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2012

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Mobility fulfillment among low-car households: Implications for reducing auto dependence in the United States

By

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DISSERTATION

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Abstract

There is widespread interest in reducing vehicle-miles of travel as a policy goal. Any progress toward that goal requires a better understanding of the potential for incremental reduction in vehicle use in the context of ubiquitous ownership and auto-oriented communities, as we have in the United States today. A key to incremental reductions in vehicle use may be new paradigms for using cars only sometimes, by sharing cars and rides. To explore this potential, this dissertation examines the use of cars outside of conventional ownership, among members of no-car and low-car households in the United States. I use the National Household Travel Survey to characterize the volume and nature of car use by levels of car ownership nationwide. Next I develop a method for estimating benchmark mobility levels based on demographic attributes, in order to evaluate overall mobility fulfillment among non-car-owners. Comparing fulfillment levels among different subgroups helps to identify circumstances in which non-ownership does and does not indicate hardship. I supplement this quantitative nationwide assessment with a qualitative examination of the experiences of a particular subpopulation with limited vehicle access, recent immigrants to California from Mexico participating in focus group interviews. Collectively the results characterize most likely circumstances, social contexts, practical logistics, and overall mobility outcomes for those using cars outside of the context of conventional ownership. The findings point to circumstances in which innovative sharing-enabling services might be adopted more readily. They also point to the circumstances in which services or policies might provide the most added value, filling important gaps, improving non-owner quality of life, and complementing overall vehicle-reduction goals.

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1 Introduction

The long-term trend virtually everywhere is an increase in vehicle ownership and use. In 1960 in the United States, about 22 percent of households had no car; by 2009, just 9 percent of households had no car (see Table 1). For most households, the question is not if to own a car, but how many. Almost a quarter (22.7 percent) have three or more. The majority (68.6 percent) have at least two. While there has actually been a tapering of the increase in vehicle ownership and use in recent years, with the 2009 National Household Travel Survey (NHTS) actually measuring small decreases (Santos, McGuckin, Nakamoto, Gray, & Liss, 2011), this has been attributed to the fact that vehicle use may have reached saturation levels in the United States (Millard-Ball & Schipper, 2011) though also potentially reflecting a new trend among young people who are driving less, buying fewer cars, and less likely to get a driver's license than previous generations (Davis, Dutzik, & Baxandall, 2012). As of 2009, the average U.S. household had 1.86 vehicles and 1.88 drivers (Santos et al., 2011).

Table 1. Household vehicle ownership in the United States, 1960-2010

	Percent of households owning:			
Data source	No vehicles	One vehicle	Two vehicles	Three or more
U.S. Census				
1960	21.5%	56.9%	19.0%	2.5%
1970	17.5%	47.7%	29.3%	5.5%
1980	12.9%	35.5%	34.0%	17.5%
1990	11.5%	33.7%	37.4%	17.3%
2000	9.4%	33.8%	38.6%	18.3%
2010	9.1%	33.8%	37.6%	19.5%
NPTS/NHTS				
1969*	20.6%	48.4%	26.4%	4.6%
1977	15.3%	34.6%	34.4%	15.7%
1983	13.5%	33.7%	33.5%	19.2%
1990	9.2%	32.8%	38.4%	19.6%
1995	8.1%	32.4%	40.4%	19.1%
2001	8.1%	31.4%	37.2%	23.2%
2009	8.7%	32.3%	36.3%	22.7%

* The 1969 survey excludes pickups and light trucks, so ownership rates appear less than they otherwise would.
Sources: 1960-2000 Census data as reported in Davis, Diegel, and Boundy (2012, Table 8.4); 2010 Census data from 2010 American Community Survey (1-year estimates for United States); 1969-2001 NHTS data as reported in Hu and Reuscher (2004), 2009 NHTS data calculated by author, version 2.1, weighted by household.

This trend toward automobility reflects both economic prosperity — the relative affordability of owning a car, even among the poorest Americans (Pucher & Renne, 2003; Pisarski, 1999; Lave & Crepeau, 1994) — as well as auto-oriented development patterns that accommodate and often require vehicle travel. As many have noted, the trend is also self-reinforcing: as auto use increases, our physical environment has become more auto-oriented, which in turn encourages more ownership and use.

It is in this context of nearly universal vehicle ownership and use that an examination of the exceptions to the trend is especially worthwhile. First, if those who are car-less are a shrinking minority, they are increasingly distant from the mainstream and therefore at greater risk for physical isolation, poor access, and social exclusion (e.g. Lyons, 2003; Lucas, 2004). In most parts of the United States, they consist primarily of those who have no choice, due to economic hardship, age, disability, or cultural barriers. An assessment of the extent of this hardship should be of interest to policymakers, along with understanding what sorts of coping strategies are working best. Because providing transportation services to this needy minority within an auto-oriented landscape (often consisting of dispersed riders and destinations) can be challenging and costly, study of the issue is particularly relevant.

Another reason to consider the exceptions to vehicle dependence is the mounting interest in reducing vehicle-miles traveled (VMT) as a policy goal, due to concern over greenhouse gas emissions, dependence on petroleum, and generally improving the efficiency of urban centers. As mentioned, there is already evidence of decreased vehicle use among young people (Davis, Dutzik, & Baxandall, 2012). Whether economic or social factors have motivated this shift (e.g. Thompson & Weissmann, 2012; Chozick, 2012), it offers policymakers an opportunity to cultivate a sustained trend among this group, as well as potential momentum for a broader movement in the population at large. Though reducing vehicle use is a common policy goal, the path of transition from an auto-dependent society to an alternative model is unclear. Our best examples of alternative models are places where automobility has never, or not yet, taken hold. How an already auto-oriented place might become *less* so necessarily requires a different transitional process. With this in mind, it may be useful to consider the extent and ways people do manage without cars or with fewer cars in an auto-oriented landscape, as lessons on the sorts of vehicle-use reductions that might be possible, and the circumstances in which it might be most likely, here in the United States. This has been suggested in the Australian context by Delbosc and Currie (2012), who note that the transition from two cars to one is more probable than expecting households to go without altogether — making vehicle-sharing, whether within or across households, especially relevant.

Thus, the focus of this dissertation is travel among no-car and low-car households in the United States. The first objective is to examine actual behavior, in terms of travel volumes and by what means. There is surprisingly little research on the travel patterns of this group, especially their use of private vehicles. A second objective is an attempt to evaluate welfare among them, particularly identifying subgroups for whom non-ownership is working better and worse to achieve sufficient mobility.

1.1 Vehicle use among non-owners: New and old paradigms

I examine the travel of no-car and low-car households in order to gain a better understanding of the existing practice of using cars *other than* by the conventional U.S. model of saturated ownership and ubiquitous use. If we are to consider ways that households can manage without a car, or with fewer cars, there are three possible options. First, they can forgo travel. If they have few needs, or can consolidate trips, or replace some of their travel with in-home activities, it avoids the issue. But presumably this is neither desirable nor reasonable for many people in most situations. Second, they can utilize alternative means of transportation, such as walking or riding transit. The feasibility of this option is enmeshed in the built environment, the existing development patterns and quality of transit service in their communities. While opportunity for car-free alternatives are rich in some places in the U.S., and may be cultivated more in the long-run, in the meantime these options are not entirely sufficient for many Americans. The final option is using vehicles without owning, to supplement other routines. This source of mobility is the focus of this work.

Vehicle use by means other than driving one's own car can take a variety of forms. The most common is to get a ride with someone else, referred to as carpooling, ridesharing, or getting a lift. People may also use taxis or rental cars, or borrow a car from a friend or neighbor. Added to these practices are some new paradigms for sharing, differing from their predecessors mostly because of new technologies that facilitate exchange, as well as enabling more real-time (on-the-fly) decision-making and incremental purchasing. These include carsharing (car clubs), peer-to-peer carsharing, ridesharing enhanced with online networking and/or social media, dynamic ridesharing, and dynamic taxi requests and pricing. The advent of these new kinds of systems has spurred in the last decade renewed interest in shared rides and vehicles as a means of reducing overall auto dependence. Preliminary evidence on carsharing indicates a net reduction in VMT and vehicle ownership among early adopters (Cervero, Golub, & Nee, 2007; Martin, Shaheen, & Lidicker, 2010). Other models, such as dynamic peer-to-peer ridesharing, have had no widespread adoption in any organized form (see a review in Deakin, Frick, & Shively, 2010), but some researchers have documented the impact of informal mobile phone use for coordinated unplanned activity and especially ridesharing (Srinivasan & Raghavender, 2006). In addition, private companies utilizing dynamic (demand-based) pricing to match livery cabs to passengers (who request rides via GPS-enabled mobile-phone applications) have grown rapidly since their inception in 2009 (e.g. Economist, 2012; Bilton, 2012), although the long-term broader impact, if any, of all of these ideas remains to be seen.

While some of these forms of vehicle use are structured as a service purchased from an organization, others are informally acquired through social networks, such as getting a ride from a friend or neighbor. (Still others are somewhere between, such as ridesharing applications that piggyback on social networking sites.) The latter situation makes ride acquisition a much different process, informal and with a social dimension, and one that has not been the focus of much travel behavior research. It justifies further attention because it is so prevalent. The informal sort of sharing — such as getting rides with friends and family or carpooling to work — is very common, much more widespread as a percent of trips than rentals, formal carsharing, or dynamic cab livery. Understanding the circumstances and factors affecting the sharing of rides and cars through informal channels is an important element of non-owner vehicle use, in its conventional and more high-tech forms.

1.2 The nature of ridesharing and borrowing cars as a form of travel

There has been little research on the process of accessing rides and cars through informal channels. One body of literature has focused on intra-household resource-sharing, especially as activity-based travel behavior models have become more sophisticated. Research on negotiations *outside* one's household has mostly focused on some of the particular population groups that are most likely to rely on it, including the elderly, disabled, children, and immigrants. While these groups are different from one another in a variety of ways, a commonality among their experiences is the affective and intangible factors – often embedded in interpersonal relationships – not typically accounted for in travel behavior models.

Examining immigrants, Blumenberg and Smart (2010) find increased propensity to carpool, both from within households and getting rides with others, even after controlling for other factors such as income and residential location that might distinguish them from the native-born. They find across-household sharing is especially prevalent among Hispanic immigrants (though within-household carpooling is still more prevalent overall). While not tested by their research design, the authors present hypotheses to explain immigrant ride-sharing relating to resource sharing in ethnic enclaves, the emergence of direct immigration into suburban neighborhoods (rather than central-city ports of entry, as was more common in the past), and culturally specific preferences or obstacles.

Schwanen (2008) focuses on the social context and affective experience of arranging for rides in an examination of how parents handle uncertainty about arrival times in picking up children from schools and daycare. He finds parents relying on a variety of social contacts to fill gaps, including not only other household members but also friends, relatives, neighbors, and teachers. He points out that in devising solutions, parents do not make choices in isolation, but rather in some social context—depending on the existence and availability of other individuals (spouse, babysitter, neighbor, friend, relative, teacher)—as well as in some technical context (depending on the existence and availability of non-human agents such as mobile phones, transport, and spatial-temporal constraints). He notes the important of trust as a condition for negotiating arrangements.

In addition to trust, studies of the experiences of elderly point to other emotions that can play a role in finding rides. In focus groups with participants over age 70, Burkhardt (1999) finds that major concerns for those who relied on friends and family for rides were reluctance to inconvenience the other party and dread at having to ask for a favor. Many insisted on trying to reciprocate in some way, such as offering cash, cooking, babysitting, or other favors, and tried to arrange trips to minimally inconvenience others. Perhaps partly as a result of this effort, participants reported numerous downsides to getting rides as a form of travel, including the need to plan in advance, forgoing spontaneity and flexibility, having longer travel times and wait times, compromising on destinations and schedule, coping with unreliability, and skipping most evening, social, or recreational trips.

Burkhardt also reports that those who were able to meet their basic needs without driving either used another mode, such as walking, transit, or paying a driver; or had strong personal networks, such as spouses or significant others who drove, children in the area, or heavy involvement with a religious institution. Similarly, in a study of 174 adults over 65 in Vancouver, Cvitkovich and Wister (2001) find that those who reported tapping a larger social network for rides, including friends and neighbors rather than just family, were statistically significantly more likely to report that their transportation needs were fulfilled.

This connection between social networks and finding rides is the focus of Gray, Shaw, and Farrington (2006), who propose that "strong local social capital appears important in conferring mobility on certain social groups, especially those without access to a car" in rural parts of the U.K. (p. 89). As evidence, they cite extensive provision of rides in Scotland and Ireland to the young, elderly, and car-less in tight-knit rural communities where "strong intra-community ties and networks have been maintained" (p. 92). They then propose that the presence or absence of social capital in a community may be used to help explain individuals' mobility levels and travel choices. In the next section I further develop the concept of social capital and the social exchange theory to help frame the study of access to rides and borrowed cars.

1.3 Social exchange theory applied to getting rides and borrowing cars

The premise of social exchange theory is that all interactions between people can be viewed as "an exchange of goods, material and non-material" (Homans, 1958, p. 597). Although in the special case of economic exchange people trade money for goods or services in the context of a formal business transaction, other exchanges might involve informal trades of things like companionship, ideas, emotional support, or favors – such as giving someone a ride. This meshes with Schwanen's notion that the sorts of favors exchanged among parents managing school pick-up were "part of a larger exchange of support," which could take on myriad forms (2008, p. 1000).

While some of the theories about economic exchange, such as rational choice and profit-maximization, may apply to social exchange more broadly (e.g. individuals engage in exchanges that maximize their returns or rewards), these sorts of informal exchange can differ from conventional business transactions in important ways. First, because resources other than money are exchanged, it is possible to extract resources without paying money for them. Second, the terms of the exchange are not generally negotiated nor contained in a single transaction; rather the value of what is exchanged is implied rather than explicit, and likely conferred over a series of repeated interactions, without necessarily expecting balanced accounting between each pair of exchange partners (Molm, 2003). So at the point when an individual is choosing whether to engage in an exchange, reciprocation may not be guaranteed. Even if reciprocation is forthcoming, it may be asymmetric (e.g. offering goodwill in exchange for a logistical favor); it may be delayed without any explicit schedule for repayment (e.g. offering emotional support to a friend, without calculating when that friend will be comparably useful to you); and it may be transferred to a different party altogether (e.g. someone helped me once, so I will help this person). All of these aspects of social exchange serve to diversify and expand the ways that people might come by transportation resources—that is, getting rides or borrowing cars, without having to buy them.

The concept of capital is useful when considering who might be well positioned to accrue resources, in this case resources such as getting rides or borrowing a car. Broadly speaking, capital represents an accumulation that can be transformed into rewards in the future. Bourdieu identifies various types of capital aside from economic capital, including cultural capital (knowledge, experience, or connections that enable success), symbolic capital (access to resources on the basis of honor, prestige, or recognition), and social capital (the value of connections with others, or the value of actual or potential resources embedded in one's social networks) (1984, 1986). The various types of capital an individual accumulates can represent different routes to securing rewards. For instance, a ride might be achieved by tapping either economic capital—by paying for a taxi or buying a car—or by social capital, by asking for a favor from a friend.

Depending on the circumstances of their ownership choice, some non-owners may be relatively poor with respect to what Urry (2007) terms "network capital," referring to the array of documents, means of physical mobility, and communication devices (virtual mobility) that enable individuals to access services, facilities, and opportunities. On the one hand, the sorts of hardship resulting in an inability to afford or drive a car may also mean a lack of these other types of assets. For others, things like tech-savvy connectivity may expand access to rides and resources. With or without this sort of network capital, non-owners may rely on social capital, securing rides and vehicles through their friends, coworkers, and other contacts. What factors facilitate the exchange of these kinds of transportation resources?

There have been numerous studies on resource exchange in a social context, some of which may apply to the exchange of transportation resources in particular. In general, closer ties are thought to enable more supportive relationships (Wellman & Wortley, 1990; Portes, 1998; Astone, Nathanson, Schoen, & Kim, 1999; Wellman & Frank, 2001; Plickert, Côté, & Wellman, 2007; Schwanen, 2008), but anything that triggers a friendship heuristic may help extract a small favor (Berger et al., 2006). Wellman and Wortley (1990) find that neighbors and co-workers are more likely to provide small and large favors but less likely to provide companionship or emotional support; kin is more likely to provide emotional support, financial support, and large favors; and non-neighbor friends are more likely to provide companionship and emotional support. Magdol and Bessel (2003) suggest that the spatial distance between ties matters for certain types of resources, finding that distance inhibits the exchange of tangible favors and of companionship, but not the exchange of emotional or financial support. Because origin and destination are relevant in giving rides, it seems likely that spatial proximity would matter for the exchange of this type of favor as well, as found by Schwanen (2008). Some studies have associated female gender with giving, receiving, and reciprocating support (Plickert et al., 2007; Wellman & Frank, 2001) especially emotional support (Wellman & Wortley, 1990), although van Emmerik (2006) finds men in a group of co-workers to be just as likely to generate emotional support and more likely to produce “task-oriented resources” (p.25). This may mean that as a task-oriented resource, giving rides and lending cars may be more likely to be provided by and to men, especially among groups in which men are more likely to drive, such as the elderly (Rosenbloom, 2001) and immigrant groups such as Mexicans, considered in Chapter 6 (Pisarski, 1999; Stowell-Ritter, Straight, & Evans, 2002). On the other hand, women are more likely to attend to childcare and other care-giving tasks, which at least in the general population is associated with providing rides—chauffeuring children or other dependents, both within and across households (Rosenbloom, 1992; Siren & Hakamies-Blomqvist, 2005; Schwanen, 2008). This might make women more likely to provide rides here as well.

Theoretically, the effect of aggregation would mean that larger social networks would offer more potential sources of support (Wellman & Frank, 2001; and others). However, other aspects of the network may also make a difference. For instance, Wellman and Frank (2001) find that having more mutual ties within a network generates more support. Others show that people are more likely to help those that are like themselves (e.g. Gibbons & Olk, 2003; Wellman & Wortley, 1990), and therefore common group membership or a homogenous network may be useful. For instance, Charles and Kline (2006) find carpooling propensity associated with those living in more racially homogenous neighborhoods. Whether because they are homogeneous or large or for other reasons, ethnic enclaves have been identified as potentially rich sources of support, and it has been observed that Hispanic immigrant groups—such as in this study—tend to develop particularly supportive and loyal networks (Boyd, 1989; Menjivar, 1997; Denner, Kirby, Coyle, & Brindis, 2001; Janjuha-Jivraj, 2003). However, benefits of enclave membership can vary depending on the extent to which the community possesses necessary resources. For instance, Portes and Zhou (1993) find that enclave membership can inhibit assimilation and ultimately thwart members' economic mobility. Granovetter's (1973, 1982) and Wellman and Wortley's (1990) emphasis on the value of weak ties and in-network diversity, like Putnam's bridging capital (2000), may be relevant in ensuring that the network provides a desirable mix of resources.

The circumstances of non-vehicle-owners may differ from typical social exchanges since those most in need of transportation resources are unlikely to be able to reciprocate in kind. The inherent asymmetry of these exchanges may have similarities with those in caregiving/receiving roles, where "the dependent is seldom in a position to reciprocate in kind" (Kittay, 1999, p. 68), potentially implying what are often "neglected issues of power" (Fine & Glendinning, 2005, p. 612), although with some important differences. As suggested by the guilt and dread described by the elderly in Burkhardt's (1999) study, this asymmetry may impact the recipients of aid in various ways. Molm (2003) suggests that the outcomes for disadvantaged members of a network—for instance, those more reliant on aid from others—differs depending on whether an exchange is "negotiated" (with the two parties explicitly agreeing on terms for a self-contained transaction) or "reciprocal" (without explicit bargaining, potentially as part of an ongoing series of exchanges in an enduring relationship). She finds those who are disadvantaged are better off when engaging in reciprocal rather than negotiated exchange, since there is a tendency to value the reciprocity itself over the particular value of the benefits exchanged, which are glossed over in a spirit of collaboration. By contrast, negotiated exchange emphasizes the terms of the agreement. Those offering too little risk being excluded from the exchange altogether, perhaps pressuring them to overpay in order to avoid this risk. In the case of finding rides, this would mean that those engaging in reciprocal exchanges might have an easier time securing rides, while those engaging in negotiated exchange might feel squeezed into overpaying.

