cities in the late 2000s and early 2010s, reversing decades of population decline in central cities, but those changes may not be permanent (Myers 2016). Moreover, Millennials move less than previous generations and are the primary reason that the United States has experienced its lowest mobility rate in decades (Frey 2019). While some Millennials have moved to cities, suburbanization is the dominant trend in the United States, with other population groups like immigrants moving from central cities to suburbs (Myers 2016). Even Millennials are more likely to live in suburban areas than urban areas, with the percentage of suburban Millennials increasing since 2000 (Blumenberg et al. 2019). Finally, while new transportation developments like the rise of ride-hailing services may offer important mobility options for households, they have not induced most users to change their levels of vehicle ownership (Clewlow and Mishra 2017).

This dissertation marks a first step toward constructing models that planners can use to predict patterns of vehicle ownership in a household over its life course. Developing models that could predict vehicle ownership patterns with reasonable accuracy could inform aggregate models of vehicle ownership for land use, transportation, and environmental modeling. The modeling results could also inform policy responses involving family vehicle ownership and access. These policy responses have three potential goals: reducing vehicle ownership; promoting vehicle ownership; and maintaining vehicle ownership.

Policies to reduce vehicle ownership seek to reduce the negative externalities and financial burdens of using automobiles. Policymakers may focus on investments in transit and pedestrian infrastructure and on transit-oriented development to facilitate car-free lifestyles. Smart and Klein (2018), who find that people who are exposed to transit in young adulthood own fewer cars and use transit more often later in life, suggest encouraging a "transit habit" by subsidizing transit for school- and college-age students, recent movers, and new employees. The results of this dissertation suggest that people rarely give up vehicles altogether, however. Families with one vehicle, for example, may be unwilling to give up a vehicle, even if they can reliably use other modes for most of their trips, in case of emergencies.

Policymakers may counter that, even if such policies do not substantially reduce vehicle ownership, the policies will still reduce the negative externalities associated with automobile use. As the analysis of multi-mobility shows, however, families are willing to own more vehicles than people, and anecdotal evidence suggests that families are willing to own vehicles they drive only occasionally, like on weekends (Reddit 2017). If policies to reduce vehicle ownership mostly lead to families shedding "extra" vehicles, the policies may be much less effective than expected. Dill (2004), evaluating two vehicle retirement programs in the Bay Area and Los Angeles, found that the programs attracted more households with multiple vehicles than expected and that households reported driving those vehicles less often than the statewide average for the vehicle model year. Nonetheless, planners and policymakers can address the negative consequences of vehicle use through other policies without reducing vehicle ownership—in particular, by reassessing policies like minimum parking requirements and low fuel taxes that subsidize driving (Taylor 2006). Moreover, negative externalities of vehicle use like traffic congestion are often unpriced (Taylor 2006); policymakers can implement pricing to compensate for these externalities and better manage travel demand.

In contrast, other policies may promote car ownership for families with no or low levels of vehicle access. Programs that promote car ownership are much less common than programs that promote transit use (Cervero and Tsai 2003), in part because using money to subsidize vehicle ownership sparks controversy from environmentalists as well as from critics of welfare programs (Wachs and Taylor 1998). Nonetheless, the few studies of car ownership programs available show positive economic results for participants (Lucas and Nicholson 2003; Blumenberg and Waller 2003). While policymakers assert that increasing access to public transit can also improve economic outcomes for low-income riders, empirical evidence suggests that it does not except in limited circumstances (Sanchez, Shen, and Peng 2004;

Ong and Houston 2002; Kawabata 2003).

Finally, other policies involve maintaining minimal levels of vehicle access for families who are vulnerable to losing access—and are therefore vulnerable to losing employment. One way to maintain access is to help families maintain and repair vehicles. Vehicle repair subsidies, like the Tune In and Tune Up program in California's San Joaquin Valley (Mérel and Wimberger 2012), are one example of a policy action to maintain access. A much smaller-scale option to maintain ownership is improving outreach efforts for recalls and manufacturer service actions, also known as "secret warranties," for components that fail at greater rates than predicted (Sovern 1995). Vehicle-keeping programs may be more politically palatable than programs to increase car ownership, especially if vehicle-keeping programs are framed as programs to help people maintain employment and, in the case of programs like Tune In and Tune Up, to improve the environment.

While some families may need to use vehicles daily, other families may need vehicles only on occasion—for example, while looking for employment or accessing healthcare. For the other families, an alternative policy approach to maintaining vehicle access is to subsidize ride-hailing and shared mobility services. In her examination of Lyft use in Los Angeles, Brown (2019) finds that most customers use the service for occasional travel needs, and that such services can offer vehicle access to low-income families even in suburban and rural areas.

Consistent vehicle access cannot by itself address the complex and interrelated problems associated with poverty—for example, inadequate education and poor health. Nor will vehicle access help if it only connects low-income households to jobs that pay little and offer little hope of advancement. Effective transportation policy can, however, remove one of the persistent barriers to economic and social opportunity that low-income households face over the life course.

APPENDIX A

Technical Information

This appendix contains supplemental technical information for the data and methods I use in the three analytic chapters. The primary source of data is the confidential geocoded version of the Panel Study of Income Dynamics (PSID). For most of the analysis, I use data from the 2001 to 2017 waves; for the birth cohort analysis in Chapter 2, I use the 1969 to 1987 waves and the 1997 wave as well. (The PSID did not collect vehicle information in 1975 and from 1989 to 1998.) The PSID is a biennial longitudinal household survey that measures employment, wealth, spending, and other social factors in American families (Institute for Social Research 2017). In 2017, 9,607 families with 26,445 individuals took part in the survey. The confidential geocoded version of the PSID has the Census tract and block group of respondents.

A.1 Statistical computing and analysis

I perform the statistical and geospatial analysis using R, an open-source statistical software environment (R Core Team 2018). Major R packages used in the analysis include:

- `TraMineR` to perform sequence analysis (Gabadinho, Ritschard, Müller, et al. 2011)
- `tidycensus` to download and process U.S. Census Bureau data (Walker and Eberwein 2018)
- `sf` and `rgdal` to manipulate spatial data and perform spatial analysis (Pebesma et al. 2018; Bivand et al. 2018)

A.2 Neighborhood characteristics

I measure neighborhood density for respondents at the Census tract level by combining population measures from the Longitudinal Tract Data Base (LTDB) with land area measures from the U.S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER) database. The LTDB, developed by Logan, Xu, and Stults (2014), harmonizes Census tract data from 1970 to 2010 using 2010 tract boundaries. For analysis with respondents in the 2001 to 2009 waves, I use density measures from 2000; for respondents in the 2001 to 2017 waves, I use density measures from 2010.