1.4 Mobility and vehicle use in the context of well-being

To evaluate any hardship experienced by the low-car minority, or before holding them up as an example of a direction for policies aiming to reduce VMT, some means of evaluating well-being is needed. We know that they travel less on average, but is this reduction out of hardship or choice? Whether voluntary or involuntary, how satisfied are they with what they do? There is likely a range in satisfaction levels. What are the circumstances in which outcomes are better or worse?

Answers to these questions are not immediately apparent from the sort of data typically collected as a part of travel surveys, which usually measure travel actually executed. But someone may travel very little and be content or not content at all. Underlying preferences, or unrealized demand for more (or less) activity than was executed, is not typically measured.

The idea that preferences do not always align with behavior is not new, rather is explored in a variety of contexts in evaluating social policy. Ettema, Gärling, Olsson, and Friman (2010) provide a useful overview of the concept of subjective well-being as a tool for appraisal of policy in the transportation context. As they discuss, travel contributes to well-being in the experience of the travel itself, as well as the activity participation it enables (e.g. Stanley, Hensher, Stanley, & Vella-Brodrick, 2011; Bergstad et al., 2011). Well-being, or related concepts such as satisfaction, happiness, contentment, or different aspects of utility, has been defined variously in the academic literature. A useful organization of concepts is to consider well-being as consisting of three components: positive affect, negative affect, and a cognitive component relating to the perception and interpretation of events (Ettema et al., 2010). The general idea is that what matters for well-being is not so much what someone does but what he feels, which is inherently subjective and may differ for different individuals in the same circumstance.

Some researchers have pushed for the measure of well-being and other attitudinal measures in the interest of more accurate models of travel behavior. For instance, asserting that well-being is the ultimate goal, to be achieved through activity participation, and sometimes, correspondingly, travel, Abou-Zeid and Ben-Akiva (2012) posit that effective prediction of travel requires measurement of and incorporation of well-being into the modeling framework. This is related to literature generally exploring the role of attitudes in travel behavior (e.g. Kitamura, Mokhtarian, & Laidet, 1997; Mokhtarian & Salomon, 2001). Other researchers have focused on subjective measures of well-being for the explicit purpose of evaluating the welfare of specific populations with mobility disadvantages (e.g. Hough 2007; Páez & Farber, 2012; Marston & Golledge, 2003; Páez, Scott, Potoglou, Kanaroglou, & Newbold, 2007; Delbosc & Currie, 2010).

One of the challenges in assessing well-being, and stemming from how to define it, is how to measure it. A variety of indices and survey instruments have been developed to capture different aspects of well-being, satisfaction, affect, and other attitudinal orientations that might affect travel behavior, such as those used by Delbosc and Currie (2010, 2012). Another method is to assess latent demand, by asking about unfilled travel desires, such as in Hough (2007). However neither of these types of measures is typically included in major national surveys.

In the absence of such measures in national surveys, in this dissertation I propose an alternative means of interpreting the mobility levels of low-car households by developing a relevant benchmark to which to compare them. If a reasonably meaningful benchmark can be identified, then the mobility levels can be evaluated on the basis of the extent to which they match the benchmark level. This is the framework I use to evaluate the well-being of low-car households — the extent of apparent mobility fulfillment, relative to a benchmark level — in Chapters 4 and 5.

Qualitative research is another means of capturing subjective experiences, as well as the “how” and “why” of behavior that is harder to capture in travel diaries or traffic counts. Thus, I supplement the NHTS results with qualitative findings from focus groups, in which low-car immigrants describe their transportation experiences (in Chapter 6).

1.5 Expected outcomes among non-owners

An important factor for both the behavior and welfare of non-owners is the circumstances of their situation. Is it by choice or necessity? If it is entirely by choice, then it is expected that their living situation is consonant with their ownership decision: they have some other means to get around to the extent that they desire, such as being able to walk to most activities, living in an urban environment with good public transit, using taxis or car-sharing, and/or having friends and family that give them rides when needed.

It is an unfortunate paradox that some of the circumstances resulting in limited use of a car (including the inability to own and/or drive) may also make use of alternative modes difficult. For instance, with disability and old age, driving becomes difficult, but active modes and arduous transit connections may be even more difficult for these people, making them especially car-dependent. In addition, those experiencing the sort of poverty precluding vehicle ownership may be least able to select a neighborhood centrally located to their needs and with high-quality public transit, or to pay for the occasional taxi ride that might make car-free lifestyles manageable.

Delbosc and Currie (2012) is one of the few studies explicitly examining well-being and mobility among low-car households. Their results emphasize differences in outcomes depending on whether the low-car status is voluntary versus involuntary (based on respondents' self-reported ability to financially afford an additional vehicle, among households with 2 or more adults, but only one car, in Melbourne, Australia). In particular, voluntarily low-car households reported less transport disadvantage, experienced less social exclusion, and reported well-being levels as high as multi-car owners, despite high unemployment and low-income. By contrast, the involuntarily low-car households experienced more disadvantage, more social exclusion, and lower well-being levels (as well as even lower income and employment levels). Those voluntarily owning fewer cars also were more likely to live in inner Melbourne, close to a business zone, with more transit service; correspondingly, they made a greater share of trips by alternative modes, while those in involuntary situations used cars for more of their trips (70% versus 50%), and made more trips as drivers. They traveled more vehicle-miles than voluntarily low-car households, though substantially less than multi-car households. As the authors report, this suggests that those in voluntarily low-car households either self-selected into residential environments that supported low-car lifestyles or elected to own fewer cars once in that environment. This seems an important aspect to their mobility fulfillment and overall well-being, though higher income and employment may also play a role.

A reasonable hypothesis is that greater fulfillment and welfare will be found among non-owners living in locations that better support car-free lifestyles, with good options for walking and transit. Second, any indications of non-owning by choice, rather than necessity, should also be predictors of greater fulfillment. Higher incomes suggest that someone chooses not to buy, despite being able to afford to, as well as suggesting an increased likelihood of being able to self-select into an accommodating community type, or other generally consonant living situation, given their ownership status.

Outcomes with respect to vehicle use may be mixed. Generally speaking, vehicle use reflects the availability of alternative modes versus the availability of vehicles; the attractiveness of using a vehicle versus another mode for the activity or trip at hand; and the attractiveness of using a vehicle versus another mode given an individual's abilities and preferences. However, in the non-owning context, any use of vehicles may be an indication that the alternative options are really unattractive — for that person or that situation. From this perspective, use of vehicles by non-owners may be evidence of an inherent dissonance: Use is evidence of need and the failure of alternatives such as walking or transit to fulfill a need, but lack of ownership indicates constraint, whether owning to lack of financial means, old age, or physical disability. Thus, more vehicle use among non-owners may be associated with less overall well-being, as found by Delbosc and Currie (2012). Although there may be particular types of activities in which vehicle use is sensible even for non-owners, and therefore not necessarily evidence of constraint — such as certain types of social outings in which it is convenient to go along, or perhaps traveling to a worksite along with co-workers or a crew — a reasonable hypothesis is that less dependence on vehicles is associated with more fulfillment in the non-owning context.

Table 2 summarizes factors hypothesized to influence vehicle use in the non-owning context, which is recognized to be but one means to an end (the goal of which is travel, which in turn is a means of participation in activities that lead to overall well-being). For non-owners, in contrast to owners, the availability of vehicles, presumably as the opportunity for getting rides or for borrowing or renting cars, is difficult to assess. It is determined by factors such as the likelihood of social exchange, as reviewed in the previous section, including attributes of the individual, his social milieu, perhaps his network capital, and any other environment factors that promote or inhibit this sort of exchange.

Table 2. Factors theoretically affecting vehicle use

Type of factor	Factors resulting in more vehicle use	Factors resulting in less vehicle use
Vehicle resources	Owns any or more vehicles Has money for taxis and/or rentals Access to rides/cars through social capital	Owns no or fewer vehicles No money for taxis and/or rentals Short on social capital and/or social circle are themselves vehicle-poor
Disability	Disability or age makes walking, transit use difficult Able to drive	Disability or age makes driving difficult Ability to walk and use transit
Built environment	Lack of transit Walking/biking not feasible Has taxis Nearby neighbors for rides Easy parking	Good transit Walking/biking feasible Taxis difficult or expensive So low density that rides are scarce Lack of parking
Activities	Bad for transit and/or good for vehicles (e.g. heavy loads, keeping erratic hours, transporting others)	Good/okay for transit and/or bad for cars (e.g. rush-hour commuting)
Preference/ habit/ culture	Pro-vehicle and/or anti-alternative habit or culture (e.g. typical U.S. experience) Household role results in more vehicle-intensive activities More social, for getting rides and borrowing	Anti-vehicle and/or pro-alternative habit or culture (e.g. barriers to learning to drive, pro-environment attitude, etc.) Household role results in fewer vehicle-intensive activities Less social, or less inclined to ask for rides or borrow through social contacts

1.6 Contribution of this dissertation

While previous work has examined some of the travel choices of low-car households in the U.S., especially in their capacity as potential transit-riders or as special subpopulations such as the elderly or poor, less is known about the overall range of well-being or mobility fulfillment among them. Further, little is known about circumstances of their vehicle use, especially among non-owners. To this end:

- Chapter 2 provides a description of the NHTS data and a demographic profile of the non-owning and low-owning households in the United States.

- Chapter 3 describes vehicle use among non-owners, including its extent, attributes of vehicle trips, and attributes of vehicle-trip-makers, among the non-owning segment.
- Chapter 4 develops a method for generating benchmark mobility levels for a given demographic profile.
- Chapter 5 uses the benchmark model developed in Chapter 4 to evaluate mobility fulfillment among no-car and low-car households, and various subgroups among them.
- Chapter 6 provides a qualitative exploration of the experiences of a particular subpopulation with limited vehicle access – recent immigrants to California from Mexico – describing their informal use of vehicles, borrowing cars and getting rides, within the context of social exchange theory.
- Chapter 7 provides a summary, and discusses overall conclusions and policy implications.

2 Data overview

2.1 About the NHTS data

This dissertation draws on two data sources. Chapters 3, 4, and 5 use data from the 2009 National Household Travel Survey (NHTS), described below. Chapter 6 draws on findings from ten focus group discussions held with recent immigrants from Mexico living in California, described in more detail in that chapter.

The NHTS is administered by the U.S. Department of Transportation Federal Highway Administration and available online at http://nhts.ornl.gov. The survey is a one-day travel diary collected from households nationwide as a cross-sectional snapshot of travel patterns in the United States. A sample of households was recruited using landline telephone numbers, with 19.8% completing the survey (U.S. Department of Transportation, 2011a). Some local jurisdictions partner with the NHTS to over-sample their region to ensure sufficient sample sizes for local-area analysis. For this reason and due to non-response, the raw dataset is not nationally representative. However, the NHTS provides weights to be applied either to individuals, households, or trips (depending on the analysis of interest), which make the sample proportionately representative with respect to key demographic attributes as well as inflated to the volume of the U.S. population.

Results presented in this dissertation are weighted or unweighted, as noted below each table or figure. In general, the descriptive statistics I present are weighted, since their purpose is to give a sense of the prevalence of patterns in the general population. I use a version of the NHTS-provided weights[1] that adjusts the proportions of cases to reflect the distribution in the population as a whole but retains the original sample size, so that statistical tests (where performed) are more robust and to retain a sense of the number of cases on which each statistic

[1] As the NHTS-provided inflation factor divided by the total sample size.

is based. However, the modeling was conducted with unweighted data, since its purpose is to examine relationships between variables.

For each participating household, the survey attempts to complete a travel diary for all household members over the age of 5.[2] Thus, the dataset includes records from multiple members of the same household, including children, though I restrict my analysis to adults age 18 and over. In total, the unweighted sample includes 150,147 households, including 308,901 individuals (including 263,572 adults), who make a total of 1,167,321 recorded trips. I examine a subset of these for various pieces of my analysis, as described.

The main type of data collected in the survey is the one-day travel diary, recording each occasion each household member goes from one address to another during an assigned 24-hour period. A variety of pieces of information are recorded about each occasion, including the time, means of transportation used, distance covered, household vehicle used and which household member was driving (if applicable), number of other people on the trip, and purpose of the trip.

In addition, the survey collects basic demographic information for each individual, including age, gender, highest educational attainment, race, Hispanic status, nativity (and year of immigration), driver status, and medical conditions affecting ability to travel; as well as household-level data such as total household income, number and type of vehicles owned, type of dwelling unit, and home-ownership status. A potentially important aspect of the household income level is that it is measured categorically, in increments of $5,000, with the highest category defined as $100,000 or greater. Thus, the maximum measured level of income for a two-adult household is $50,000 or more per adult, with no way of distinguishing variation across households in excess of this threshold.

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[2] Surveys were considered useable if at least 50% of the adults in the household completed retrieval interviews. Interviews were completed for 92.8 percent of eligible adults and 82.3% of children (by themselves or by proxy).

Finally, there is only minimal information in the publically available dataset on respondents' geographic location and its character. The Census tract is not identified, but several of its attributes (net density of population, housing units, and employees, as well as percent of units owner-occupied) are given. In addition, each household is categorized as locating in one of four community types: urban, second city, suburban, or town/country, categories developed by an external consultant, based on supplemental grid-based (rather than Census tract or block group based) analysis of density and land use characteristics, taking into account not just the immediate zone but also neighboring zones, for a more accurate characterization than is likely based solely on attributes of sometimes arbitrarily sized and demarcated Census tracts. The following table characterizes each type.

Table 3. Description of four community-type categories

Type	Description	Percent of households (weighted)
Urban	Highest population densities, with 94% of block groups with density centiles in the range 75-99. Usually downtown areas of major cities and surrounding neighborhoods.	17.7%
Suburban	*Not* the population center of the surrounding community. Usually surrounding an urban area. 99% of block groups with density centiles in the range 40-90.	24.5%
Second city	The population center of a surrounding community. 96% of block groups with density centiles in the range 40-90. Often a satellite city surrounding a major metropolitan area.	18.2%
Town/country	Exurbs, farming, communities and rural areas. 100% of country block groups have density centiles in the range 0-20, and 98% of town block groups have centiles in the range 20-40.	39.8%

Source: U.S. Department of Transportation, 2011b.

At a regional scale, the home Census Division for each household is provided, as well as the CBSA (Core Based Statistical Area, similar to an MSA) in which the household lives, but only for those living in areas with greater than 1 million people. For those in smaller metro areas or outside of a CBSA, the location is suppressed to protect respondents' identities. For cases in which the CBSA is known, CBSA -level data from other sources can be appended.

For my analysis, I appended the "transit score" for each known MSA, a numerical scale valued 0 to 100, developed by the makers of WalkScore® to characterize how well a location is served by public transit (either a particular address or as a city-wide average). Scores are based on the distance to the nearest stop on a transit route, the frequency of the route, and type of route, as indicated by publically available data from transit agencies (see http://www.walkscore.com/transit/). As illustrative examples, the location of Grand Central Station in New York City scores a 98; downtown Davis, CA (at 2nd and B Streets) scores a 44; and downtown Berkeley, CA (at Shattuck and Bancroft) scores a 70.

2.2 Attributes of households by vehicle-ownership level

Vehicle ownership is correlated with a variety of other demographic and geographic attributes. As mentioned in the introduction, an estimated 8.7% of U.S. households own zero vehicles, and another 16.5% can be categorized as low-owning, with fewer cars than adults.[3] As shown in Table 4, no-car households are disproportionately lower income and living in urban areas. They are much less likely to be employed, as well as less likely to have any children. Almost half of no-car households include someone over age 65. That said, almost 20% of no-car households have children and 10% are in the upper income quartile. More than half are living outside of “urban” areas, and a third outside of city areas (“urban” or “second” city), in either “suburban” or “town/country”-type communities.

The low-owning households (with fewer than one car per adult household member) are in some ways more similar to the high-owning households, and in other ways more similar to the no-car households. For instance, more of them have children (approximately a third, similar to the high-owning households), while a smaller percentage of no-car households have children. Employment rates are approximately similar among low-owning and high-owning segments (71.2% and 78.0%, respectively), but much lower in the no-car segment (37.3%). By contrast,

[3] Other definitions of vehicle-ownership level (such as vehicles per driver versus per driving-age household member) are examined in section 4.1, starting on page 29.

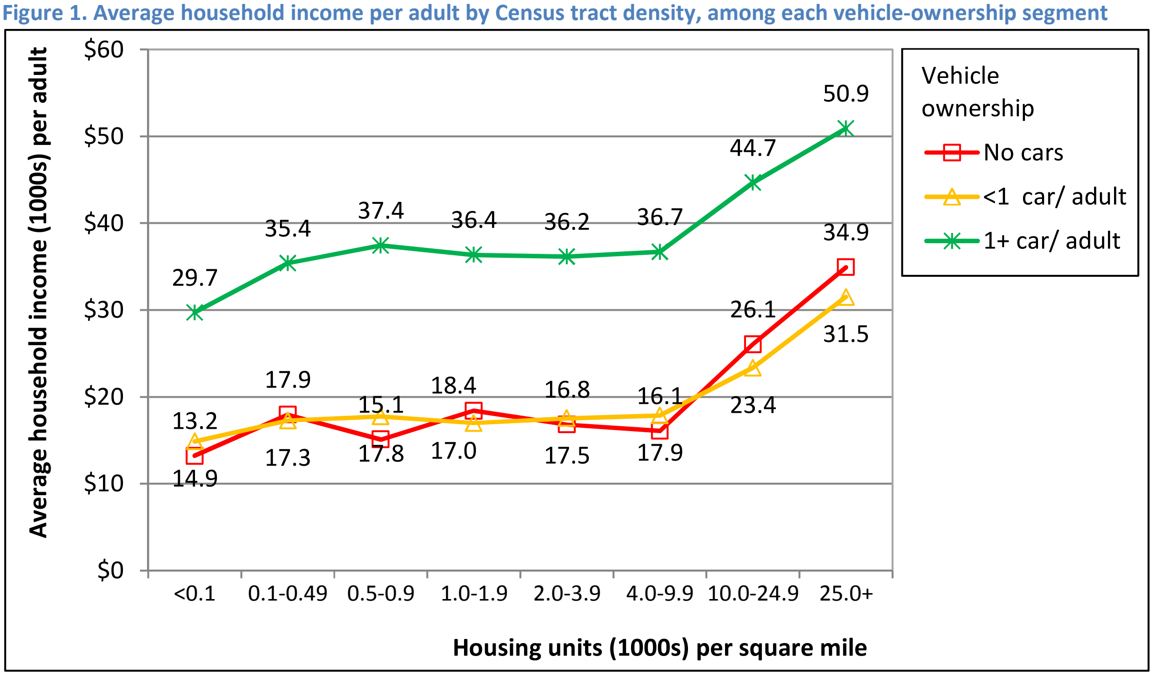
income levels are similarly low among the no-car and low-car households, and substantially higher among the high-car households (see Table 4 and Figure 1). By other measures, the low-owners are roughly half-way between the no-car households and high-owner households, such as the percent who are elderly and the percent who own their own home (Table 4).