A.3 Transit access

I measure transit access using distances to rail stations, as discussed in Chapter 1. I use the National Transit-Oriented Development (TOD) Database (Center for Transit-Oriented Development 2012) as the primary dataset to identify stations and their opening years. The database has information on 4,400 fixed-guideway transit stations in the United States as of 2011, the opening years if the stations opened after 2000, and the station latitudes and longitudes. To add information for stations that opened from 2012 to 2017, I compiled a list of stations using two sources. For station names and opening years, I used station lists compiled on Wikipedia to identify stations that opened after 2011 and checked the information using transit agency websites or newspaper articles. For station locations, I used data from Transit Explorer, an interactive map of transit stations and lines produced by The Transport Politic Blog, which has information for new stations up to 2017 and beyond (Freemark and Vance 2018). The list of transit stations and locations is at `http://github.com/sbrumb/stationlist/` for interested researchers.

I identify whether families live within a half-mile radius of one or more rail stations each survey year. To identify the correct map projections to use for calculating buffers, I use a county-level list of map projections prepared by Neil Freeman at `https://gist.github.com/fitnr/10795511`. I identify any Census block group (the lowest level of geographical detail available in the geocoded PSID) that overlaps the half-mile buffer as being "within" in it. The number of Census block groups from the 100 most populated MSAs within half a mile of a transit station increased from 20,769 in 2005 to 22,509 in 2017, for an 8.4 percent increase. The code I use to calculate the buffers is available at `https://github.com/sbrumb/railbuffers`.

A.4 Vehicle information and fuel economy

The PSID occasionally changes the earliest model year it records for vehicles, and codes vehicles with earlier model years as "9997." These changes effectively top-code vehicle ages in the PSID at 19 to 41 years old depending on the survey wave, as shown in Table A.1. For vehicles coded "9997" in a survey wave, I use the maximum age available.

Table A.1: Earliest vehicle model year recorded by survey wave

Survey year	Earliest vehicle year	Oldest vehicle age
2001	1960	41
2003	1984	19
2005	1986	19
2007	1987	20
2009	1987	22
2011	1987	24
2013	1987	26
2015	1993	22
2017	1998	19

To derive estimates of fuel economy, I combine vehicle information in the PSID with data from Environmental Protection Agency (2020) (Supplemental Table J), which lists average MPG by manufacturer and vehicle type from 1975 to 2018 weighted by production share for vehicles in each group. A separate confidential version of the PSID, not obtained for this analysis, contains vehicle models. While having additional vehicle information like model and trim would allow for more accurate MPG estimates, actual MPG may still vary greatly depending on a family's driving patterns and vehicle maintenance. For sport utility vehicles (SUVs), which EPA separates by truck and car SUV, I derive an average weighted by production share. For vehicle manufacturers in the PSID that are not in the EPA data, I use the average miles per gallon (MPG) for “all manufacturers” for the year and vehicle type.

APPENDIX B

Supplemental Tables

This appendix contains supplemental tables for the three analytic chapters.

B.1 Vehicle ownership ratios and families with teenagers

The analysis in Chapters 1 and 2 uses a "vehicles per adult" ratio to measure vehicle access. As discussed in Chapter 1, some teenagers age 16 and 17 may drive, complicating analysis. Table B.1 shows the percentage of teenagers age 16 and 17 in each vehicle ownership group.

Table B.1: Families with 16- or 17-year-olds by year and vehicle ownership ratio

Year	A (0 cars)	B (<1 car/adult)	C (1 car/adult)	D (>1 car/adult)
2001	4.6%	11.0%	5.4%	17.1%
2003	7.9%	11.0%	4.8%	15.7%
2005	6.7%	10.3%	5.6%	17.2%
2007	7.7%	11.4%	6.7%	15.0%
2009	6.3%	12.1%	7.3%	14.0%
2011	9.2%	10.7%	5.9%	11.5%
2013	7.8%	10.1%	6.7%	16.5%
2015	12.2%	10.0%	6.0%	14.3%
2017	11.5%	13.2%	5.3%	13.7%

B.2 Alternative vehicle ownership ratio results

This section presents descriptive statistics and modeling results from Chapter 1 recalculated using the ratio of vehicles to adults plus teenagers age 16 and older.

Table B.2: PSID family descriptive statistics (alternative specification)

Group	Group A (0 cars)	Group B (<1 car/driver)	Group C (1 car/driver)	Group D (>1 car/driver)
Household size	1.7	3.4	2.1	2.3
Children	0.3	0.8	0.5	0.5
Age (head)	53.7	51.5	50.1	51.4
Female-headed	57.0%	23.9%	32.2%	14.4%
Median income (2017 dollars)	$18,538	$59,554	$60,570	$79,996
White (head)	54.9%	63.7%	79.9%	81.9%
Black (head)	32.0%	16.1%	10.4%	9.9%
Hispanic (head)	9.3%	14.0%	6.3%	5.6%
Asian (head)	1.3%	2.8%	1.5%	1.1%
High school (head)	68.6%	76.1%	88.8%	89.2%
College (head)	13.4%	23.3%	33.7%	27.5%
Metropolitan area	56.8%	58.5%	56.1%	46.7%
n (family-year)	11703	19784	35124	10200

Table B.3: Groups of vehicle ownership trajectories (alternative specification)

Group	Percentage	Typical trajectory
Fully equipped	39.1%	Has one car per adult for most or all years
Gaining access	22.5%	Starts with fewer than one car per adult then later has one car per adult
Multi-mobile	11.4%	Has more than one car per adult for most or all years
Becoming multi-mobile	10.4%	Switches between having one car per adult and having more than one car per adult
Sharing cars	6.4%	Has at least one car but less than one car per adult for most years; includes some families that occasionally have one car per adult
Mostly carless	5.2%	Starts with one car per adult then later has fewer than one car per adult
Turbulent	4.9%	Switches multiple states including zero cars

Table B.4: Characteristics of groups (alternative specification)

Group	Fully equipped	Turbulent	Multi-mobile	Sharing cars	Gaining access	Mostly carless	Becoming multi-mobile
Household size (2001)	2.1	2.1	2.4	3.9	3.5	1.9	2.9
Household size (2017)	2.1	2.3	2.2	3.2	2.8	1.6	2.4
Median income (2001, 2017 dollars)	$72,211	$28,740	$87,852	$62,327	$84,304	$24,989	$86,815
Median income (2017)	$68,060	$31,085	$78,078	$51,708	$79,000	$14,257	$91,549
Lives in metropolitan area (2001)	76.4%	76.4%	60.0%	81.1%	75.8%	83.2%	69.8%
Lives in metropolitan area (2017)	76.4%	76.4%	60.0%	81.1%	75.8%	83.2%	69.8%
Does not own home (2001)	30.6%	68.8%	15.5%	32.6%	26.1%	80.0%	22.1%
Does not own home (2017)	21.6%	62.4%	7.4%	30.1%	21.0%	79.6%	12.9%
Near rail (2001)	6.9%	10.1%	3.1%	13.9%	7.9%	28.2%	4.3%
Near rail (2017)	7.1%	10.0%	5.3%	13.8%	7.1%	26.9%	4.3%
White (head)	86.3%	52.0%	85.3%	54.5%	73.8%	37.1%	84.0%
Black (head)	6.9%	31.5%	8.8%	13.6%	11.2%	53.3%	10.5%
Hispanic (head)	2.0%	12.5%	1.8%	19.9%	8.9%	6.1%	2.9%
Asian (head)	2.1%	0.6%	0.9%	6.4%	2.6%	1.7%	0.5%
Immigrant	2.6%	12.1%	1.3%	28.7%	10.8%	7.2%	2.8%
High school (2017)	94.8%	70.2%	90.3%	69.6%	86.3%	65.1%	91.2%
College (2017)	40.5%	10.5%	31.4%	23.7%	33.4%	14.2%	38.5%
n (families)	1053	196	340	262	892	246	353

B.3 Birth cohort years

Table B.5 shows the number of usable sequences for a set of ages tested for the cohort analysis in Chapter 2. I defined a usable family sequence as a sequence with zero or one missing state.

Table B.5: Usable family sequences by age range (four or more survey waves)

Starting age	24	26	28	30	32
18	646	412	293	176	95
20		1337	1027	641	434
22			2220	1459	1063
24				2620	1977
26					2672

References

Abbott, Andrew. 1995. "Sequence Analysis: New Methods for Old Ideas." *Annual Review of Sociology* 21:93–113. https://www.jstor.org/stable/2083405.

Abbott, Andrew, and Angela Tsay. 2000. "Sequence Analysis and Optimal Matching Methods in Sociology: Review and Prospect." *Sociological Methods & Research* 29, no. 1 (August): 3–33. DOI: 10.1177/0049124100029001001.

American Public Transportation Association. 2019. *2019 Public Transportation Fact Book.* Technical report. April. https://www.apta.com/wp-content/uploads/APTA_Fact-Book-2019_FINAL.pdf.

Arsenault, Paul M. 2004. "Validating Generational Differences: A Legitimate Diversity and Leadership Issue." *Leadership & Organization Development Journal* 25, no. 2 (January): 124–141. DOI: 10.1108/01437730410521813.

AutoGuide.com. 2016. *Here's What You Need to Know About Millennial Car Shopping Habits,* November. https://www.autoguide.com/auto-news/2016/11/here-s-what-you-need-to-know-about-millennial-car-shopping-habits.html.

Baum, Charles L. 2009. "The Effects of Vehicle Ownership on Employment." *Journal of Urban Economics* 66, no. 3 (November): 151–163. DOI: 10.1016/j.jue.2009.06.003.

Bivand, Roger, Tim Keitt, Barry Rowlingson, Edzer Pebesma, Michael Sumner, Robert Hijmans, Even Rouault, Frank Warmerdam, Jeroen Ooms, and Colin Rundel. 2018. *Rgdal: Bindings for the 'Geospatial' Data Abstraction Library,* October. https://CRAN.R-project.org/package=rgdal.

Blumenberg, Evelyn. 2003. "En-Gendering Effective Planning: Transportation Policy and Low-Income Women." *Journal of the American Planning Association* 70 (3): 269–281.

Blumenberg, Evelyn, Anne E. Brown, and Andrew Schouten. 2018a. *Auto-Deficit Households: Determinants, Travel Behavior, and the Gender Division of Household Car Use.* Technical report. March. http://ucconnect.berkeley.edu/auto-deficit-households-determinants-travel-behavior-and-gender-division-household-car-use.

———. 2018b. "Car-Deficit Households: Determinants and Implications for Household Travel in the U.S." *Transportation* (December). DOI: 10.1007/s11116-018-9956-6.

Blumenberg, Evelyn, Anne Brown, Kelcie Ralph, Brian D. Taylor, and Carole Turley Voulgaris. 2019. "A Resurgence in Urban Living? Trends in Residential Location Patterns of Young and Older Adults since 2000." *Urban Geography* 40, no. 9 (October): 1375–1397. DOI: 10.1080/02723638.2019.1597594.

Blumenberg, Evelyn, Stephen Brumbaugh, and Jane Pollard. 2018. "Vehicle Loan Financing in Low-Income and Minority Households." In *Transportation Research Board 97th Annual Meeting.* January. https://trid.trb.org/view/1496999.

Blumenberg, Evelyn, and Gregory Pierce. 2012. "Automobile Ownership and Travel by the Poor: Evidence from the 2009 National Household Travel Survey." *Transportation Research Record* 2320, no. 1 (January): 28–36. DOI: 10.3141/2320-04.

———. 2014. "A Driving Factor in Mobility? Transportation's Role in Connecting Subsidized Housing and Employment Outcomes in the Moving to Opportunity (MTO) Program." *Journal of the American Planning Association* 80 (1): 52–66.

Blumenberg, Evelyn, and Kimiko Shiki. 2007. "Transportation Assimilation: Immigrants, Race and Ethnicity, and Mode Choice." In *Transportation Research Board 86th Annual Meeting.* https://trid.trb.org/view/802238.

Blumenberg, Evelyn, and Michael Smart. 2010. "Getting by with a Little Help from My Friends…and Family: Immigrants and Carpooling." *Transportation* 37, no. 3 (May): 429–446. DOI: 10.1007/s11116-010-9262-4.

Blumenberg, Evelyn, Brian D. Taylor, Michael Smart, Kelcie Ralph, Madeline Wander, and Stephen Brumbaugh. 2012. *What's Youth Got to Do with It? Exploring the Travel Behavior of Teens and Young Adults.* Technical report UCTC-FR-2012-14. University of California Transportation Center, September. https://escholarship.org/uc/item/9c14p6d5.

Blumenberg, Evelyn, and Margy Waller. 2003. *The Long Journey to Work: A Federal Transportation Policy for Working Families.* Technical report. Washington DC, Brookings Institution. https://www.brookings.edu/research/the-long-journey-to-work-a-federal-transportation-policy-for-working-families/.

Boomhower, Judson, and Lucas W. Davis. 2014. "A Credible Approach for Measuring Inframarginal Participation in Energy Efficiency Programs." *Journal of Public Economics* 113 (May): 67–79. DOI: 10.1016/j.jpubeco.2014.03.009.