Table 4. Basic demographic characteristics by vehicle-ownership level

	By vehicle-ownership level			
Attribute	None	<1 /adult	1+ / adult	Overall
Average household size	1.81	3.24	2.38	2.47
Average number of vehicles	0	1.36	2.19	1.86
% with any drivers	48.2%	99.4%	99.5%	95.0%
% with any children (<18 age)	18.9%	36.6%	31.5%	31.2%
% with anyone age 65+	45.7%	37.7%	26.4%	29.9%
% with anyone employed	37.3%	71.2%	78.0%	73.3%
% with income < $16,2500/adult	52.3%	59.9%	14.9%	25.5%
% with income > $45,000/adult	9.5%	4.2%	27.9%	22.5%
% own home	17.8%	53.2%	75.3%	66.6%
% in an “urban” community type	45.9%	26.2%	12.5%	17.7%
% in a “second city” community type	18.5%	20.2%	17.8%	18.2%
% in an “suburban” community type	15.3%	23.1%	25.5%	24.3%
% in an “town/country” community type	20.3%	30.5%	44.2%	39.8%
Total weighted N (households)	13,047.1	24,811.1	112,288.8	150,147.0
% of total N in this group	8.7%	16.5%	74.8%	100.0%

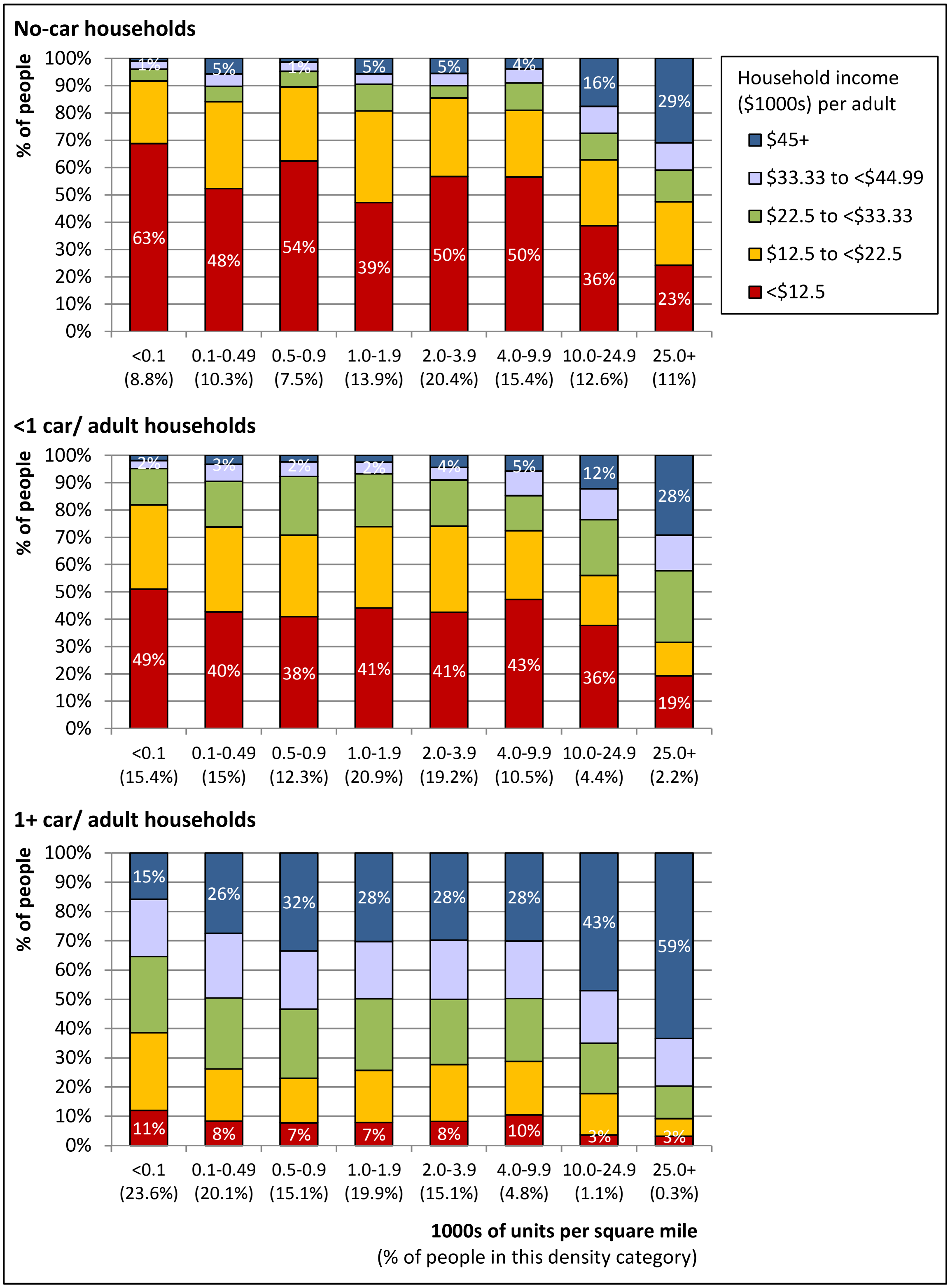
Source: 2009 NHTS version 2.1, weighted sample of households (using a version of WTHHFIN that is a portion weight rather than an expansion factor the total sample size remains the same but portions change).

Figure 1. Average household income per adult by Census tract density, among each vehicle-ownership segment



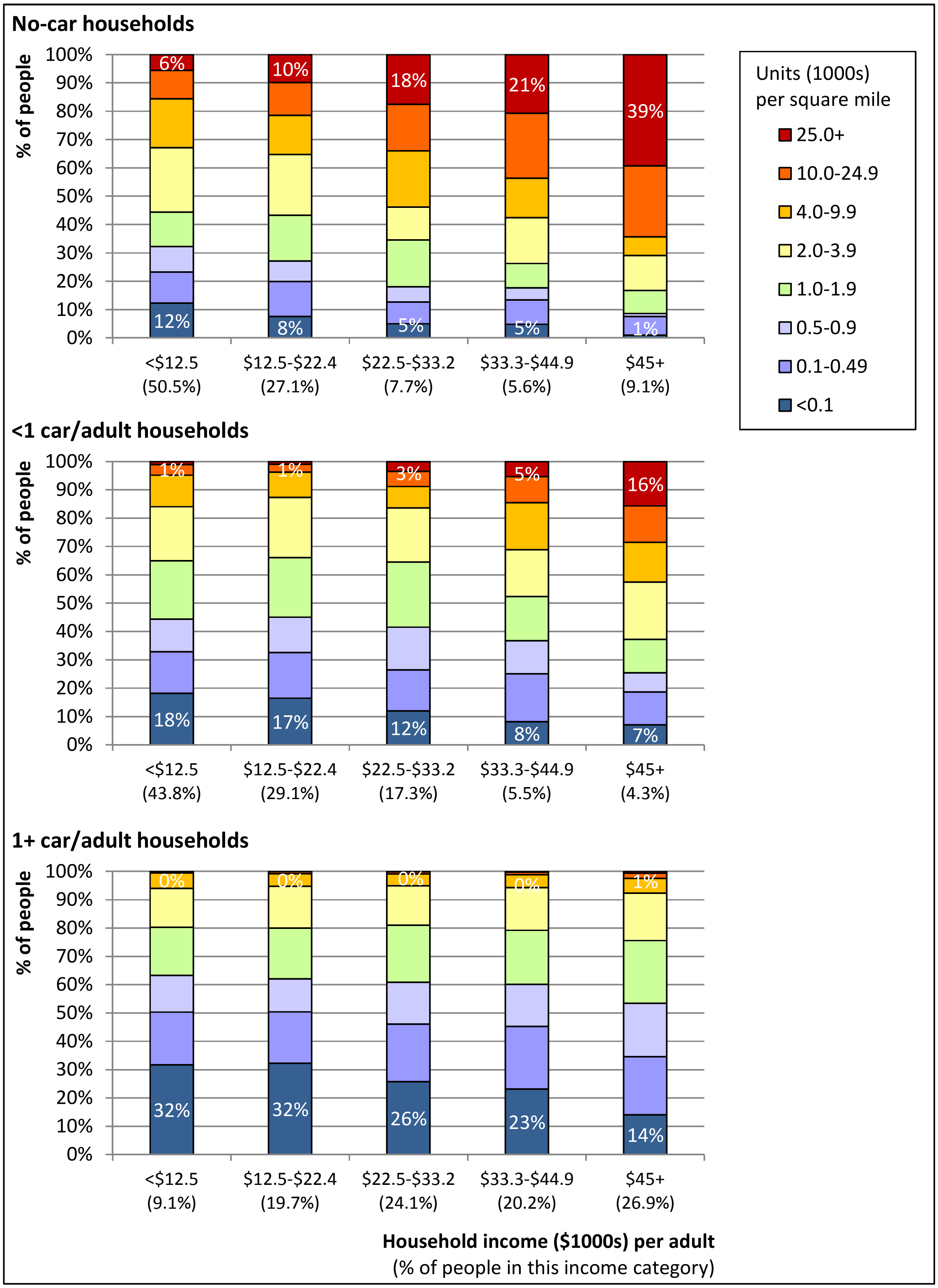
Source: NHTS 2009, v.2.1, weighted individuals among adults age 18+.

Figure 2. Income distribution by housing density, within each vehicle-ownership segment



Source: NHTS 2009, v.2.1, weighted individuals among adults age 18+.

Figure 3. Distribution of housing density by income, within each vehicle-ownership segment



Source: NHTS 2009, v.2.1, weighted individuals among adults age 18+.

There is a strong correspondence between income level and residential location. For all vehicle-ownership groups, average household incomes are higher in the higher-density urban areas (Figure 1). Comparative distributions of income by density for the three vehicle-ownership groups are shown in Figure 2 and Figure 3, showing that the percent of households with high incomes is greater in the high-density areas, among all vehicle-ownership groups (Figure 2); and that the percent of high-income households living in high-density areas is especially high among the no-car households, but more evenly distributed for high-owner households (Figure 3).

2.3 Overall travel patterns by vehicle-ownership level

As shown in Table 5, travel patterns are markedly different among those in no- and low-car households versus high-own households. They travel substantially fewer miles, and fewer miles by vehicle. Although they have much more reliance on alternative means of transportation than car-owners, over 40% of non-owners made at least one trip in a vehicle (private vehicle or taxi) on the survey day.

Table 5. Basic travel outcomes among individuals, by household vehicle ownership

	By vehicle-ownership level			
Outcome	None	<1 /adult	1+ / adult	Overall
Average daily miles traveled (PMT)	11.080	28.990	42.813	37.986
Average daily vehicle-miles traveled (VMT)	5.416	25.382	38.981	33.887
Average number of trips	2.711	3.547	4.201	3.960
% with no trips (stayed in sample place all day)	27.8%	18.5%	10.0%	13.0%
% with at least one trip	72.2%	81.5%	90.0%	87.0%
Among those with at least one trip, % with any trips by:				
Vehicle	40.7%	86.2%	96.7%	91.1%
as driver	6.8%	57.9%	88.3%	77.8%
as passenger	33.9%	36.4%	18.1%	22.2%
Public transit	41.7%	9.0%	1.7%	5.7%
Biking or walking	54.6%	24.7%	17.0%	20.9%
Driving ability				
Currently drives	51.3%	80.5%	99.0%	92.6%
Formerly drove	21.5%	6.5%	0.5%	2.9%
Never drove	27.2%	13.0%	0.5%	4.5%
Weighted N (individual adults age 18+)	11,681.6	24,814.6	103,098.4	139,594.6
% of Total N	8.4%	17.8%	73.9%	100.0%

Source: 2009 NHTS version 2.1, weighted sample of individual persons (using a version of WTPERFIN that is a portion weight rather than an expansion factor; the total sample size remains the same but portions change), among those age 18 and over.

3 Attributes of vehicle trips made by members of zero-vehicle households

The purpose of this chapter is to examine vehicle trips made by those in no-car households specifically. As a category of travel, it is necessarily different from others because, except for taxis, rental cars, and formal carsharing, it requires the traveler to draw resources from outside his household. It is also potentially perplexing, since vehicle use is seemingly dissonant with non-ownership, and yet relatively pervasive. Trips in private vehicles comprise a sizable share of the overall travel of those in non-owning households: An estimated 29.0% of their total trips are in vehicles, including 21.6% as a passenger in a private vehicle, 7.4% as the driver of a private vehicle they do not own (potentially borrowed, rented, or a work vehicle), and 2.5% in a taxi (see Table 6).

There is little attention to this category of travel, either among researchers or policymakers and planners. More attention has been devoted to non-owners' use of transit, since many transit-riders are non-owners: 46.9% of all transit trips are made by members of zero-vehicle households.[4] Because governments are the ones providing transit service and oriented to serving the needs of potentially dependent constituents, they are inherently interested in current and potential transit-riders. Thus, it is in their capacity as an important part of the potential market for public transit that no-car households are most often considered (e.g. Chu, 2012). However, non-owners make more trips in cars than they do by transit, with 29.0% of their trips by private vehicle versus 26.4% by some form of public transportation (Table 6). This is also true of other specific populations sometimes considered as important parts of the potential market for transit, such as immigrants, who, as noted by Blumenberg and Smart (2010), make as many as twelve times as many trips by carpooling as by public transit.

[4] From NHTS 2009, version 2.1, among weighted trips made by adults age 18+.

One reason that vehicle trips among non-owning households have not been the focus of more research is that they are a very small minority of all vehicle trips, representing just 1.5% of vehicle-trips nationwide in 2009.[4] Sensibly, these trips are not the focus of studies interested in capturing major trends or volumes. And because they comprise such a small minority, any unique aspects of non-owner vehicle trips would likely be lost in any statistical analyses focusing on the 98.5% of trips made by vehicle-owners. For instance, travel behavior models usually draw on a set of predictors that include vehicle ownership and therefore consider it “controlled for” when evaluating the role of other factors such as income, density, or proximity to transit. But this means that these models only capture the average effect of these predictors for the entire sample, without accounting for any differences in their role among non-owners versus owners. It seems plausible that there would be differences, with some factors either mattering to a different degree or being altogether different in the non-owning context.

To better understand the circumstances of vehicle use by non-owners, their travel patterns must be examined separately from the rest of the population. Thus in this chapter, I examine what is evident about non-owner vehicle travel and the circumstances in which it occurs using the NHTS dataset.

3.1 Method of analysis

I examine non-owner vehicle trips using descriptive statistics as well as a simple mode-choice model. In particular, I present descriptive statistics about the trips themselves, as available in the NHTS data: distances traveled, time of day, trip purpose, who drove, number of passengers, number of other stops made on the same outing (tour). I also present statistics on who (among non-owners) are making these trips, as characterized by the demographic and geographic attributes of respondents that are available in the NHTS data. Finally, I estimate a binary logit model of whether a given trip was made in a vehicle or not, to help disentangle the roles of different factors associated with vehicle use that may be correlated with each other.

While the focus is on travel by non-owners, analogous results for owners provide a useful point of comparison. Thus for some of the descriptive statistics as well as for the modeling, described in more detail below, I estimate three sets of results, one for each of three vehicle-ownership levels — zero cars, fewer than one car per adult (“low-own”), and one or more cars per adults (“high-own”).

3.1.1 Modeling strategy

I use a binary logit model (mathematically equivalent to logistic regression) to relate the effect of explanatory variables such as an individuals’ geographic and demographic attributes, as well as trip attributes such as trip purpose, on the probability that a given trip is made by vehicle or not. The unit of analysis is a trip. The overall sample includes more than one trip per person (for all the trips they made on the survey day), as well as trips from more than one person per household (for however many people are in each household). This means that many of the records in the sample would be interrelated, since household coordination is an important component of trip scheduling (Vovsha, Petersen, & Donnelly, 2004). To ensure an independent sample, I randomly selected just one trip from all those made in each household for inclusion in this analysis.

Several other assumptions of this modeling framework may be violated, however. Some of the explanatory variables may be interrelated with one another, and others may be endogenous to mode choice (such as built environment, trip time, trip purpose), though I excluded those that seemed by definition related, especially in the non-owning context: who drove, number of people on the trip (since others are usually the source of the ride), trip distance, and trip duration. With the caveats that coefficients of interrelated variables should be interpreted with caution, and that the direction of causality may sometimes be other than implied by the framework of the model, I use the model as a diagnostic tool to evaluate which among related factors tend to dominate.

For the final specification presented (Table 20), I used the same specification for each ownership segment, to enable comparisons across ownership segments. I opted for sets of variables that were most theoretically interpretable in addition to having significant coefficients and/or seeming to capture the most variation in the dependent variable, in at least one or more of the three segments. Some variables were retained that do not have significance in one or more of the segments, but seemed useful for the overall story. As shown in Table 20, the final specification includes 55 explanatory variables, producing pseudo-R^2 values ranging from 0.139 to 0.169 for each of the three models. The process of experimenting with alternative specifications (observing which variables tend to conflict with one another, and which are significant in one another's presence) is almost as informative as the final modeling result, and some of these intermediary results are discussed.

3.1.2 Issues with comparing model coefficients across ownership segments

Although the main purpose of this chapter is to examine vehicle trips among no-car households only, the findings are more meaningful in contrast to the other ownership groups. However there are two problems with comparing results across segments: differing sample sizes, affecting the precision of the estimates, and potentially different amounts of unexplained variation in each model, which is confounded with the coefficient estimates for a logit model, making cross-segment comparisons questionable.

The first problem is solved by randomly selecting a subset of cases from among each of the car-owning segments so that all three segments have the same sample size (n=4,249). This means that I can at least compare which variables have significant effects within a given segment's model. The second problem is more difficult to remedy (see Allison, 1999; Hoetker, 2007). As a minimum treatment, I applied a relatively simple strategy, described in Liao (2003), first conducting a test to detect dispersion heterogeneity across groups, and then adjusting the standard errors of the estimated coefficients in each model by a factor equal to the estimated dispersion parameter for each model, effectively increasing the standard errors for the coefficients in models with more dispersion and decreasing them for models with less. While the raw coefficients in each model do not change, the outcome of statistical tests comparing coefficients across segments are hopefully more robust.[5] In this case, the estimated dispersion of the no-car and low-own segments were very close to one (see the last row of Table 20), and tests using the adjusted standard errors have the same outcome as using the originals.

3.2 Results: Attributes of non-owner vehicle trips

Section 3.2 presents findings on the attributes of trips themselves. Section 3.3 presents findings on people making the trips. In both sections, the descriptive statistics and modeling results (when applicable, indicated by sections with asterisks) are discussed together, as they inform the findings for each attribute category. (Attribute categories that were considered for inclusion in the model are indicated with an asterisk in their section heading.)

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[5] The idea is that the model "dispersion" is theoretically equal to one, but departures are common and an estimate of the true dispersion within any given segment can be calculated by $\hat{\phi}_g = \frac{1}{N_g - k} \sum_{i=1}^{N_g} \frac{(y_i - \hat{y}_i)^2}{\hat{y}_i(1-\hat{y}_i)}$, where y_i are the observed value of the dependent variable for case i in segment g, $\hat{y}_i$ is the predicted probability based on the model for segment g, N_g is the number of cases in segment g, and k is the number of parameters in the model, common across all segments. The summed term is also known as the Pearson deviance statistic (Liao, 2003; Hilbe, 2011.) To compare the magnitudes of $\hat{\phi}$'s across segments, the test-statistic $\frac{\hat{\phi}_g}{\hat{\phi}_h}$ is F-distributed, with $N_g - k$ and $N_h - k$ degrees of freedom. In this case, the dispersion parameters for all three segments are close to one, but statistically significantly different from one another at $p < 0.1$, with somewhat greater dispersion in the non-car segment and less in the high-own segment. See Table 20.

3.2.1 Whose car and who drove

Uniquely interesting in the non-owner context is who provided the car and/or ride. For private vehicle trips, the NHTS collects data on who was driving (either the subject, some other household member, or neither of these) as well as whether (and which) household vehicles were used for a given trip. If no one in the household was driving, then by process of elimination, it is evident that someone outside the household was driving, and if no household vehicles were used, that it was in someone else's vehicle. Unfortunately, there is no detailed information about the source or circumstances of these rides, but they could potentially include a rental car, a car-sharing vehicle, or a work vehicle, in addition to the private vehicles of friends, neighbors, and other associates – either getting a ride from someone or borrowing their car. Trips in taxicabs are counted separately. Though often excluded from tabulations of vehicle travel, I consider taxicabs here since it is an alternative means of traveling by vehicle that is available to non-owners.

Table 6 shows the portion of trips made using each mode, including a breakdown of vehicle trips made in one's own car versus someone else's car or in a taxi (for non-owners as well as owners, for comparison). Including taxis, non-owners make 29.0% of their trips by vehicle, the vast majority (91.2%) in a private vehicle that is not a taxi. While use of taxis is much more common among non-owners than among owners (8.8% versus 0.1% of vehicle trips, on average), it is still a small minority of non-owners' overall trip-making (2.5% of all trips), on average.