Borenstein, Severin, and Lucas W. Davis. 2016. "The Distributional Effects of US Clean Energy Tax Credits." *Tax Policy and the Economy* 30, no. 1 (January): 191–234. DOI: 10.1086/685597.

Brenan, Megan. 2018. *83% of U.S. Adults Drive Frequently; Fewer Enjoy It a Lot,* July. https://news.gallup.com/poll/236813/adults-drive-frequently-fewer-enjoy-lot.aspx.

Bricker, Jesse, Lisa J Dettling, Alice Henriques, Joanne W Hsu, Lindsay Jacobs, Sarah Pack, John Sabelhaus, and Jeffrey Thompson. 2017. *Changes in U.S. Family Finances from 2013 to 2016: Evidence from the Survey of Consumer Finances.* Technical report. Federal Reserve Board, September.

Brown, Anne E. 2017. “Car-Less or Car-Free? Socioeconomic and Mobility Differences among Zero-Car Households.” *Transport Policy* 60 (November): 152–159. DOI: 10.1016/j.tranpol.2017.09.016.

———. 2019. “Redefining Car Access.” *Journal of the American Planning Association* 85, no. 2 (April): 83–95. DOI: 10.1080/01944363.2019.1603761.

Brzinsky-Fay, Christian, and Ulrich Kohler. 2010. “New Developments in Sequence Analysis.” *Sociological Methods & Research* 38, no. 3 (February): 359–364. DOI: 10.1177/0049124110363371.

Buehler, Ralph. 2010. “Transport Policies, Automobile Use, and Sustainable Transport: A Comparison of Germany and the United States.” *Journal of Planning Education and Research* 30, no. 1 (September): 76–93. DOI: 10.1177/0739456X10366302.

Bureau of Labor Statistics. 2018. *Consumer Expenditure Survey.* https://www.bls.gov/cex/.

Cao, Xinyu, Patricia L. Mokhtarian, and Susan L. Handy. 2009. “Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings.” *Transport Reviews* 29, no. 3 (May): 359–395. DOI: 10.1080/01441640802539195.

CarGurus. 2020. *Used Car Price Trends,* January. https://www.cargurus.com/Cars/price-trends/.

Center for Transit-Oriented Development. 2012. *National TOD Database.* https://toddata.cnt.org/.

Cervero, Robert, and Yu-Hsin Tsai. 2003. “Job Access and Reverse Commuting Initiatives in California: Review and Assessment.” *Transportation Research Record: Journal of the Transportation Research Board* 1859 (January): 78–86. DOI: 10.3141/1859-10.

Chatman, Daniel G. 2013. “Does TOD Need the T?” *Journal of the American Planning Association* 79, no. 1 (January): 17–31. DOI: 10.1080/01944363.2013.791008.

Clark, Ben, Kiron Chatterjee, Steve Melia, Gundi Knies, and Heather Laurie. 2014. “Life Events and Travel Behavior: Exploring the Interrelationship Using UK Household Longitudinal Study Data.” *Transportation Research Record* 2413, no. 1 (January): 54–64. DOI: 10.3141/2413-06.

Clewlow, Regina R., and Gouri S. Mishra. 2017. “Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States” (October). https://escholarship.org/uc/item/82w2z91j.

Congressional Budget Office. 2020. *The Foreign-Born Population and Its Effects on the U.S. Economy and the Federal Budget: An Overview.* Technical report. January. https://www.cbo.gov/publication/55967.

Connolly, Rachel, Gregory Pierce, Julien Gattaciecca, and Yifang Zhu. 2019. “Estimating Mortality Impacts from Vehicle Emission Reduction Efforts: The Tune In and Tune Up Program in the San Joaquin Valley.” *Transportation Research Part D: Transport and Environment* (December). DOI: 10.1016/j.trd.2019.11.019.

Consumer Reports. 2018. *Make Your Car Last 200,000 Miles,* November. https://www.consumerreports.org/car-repair-maintenance/make-your-car-last-200-000-miles/.

———. 2019. *The Rise of the Crossover: The Segment That’s Really Driving the Auto Industry’s Sales,* December. https://advocacy.consumerreports.org/research/the-rise-of-the-crossover-the-segment-thats-really-driving-the-auto-industrys-sales/.

Dargay, Joyce M. 2001. "The Effect of Income on Car Ownership: Evidence of Asymmetry." *Transportation Research Part A: Policy and Practice* 35, no. 9 (November): 807–821. DOI: 10.1016/S0965-8564(00)00018-5.

Dargay, Joyce, Dermot Gately, and Martin Sommer. 2007. "Vehicle Ownership and Income Growth, Worldwide: 1960-2030." *The Energy Journal* Volume 28 (Number 4): 143–170. https://econpapers.repec.org/article/aenjournl/2007v28-04-a07.htm.

Davis, Lucas W. 2019. "Evidence of a Homeowner-Renter Gap for Electric Vehicles." *Applied Economics Letters* 26, no. 11 (June): 927–932. DOI: 10.1080/13504851.2018.1523611.

Davis, Stacy C., and Robert G. Boundy. 2019. *Transportation Energy Data Book.* Technical report 37.2. Oak Ridge National Laboratory, August. https://tedb.ornl.gov/.

Delmelle, Elizabeth C. 2015. "Five Decades of Neighborhood Classifications and Their Transitions: A Comparison of Four US Cities, 1970–2010." *Applied Geography* 57 (February): 1–11. DOI: 10.1016/j.apgeog.2014.12.002.

Dill, Jennifer. 2004. "Estimating Emissions Reductions from Accelerated Vehicle Retirement Programs." *Transportation Research Part D: Transport and Environment* 9, no. 2 (March): 87–106. DOI: 10.1016/S1361-9209(03)00072-5.

Dittmar, Hank, and Gloria Ohland. 2012. *The New Transit Town: Best Practices In Transit-Oriented Development.* Island Press, June. ISBN: 978-1-59726-894-3.

Dorsett, Richard, and Paolo Lucchino. 2014. "Explaining Patterns in the School-to-Work Transition: An Analysis Using Optimal Matching." *Advances in Life Course Research* 22 (December): 1–14. DOI: 10.1016/j.alcr.2014.07.002.

Dua, Rubal, Kenneth White, and Rebecca Lindland. 2019. "Understanding Potential for Battery Electric Vehicle Adoption Using Large-Scale Consumer Profile Data." *Energy Reports* 5 (November): 515–524. DOI: 10.1016/j.egyr.2019.04.013.