Table 6 also shows who was driving. Among the trips made by non-owners in other people's vehicles (potentially including friends' or neighbors' cars, rentals, car-sharing, or work vehicles, but excluding taxis), for 65.5% of trips someone outside the household drove, suggesting the subject was getting a ride in that person's car. For the remaining trips, either the subject or someone in his household drove the vehicle – wherever it came from – including 27.9% in which the subject drove and 6.6% in which another household member drove. Those in car-owning households also make trips in private vehicles they do not own (such as getting a ride with someone else, etc.), but it is a relatively small share of their travel, comprising 4.8% of all their vehicle trips and 4.3% of their total trips (among adults age 18 and over in households with at least one car, nationwide). While vehicle-owners travel in other people's cars (in vehicles their household does not own) much less frequently, it is notable that they are themselves the drivers rather than passengers on almost half (44.4%) of those trips.

Table 6. Distribution of trips by mode, vehicle source, and who drove, by vehicle-ownership group

	Number of vehicles owned			
	0	<1 / adult	1+ / adult	Overall
Among all vehicle trips, percent:				
As driver	25.5%	69.3%	86.7%	82.4%
As passenger	74.5%	30.7%	13.3%	17.6%
Using household's own vehicle:	n/a	92.4%	95.9%	93.8%
As driver	n/a	67.1%	84.6%	80.0%
As passenger, HH driver	n/a	23.0%	10.1%	12.5%
As passenger, non-HH driver	n/a	2.3%	1.1%	1.3%
Using someone else's vehicle	100.0%	7.6%	4.1%	6.2%
As driver	25.5%	2.3%	2.1%	2.5%
As passenger, HH driver	6.0%	0.3%	0.1%	0.2%
As passenger, non-HH driver	59.8%	4.8%	1.9%	3.3%
Taxi	8.8%	0.3%	0.1%	0.2%
Total vehicle trips (weighted)	3,529.3	46,440.9	188,826.0	238,796.2
Among all trips, percent:				
By private vehicle or taxi	29.0%	81.5%	90.9%	86.3%
As driver	7.4%	56.5%	78.9%	71.1%
As passenger	21.6%	25.0%	12.1%	15.1%
Using household's own vehicle:	n/a	75.3%	87.1%	80.9%
As driver	n/a	54.7%	76.9%	69.0%
As passenger, HH driver	n/a	18.8%	9.2%	10.8%
As passenger, non-HH driver	n/a	1.9%	1.0%	1.2%
Using someone else's vehicle	29.0%	6.2%	3.8%	5.4%
As driver	7.4%	1.9%	1.9%	2.1%
As passenger, HH driver	1.7%	0.2%	0.1%	0.2%
As passenger, non-HH driver	17.3%	3.9%	1.7%	2.9%
Taxi	2.5%	0.2%	0.1%	0.2%
By another mode	71.0%	18.5%	9.1%	13.7%
Transit	26.4%	4.1%	0.6%	2.5%
Bicycle	40.1%	12.4%	7.4%	9.9%
Walk	2.5%	1.0%	0.5%	0.7%
Other	2.0%	1.0%	0.5%	0.7%
Total trips (weighted)	12,167.5	56,960.5	207,681.0	276,809.0

Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ who were not out of town on the survey day. Private vehicles include car, van, SUV, pickup truck, other truck, RV, and motorcycle (and excludes light electric vehicles, golf carts, and all other modes).

3.2.2 Distance and duration

As would be expected, vehicle trips tend to be to farther destinations than those by other modes (7.5 versus 2.8 miles per trip made among non-owners, on average), and faster per mile (9.4 versus 29.9 minutes per mile; see Table 7). However non-owners' trips are slower, on average, by all modes of travel. For instance, the ratio of average minutes spent to average miles traveled is 6.15 minutes per mile among non-owners who drove themselves in someone else's car, versus 3.97 among owners driving themselves. Getting a ride with someone outside the household appears to be particularly slow for non-owners, taking almost twice as long per mile traveled (about 11 minutes per mile, on average), compared to when they are themselves driving, *or* compared to when car-owners get rides outside their households.

Table 7. Average time and distance per trip, by mode and vehicle-ownership group

	Average duration (minutes)			Average distance (miles)			Average speed (mins / mile)		
Mode	0	<1 / adult	1+ / adult	0	<1 / adult	1+ / adult	0	<1 / adult	1+ / adult
Private vehicle and taxi	28.4	23.5	20.0	2.8	6.4	10.4	9.41	5.27	3.98
As driver	23.4	18.5	18.7	10.1	8.6	9.9	6.15	5.23	3.97
As passenger, HH driver	28.9	20.6	22.6	10.1	10.4	13.7	5.46	5.27	3.78
As passenger, non-HH driver	26.5	23.2	27.4	6.5	10.9	15.9	10.87	5.51	5.11
In a taxi	22.3	24.4	21.1	4.1	5.4	9.9	13.72	9.20	4.79
Other mode	25.6	19.3	19.4	7.5	9.2	10.5	29.92	26.75	25.27
Transit	46.1	48.9	50.5	6.6	12.0	17.7	19.89	17.56	11.59
Bicycle	17.1	14.7	14.4	0.7	0.7	0.7	36.00	31.98	28.72
Walk	21.8	21.2	23.7	1.8	3.0	3.7	19.54	12.26	11.56
Other	27.5	32.4	59.4	5.0	65.9	157.4	29.44	7.10	5.12
Overall	27.5	20.1	19.4	4.1	8.7	10.5	23.95	9.13	5.89

Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ who were not out of town on the survey day. Private vehicles include car, van, SUV, pickup truck, other truck, RV, and motorcycle; Transit includes Local public bus, commuter bus, school bus, charter/tour bus, shuttle bus, Amtrak/intercity train, commuter train, subway/elevated train, street car/trolley, ferry, and special transit for people w/disabilities; Other includes light electric vehicles (e.g. golf carts), airplanes, and "other".

Possible explanations for the differences in travel times include: (1) less of the non-owners' travel is on the highway (that is, the mix of high-speed highway travel relative to lower-speed local travel is greater among trips made by owners), consistent with the fact that more of them live in more urban areas; (2) the non-owners are more prone to underestimate the distance they traveled (but not time), especially when getting rides with others; (3) more of the non-owners have other conditions that make them move slowly, such as disability or old age, which could affect the overall travel time at the beginning and end of the trip. Providing some support for the last explanation, the non-owners' trips are slower, on average, on all modes, including walking and biking. The slower transit speeds may reflect the type of transit used, such as slower local buses compared to higher-speed commuter trains.

3.2.3 Trip purpose*

Next I examined mode-use trends among the ten major trip-purpose categories (trip purpose summary in the variable WHYTRP1S) as well as the more detailed trip purposes (in WHYTO) and based on this preliminary analysis created thirteen new categories (shown in Table 8) that better grouped purposes with similar mode-use trends. For instance, I separated exercise / sports activities and dog-walking from other social/recreational and family / personal business activities, respectively, since they have much higher incidence of active modes. I separated buying gas from other shopping/errands. I separated trips to school from religious activities, since the latter exhibited more atypical mode splits while mode split for school trips were more similar to overall splits within a given segment. I separated return-to-work trips (more likely to be mid-day walking) from to-work and work-related trips. Further, I separated to-work trips into two groups, based on respondents' reported occupational category, with manual labor (listed as manufacturing / construction / maintenance / farming occupations) in one group, and all other occupations in another (including the categories Sales / service; Clerical / admin support; Professional, managerial, or technical; or Other).

Among the purpose categories defined in Table 8, vehicle use among non-owners is greatest for the purposes of transporting someone, medical visits, going out to eat, religious activities, and for (commuting to or engaging in) work in manual-labor occupations; vehicle use is least for exercise/pet-care, non-manual-labor work, and shopping/errands (Table 9). However, because of their overall frequency, trips home and shopping/errands together make up more than half of the vehicle trips made by non-owners.

There is also evidence of the differing circumstances for certain categories of activities in who was driving (also Table 9). For instance, getting a ride from outside the household is more prevalent for social/recreational trips (74.9% of them) and religious activities (72.3% of them), and driving oneself is more likely for trips whose purpose was to transport someone else (47.5% of them). A disproportionate share of trips to medical services is made by taxi (26.7% of those made by vehicle, and 12.1% of all medical visits).

Table 8. Trip purpose definitions

New category	Description	WHYTO codes	% of trips
Home	Home	01	34.5%
Work (non-manual labor)	Go to work and work-related activity (but excluding return to work, attend business meeting /trip) for anyone whose occupational category is anything *other* than manufacturing / construction / maintenance /farming	11, 14	9.8%
Work (manual labor)	As above, for anyone whose occupational category is manufacturing / construction / maintenance /farming.	11, 14	2.3%
Religious activity	Religious activity	22	1.9%
Medical/ dental	Medical/dental services	3	1.8%
Shopping/ errands	All shopping/ errands *except* buying gas: buy goods (groceries/clothing/ hardware store) and services (video rentals/dry cleaner/post office/car service/bank)	4, 41, 42	17.1%
Get gas	Buy gas	43	1.8%
Exercise, sports, pet care	Go to gym/exercise/ play sports and pet care (walk the dog/vet visits)	51, 64	3.9%
Social / recreational	Social/recreational *except* exercise: Rest or relaxation/vacation; Visit friends/relatives; Go out/hang out: entertainment /theater/ sports event/go to bar	5, 52, 53, 54	7.2%
Family / personal business	Family personal business/ obligations *except* pet care: Use professional services (attorney/ accountant); Attend funeral/wedding; Use personal services (grooming/ haircut/nails); Attend meeting (PTA/home owners association/local government)	6, 61, 62, 63, 65	2.6%
Transport someone	Transport someone, including pick up, take and wait, drop off	7, 71, 72, 73	6.7%
Go out to meal	Meal events, including social events and get/eat meal (excludes coffee, ice cream, snacks)	81, 82	5.9%
Other activity	School (Go to school as student; Go to library: school related, OS - Day care, unspecified school/religious); Coffee/ice cream/snacks; Return to work; Attend business meeting/trip; Other	12, 13, 2, 21, 23, 24, 8, 3, 97	4.6%

Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in all households who were not out of town.

Table 9. Vehicle use and who drove on trips made by non-owners, by trip purpose

	Trip purpose						
	Home	Work (non-labor)	Work (manual labor)	Religious activity	Medical/ dental	Shopping/ errands	Get gas
Among all trips, %							
By any vehicle	28.6%	21.4%	36.1%	36.4%	45.3%	28.5%	99.5%
As driver	6.3%	10.3%	10.6%	9.0%	3.9%	7.5%	48.7%
As passenger, HH driver	1.6%	0.3%	3.7%	0.4%	2.9%	2.2%	7.1%
As passenger, non-HH driver	16.9%	8.5%	21.2%	26.3%	25.2%	17.0%	43.7%
In a taxi	3.2%	2.2%	0.4%	0.3%	12.1%	1.2%	0.0%
Total trips (weighted)	4,546.1	768.0	196.7	265.2	473.8	2,616.5	73.5
Among vehicle trips, %							
As driver	22.1%	48.1%	29.4%	24.7%	8.6%	26.5%	48.9%
As passenger, HH driver	5.6%	1.4%	10.1%	1.1%	6.5%	7.6%	7.1%
As passenger, non-HH driver	58.9%	39.4%	58.6%	72.3%	55.5%	59.5%	44.0%
In a taxi	11.0%	10.5%	1.1%	0.7%	26.7%	4.3%	0.0%
Total vehicle trips (weighted)	1,301.9	164.7	71.1	96.5	214.8	746.0	73.2
% of total vehicle trips	35.7%	4.5%	1.9%	2.6%	5.9%	20.4%	2.0%

	Trip purpose (continued)						
	Exercise, sports, pet care	Social / rec	Family / personal business	Transport someone	Go out to meal	Other activity	Overall
Among all trips, %							
By any vehicle	6.7%	30.8%	35.0%	47.0%	37.2%	16.2%	29.7%
As driver	3.9%	4.6%	10.3%	22.3%	7.6%	3.5%	7.4%
As passenger, HH driver	0.5%	0.5%	0.3%	1.2%	4.2%	3.1%	1.7%
As passenger, non-HH driver	2.2%	23.1%	22.3%	19.3%	21.7%	6.9%	17.3%
In a taxi	0.0%	1.7%	1.2%	3.8%	2.2%	2.1%	2.5%
Total trips (weighted)	353.7	1,204.0	322.5	355.0	608.5	500.4	12,284.0
Among vehicle trips, %							
As driver	58.5%	15.0%	29.3%	47.5%	20.4%	21.8%	24.9%
As passenger, HH driver	7.4%	1.6%	1.0%	2.6%	11.2%	19.3%	5.9%
As passenger, non-HH driver	32.8%	74.9%	63.7%	41.1%	58.2%	42.3%	58.3%
In a taxi	0.0%	5.4%	3.4%	8.0%	6.0%	13.3%	8.6%
Total vehicle trips (weighted)	23.7	370.8	113.0	166.7	226.5	81.1	3,650.0
% of total vehicle trips	0.6%	10.2%	3.1%	4.6%	6.2%	2.2%	100.0%

Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in zero-vehicle households who were not out of town.

The modeling results (in which "home" is the omitted reference category; see Table 20) generally match the patterns in the descriptive statistics, suggesting they are not driven (or not entirely) by other factors, such as the demographics of who tends to make trips of each purpose type. In comparing across ownership segments, there are several trip categories with opposite effects and/or significantly different magnitudes. For instance, while medical/dental visits have a higher probability of vehicle use in all segments, it is greater in the higher-own segment[6], meaning that relative to their baseline car use, owners are especially likely to use their cars for medical visits. There are even greater differences across segments for shopping/errands, a category of activity for which owners are significantly more likely to use their cars than for other purposes, but non-owners are only slightly more likely, relative to their baseline use. Finally, social/recreational trips have an opposite effect across segments: Relative to their baseline level of vehicle use, non-owners are *more* likely to use cars for social/recreational outings than owners, but for owners, there is less probability of use for that type of outing, relative to their baseline level. There is no difference across segments for trips for religious activities, getting gas, family/personal business, and transporting others – that is, the probability of using a vehicle for those purposes is *as different* from the probability of using a vehicle for trips home (serving as a baseline) within each segment, all else equal.

3.2.4 Number of people on the trip

Since 75% of non-owner vehicle trips are as passengers, the number of people on the trip is clearly endogenous to the mode choice and how the person found a ride. Thus, as would be expected, there is a higher incidence of vehicle use the greater the number of people on the trip, with just 11.8% of solo trips made in a vehicle, increasing to 61.1% of trips made with one other person (2-person trips). Not necessarily obvious is that vehicle use is even higher among trips with greater numbers of people, up to 89.3% of trips with 5 people (Table 10). Due to their greater overall frequency, the most common circumstance for a vehicle trip among non-owners is a two-person trip (34.8% of vehicle trips), and most of these (79.6%) occur as a ride from

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[6] It is almost significantly greater according to a t-test at p=0.107 in the specification in Table 20, and has greater significance in other specifications with fewer variables included.

someone outside the household, followed by lone trips (comprising 27.0% of vehicle trips, including taxi rides), and then successively higher numbers of people.

Table 10. Vehicle use and who drove on trips made by non-owners, by number of people on the trip

	Number of people						
	1	2	3	4	5	6+	Overall
Among all trips, %							
By any vehicle (private or taxi)	11.8%	61.1%	72.7%	78.1%	89.3%	73.8%	29.8%
As driver	7.1%	7.9%	7.2%	6.2%	4.7%	18.0%	7.4%
As passenger, HH driver	0.0%	3.5%	8.0%	3.8%	3.2%	17.7%	1.7%
As passenger, non-HH driver	0.0%	48.6%	55.9%	67.7%	80.8%	38.1%	17.3%
In a taxi	3.3%	1.1%	1.6%	0.3%	0.6%	0.0%	2.5%
Total trips (weighted)	8,392.0	2,085.7	923.8	350.3	312.4	234.0	12,298.2
Among vehicle trips, %							
As driver	60.7%	13.0%	9.9%	7.9%	5.3%	24.4%	24.9%
As passenger, HH driver	0.0%	5.7%	11.0%	4.9%	3.6%	24.0%	5.8%
As passenger, non-HH driver	0.0%	79.6%	76.9%	86.7%	90.4%	51.6%	58.3%
In a taxi	27.7%	1.8%	2.3%	0.4%	0.7%	0.0%	8.6%
Total vehicle trips (weighted)	987.6	1,275.1	672.0	273.5	279.1	172.7	3,660.0
% of total vehicle trips	27.0%	34.8%	18.4%	7.5%	7.6%	4.7%	100.0%

Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in zero-vehicle households who were not out of town.

3.2.5 Tour context*

In general (considering all modes), trips that are part of an outing with no stops made along the way are the most common type of trip (comprising over half of all trips), followed by outings with one stop along the way, with successively higher numbers of stops being less common. Among these, no-stop trips are somewhat more likely to be vehicle trips, on average, while one-stop trips are less likely to be vehicle trips, on average (Table 11). This suggests that the type of outing in which someone might make a stop along the way is *less* likely to be made in a vehicle; or, conversely, that when not in a vehicle, someone is *more* likely to make a stop. However, among the less-common phenomena of journeys with two and three or more stops, vehicle use is even more likely, suggesting that the type of outing in which someone makes higher numbers of stops is more likely to be made in a vehicle; or that when in a vehicle, someone is likely to make either no stops or else many stops (or that when not in a vehicle, someone is more likely to make one stop, but not many stops).

Table 11. Vehicle use and who drove on trips made by non-owners, by tour length

	Trip is part of a tour with this number of mid-tour stops				
	0	1	2	3+	Overall
Among all trips, %					
By any vehicle (private or taxi)	31.0%	21.7%	40.0%	43.8%	29.7%
As driver	7.0%	5.9%	9.1%	16.9%	7.4%
As passenger, HH driver	1.7%	1.3%	1.4%	4.7%	1.7%
As passenger, non-HH driver	18.0%	12.1%	28.1%	21.4%	17.3%
In a taxi	3.3%	2.0%	0.7%	0.5%	2.5%
Total trips (weighted)	6,638.9	3,788.6	1,067.3	742.0	12,236.7
Among vehicle trips, %	54.3%	31.0%	8.7%	6.1%	100.0%
As driver					
As passenger, HH driver	22.4%	27.1%	22.8%	38.5%	25.0%
As passenger, non-HH driver	5.6%	6.0%	3.4%	10.7%	5.9%
In a taxi	58.2%	55.8%	70.2%	48.9%	58.2%
Total vehicle trips (weighted)	10.7%	9.2%	1.8%	1.2%	8.4%
% of total vehicle trips	2,057.2	822.2	426.8	325.2	3,631.4
Among all trips, %	56.7%	22.6%	11.8%	9.0%	100.0%

Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in zero-vehicle households who were not out of town.

In the model (Table 20), higher numbers of stops is measured as having a negative effect on the probability of using a vehicle, with no difference in the magnitude of the effect across ownership segments. If causal, this suggests that people are more likely to use a vehicle for occasions going directly somewhere with fewer stops along the way. (If the causality is reversed, it suggests that someone is less likely to make stops once in a vehicle.)

3.2.6 Day of the week*

There are no dramatic differences in use of vehicles on weekdays versus weekends or day of the week, on average, among non-owners (Table 12). The incidence of vehicle use is somewhat less on Sundays, and therefore on weekends in general, on average. But in the model this is reversed, with weekends increasing the probability of vehicle use, once other factors are accounted for (Table 20). This suggests that once factors such as trip purpose and individual demographics are accounted for, weekend trip-making is more likely. The positive effect of weekends is also apparent among low-own households (a significant positive coefficient in the model, as well as higher overall average rates of use on weekends among this segment), but not among high-own households. This is logical if the former are more likely to get rides as a part of social outings or group outings with other household members. As shown in Table 12, non-owners are indeed somewhat more likely to get rides as passengers in private cars on weekends (69.1% of weekend vehicle trips versus 61.9% of weekday vehicle trips, on average), and more likely to make trips driving themselves or by taxi on weekdays.

Table 12. Vehicle use and who drove on trips made by non-owners, by day of the week

	Day of the week				
	Mon	Tues	Wed	Thur	Fri
Among all trips, %					
By any vehicle	29.9%	29.5%	27.2%	32.9%	32.6%
As driver	9.0%	5.0%	8.7%	5.1%	11.8%
As passenger, HH driver	1.7%	1.5%	0.5%	1.2%	2.3%
As passenger, non-HH driver	15.6%	20.6%	14.4%	22.2%	14.4%
In a taxi	3.2%	1.8%	3.1%	2.2%	3.3%
Total trips (weighted)	1,704.0	1,574.5	2,017.6	1,631.5	2,002.1
% of total trips	13.9%	12.8%	16.4%	13.3%	16.3%
Among vehicle trips, %					
As driver	30.2%	16.9%	32.0%	15.6%	36.2%
As passenger, HH driver	5.6%	5.3%	1.9%	3.7%	7.1%
As passenger, non-HH driver	52.4%	70.0%	53.0%	67.4%	44.2%
In a taxi	10.7%	6.3%	11.3%	6.7%	10.1%
Total vehicle trips (weighted)	508.9	464.2	548.5	537.5	652.0
	Day of the week (continued)				
	Sat	Sun	Overall, weekdays	Overall, weekends	Overall
Among all trips, %					
By any vehicle	30.3%	26.3%	30.2%	28.8%	29.8%
As driver	5.7%	5.1%	8.0%	6.1%	7.4%
As passenger, HH driver	2.5%	2.4%	1.3%	2.7%	1.7%
As passenger, non-HH driver	19.2%	16.7%	17.4%	17.2%	17.3%
In a taxi	2.2%	1.7%	2.7%	2.3%	2.5%
Total trips (weighted)	1,554.0	1,814.6	8,464.4	3,833.8	12,298.2
% of total trips	12.6%	14.8%	68.8%	31.2%	100.0%
Among vehicle trips, %					
As driver	18.8%	19.4%	26.4%	21.2%	24.9%
As passenger, HH driver	8.3%	9.3%	4.4%	9.2%	5.8%
As passenger, non-HH driver	63.4%	63.3%	57.6%	59.9%	58.3%
In a taxi	7.2%	6.6%	8.8%	7.9%	8.6%
Total vehicle trips (weighted)	471.1	477.9	2,557.2	1,102.8	3,660.0

Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in zero-vehicle households who were not out of town.

3.2.7 Time of day*

The bulk of non-owners' vehicle trips are spread throughout the day, in approximate proportion with overall trip-making, despite dips in the portion of trips made by vehicle during the morning commute hours (8am-10am) and later evening hours (8pm-10pm), when vehicle trips are about a quarter of all trips, versus about a third during other times (Table 13). Late-night trips have a higher incidence of vehicle use, comprising 44.4% of trips made from 11pm-4am, including taxi use, which is especially high during these hours. However, these nighttime trips are relatively infrequent and the sample size is small, all together comprising just 2.2% of all trips made by non-owners and 3.3% of their vehicle trips.

In the model, the evening pattern is reversed, showing a greater probability of vehicle use from 7pm-11:59pm among non-owners (once other factors such as demographics and trip purpose have been accounted for), which is significantly different from the effect among owners, for whom use during these hours is *less* probable, all else equal (Table 20).

Vehicle trips made in the morning hours (5-10am) have somewhat lower rates of being rides from outside the household relative to at other times of day (about 46% of vehicle trips made during 5-10am versus 60% of those made at other times) and higher rates of driving oneself, which may contribute to their scarcity (Table 13). The rate at which vehicle trips consist of rides from outside the household is highest during the evening hours (5pm-10pm), which may contribute to the positive effect measured in the model, all else equal.

Table 13. Vehicle use and who drove on trips made by non-owners, by time of day

	Time of day							
	5am-7am	8am-10am	11am-1pm	2pm-4pm	5pm-7pm	8pm-10pm	11pm-4am	Overall
Among all trips, %								
By any vehicle	31.3%	25.5%	29.7%	30.5%	32.7%	25.4%	44.3%	29.7%
As driver	13.3%	8.5%	6.5%	7.1%	7.5%	5.5%	9.0%	7.4%
As passenger, HH driver	0.9%	1.5%	1.7%	2.1%	2.0%	1.1%	2.1%	1.7%
As passenger, non-HH driver	14.3%	12.0%	17.5%	18.6%	20.5%	16.5%	23.7%	17.3%
In a taxi	2.3%	2.4%	2.9%	2.0%	2.3%	1.9%	9.3%	2.5%
Total trips (weighted)	469.3	2,151.6	2,991.7	2,907.8	2,237.6	1,208.0	270.8	12,236.7
% of total trips	3.8%	17.6%	24.4%	23.8%	18.3%	9.9%	2.2%	100.0%
Among vehicle trips, %								
As driver	42.4%	33.3%	22.0%	23.3%	23.0%	21.8%	20.2%	25.0%
As passenger, HH driver	2.7%	5.7%	5.8%	7.0%	6.2%	4.3%	4.8%	5.9%
As passenger, non-HH driver	45.7%	47.1%	59.0%	60.9%	62.5%	64.8%	53.5%	58.2%
In a taxi	7.3%	9.3%	9.8%	6.6%	7.0%	7.4%	20.9%	8.4%
Total vehicle trips (weighted)	146.8	548.8	888.8	887.8	732.4	306.8	120.1	3,631.4
% of total vehicle trips	4.0%	15.1%	24.5%	24.4%	20.2%	8.4%	3.3%	100.0%

Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in zero-vehicle households who were not out of town.

3.3 Results: Attributes of non-owners who make vehicle trips

3.3.1 Economic status*

Non-owning households already consist of disproportionately lower-income households: 75.1% of non-owners are in households in the lowest two income quintiles (as defined for the entire population, with less than $22,500 in household income per adult) and almost half are in the lowest income quintile (with less than $12,500 per adult; see Table 14). The majority (62.2%) have no more than a high school degree. But in addition, among non-owners, vehicle use is *greater* for those with lower incomes and less education, on average. As a result, the overwhelming majority of vehicle trips made by non-owners are made by those in households with very low incomes: 81.3% of non-owner vehicle trips are by people whose household incomes are less than $22,500 per adult (that is, in the lowest two income quintiles as defined for the overall population); 83.7% percent are made by people with less than a four-year college degree. Those in the highest income quintile comprise 8.6% of non-owners overall, but account for only 4.4% of non-owner vehicle trips.

There are also differences in the circumstances of vehicle trips across different income levels. The incidence of getting a ride with someone outside the household is much greater among lower-income households than higher-income households – about twice as many of their vehicle trips are this situation (Table 14). By contrast the incidence of driving oneself generally increases with income.

Table 14. Vehicle use and who drove on trips made by non-owners, by household income level

	Household income per adult household member ($1,000s)					
	Less than $12.5	$12.5 to $22.49	$22.5 to $33.32	$33.33 to $44.99	$45 and above	Overall
Among all trips, %						
By any vehicle	31.3%	30.2%	27.7%	34.6%	12.0%	29.0%
As driver	4.5%	9.8%	8.6%	21.9%	4.3%	7.1%
As passenger, HH driver	1.8%	2.5%	0.5%	0.0%	0.0%	1.6%
As passenger, non-HH driver	21.9%	15.8%	16.3%	4.7%	4.4%	17.1%
In a taxi	2.5%	1.4%	2.1%	5.0%	3.2%	2.4%
Total trips (weighted)	6,083.0	2,742.6	846.3	718.1	1,227.7	11,617.7
% of total trips	52.4%	23.6%	7.3%	6.2%	10.6%	100.0%
Among vehicle trips, %						
As driver	14.5%	32.4%	30.9%	63.4%	35.8%	24.5%
As passenger, HH driver	5.7%	8.3%	1.7%	0.0%	0.1%	5.4%
As passenger, non-HH driver	69.8%	52.3%	58.8%	13.7%	36.2%	59.2%
In a taxi	8.0%	4.7%	7.7%	14.5%	26.8%	8.4%
Total vehicle trips (weighted)	1,905.3	828.6	234.7	248.2	147.6	3,364.4
% of total vehicle trips	56.6%	24.6%	7.0%	7.4%	4.4%	100.0%
% of people	46.6%	28.5%	10.9%	5.4%	8.6%	100.0%

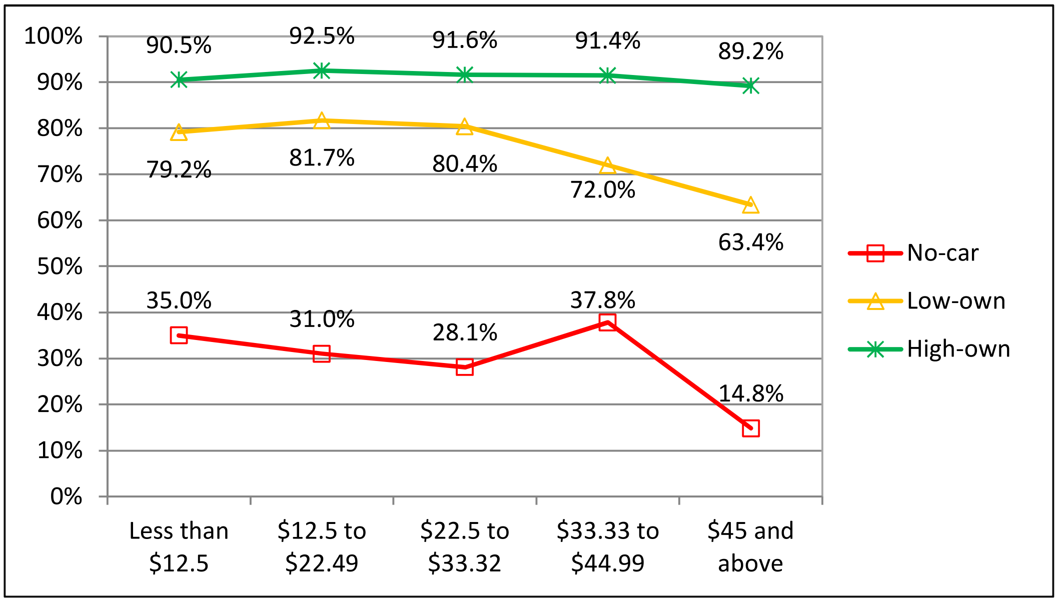
Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in zero-vehicle households who were not out of town.

Table 15. Vehicle use and who drove on trips made by non-owners, by educational attainment

	Highest educational attainment					
	Less than high school	High School	Some college / Associate's	Bachelor's	Graduate or professional	Overall
Among all trips, %						
By any vehicle	32.4%	33.5%	28.4%	25.9%	17.7%	29.6%
As driver	4.8%	4.7%	10.9%	9.1%	10.0%	7.2%
As passenger, HH driver	2.5%	2.0%	2.0%	0.3%	0.0%	1.7%
As passenger, non-HH driver	20.3%	24.3%	13.3%	11.5%	4.8%	17.4%
In a taxi	3.3%	2.2%	2.0%	3.2%	2.8%	2.6%
Total trips (weighted)	2,637.9	4,064.5	2,749.2	1,355.8	1,318.5	12,125.8
% of total trips	21.8%	33.5%	22.7%	11.2%	10.9%	100.0%
Among vehicle trips, %						
As driver	14.7%	13.9%	38.3%	35.1%	56.6%	24.3%
As passenger, HH driver	7.7%	6.1%	7.1%	1.0%	0.1%	5.8%
As passenger, non-HH driver	62.5%	72.5%	46.7%	44.4%	27.1%	58.7%
In a taxi	10.1%	6.4%	7.2%	12.4%	15.9%	8.7%
Total vehicle trips (weighted)	855.8	1,362.4	781.4	351.0	233.5	3,584.2
% of total vehicle trips	23.9%	38.0%	21.8%	9.8%	6.5%	100.0%
% of people	27.2%	35.0%	21.3%	9.1%	7.4%	100.0%

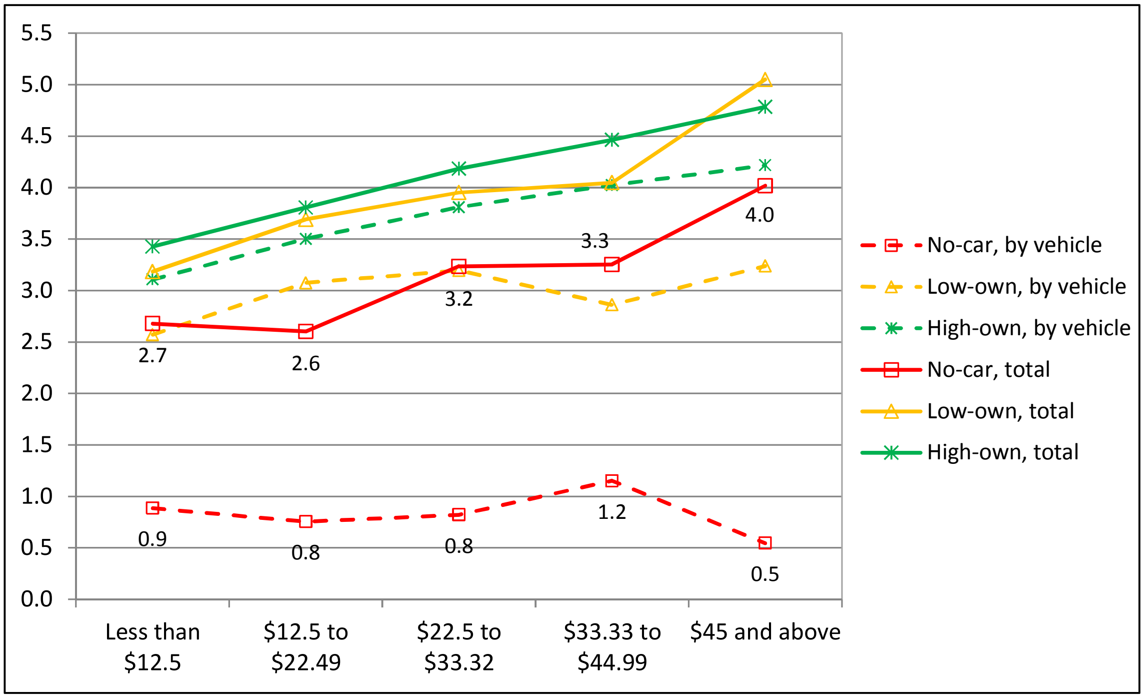
Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in zero-vehicle households who were not out of town.

Figure 4. Percent of daily trips made by vehicle at each income quintile, by vehicle-ownership level



Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ who were not out of town.

Figure 5. Average volume of daily trips, total and by vehicle, by income, among each vehicle-ownership segment



Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ who were not out of town.

While I have been emphasizing trends in the *percent* of trips made by vehicle, the total volume of trips offers important context. Comparing how vehicle use volume changes with income level among owners versus non-owners reveals differences in the apparent role of vehicles in overall trip-making in each segment. In all the ownership segments, total trip volume (by any mode) increases with income, on average. Among vehicle owners, the volume of vehicle trips increases steadily with income, but the volume of total trips increases even faster. Thus, although the percent of trips in vehicles decreases with income among owners, it is not because vehicle travel diminishes, but because non-vehicle travel increases, perhaps reflecting a greater incidence of active recreational trips (walking and biking for leisure), or more stop-making on their walking tours, or residence in major metro areas with choice transit ridership. (See Figure 4 versus Figure 5.)

By contrast, among non-owners, although the overall trip volume increases with income, the volume of vehicle trips is about the same among the three lowest income quintiles, is somewhat higher among the fourth quintile, and then drops to its lowest among those in the highest income quintile. The drop is likely associated with choice of a consonant environment, supported by the fact that incomes are highest in the higher density Census tracts, where vehicles are probably less essential (see Figure 1 through Figure 3). When included in a model, income is measured to have a significant negative effect on the probability of vehicle use when included as an explanatory variable by itself (or only with age), but becomes insignificant (when entered as a series of dummy variables for each of five levels) or with a small positive sign (when entered as a continuous variable) in the presence of the environmental measures, such as neighborhood density (Table 20). This suggests that vehicle use is generally lower among non-owners living in environments where vehicles are not needed, which correlates with income – beyond this, income level makes either no measurable difference or a small positive difference in the probability of traveling by vehicle. Interestingly, educational attainment *does* have a significant effect in the non-owner model, seemingly no matter what else is included: increasing levels of attainment have a *negative* influence on vehicle use. This suggests that educational attainment captures something that income does not, and that is also not fully captured by the other explanatory variables in the model, such as density, home-ownership, home type, or age. Perhaps education captures the degree of choice (self-selection into the non-owning segment and a consonant environment) better than income does. As educational attainment increases, and the environment becomes more consonant with the household's (non-) ownership status, vehicle use is less necessary,

Home-ownership is also strongly associated with more vehicle use, on average, among all vehicle-ownership groups. Home-ownership may indicate more access to tangible resources, as well as correlate with living in lower-density built environments better suited to vehicle use. When included in the model with potentially related variables such as income, education, household size, density, housing type, and community type, home ownership still has a significant effect, but only among the non-owners (Table 20). This suggests that even after accounting for style of housing (and the other factors), home-ownership makes a meaningful difference among non-owners, perhaps reflecting greater access to tangible resources. Alternatively, home-ownership without vehicle-ownership may reflect non-financial constraint on vehicle use, such as old age or disability, which would in turn also be associated with greater vehicle dependence, despite the inability to drive or own. This would corroborate the finding in Chapter 5 that non-vehicle-owning home-owners experience less mobility fulfillment, all else equal.

3.3.2 Driving and physical ability*

As conventional measures of vehicle resources, the ability to drive and owning higher numbers of vehicles is clearly associated with increased vehicle use on average, as use is substantially higher among owners versus non-owners, and among high-level owners versus lower-level owners. However, within the different ownership strata, driving ability and vehicle ownership take on different roles relative to the other members of the segment.

Among those with limiting medical conditions (and specifically those with conditions resulting in giving up driving), vehicle use is substantially greater at each ownership level. (That is, the medically limited in owning households use cars more than the medically limited in non-owning households.) But within non-owners, use is greater relative to others in the segment, while among owners it is less than the segment average.

Similarly, among drivers, vehicle use increases substantially at each ownership level. (That is, drivers in owning households use cars more than drivers in non-owning households.) And among vehicle-owners, those who drive use vehicles substantially more than those who do not (who presumably live with others who drive). Among non-owners however, there is an opposite effect, with those who drive making substantially *fewer* vehicle trips than non-drivers (35.4% versus 25.8% of trips). This holds even in the model, after accounting for residential location, age, and other related factors. This suggests that among non-owners, driver status serves as an indicator for those with more choice – either in choosing not to own a car and/or in the apparent ability to use transportation alternatives consonant with their ownership choice. By contrast, for non-drivers, there may be some circumstance preventing them driving that also might make them more reliant on vehicle transportation, such as old age or disability. In total, about half of all vehicle trips made by non-owners are made by people who themselves are not drivers. This makes the nature of their vehicle-travel very different from that of the general population.

In-household vehicle resources also have a seeming different effect in the context of the two different ownership levels considered. In low-owning households, more vehicles per person is associated with more vehicle use – possibly reflecting additional access as well as additional need for vehicles (they own them because they need/want them; once they have them, they use them; or both). Among high-ownership households, additional vehicles beyond one per adult is actually associated with *less* vehicle use, however, perhaps reflecting a level of wealth not reflected in the household income levels (with those above $100,000 all grouped together) and corresponding, additional more active-mode trips for leisure, and/or a preference for a more active lifestyle that corresponds to owning excess cars (e.g. a Jeep, a motorcycle, *and* a sports car) as well as making additional active (non-vehicle) trips, all else equal. (That is, as the additional number of active, leisure trips increases, the probability of any one trip being a vehicle trip decreases.) In both high- and low-ownership households, the total number of adults and/or drivers has little effect on vehicle use, after accounting for the number of vehicles. (In particular, in the high-ownership model, the coefficients are not significant; in the low-ownership model, coefficients for the number of adults and number of drivers are statistically significant but with opposite signs, likely conflicting and canceling each other out.)