Dutzik, Tony, and Phineas Baxandall. 2013. *A New Direction: Our Changing Relationship with Driving and the Implications for America's Future.* Technical report. U.S. PIRG Education Fund. https://uspirg.org/reports/usp/new-direction.

Dynan, Karen, Douglas Elmendorf, and Daniel Sichel. 2012. "The Evolution of Household Income Volatility." *The B.E. Journal of Economic Analysis & Policy* 12, no. 2 (December). DOI: 10.1515/1935-1682.3347.

Elder, Glen H. 1994. "Time, Human Agency, and Social Change: Perspectives on the Life Course." *Social Psychology Quarterly* 57 (1): 4–15. DOI: 10.2307/2786971.

Elzinga, Cees H. 2010. "Complexity of Categorical Time Series." *Sociological Methods & Research* (April). DOI: 10.1177/0049124109357535.

Elzinga, Cees H., and Aart C. Liefbroer. 2007. "De-Standardization of Family-Life Trajectories of Young Adults: A Cross-National Comparison Using Sequence Analysis." *European Journal of Population / Revue européenne de Démographie* 23, no. 3 (October): 225–250. DOI: 10.1007/s10680-007-9133-7.

Environmental Protection Agency. 2019. *The EPA Automotive Trends Report.* Data and Tools. March. https://www.epa.gov/automotive-trends.

———. 2020. *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2018.* Reports and Assessments, April. https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks.

Eurostat. 2019. *Passenger Cars in the EU - Statistics Explained,* April. https://ec.europa.eu/eurostat/statistics-explained/index.php/Passenger_cars_in_the_EU.

Federal Highway Administration. 2017. *National Household Travel Survey.* https://nhts.ornl.gov/.

Federal Highway Administration. 2019. *Forecasts of Vehicle Miles Traveled, Spring 2019,* May. https://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_forecast_sum.cfm.

Feng, Ye, Don Fullerton, and Li Gan. 2013. "Vehicle Choices, Miles Driven, and Pollution Policies." *Journal of Regulatory Economics* 44, no. 1 (August): 4–29. DOI: 10.1007/s11149-013-9221-z.

Foldy, Ben. 2019. "'The Minivan Is Out of Style'; Sales Fade as SUVs Gain Traction." *Wall Street Journal* (July). https://www.wsj.com/articles/minivan-sales-fade-as-families-opt-for-suvs-11564322401.

———. 2020. "Auto Makers See SUVs, Trucks Charging Electric-Vehicle Sales." *Wall Street Journal* (January). https://www.wsj.com/articles/auto-makers-see-suvs-trucks-charging-electric-vehicle-sales-11578758107.

Fothergill, Alice, and Lori A. Peek. 2004. "Poverty and Disasters in the United States: A Review of Recent Sociological Findings." *Natural Hazards* 32, no. 1 (May): 89–110. DOI: 10.1023/B:NHAZ.0000026792.76181.d9.

Freemark, Yonah, and Steven Vance. 2018. *The Transport Politic - Transit Explorer.* http://www.thetransportpolitic.com/transitexplorer/.

Frey, William H. 2019. *For the First Time on Record, Fewer than 10% of Americans Moved in a Year,* November. https://www.brookings.edu/blog/the-avenue/2019/11/22/for-the-first-time-on-record-fewer-than-10-of-americans-moved-in-a-year/.

Gabadinho, Alexis, Gilbert Ritschard, Nicolas S. Müller, and Matthias Studer. 2011. "Analyzing and Visualizing State Sequences in R with TraMineR." *Journal of Statistical Software* 40 (4): 1–37. DOI: 10.18637/jss.v040.i04.

Gabadinho, Alexis, Gilbert Ritschard, Matthias Studer, and Nicolas S. Müller. 2011. "Extracting and Rendering Representative Sequences." In *Knowledge Discovery, Knowledge Engineering and Knowledge Management,* edited by Ana Fred, Jan L. G. Dietz, Kecheng Liu, and Joaquim Filipe, 94–106. Communications in Computer and Information Science. Springer Berlin Heidelberg. ISBN: 978-3-642-19032-2.

Gautier, Pieter A., and Yves Zenou. 2010. "Car Ownership and the Labor Market of Ethnic Minorities." *Journal of Urban Economics* 67, no. 3 (May): 392–403. DOI: `10.1016/j.jue.2009.11.005`.

Glaeser, Edward L., Matthew E. Kahn, and Jordan Rappaport. 2008. "Why Do the Poor Live in Cities? The Role of Public Transportation." *Journal of Urban Economics* 63, no. 1 (January): 1–24. DOI: `10.1016/j.jue.2006.12.004`.

Goodwin, Phil, and Kurt Van Dender. 2013. "'Peak Car' — Themes and Issues." *Transport Reviews* 33, no. 3 (May): 243–254. DOI: `10.1080/01441647.2013.804133`.

Greene, David L., and Jilleah G. Welch. 2018. "Impacts of Fuel Economy Improvements on the Distribution of Income in the U.S." *Energy Policy* 122 (November): 528–541. DOI: `10.1016/j.enpol.2018.08.005`.

Guerra, Erick, Robert Cervero, and Daniel Tischler. 2012. "Half-Mile Circle: Does It Best Represent Transit Station Catchments?" *Transportation Research Record: Journal of the Transportation Research Board* 2276, no. 1 (January): 101–109. DOI: `10.3141/2276-12`.

Gurley, Tami, and Donald Bruce. 2005. "The Effects of Car Access on Employment Outcomes for Welfare Recipients." *Journal of Urban Economics* 58:250–272.

Hannagan, Anthony, and Jonathan Morduch. 2015. *Income Gains and Month-to-Month Income Volatility: Household Evidence from the US Financial Diaries.* US FINANCIAL DIARIES WORKING PAPER. NYU Wagner, September. `http://www.ssrn.com/abstract=2659883`.

Houston, Douglas, Jun Wu, Paul Ong, and Arthur Winer. 2004. “Structural Disparities of Urban Traffic in Southern California: Implications for Vehicle-Related Air Pollution Exposure in Minority and High-Poverty Neighborhoods.” *Journal of Urban Affairs* 26, no. 5 (December): 565–592. DOI: 10.1111/j.0735-2166.2004.00215.x.

Institute for Social Research. 2017. *PSID Main Interview User Manual: Release 2017.* Technical report. University of Michigan, May. https://psidonline.isr.umich.edu/data/Documentation/UserGuide2015.pdf.

Jacobsen, Mark R. 2013. “Evaluating US Fuel Economy Standards in a Model with Producer and Household Heterogeneity.” *American Economic Journal: Economic Policy* 5, no. 2 (May): 148–187. DOI: 10.1257/pol.5.2.148.

Johnson, David S., Katherine A. McGonagle, Vicki A. Freedman, and Narayan Sastry. 2018. “Fifty Years of the Panel Study of Income Dynamics: Past, Present, and Future.” *The Annals of the American Academy of Political and Social Science* 680, no. 1 (November): 9–28. DOI: 10.1177/0002716218809363.

Joseph, Noah. 2020. *Station Wagons Sell in U.S. Mainly When They’re Disguised as SUVs,* February. https://www.caranddriver.com/news/a31069594/station-wagons-disguised-suvs/.

Kassel, Matthew. 2019. “How Cities Are Trying to Reinvent the Bus.” *Wall Street Journal* (May). https://www.wsj.com/articles/how-cities-are-trying-to-reinvent-the-bus-11558378863.

Kawabata, Mizuki. 2003. “Job Access and Employment among Low-Skilled Autoless Workers in US Metropolitan Areas.” *Environment and Planning A: Economy and Space* 35, no. 9 (September): 1651–1668. DOI: 10.1068/a35209.

Kawabata, Mizuki, and Qing Shen. 2007. "Commuting Inequality between Cars and Public Transit: The Case of the San Francisco Bay Area, 1990-2000." *Urban Studies* 44 (9): 1759–1780. DOI: 10.1080/00420980701426616.

Keith, David R., Samantha Houston, and Sergey Naumov. 2019. "Vehicle Fleet Turnover and the Future of Fuel Economy." *Environmental Research Letters* 14, no. 2 (February): 021001. DOI: 10.1088/1748-9326/aaf4d2.

Kim, Hong Sok, and Eungcheol Kim. 2004. "Effects of Public Transit on Automobile Ownership and Use in Households of the USA." *Review of Urban & Regional Development Studies* 16 (3): 245–262. DOI: 10.1111/j.1467-940X.2005.00090.x.

Klein, Nicholas J., and Michael J. Smart. 2017a. "Car Today, Gone Tomorrow: The Ephemeral Car in Low-Income, Immigrant and Minority Families." *Transportation* 44, no. 3 (May): 495–510. DOI: 10.1007/s11116-015-9664-4.

———. 2017b. "Millennials and Car Ownership: Less Money, Fewer Cars." *Transport Policy* 53 (January): 20–29. DOI: 10.1016/j.tranpol.2016.08.010.

———. 2019. "Life Events, Poverty, and Car Ownership in the United States: A Mobility Biography Approach." *Journal of Transport and Land Use* 12, no. 1 (May). DOI: 10.5198/jtlu.2019.1482.

Klein, Nicholas J., Michael J. Smart, and Rounaq Basu. 2019. *Analyzing the Causes and Duration of Spells of Carlessness among Low-Income Families.* Greenville, SC, October.

Laird, Elizabeth, and Carole Trippe. 2014. *Programs Conferring Categorical Eligibility for SNAP: State Policies and the Number and Characteristics of Households Affected.* Technical report. Washington, D.C.: Mathematica Policy Research, February. https://www.mathematica.org/our-publications-and-findings/publications/programs-conferring-categorical-eligibility-for-snap-state-policies-and-the-number-and-characteristics-of-households-affected.

Liu, Cathy Yang, and Gary Painter. 2012. "Travel Behavior among Latino Immigrants: The Role of Ethnic Concentration and Ethnic Employment." *Journal of Planning Education and Research* 32, no. 1 (March): 62–80. DOI: 10.1177/0739456X11422070.

Logan, John R., Zengwang Xu, and Brian J. Stults. 2014. "Interpolating U.S. Decennial Census Tract Data from as Early as 1970 to 2010: A Longitudinal Tract Database." *The Professional Geographer* 66, no. 3 (July): 412–420. DOI: 10.1080/00330124.2014.905156.

Lucas, Marilyn T., and Charles F. Nicholson. 2003. "Subsidized Vehicle Acquisition and Earned Income in the Transition from Welfare to Work." *Transportation* 30 (4): 483–501. DOI: 10.1023/A:1024724224634.

Lutsey, Nicholas, and Daniel Sperling. 2005. "Energy Efficiency, Fuel Economy, and Policy Implications." *Transportation Research Record* 1941, no. 1 (January): 8–17. DOI: 10.1177/0361198105194100102.

Manville, Michael, and Emily Goldman. 2018. "Would Congestion Pricing Harm the Poor? Do Free Roads Help the Poor?" *Journal of Planning Education and Research* 38, no. 3 (September): 329–344. DOI: 10.1177/0739456X17696944.

Manville, Michael, Brian D. Taylor, and Evelyn Blumenberg. 2018a. *Falling Transit Ridership: California and Southern California.* Technical report. UCLA Institute of Transportation Studies, January. https://www.scag.ca.gov/Documents/ITS_SCAG_Transit_Ridership.pdf.

———. 2018b. "Transit in the 2000s: Where Does It Stand and Where Is It Headed?" *Journal of Public Transportation* 21, no. 1 (January). DOI: http://doi.org/10.5038/2375-0901.21.1.11.

McDonald, Noreen C. 2015. "Are Millennials Really the "Go-Nowhere" Generation?" *Journal of the American Planning Association* 81, no. 2 (April): 90–103. DOI: 10.1080/01944363.2015.1057196.

McGonagle, Katherine A., Robert F. Schoeni, Narayan Sastry, and Vicki A. Freedman. 2012. "The Panel Study of Income Dynamics: Overview, Recent Innovations, and Potential for Life Course Research." *Longitudinal and Life Course Studies* 3 (2): 268–284. DOI: 10.14301/llcs.v3i2.188.

McGuckin, Nancy, and Anthony Fucci. 2018. *Summary of Travel Trends 2001 National Household Travel Survey.* Technical report. Federal Highway Administration, July. DOI: 10.2172/885762.

McMunn, Anne, Rebecca Lacey, Diana Worts, Peggy McDonough, Mai Stafford, Cara Booker, Meena Kumari, and Amanda Sacker. 2015. "De-Standardization and Gender Convergence in Work–Family Life Courses in Great Britain: A Multi-Channel Sequence Analysis." *Advances in Life Course Research* 26 (December): 60–75. DOI: 10.1016/j.alcr.2015.06.002.

Mérel, Pierre, and Emily Wimberger. 2012. "Improving Air Quality in California's San Joaquin Valley: The Role of Vehicle Heterogeneity in Optimal Emissions Abatement." *Journal of Environmental Economics and Management* 63, no. 2 (March): 169–186. DOI: 10.1016/j.jeem.2011.10.004.