3.3.3 Built environment*

As hypothesized, vehicle use is higher among non-owners in lower-density, less urban communities and lower in higher-density, more urban communities, on average. Averages range from a high of 59.1% of trips among those in areas classified as “town/country” (and 62.6% of those in the most sparsely developed Census tracts) to a low of 16.4% of trips among those in areas classified as “urban” (and about 9% in the most densely developed Census tracts) (see Table 16 and Table 17). Surprisingly, vehicles are used for a slightly greater percent of trips among those in “second city” areas than in “suburban” areas (42.0% versus 39.6%), on average, types with comparable density but different context within the greater region (recall Table 3). Comparing the relationship between vehicle use and density among the different ownership groups, vehicle use drops off only in the most densely populated areas among owners (and especially high-level owners), but among non-owners, vehicle use is both lower overall and declines incrementally at successively more densely populated areas, on average (Table 17 and Figure 6).

Table 16. Vehicle use and who drove on trips made by non-owners, by community type

	Community type (location of residence)				
	Urban	Second City	Suburban	Town/ country	Overall
Among all trips, %					
By any vehicle (private or taxi)	16.4%	42.0%	39.6%	59.1%	29.8%
As driver	2.8%	11.0%	13.4%	16.3%	7.4%
As passenger, HH driver	0.8%	1.5%	4.3%	3.6%	1.7%
As passenger, non-HH driver	8.6%	26.1%	20.9%	38.0%	17.3%
In a taxi	3.5%	2.4%	0.5%	0.8%	2.5%
Total trips (weighted)	7,059.1	1,832.1	1,434.4	1,971.4	12,297.0
% of total trips	57.4%	14.9%	11.7%	16.0%	100.0%
Among vehicle trips, %					
As driver	16.8%	26.1%	33.9%	27.6%	24.9%
As passenger, HH driver	4.7%	3.5%	11.0%	6.0%	5.8%
As passenger, non-HH driver	52.2%	62.2%	52.7%	64.4%	58.3%
In a taxi	21.2%	5.8%	1.3%	1.4%	8.6%
Total vehicle trips	1,157.5	769.6	568.2	1,164.7	3,660.0
% of total vehicle trips	31.6%	21.0%	15.5%	31.8%	100.0%
% of people	47.8%	17.6%	14.5%	20.1%	100.0%

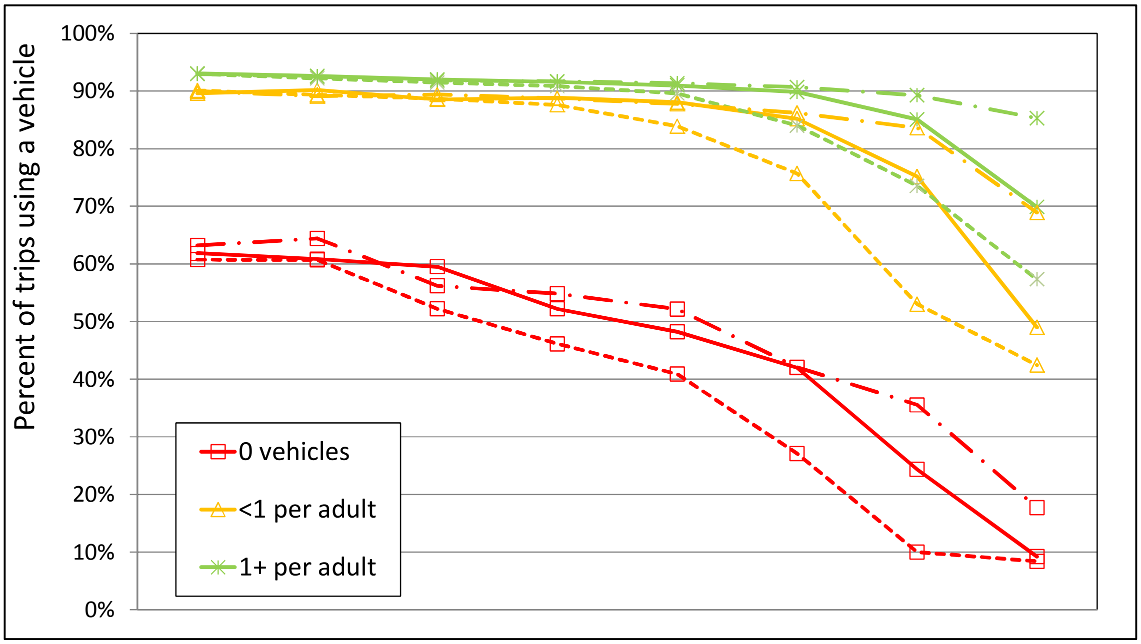
Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in zero-vehicle households who were not out of town.

Table 17. Vehicle use and who drove on trips made by non-owners, by housing density

	Housing units per square mile in home Census tract								
	0-99	100-499	500-999	1,000-1,999	2,000-3,999	4,000-9,999	10,000-24,999	25,000-999,999	Total
Among all trips, %									
By any vehicle	62.6%	61.4%	45.7%	38.4%	39.9%	18.5%	9.1%	10.1%	29.8%
As driver	22.9%	14.8%	12.4%	9.1%	10.0%	3.4%	1.2%	2.0%	7.4%
As passenger, HH driver	2.9%	4.4%	5.2%	3.8%	0.6%	0.7%	1.7%	0.0%	1.7%
As passenger, non-HH driver	36.1%	40.7%	26.2%	22.0%	23.7%	12.3%	3.9%	3.5%	17.3%
In a taxi	0.3%	1.2%	1.3%	2.9%	3.6%	1.5%	2.2%	4.5%	2.5%
Total trips (weighted)	809.8	1,041.3	691.1	1,324.2	2,264.6	2,161.3	1,839.3	2,166.7	12,298.2
Among vehicle trips, %									
As driver	36.6%	24.1%	27.1%	23.6%	25.1%	18.6%	13.5%	20.2%	24.9%
As passenger, HH driver	4.6%	7.1%	11.3%	10.0%	1.4%	3.7%	18.3%	0.0%	5.8%
As passenger, non-HH driver	57.7%	66.3%	57.4%	57.2%	59.5%	66.8%	42.4%	34.7%	58.3%
In a taxi	0.5%	2.0%	2.8%	7.7%	9.0%	8.1%	23.6%	44.3%	8.6%
Total vehicle trips	507.1	639.3	315.8	508.9	903.1	399.7	167.5	218.7	3,660.0
% of total vehicle trips	13.9%	17.5%	8.6%	13.9%	24.7%	10.9%	4.6%	6.0%	100.0%
% of people	8.8%	10.3%	7.5%	13.9%	20.4%	15.4%	12.6%	11.0%	100.0%

Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in zero-vehicle households who were not out of town.

Figure 6. Average percent of trips using a vehicle among those at each level of density (for three types), by vehicle-ownership group



In the model, the community-type indicators clearly have the greatest effect among non-owners. Including density indicators along with the community-type indicators diminishes the magnitude and significance of the community-type indicators, as does home type (an indicator for detached, single-family home). The density measures conflict with the community-type indicators even more among the higher -ownership segments, perhaps suggesting that density in the immediate area matters more for owners, while the broader neighborhood context matters more for non-owners (or that the effect is small, and harder to have significant coefficients on two related variables capturing a similar effect).

Vehicle use generally decreases with higher transit scores, though once included in the model with other variables it is only significant in the no-car and low-car models. It has a (statistically significant) negative sign, suggesting that even after accounting for attributes that account for the character of the environment in the immediate vicinity of their home (such as the type of home, density of the Census tract, and community type), metro-level transit availability is associated with an additionally diminished probability of vehicle use.

Although a relatively smaller share of urban residents make vehicle trips, because so many people (especially non-owners) live in urban areas – accounting for more than half of all trips made by non-owners– almost a third of all vehicle-trips made by non-owners are among people living in urban areas.

There are also differences in the most likely source of rides in different built environments. Taxis are logically much more common in urban areas, comprising 21.2% of vehicle trips in those areas (versus 5.8% in second city areas, for instance). In suburban areas, a bigger share of non-owner vehicle trips are made with another household member driving (someone else's car), perhaps having to do with typical household composition among those living in the suburban areas, where there are more coupled adult house members, and therefore more chance of making trips with one another, versus areas where a greater share of people live alone. Correspondingly, a smaller percent of suburbanites' vehicle trips are with people outside their household (53.0% of their private vehicle trips, versus about 65% of the vehicle trips made by people living elsewhere). As a share of overall trips, rides from people outside the household are most common among those in town/country areas (38.0% of all trips), followed by second city areas (26.1%), suburban (20.9%), and urban (8.6%).

3.3.4 Specific metro area

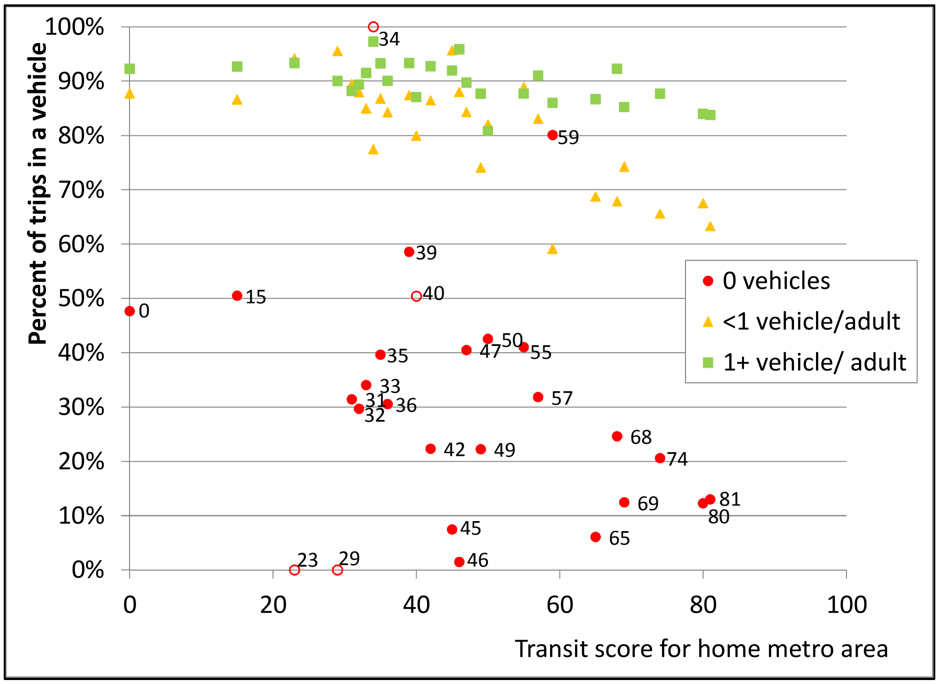
Variations in vehicle use across metro areas perhaps meaningfully reflect the prevalence (or lack) of other alternative means of transportation such as walking and biking. Table 18 lists the transit score for the MSAs for which the data are available, and the percent of trips made by vehicle among the trips reported from that MSA. Figure 7 plots transit score (on the x-axis) versus the percent of trips made in a vehicle (on the y-axis) among each vehicle-ownership group, no-car, low-own, and high-own. Table 18 lists the cities corresponding to each transit score, the percent of trips made by vehicle among the non-car owners in each, and the total trips (that is, the available sample size) for each. (Note several cities with very small sample sizes; those with fewer than 100 cases are indicated with an open rather than closed circle in Figure 7). Considering the plot in Figure 7, cities with seemingly high vehicle use among non-owners relative to their transit score include Dallas and Seattle; cities with seemingly low vehicle use relative to their transit score include Cleveland, St. Louis, and Chicago.

Table 18. Percent of trips made by vehicle among non-owners, by metro area and its corresponding "transit score"

Transit score and corresponding metro area(s)	% of trips in vehicle	Total trips (sample size)
0 =MSA < 1 million (location suppressed)	47.7%	12,097
15=transit score missing for this MSA*	50.5%	3906
23=Raleigh-Cary, NC	0.0%	8
29=Columbus, OH	0.0%	39
31=Tampa-St. Petersburg-Clearwater, FL	31.4%	300
32=Las Vegas-Paradise, NV & Sacramento—Arden-Arcade—Roseville, CA	29.7%	308
33=Austin-Round Rock, TX	34.0%	180
34=Kansas City, MO-KS	100.0%	17
35=San Antonio, TX	39.6%	192
36=Houston-Sugar Land-Baytown, TX & San Diego-Carlsbad-San Marcos, CA	30.5%	725
39=Dallas-Fort Worth-Arlington, TX	58.6%	412
40=San Jose-Sunnyvale-Santa Clara, CA	50.4%	83
42=Salt Lake City, UT	22.3%	317
45=Cleveland-Elyria-Mentor, OH	7.4%	136
46=St. Louis, MO-IL	1.5%	219
47=Buffalo-Niagara Falls, NY & Denver-Aurora-Broomfield, CO	40.5%	423
49=Los Angeles-Long Beach-Santa Ana, CA & Milwaukee-Waukesha-West Allis, WI	22.2%	2312
50=Portland-Vancouver-Beaverton, OR-WA	42.5%	361
55=Pittsburgh, PA	41.0%	329
57=Baltimore-Towson, MD & Miami-Fort Lauderdale-Pompano Beach, FL	31.8%	1099
59=Seattle-Tacoma-Bellevue, WA	80.1%	334
65=Chicago-Naperville-Joliet, IL-IN-WI	6.1%	2533
68=Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	24.6%	1207
69=Minneapolis-St. Paul-Bloomington, MN-WI & Washington-Arlington-Alexandria, DC-VA-MD-WV	12.5%	1195
74=Boston-Cambridge-Quincy, MA-NH	20.6%	1101
80=San Francisco-Oakland-Fremont, CA	12.3%	890
81=New York-Northern New Jersey-Long Island, NY-NJ-PA	13.0%	12,203
Overall	29.8%	42,923

Source: NHTS 2009, v.2.1, trips made by weighted sample of individuals, among adults age 18+ in zero-vehicle households who made at least on trip and were not out of town on the survey day. City is unknown (suppressed in the NHTS dataset) for anyone in an MSA of <1 million; these are assigned a transit score of 0. Transit scores are missing for 20 MSAs with over 1 million in population; these are assigned a transit score of 15 (the U.S. average).

Figure 7. Average rate of vehicle use versus transit score, by vehicle-ownership group



3.3.5 Lifecycle stage, gender, and household roles*

Vehicle use is comparable among people of all ages who have high ownership levels (that is, among those in the high-own segment), at around 91% of all trips (Figure 8). Vehicle use varies more depending on the age of those in low-owning households and non-owning households, though it is important to keep in mind that an individual my move between ownership groups over the course of a lifetime. By contrast, the averages considered here are the behavior of those who are in low-owning households and are of a certain age, cross-sectionally. In general, those who are in low-owning households and younger make a smaller portion of their trips in a vehicle, with increasing rates with age, especially among those over 60. However the overall variation is moderate, ranging from 77.5% (among those age 18-24) to 89.0% of trips (among those in their 80s and older).

Among non-owning households, there is even more variation in vehicle use among those of different ages (Figure 8 and Table 19). As among owners, vehicle use is higher among older people, increasing with age after about age 60. But it is also higher (relative to non-owners of other ages) among those around college-age, age 18-24. There are several possible explanations for this: (1) it may be easier for people this age to find rides and borrow cars than non-owners of other ages; (2) people may hold off to buy a car until after college, so that a portion of people otherwise prone to use vehicles suddenly moves from the non-owning segment to one of the owning segments around age 25, causing a dip in vehicle use among the remaining non-owners age 25+; or (3) a cohort or learning effect, whereby those age 25-29 are more oriented to auto-dependent lifestyle, perhaps informed by their relatively recent experiences as minors in vehicle-owning households. Whatever the cause, the apparent effect is somewhat attenuated in the model (in which the coefficient for this age group does have a smaller magnitude than for the others, meaning less different from the those in their 80s, the reference group, meaning more vehicle use but not by much; see Table 20).

There are also differences in vehicle use among non-owners by gender, with females using cars more frequently than males, at almost every age, though with less difference among the young (in their 20s and 30s) and old (70s and older) (Figure 8 and Table 19). There is a particularly large gap among those of college-age (age 18-24), with non-owning college-age females using vehicles for about half of their trips (50.6%) – more than even the elderly of either gender – compared to 34.9% for males of the same age. Furthermore, comparing total volumes of trips among male versus female non-owners, it appears that females have no fewer total trips (Figure 9), making their vehicle use appear as an overall mobility boost. The gender effect is significant in the model as well, even after accounting for variables such as age, presence of children, employment, residential location, and trip purpose (Table 20). There are no major differences in vehicle use by presence of children or employment, or with either interacted with gender. On average, females with children use vehicles somewhat less than females without, while males with children use vehicles somewhat more, but the difference is small and the effects are not significant in the model, once other factors are accounted for.

There are also gender differences in the means by which non-owners use vehicles at different ages, with males age 18-24 and age 60+ much more likely to make a trip as a driver than are females. There is little gender gap in the incidence of driving among those aged 25-59. Since a disproportionate share of non-owners are female (about two-thirds) and because female non-owners use vehicles more than males, females account for 70.7% of all vehicle trips made by non-owners.