Mian, Atif, and Amir Sufi. 2012. "The Effects of Fiscal Stimulus: Evidence from the 2009 Cash for Clunkers Program*." *The Quarterly Journal of Economics* 127, no. 3 (August): 1107–1142. DOI: 10.1093/qje/qjs024.

Mitra, Suman K., and Jean-Daniel M. Saphores. 2019. "How Do They Get by without Cars? An Analysis of Travel Characteristics of Carless Households in California." *Transportation* (March). DOI: 10.1007/s11116-019-09994-6.

Müggenburg, Hannah, Annika Busch-Geertsema, and Martin Lanzendorf. 2015. "Mobility Biographies: A Review of Achievements and Challenges of the Mobility Biographies Approach and a Framework for Further Research." *Journal of Transport Geography* 46 (June): 151–163. DOI: 10.1016/j.jtrangeo.2015.06.004.

Myers, Dowell. 2016. “Peak Millennials: Three Reinforcing Cycles That Amplify the Rise and Fall of Urban Concentration by Millennials.” *Housing Policy Debate* 26, no. 6 (November): 928–947. DOI: 10.1080/10511482.2016.1165722.

New Zealand Ministry of Transport. 2019. *Transport Dashboard,* February. https://www.transport.govt.nz/mot-resources/transport-dashboard/2-road-transport/rd027-vehicle-ownership-per-capita/.

Oakil, Abu Toasin Md, Dick Ettema, Theo Arentze, and Harry Timmermans. 2014. “Changing Household Car Ownership Level and Life Cycle Events: An Action in Anticipation or an Action on Occurrence.” *Transportation* 41, no. 4 (July): 889–904. DOI: 10.1007/s11116-013-9507-0.

Office of the Press Secretary. 2012. *Obama Administration Finalizes Historic 54.5 MPG Fuel Efficiency Standards,* August. https://obamawhitehouse.archives.gov/the-press-office/2012/08/28/obama-administration-finalizes-historic-545-MPG-fuel-efficiency-standard.

Omar, Mildred A., Gayle Coleman, and Sharon Hoerr. 2001. “Healthy Eating for Rural Low-Income Toddlers: Caregivers’ Perceptions.” *Journal of Community Health Nursing* 18, no. 2 (June): 93–106. DOI: 10.1207/S15327655JCHN1802_03.

Ong, Paul M. 2002. “Car Ownership and Welfare-to-Work.” *Journal of Policy Analysis and Management* 21 (2): 239–252.

Ong, Paul M., and Silvia R. Gonzalez. 2019. “Employment and Spatial Transportation Mismatch.” In *Uneven Urbanscape: Spatial Structures and Ethnoracial Inequality,* 109–142. Cambridge Studies in Stratification Economics: Economics and Social Identity. Cambridge University Press.

Ong, Paul M., and Douglas Houston. 2002. “Transit, Employment and Women on Welfare.” *Urban Geography* 23, no. 4 (June): 344–364. DOI: 10.2747/0272-3638.23.4.344.

Park, Seong Suk, Abhilash Vijayan, Steve L. Mara, and Jorn D. Herner. 2016. "Investigating the Real-World Emission Characteristics of Light-Duty Gasoline Vehicles and Their Relationship to Local Socioeconomic Conditions in Three Communities in Los Angeles, California." *Journal of the Air & Waste Management Association* 66, no. 10 (October): 1031–1044. DOI: 10.1080/10962247.2016.1197166.

Paszkiewicz, Laura. 2003. "The Cost and Demographics of Vehicle Acquisition." In *Consumer Expenditure Survey Anthology, 2003,* 61–66. Bureau of Labor Statistics, September. https://www.bls.gov/cex/csxanthol03.htm.

Pebesma, Edzer, Roger Bivand, Etienne Racine, Michael Sumner, Ian Cook, Tim Keitt, Robin Lovelace, Hadley Wickham, Jeroen Ooms, and Kirill Müller. 2018. *Sf: Simple Features for R,* October. https://CRAN.R-project.org/package=sf.

Pfirrmann-Powell, Ryan. 2014. *Americans' Aging Autos.* Technical report. Bureau of Labor Statistics, May. https://www.bls.gov/opub/btn/volume-3/americans-aging-autos.htm.

Pierce, Gregory, J. R. DeShazo, Tamara Sheldon, Britta McOmber, and Evelyn Blumenberg. 2019. *Designing Light-Duty Vehicle Incentives for Low- and Moderate-Income Households.* Technical report. UCLA Luskin Center for Innovation, March.

Prillwitz, Jan, Sylvia Harms, and Martin Lanzendorf. 2006. "Impact of Life-Course Events on Car Ownership." *Transportation Research Record* 1985, no. 1 (January): 71–77. DOI: 10.1177/0361198106198500108.

Pucher, John, and John L. Renne. 2003. "Socioeconomics of Urban Travel: Evidence from the 2001 NHTS." *Transportation Quarterly* 57 (3). https://trid.trb.org/view/662423.

———. 2005. "Rural Mobility and Mode Choice: Evidence from the 2001 National Household Travel Survey." *Transportation* 32, no. 2 (March): 165–186. DOI: 10.1007/s11116-004-5508-3.

R Core Team. 2018. *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing. Vienna, Austria. https://www.R-project.org/.

Ralph, Kelcie M. 2017. “Multimodal Millennials? The Four Traveler Types of Young People in the United States in 2009.” *Journal of Planning Education and Research* 37, no. 2 (June): 150–163. DOI: 10.1177/0739456X16651930.

Raphael, S., A. Berube, and Elizabeth Deakin. 2006. “Socioeconomic Differences in Household Automobile Ownership Rates: Implications for Evacuation Policy.” https://escholarship.org/uc/item/7bp4n2f6.

Raphael, Steven, and Michael Stoll. 2001. “Can Boosting Minority Car-Ownership Rates Narrow Inter-Racial Employment Gaps?” (August). https://escholarship.org/uc/item/4k4519pw%5C#author.

Reddit. 2017. *R/AskAnAmerican - How Common Is Owning More than One Vehicle?,* January. https://www.reddit.com/r/AskAnAmerican/comments/5qrfwa/how_common_is_owning_more_than_one_vehicle/.

Redshaw, Sarah. 2017. “Mobile My Spaces: Home in Cars, Working Vehicles and Contrasting Dwelling for Backpackers in Campervans and Homeless Car Sleepers.” *Reimagining Home in the 21st Century* (February). https://www.elgaronline.com/view/edcoll/9781786432926/9781786432926.00013.xml.

Ritschard, Gilbert, Alexis Gabadinho, and Matthias Studer. 2012. *Sequential Data Analysis Issues With Sequential Data.* University of Geneva. http://www.orgdna.net/traminer/.