Figure 8. Vehicle use by age, gender, and vehicle-ownership group

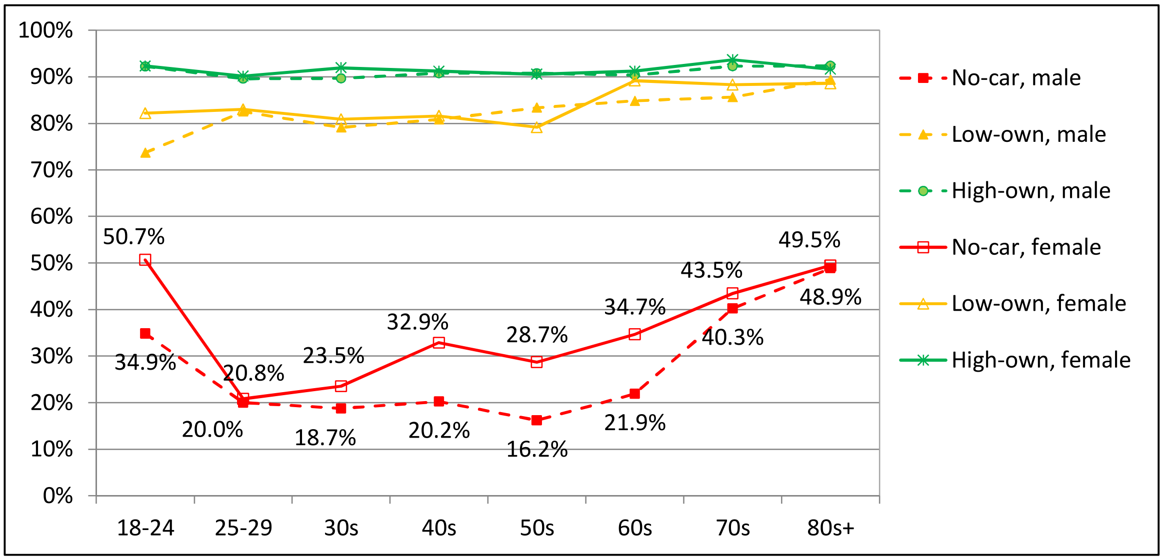


Figure 9. Average daily trip volume, by vehicle and overall, by gender, in no-car households

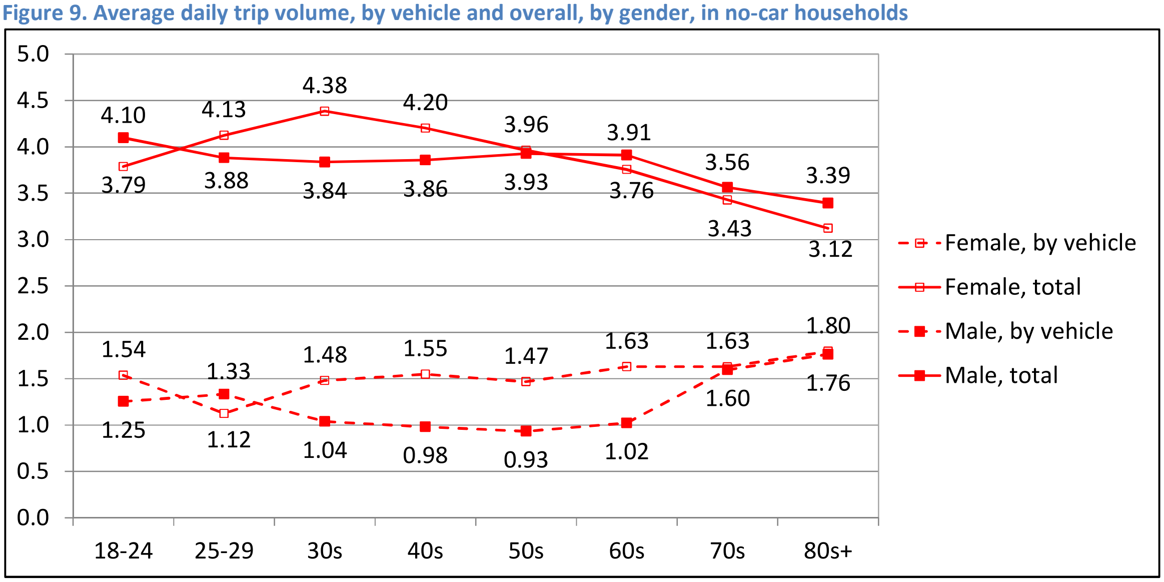


Table 19. Vehicle use and who drove on trips made by non-owners, by gender and age group

	Age group								
	18-24	25-29	30s	40s	50s	60s	70s	80s+	Overall
Among males									
Among all male trips, %									
By any vehicle	34.9%	20.0%	18.7%	20.2%	16.0%	21.9%	40.3%	48.9%	23.4%
As driver	11.6%	5.4%	9.9%	5.7%	5.3%	12.7%	20.6%	5.6%	9.2%
As passenger, HH driver	7.8%	0.8%	0.0%	2.4%	1.5%	0.0%	0.8%	0.1%	1.8%
As passenger, non-HH	15.5%	11.6%	7.1%	9.5%	7.7%	8.3%	11.4%	24.8%	9.9%
In a taxi	0.02%	2.2%	1.5%	1.9%	1.1%	0.9%	4.1%	4.5%	1.5%
Total trips	547.4	369.3	969.3	809.7	813.5	592.0	319.9	146.4	4,567.5
% of total trips	12.0%	8.1%	21.2%	17.7%	17.8%	13.0%	7.0%	3.2%	100.0%
Among male vehicle trips, %									
As driver	33.2%	27.1%	53.0%	28.3%	33.1%	58.0%	51.3%	11.4%	39.0%
As passenger, HH driver	22.3%	4.0%	0.0%	11.9%	9.6%	0.1%	2.0%	0.2%	7.6%
As passenger, non-HH	44.5%	57.8%	38.1%	47.2%	47.9%	37.7%	28.2%	50.6%	42.3%
In a taxi	0.1%	11.0%	7.9%	9.5%	6.9%	3.9%	10.1%	9.2%	6.6%
Total vehicle trips	190.9	73.8	181.7	164.0	130.3	129.6	128.8	71.6	1,070.6
% of vehicle trips	17.8%	6.9%	17.0%	15.3%	12.2%	12.1%	12.0%	6.7%	100.0%
% of males in age group	9.5%	9.3%	14.4%	17.9%	21.5%	12.0%	7.5%	7.9%	100.0%
Among females									
Among all female trips, %									
By any vehicle	50.6%	20.8%	23.5%	32.9%	28.1%	34.7%	43.5%	49.0%	33.5%
As driver	6.0%	5.3%	8.7%	11.2%	4.3%	4.6%	2.4%	1.3%	6.4%
As passenger, HH driver	0.9%	6.9%	2.2%	0.7%	0.7%	0.6%	3.1%	0.5%	1.7%
As passenger, non-HH	41.9%	5.9%	8.3%	17.5%	19.0%	25.6%	32.7%	43.8%	21.7%
In a taxi	1.7%	2.0%	4.2%	3.2%	3.5%	2.5%	4.7%	1.7%	3.1%
Total trips	802.5	630.9	1,632.4	1,365.1	1,083.4	957.9	620.5	638.0	7,730.7
% of total trips	10.4%	8.2%	21.1%	17.7%	14.0%	12.4%	8.0%	8.3%	100.0%
Among female vehicle trips, %									
As driver	11.8%	25.6%	37.0%	34.0%	15.5%	13.2%	5.6%	2.6%	19.0%
As passenger, HH driver	1.8%	33.2%	9.4%	2.0%	2.6%	1.8%	7.0%	1.0%	5.1%
As passenger, non-HH	82.8%	28.5%	35.3%	53.3%	67.8%	73.9%	75.2%	89.3%	64.8%
In a taxi	3.5%	9.7%	18.0%	9.8%	12.5%	7.1%	10.9%	3.5%	9.4%
Total vehicle trips	406.1	131.4	384.1	449.0	304.1	332.0	269.7	312.9	2,589.4
% of vehicle trips	15.7%	5.1%	14.8%	17.3%	11.7%	12.8%	10.4%	12.1%	100.0%
% of females in age group	6.9%	4.5%	14.0%	11.6%	12.3%	15.3%	16.7%	18.8%	100.0%

Source: NHTS 2009, v.2.1, weighted trips by adults age 18+ in zero-vehicle households who were not out of town.

3.3.6 Foreign-born status

On average, the foreign-born in non-owning households, especially more recent immigrants, are less likely to use vehicles than non-owning native-born: those who immigrated within the last ten years make 13.3% of their trips in a car, versus 21.3% among those who immigrated more than ten years ago, and versus 33.1% among the native-born. Even after accounting for factors such as residential location and income in the model, foreign-born status is associated with less vehicle use among non-owners, with no significant effect among the other ownership groups. Among the vehicle trips non-owning foreign-born do make, they are more likely than non-owning native-borns to ride with another household member driving (presumably by borrowing a car), on average, and this rate goes up with time spent in the U.S. They are also somewhat less likely to get rides with people outside their household, a rate which further declines with time spent in the U.S., on average. Overall, immigrants account for 15.0% of the total vehicle trips made by those in non-owning households (while comprising 18.6% of all non-owners, and 13.7% of the overall population).

Table 20. Binary logit model of vehicle use, among three vehicle-ownership segments

	Model results for each ownership segment			t-tests across models		
Explanatory variable	No-car	Low-own	High-own	No vs. low	No vs. high	Low vs. high
Vehicles / adult HH member	n/a	1.993 ***	-0.022	n/a	n/a	0.001
Currently drives (vs. no)	-0.745 ***	1.021 ***	2.321 ***	0.000	0.000	0.035
Ever drove (vs. never)	0.118 *	0.106	0.100	0.967	0.981	0.994
Medical condition (vs. none)	0.326 ***	0.309 ***	0.182	0.929	0.605	0.686
Number of drivers in HH	0.403 ***	-0.229 ***	0.032	0.000	0.213	0.378
Transit score for MSA	-0.004 ***	-0.003 *	-0.001	0.784	0.403	0.635
Community type (ref= Town/ country)	***	*				
Urban	-0.646 ***	0.076	-0.022	0.036	0.134	0.830
Second city	-0.209 *	-0.031	-0.114	0.536	0.768	0.815
Suburban	-0.255 *	0.221 *	-0.198 *	0.085	0.847	0.190
Density of housing (ref=0-99)	***	***	***			
100-499 units/sq mile	0.088	-0.262 *	-0.027	0.174	0.652	0.410
500-999 units/sq mile	0.100	-0.498 ***	-0.027	0.058	0.698	0.188
1,000-1,999 units/sq mile	-0.127	-0.430 *	-0.087	0.372	0.911	0.386
2,000-3,999 units/sq mile	-0.065	-0.509 ***	0.034	0.224	0.807	0.225
4,000-9,999 units/sq mile	-0.189 *	-1.240 ***	-0.323 *	0.013	0.795	0.104
10,000+ units/sq mile	-1.270 ***	-2.027 ***	-1.964 ***	0.130	0.314	0.932
Detached home (vs. other type)	0.277 ***	0.066	0.262 *	0.196	0.941	0.365
Home-owner (vs. rents)	0.438 ***	0.448 ***	0.073	0.954	0.148	0.165
Age group (ref = 80s+)	***	***				
18-24	-0.657 ***	-0.847 ***	0.431	0.620	0.141	0.088
25-29	-0.810 ***	-0.835 ***	-0.276	0.950	0.331	0.331
30s	-0.597 ***	-0.556 ***	-0.422 *	0.902	0.680	0.770
40s	-0.882 ***	-0.501 ***	-0.283 *	0.201	0.114	0.605
50s	-0.805 ***	-0.529 ***	-0.018	0.296	0.024	0.187
60s	-0.473 ***	-0.118	0.041	0.163	0.125	0.671
70s	-0.240 ***	0.080	-0.182	0.203	0.862	0.483
One adult in HH (vs. more)	-0.026	n/a	-0.178	n/a	0.656	n/a
Number of adults in HH	-0.054	0.055	0.354 *	0.535	0.278	0.417
Has children	-0.051	0.390 ***	0.129	0.145	0.587	0.410
Female	0.302 ***	0.073	0.164 *	0.149	0.435	0.642
Female AND children	0.146	-0.309 *	0.224 *	0.194	0.840	0.166
HH income per adult	0.005 *	-0.005 *	0.001	0.090	0.422	0.347

	Model results for each ownership segment						t-tests across models		
Explanatory variable	No-car		Low-own		High-own		No vs. low	No vs. high	Low vs. high
Education (ref= < high school)		***		*		***			
High school graduate	-0.167	*	0.234	*	-0.286	*	0.058	0.760	0.213
Some college or Assoc.	-0.235	***	0.076		-0.327	*	0.170	0.816	0.340
Bach. degree	-0.464	***	0.028		-0.685	***	0.071	0.595	0.104
Grad. or Prof. degree	-0.675	***	-0.240	*	-0.800	***	0.156	0.776	0.215
Employed (vs. not working)	-0.097	*	0.341	***	-0.264	*	0.015	0.411	0.005
Foreign-born (vs. native-born)	-0.329	***	-0.313	***	-0.207	*	0.939	0.651	0.702
White (vs. any other race)	-0.189	***	-0.143	*	0.046		0.785	0.314	0.465
Hispanic (vs. non-Hispanic)	0.045		0.354	***	-0.316	*	0.174	0.219	0.033
Number of net daily trips	0.157	***	0.107	***	-0.006		0.285	0.001	0.025
Number of trips on tour	-0.180	***	-0.200	***	-0.179	***	0.806	0.991	0.821
Time of day (ref=10am-7pm)		***		***					
5:00am-9:59am	-0.376	***	-0.665	***	-0.218	*	0.099	0.430	0.039
7:00pm-11:59pm	0.441	***	0.076		-0.161	*	0.116	0.017	0.403
12:00am-4:59am	1.494	***	0.187		-0.062		0.125	0.039	0.774
Weekend (vs. Mon, 5:01am - Friday, 5:59pm)	0.201	***	0.261	***	-0.082		0.689	0.086	0.065
Trip purpose (ref=home)		***		***		***			
Go to work, non-manual labor occupations	0.077		0.574	***	0.818	***	0.147	0.051	0.522
Go to work, manual labor	1.393	***	1.246	***	0.580	*	0.813	0.170	0.360
Go to religious activity	0.674	***	0.835	***	1.647	***	0.760	0.203	0.342
Medical/dental services	0.639	***	0.691	***	2.276	***	0.892	0.107	0.133
Shopping/errands	0.136	*	1.050	***	1.371	***	0.000	0.000	0.309
Get gas	1.178	*	19.715		19.040		0.997	0.997	1.000
Gym/exercise & pet care	-1.794	***	-2.543	***	-2.452	***	0.037	0.064	0.751
Other social/recreational	0.464	***	-0.227	*	-0.218	*	0.005	0.012	0.976
Family personal business	0.535	***	0.075		0.938	***	0.244	0.475	0.159
Transport someone	1.303	***	1.934	***	1.598	***	0.224	0.626	0.613
Get/eat a meal	0.739	***	0.422	*	0.432	*	0.326	0.394	0.980
Other activity	-0.734	***	-0.339	*	-0.256	*	0.309	0.234	0.829
Constant	0.184		0.411	*	0.145		0.706	0.971	0.809
Model statistics									
Total N	3,799		3,799		3,799				
Observed, no vehicle	2,285		539		325				
Observed, vehicle used	1,514		3,260		3,474				
% correct, among true 0's	79.9%		26.2%		17.5%				
% correct, among true 1's	60.6%		97.9%		98.8%				
Overall % correct	72.2%		87.8%		91.9%				
K	55		55		56				
$\mathcal{L}_{\mathrm{R}}$	-2,554.5		-1,551.4		-1,109.8				
$\mathcal{L}_{\mathrm{F}}$	-2,072.5		-1,234.8		-899.4				
$\mathrm{R}^2_{\mathrm{MF}}$	0.189		0.204		0.190				
$\mathrm{R}^2_{\mathrm{MF_{adj}}}$	0.167		0.169		0.139				
AIC	7.127		38.502		46.607				
BIC	7.532		40.312		48.947				
CAIC	7.624		41.132		50.313				
QIC	7.681		43.439		54.871				
χ2-statistic = -2*($\mathcal{L}_{\mathrm{R}} - \mathcal{L}_{\mathrm{F}}$)	964.0	***	633.1	***	420.6	***			
Pearson deviance statistic	3,949.0		3,784.9		3,592.2				
Dispersion parameter	1.055		1.011		0.960		0.097	0.002	0.056

$\mathcal{L}_R$ is the log-likelihood for a "restricted" intercept-only (market share) model and $\mathcal{L}_F$ is that for the full model (as specified here). Formulas for all fit statistics are as shown in the appendix to Chapter 4, section 4.8.4. Significant values are indicated for p <0.20 (.), < 0.10 (-), <0.05 (*), <0.01 (**), or <0.001 (***).

3.4 Summary and conclusions

This chapter provides a descriptive overview of the incidence of vehicle trips among non-vehicle-owners, and the sorts of circumstances in which they are most common. Partly reflecting who comprises the non-owner segment, the vast majority of non-owner vehicle trips are made by those in very low-income households. Almost half are made by people who do not themselves drive; perhaps surprisingly, for another quarter the subject was himself or herself the driver. While the incidence of vehicle use is much greater in lower-density and town/country environments, because so many non-owners live in cities, about half of non-owner vehicle trips are made by residents of urban and second-city neighborhoods. About a third are made by people over age 60, but a disproportionate share are made by young adults (18-24), especially females getting rides and males driving other people's cars.

A gender difference among young adults is apparent in most age groups, with females making a greater share of their trips by car than males do, on average, with more equal rates only among ages 25-29 and the elderly. Furthermore, among the vehicle trips they make, females are much more likely to get rides with people outside their household, on average, while males are more likely to drive someone's car. It is unclear why this is the case or if it is meaningful, but suggests differences in the proclivity to access vehicles as drivers versus as passengers among non-owners, and perhaps the extent to which the exchange is mediated through social connections. If women are more social or engaged in more activities where shared rides are sensible, they might be more likely to carpool; conversely if women are unable, more reticent, or face barriers to driving, they may shy away from driving as much as men do; or men may be more often in circumstances in which driving is necessary, such as a part of work duties that differ, on average, from women's. Whatever the cause, females make *more* trips overall than males, suggesting that vehicle travel adds more to their mobility than it does to males'. The gender effect (on the probability of vehicle use among non-owners) appears significant, even after accounting for other demographic factors that may differ by gender in the model.

Several differences across ownership groups have social implications. First, the evening hours (around 8-10pm) appear to be a time for cross-segment mode choice, that is, using modes of transportation potentially contrary to one's ownership segment: all else equal, non-owners appear somewhat more likely to find rides during this time, while owners are more likely to get out of their cars. There also may be some differences in the proclivity to travel with others and/or bring people along while traveling by vehicle, and also to make stops along the way (though direction of causality is difficult to tell from this analysis). These may have implications for the extent of chance encounters verses pre-planned destinations. Trip purposes with higher incidence of rides from outside the household, on average, tend to be for highly social activities: social/recreational and religious activities. Interestingly, there is less of this travel among suburbanites in general, who may have more within-household activity. The fact that driving (oneself) as a non-owner is most common in town/country areas, followed by suburban areas (and much less in urban areas), may suggest something about the difficulty of coordinating rides with others in these environments.

Variables emerging as potential indicators of choice include educational attainment, home-ownership, and driver status, more so than income, at least among non-owners. In particular, even after accounting for trip purpose, residential location, and other demographic attributes of respondents, less education, renting, and not driving are associated with *more* vehicle use. These may indicate hardships – barriers to learning to drive or barriers to obtaining other tangible resources that result in a particularly dissonant environment (whereby paradoxically vehicles are especially needed) and/or the inability to access alternative modes of transportation. On the other hand, the ability to find rides might be a reason to forego learning to drive.

Several differences in non-owners' vehicle-use patterns vis-à-vis owners would seem to reveal differences in the quality of their experience, on average. For instance, non-owner's vehicle travel (and in fact all modes of travel) is slower on average than owners', especially when getting rides from outside the household. While some of the difference may relate to residential locations (and the amount of freeway driving on a typical trip) as well as typical trip purposes, it could also reflect the general inefficiency of getting rides as a non-owner. The significant differences across segments in the probability of using vehicles for shopping trips and, especially, medical trips seem to show that if someone could use a car for those trips, they would. (In particular, the results indicate that the high-own households especially would – even after accounting for differences in the built environment, age, and other factors; the fact that model shows that non-owners would not, as much, may be evidence of constraint). The high incidence of taxi use only for medical trips among non-owners seems to also suggest some amount of urgent need in that context.

However, a limitation of examining trip-making patterns alone is that we have no way of knowing how well people are satisfied by what they have done – that is, where non-owners would lie on the spectrum ranging from abject unmet need, to making do, to prospering. Chapter 4 and 5 focus on trying to determine whether the sorts of vehicle travel used by non-owners – together with their non-vehicle travel — sufficiently meets their needs.

4 A method for estimating benchmark mobility levels

The purpose of this chapter is to develop a means of predicting a reasonable benchmark of behavior, to which the actual behavior of low-car households can be compared. The implication is that a certain amount of mobility would be desirable, and the degree that it is fulfilled, is a reflection of an individual's overall welfare.

The underlying reason I am interested in mobility is that activity participation is an important component of well-being and life satisfaction, and some activities are necessarily outside the home, requiring travel to reach them. Activities inside of the home are also important, as is the mix of different types of activities, some substitutable and others not, both in and outside the home. By focusing on travel behavior, I am inherently focusing on out-of-home activities, as just one component of overall life satisfaction.

What is a reasonable benchmark for participating in activities outside the home? Simply comparing the activity of those in zero-car households to those in car-owning households may be misleading, because of a variety of other ways the two groups differ. However, if some of those differences can be accounted for, it could help in better identifying sufficient activity levels. Specifically, I make the assumption that much of the difference between the two groups can be accounted for by demographic attributes and geographic location. After accounting for these, I can better isolate the role of vehicle ownership itself in enabling mobility.

While everyone faces constraints affecting their travel, such as time, money, and the laws of physics, I am interested in isolating the constraint imposed by not owning a car. I use a modeling strategy based on the premise that the behavior of those with "unlimited" access to vehicles demonstrates how people would behave without this constraint, all else equal. I presume that within this full-access group, people face a variety of other constraints that affect their behavior, as well as variations in preferences that motivate their travel. The outcome of these constraints and preferences is some set of representative travel patterns that serve as a benchmark, and which I presume to vary systematically by individuals' demographic attributes and geographic environments. To the extent that these travel patterns do vary systematically, I can develop a model that uses the actual travel (of those with unlimited vehicle access) to predict hypothetical travel (of everyone else in the absence of vehicle-related constraints), based on demographic and geographic attributes. This might be thought of as an estimate of the latent demand for out-of-home activities, in the absence of vehicle-related constraints, for a given demographic profile, or a benchmark of mobility levels.