Roberts, Adrienne. 2019. “Driving? The Kids Are So Over It.” *Wall Street Journal* (April). https://www.wsj.com/articles/driving-the-kids-are-so-over-it-11555732810.

Sanchez, Thomas W., Qing Shen, and Zhong-Ren Peng. 2004. "Transit Mobility, Jobs Access and Low-Income Labour Participation in US Metropolitan Areas." *Urban Studies,* no. 7: 1313–1331.

Scheiner, Joachim. 2017. "Mobility Biographies and Mobility Socialisation: New Approaches to an Old Research Field." In *Life-Oriented Behavioral Research for Urban Policy,* edited by Junyi Zhang, 385–401. Tokyo: Springer Japan. ISBN: 978-4-431-56472-0. DOI: 10.1007/978-4-431-56472-0_13.

Sexton, Rocky L., Robert G. Carlson, Carl G. Leukefeld, and Brenda M. Booth. 2008. "Barriers to Formal Drug Abuse Treatment in the Rural South: A Preliminary Ethnographic Assessment." *Journal of Psychoactive Drugs* 40, no. 2 (June): 121–129. DOI: 10.1080/02791072.2008.10400621.

Shaheen, Susan A., Adam P. Cohen, and J. Darius Roberts. 2006. "Carsharing in North America: Market Growth, Current Developments, and Future Potential." *Transportation Research Record* 1986, no. 1 (January): 116–124. DOI: 10.1177/0361198106198600115.

Sheldon, Tamara L., and Rubal Dua. 2019. "Assessing the Effectiveness of California's "Replace Your Ride"." *Energy Policy* 132 (September): 318–323. DOI: 10.1016/j.enpol.2019.05.023.

Shen, Qing. 2001. "A Spatial Analysis of Job Openings and Access in a U.S. Metropolitan Area." *Journal of the American Planning Association* 67, no. 1 (March): 53–68. DOI: 10.1080/01944360108976355.

Smart, Michael J., and Nicholas J. Klein. 2018. "Remembrance of Cars and Buses Past: How Prior Life Experiences Influence Travel." *Journal of Planning Education and Research* 38, no. 2 (June): 139–151. DOI: 10.1177/0739456X17695774.

Sorensen, Paul, Martin Wachs, Endy M. Daehner, Aaron Kofner, Liisa Ecola, Mark Alan Hanson, Allison Yoh, Thomas Light, and James Griffin. 2008. *Moving Los Angeles.* Technical report. https://www.rand.org/pubs/monographs/MG748.html.

Sovern, Jeff. 1995. "Good Will Adjustment Games: An Economic and Legal Analysis of Secret Warranty Regulation." *Missouri Law Review* 60 (2): 323–414. https://heinonline.org/HOL/P?h=hein.journals/molr60%5C&i=333.

Statistics Iceland. 2018. *Statistics Iceland: Iceland in Figures 2018.* Technical report. June. https://www.statice.is/publications/iceland-in-figures/.

Tal, Gil, and Susan Handy. 2010. "Travel Behavior of Immigrants: An Analysis of the 2001 National Household Transportation Survey." *Transport Policy* 17, no. 2 (March): 85–93. DOI: 10.1016/j.tranpol.2009.11.003.

Taylor, Brian D. 2006. "Putting a Price on Mobility: Cars and Contradictions in Planning." *Journal of the American Planning Association* 72, no. 3 (September): 279–284. DOI: 10.1080/01944360608976750.

Tefft, Brian C, Allan F Williams, and Jurek G Grabowski. 2014. "Driver Licensing and Reasons for Delaying Licensure among Young Adults Ages 18-20, United States, 2012." *Injury Epidemiology* 1 (March). DOI: 10.1186/2197-1714-1-4.

Thomas, J. A., and D. Walton. 2008. "Vehicle Size and Driver Perceptions of Safety." *International Journal of Sustainable Transportation* 2, no. 4 (June): 260–273. DOI: 10.1080/15568310701359015.

Vanderheiden, Steve. 2006. "Assessing the Case against the SUV." *Environmental Politics* 15, no. 1 (February): 23–40. DOI: 10.1080/09644010500418688.

Wachs, Martin, and Brian Taylor. 1998. "Can Transportation Strategies Help Meet the Welfare Challenge?" *Journal of the American Planning Association* 64:15–18.

Wakin, Michele. 2008. “Using Vehicles to Challenge Antisleeping Ordinances.” *City & Community* 7 (4): 309–329. DOI: 10.1111/j.1540-6040.2008.00269.x.

Walker, Kyle, and Kris Eberwein. 2018. *Tidycensus: Load US Census Boundary and Attribute Data as ’tidyverse’ and ’Sf’-Ready Data Frames,* August. https://CRAN.R-project.org/package=tidycensus.

Wang, Tingting, and Cynthia Chen. 2014. “Impact of Fuel Price on Vehicle Miles Traveled (VMT): Do the Poor Respond in the Same Way as the Rich?” *Transportation* 41, no. 1 (January): 91–105. DOI: 10.1007/s11116-013-9478-1.

Ward, Joe H. 1963. “Hierarchical Grouping to Optimize an Objective Function.” *Journal of the American Statistical Association* 58, no. 301 (March): 236–244. DOI: 10.1080/01621459.1963.10500845.

Webster, Larry. 2011. *Why 54.5 MPG Doesn’t Really Mean 54.5 MPG,* September. https://www.popularmechanics.com/cars/news/fuel-economy/obamas-fuel-economy-rules-why-54-5-mpg-doesnt-really-mean-54-5.

Whitefoot, Kate S., and Steven J. Skerlos. 2012. “Design Incentives to Increase Vehicle Size Created from the U.S. Footprint-Based Fuel Economy Standards.” *Energy Policy,* Modeling Transport (Energy) Demand and Policies, 41 (February): 402–411. DOI: 10.1016/j.enpol.2011.10.062.

Yacobucci, Brent D., and Robert Bamberger. 2010. *Automobile and Light Truck Fuel Economy: The CAFE Standards.* Technical report. Congressional Research Service, April.

Zhang, Wei, C.-Y. Cynthia Lin Lawell, and Victoria I. Umanskaya. 2017. “The Effects of License Plate-Based Driving Restrictions on Air Quality: Theory and Empirical Evidence.” *Journal of Environmental Economics and Management* 82 (March): 181–220. DOI: 10.1016/j.jeem.2016.12.002.

Zhao, Yong, and Kara M. Kockelman. 2002. “Household Vehicle Ownership by Vehicle Type: Application of a Multivariate Negative Binomial Model.” In *Transportation Research Board Annual Meeting.* Washington DC.