The ultimate goal is to use this benchmarking model to evaluate the well-being of those who don't own cars or whose access to cars is limited (in Chapter5). Specifically, I will apply the model to generate an estimate of the hypothetical (latent) demand for travel for each individual (in the absence of vehicle-related constraints), based on their demographic and geographic attributes. I compare this hypothetical prediction to their actual behavior, as an indication of the extent of fulfillment of their latent demand. A discrepancy between the actual and predicted values , in particular if the actual activity level falls short of the predicted level, theoretically offers evidence of (and an estimate of the magnitude of) the constraint experienced as a result of lack of vehicle access for a given individual . On the other hand, if actual and predicted values are close, it offers evidence that vehicle access (or lack thereof) poses little constraint. This of course hinges on the assumption that there are no other systematic differences between those with "unlimited" vehicle access and everyone else, which may or may not be true, discussed more in Chapter 5.

This overall strategy will be more effective the more accurately I can predict activity levels as a function of demographic and geographic attributes. The rest of this chapter describes the development of this predictive model. In particular, discussed below is: how to identify whose access to vehicles is "unlimited;" how to measure the extent of out-of-home activity (the dependent variable in the model); the distribution of the dependent variable and alternate modeling frameworks I might use to represent it; and finally, the specification of a "best" model and assessment of its performance.

4.1 Definition of a group with "unlimited" vehicle access

The goal is to identify a group of people whose travel choices are not likely to be limited by the inability to use a car for a given outing. Logical criteria are that they drive and own a car.[7] In addition, it seems important to account for the number of cars in households with multiple people, to distinguish between those who have to negotiate and compromise over use of shared vehicles versus those who can use one basically whenever they want. Common measures used by other researchers are the ratio of vehicles to household members (of all ages), or to adults (e.g. Delbosc & Currie, 2012), workers (e.g. Chu, 2012), drivers (e.g. Anggraini, Arentze, & Timmermans, 2008; Scheiner & Holz-Rau, 2012), or driving-age household members (e.g. Blumenberg & Smart, 2010).

As shown in Table 21, there are large differences in the portion of households with one or more vehicles per person of all ages including children, versus per adults, drivers, or teens plus adults: only 55.6% of households have 1 per person (all ages), and 92.1% of these are households with no children (among households with any children, only 14.0% have one vehicle per person of any age) and 41% are people living alone. Many households have one vehicle per driver (80.2%), and for most of these (93.3%) this also means one per adult. However, 11.7% of car-owning households have some non-driving adult household members. Limiting the criteria

[7] Throughout, I use "car" and "vehicle" interchangeably to mean any type of privately owned vehicle, including cars, motorcycles, vans, RVs, pickup trucks, other trucks, but excluding light electric vehicles, such as golf carts or electric-assist bicycles.

to households with one vehicle for every adult, whether or not they are drivers, reduces the qualifying share to 74.8% of all households.

The handling of teen drivers makes only a small difference for the overall sample because they are such a small minority of the population: about 5.5% of households have any driving-age teens. Among these households, however, it makes a big difference in how vehicles are counted: 79.4% of them have one or more car per adult, but only 42.9% per person over age 16 (including driving and non-driving teens; see Table 21). This seems too restrictive a criterion, since only 60.3% of households with driving-age teens have teens who drive. While potentially endogenous, I opted for the compromise of only counting teens who drive as potential vehicle users. Among households with any driving-age teens, 61.8% meet this criterion – one vehicle per adult plus teen driver (or equivalently, one per person but excluding minors *if* they do not drive).

Table 21. Percent of households owning one or more vehicles per person, defined in different ways

1 or more vehicles per type of person:	Type of household: All households	Households with any 16- or 17-year-olds	Households with any 16- or 17-year-olds who drive
Per person (all ages)	55.6%	27.4%	38.7%
Per adult (18+)	74.8%	79.4%	89.6%
Per member 16+	72.8%	42.9%	60.7%
Per driver (any age)	80.2%	69.3%	62.1%
Per adult plus teen driver	73.5%	61.8%	60.4%
Weighted N (households)	150,147	8,288	4,998
% of total households	100.0%	5.5%	3.3%
% of households with any 16- or 17-year-olds		100.0%	60.3%

Source: 2009 NHTS version 2.1, weighted sample of households (using a version of WTHHFIN that is a redistribution weight rather than an expansion factor; the total sample size remains the same but portions change).

Because counting children (having one car for every person, even children) seems overly restrictive – the households fulfilling this criteria might be aberrant and different from the mainstream — and because children have less autonomous activity (typically at least somewhat dependent on their parents), I exclude them from the ratio I use to identify “unlimited” ownership levels. Rather, I opt to count all of the autonomous household members who might lay claim to the car, including teens if they drive, as well as all adults, whether or not they drive.

The rationale for including non-driving adults is that they have autonomous transportation needs regardless of their driver status. Having extra non-driving adults in the household might put demands on the household vehicles(s) and so access to vehicle transportation for the remaining (driving) household members should not be considered unlimited in their presence. (By contrast, I assume the travel of non-driving minors would be accommodated as part of their parents'.)

The final criterion, that individuals themselves drive, affects only a small minority of cases, given the ownership criteria already established. Almost all (98.1%) of the adults in households that qualify with respect vehicle ownership do drive (Table 22). However, 1.9% of adults in these households do not, and are excluded from the "unlimited" category. By contrast, only 76.0% of those in households owning fewer cars and 45.0% of those with no cars drive, with 99.6% and 57.7% living with someone else who drives, in the fewer- and no-car households, respectively.

Among those that do drive in the higher ownership group, there is an additional minority (6.1%) who answer affirmatively to having "a condition or handicap that makes it difficult to travel outside of the home," including 0.4% who indicate that they have "given up driving" because of the condition (see Table 23). However because these respondents are coded as drivers, either because they actually drove on the survey day and/or self-identify as current drivers, I retained them in the group considered to have "unlimited" vehicle access (comprising n=1,385 out of a total N= 204,265, unweighted, in this subsample). By being included, they serve to represent the mobility levels that are likely among people burdened by such conditions but *with* vehicle access, which seems important for then contrasting this to the mobility levels of those with such conditions but *without* vehicles.

Table 22. Percent of individual adults who drive, by household vehicle ownership level

		Ownership level		
	Overall	None	Fewer	More
Drives	89.3%	45.0%	76.0%	98.1%
Does not drive	10.7%	55.0%	24.0%	1.9%
Someone drives	97.0%	57.7%	99.6%	99.7%
No one drives	3.0%	42.3%	0.4%	0.3%
Weighted N	244,928.2	15,642.3	59,758.5	169,527.4
Percent of total weighted N	100.0%	6.4%	24.4%	69.2%

Source: 2009 NHTS version 2.1. Among individuals, weighted, and only including adults (age 18+). "More" includes households with one or more vehicles per person excluding non-driving minors; "fewer" includes households with at least one vehicle but fewer than the total number of adults (driving and non-driving) plus teen drivers in the household.

Table 23. Percent of individual adults with limiting medical conditions, by household vehicle ownership level

		Ownership level		
	Overall	None	Fewer or does not drive	More and drives
No limiting condition	89.5%	67.9%	83.2%	93.9%
Some medical condition makes travel hard	10.5%	32.1%	16.8%	6.1%
Condition results in giving up driving	3.5%	19.3%	7.8%	0.4%
Weighted N	250,789.0	15,892.8	64,114.0	170,782.2
Percent of total weighted N	100.0%	6.3%	25.6%	68.1%

Source: 2009 NHTS version 2.1. Among individuals, weighted, and only including adults (age 18+). "More" includes households with one or more vehicles per person excluding non-driving minors; "fewer" includes households with at least one vehicle but fewer than the total number of adults (driving and non-driving) plus teen drivers in the household.

In summary, I defined three levels of access as shown in Table 24. The "unlimited" (high-access) segment is used as the basis for the benchmark model. About 67.9% of adults meet the criteria for this high-access segment, and about 72.5% of households have at least one person who meets the criteria.[8]

[8] These portions are for the weighted sample, to give a sense of what the shares are likely to be in the general population. I used the weights provided by the NHTS for this purpose, applied separately per person (using WTPERFIN) and per household (using WTHHFIN).

Table 24. Definition of three vehicle-access levels and their portion of the sample

Level	Description	Percent of weighted sample		Number of unweighted cases	
		People	Households	People	Households
High	Individual drives, and lives in a household with at least one vehicle per person (excluding non-driving minors, but including minors who drive as well as all adults, whether or not they drive)	67.9%	72.5%	198,448	119,659
Medium	Individual lives in a household with plenty of vehicles, but does not drive; or lives in a household with at least one vehicle, but with more adults or drivers than vehicles (and may or may not drive)	25.7%	18.8%	49,365	23,283
Low	Individual lives in a household with zero vehicles; may or may not drive	6.4%	8.7%	8,765	7,205
Total		100.0%	100.0%	256,578	150,147

Data are from the 2009 NHTS version 2.1. All counts exclude respondents out of town on the survey day. The people counts are for all individual adults (excluding children), potentially including multiple members from the same household. Household counts reflect the level of the highest-access member among everyone in the household (that is, categorized as "high" if at least one individual has high access, but "medium" only if the highest level of access among anyone in the household is "medium"). The unweighted counts show the number of cases available that meet the criteria for each access category. Weighted portions are for data weighted to make the sample representative of the U.S. population as a whole, using weights provided by the NHTS (WTPERFIN for individuals and WTHHFIN for households.)

4.2 Definition of "net" trips as a measure of out-of-home activity level

With the move toward activity-based behavioral models in the field of transportation research, there have been a variety of ways of accounting for activity participation, such as whether a respondent engages in particular types of activities deemed important or representative; or the range and mix of activities engaged in; or the time spent on particular types of activities. In this analysis, I use the volume of trips (that is, number of addresses visited) to represent overall volume of activity. Respondents reported all their activity for a single 24-hour period, collectively scattered over every day of the week. The NHTS measures trips as any time a person goes from one address to another, by any means of transportation. The more addresses someone visits, the more trips are recorded. Although this is a coarse measure of the extent of participation in activities, and does not distinguish between different types of activity (e.g. different trip purposes) — counting all activity outside the home, any movement between addresses, equally – this simplification will not matter to the extent that it impacts vehicle-owners and non-owners in the same way. By contrast, mobility measures based on miles of travel would favor vehicular travel and is less connected to the derived purpose of the travel. That is, more distance to a single destination does not reflect a greater level of activity-engagement, whereas visiting more destinations, regardless of the distance, does. In this way, trip volume is a more accessibility-oriented accounting of respondents' travel.

Although the NHTS collects data for people who are traveling out of town (as long as it is within the United States), in order to focus on more typical behavior, I excluded respondents who were out of town on the travel day, which is 1.9% of weighted sample.

As recorded in the NHTS data, trips tend to occur in pairs, especially for home-based trips. That is, when someone leaves the house, they usually return home later. These are counted in the data as separate trips. But from the perspective of decision-making, they are not independent; one implies the other. In order to focus on the series of independent choices a person makes as they go places throughout the day, I decided to exclude the trips whose purpose was coded as returning home or returning to work, comprising 34.4% and 1.5% of all trips, respectively (in the weighted trip file), or an average of 36.9% and 1.3% of a given person's total daily trips (among the weighted sample of adults who made at least some trips and were not out of town on the survey day; see Table 25). While there may be other non-independent pairs of trips that are not based from home or work, they are probably more rare. The remaining trips, which I am calling "net" trips, range in number from 0 to 25, with an overall average of 2.52 trips per person (among the weighted sample of adults not out of town on the survey day) or 2.89 among those who made at least some trips.

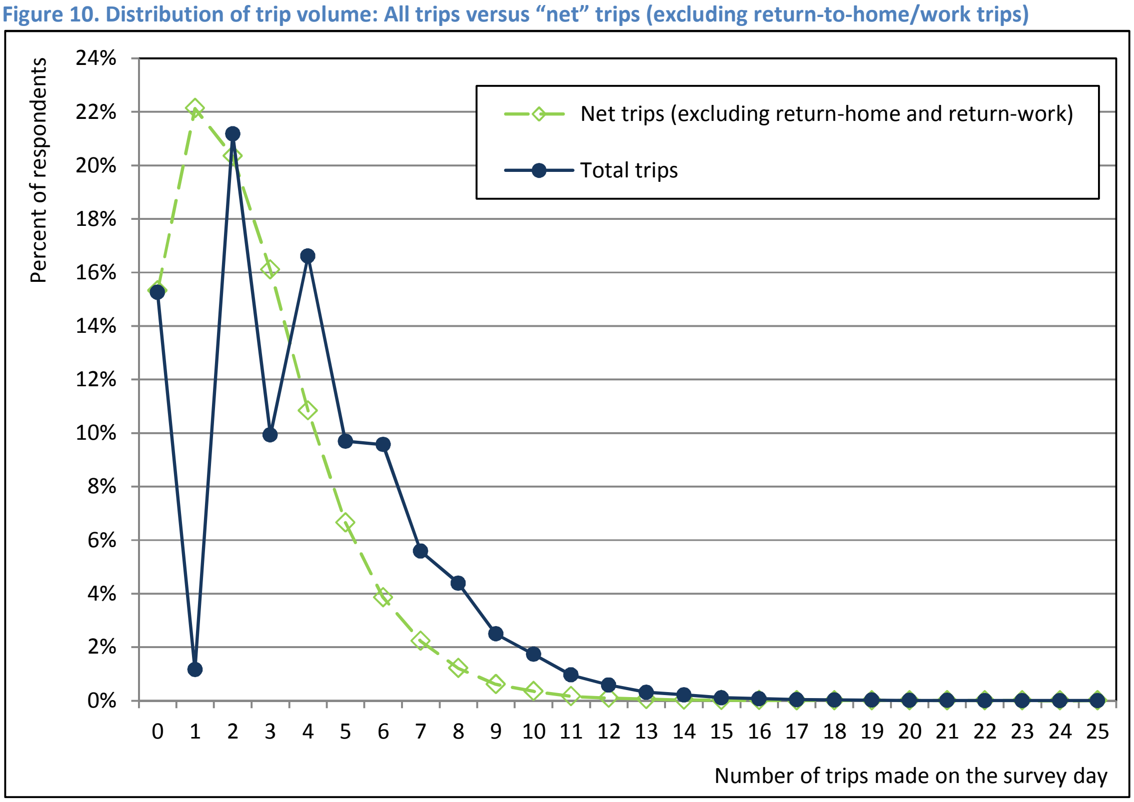
Table 25. Daily trip volume by purpose type: all, return-home, return-to-work, and net

	Volume of trips			Average % of each person's trips, among those making any
	Min.	Max.	Mean	
All	0	27	3.96	100.0%
Return-home	0	11	1.36	36.9%
Return-work	0	8	0.07	1.3%
Net (excluding return-home/work)	0	25	2.52	61.7%

Source: 2009 NHTS version 2.1. Weighted sample of individuals, among 18+, excluding those out of town on the survey day.

Figure 10 shows the overall distribution of trip counts in the sample, with and without the return-home/work trips (data are for the unweighted data set, with one qualifying adult selected from each household). When the return trips are included, the shape of the distribution is spikey, reflecting the prevalence of roundtrip pairs and favoring round numbers of trips; excluding them is effective in smoothing the curve.

Figure 10. Distribution of trip volume: All trips versus "net" trips (excluding return-to-home/work trips)



Source: 2009 NHTS version 2.1. Among individuals age 18 and over, unweighted, with one person randomly selected from each household, excluding respondents who were out of town on the survey day (N=146,347).

4.3 Factors theoretically affecting the volume of "net" trips

As mentioned, actual volume of activity is the result of the balance of preferences (needs and desires) and the ability to fulfill them subject to constraints, such as time, money, and laws of physics. Even those with theoretically unlimited access to vehicle transportation still face some of these other constraints, to varying degrees, in addition to varying needs and desires. Within this group, who would be expected to have higher levels of trip making, that is, more need, desire, and/or ability to engage in activities outside the home?

It is somewhat difficult to consider this without distinguishing between different types of activities. For instance, those who are employed full-time make more trips to work, but not necessarily more overall trips. As travel behavior researchers have moved toward activity-based models of behavior, they have examined different types of activities more closely — conducted both inside and outside of the home — some of which result in travel, depending on the geographic context, intra-household negotiations, and other factors. Thus, the overall volume of trips is a muddied mix of trips for all purposes and complexities of activity-chains, including trips relating to work, errands, socializing, exercising, transporting others, or visiting the doctor. The diversity of activities it represents, as well as the fact that sociodemographics influence both the type of activities people engage in as well as their ability to fulfill them (Lu & Pas, 1999), makes the potential predictors of overall trip volume less clear. However, likely factors include the following.

Economic status. All else equal, higher incomes, more education, and other correlates of class membership enhance the ability to fulfill preferences, due to ability to spend money on "mobility resources," such as gas, train passes, taxi rides, and other opportunities, in addition to greater ability to devote time and money on activities such as shopping, recreation, or other leisure outside the home.

Lifecycle stage. The mix of activities filling one's day changes over the course of a lifetime, some of them resulting in more out-of-home activities and others resulting in less. In general, less trip-making is expected among the elderly, as a result of fewer activities as well as mobility constraints (e.g. Rosenbloom, 2007; Transportation Research Board, 2004). Other trends may relate to career stage, marital status, or child rearing (e.g. Zimmerman, 1982).

Household roles. The division of labor within households affects each person's mix of activities, including work, errands, and time at home (Srinivasan & Bhat, 2005). Related factors whose impact may vary depending on household-role context include employment status, type of occupation, number of other workers or adults in the household, as well as the presence and age of any children. For instance, evidence suggests that regardless of employment status, women tend to engage in more household-maintenance activities resulting in more trip-making and more complicated trip-chain patterns (this would result in more "trips" but not necessarily more miles) (e.g. Rosenbloom & Burns, 1993; Taylor & Mauch, 1998; Bianco & Lawson, 1998).

Disability and age. Any sort of personal disability would likely reduce trip-making, due to its effect on the ability to travel as well as the ability or desire to participate in a variety of activities (e.g. Transportation Research Board, 2004; Páez et al., 2007; Farber & Paez, 2012; Hough, 2007; Ziems, Konduri, Sana, & Pendyala, 2010; Titheridge, Achuthan, Mackett, & Solomon, 2009; Rosenbloom, 2007; Marston & Golledge, 2003).

Built environment. The built environment might affect trip volumes by offering activity opportunities (such as shopping, recreational, or work opportunities) or in the ease of using the transportation system (by whatever mode). Better transportation would enable trip-making, while any barriers – long distances, long travel times, congested conditions – could inhibit trip-making. However, the overall effect by type of environment is not obvious. For instance, rural areas might have longer distances but less traffic. Major cities might have more congestion, but also better opportunities for alternative modes. A greater overall density of destinations could theoretically enable more efficient trip-chaining (and fewer overall trips) or less incentive to trip-chain efficiently due to shorter average trip distances (and more overall trips). Different types of communities may be conducive to participation in a different mix of activities. For instance, urban areas with cultural activities and smaller living spaces may be conducive to more out-of-home activity, while rural communities with fewer out-of-home happenings and larger private homes might invite more in-home activity. Empirical evidence suggests little overall effect, however. For instance, despite differences in distances traveled, Næss (2006) finds only modest differences in activity frequencies between residents of inner versus outer areas of the Copenhagen metropolitan area, which tend to outweigh each other. Similarly Bhat and Srinivasan (2005) find that despite differing levels of auto ownership, urban form characteristics had no effect on the weekend activity participation among residents near San Francisco, CA, which the authors theorize is due households self-sorting into neighborhoods that accommodate travel by different modes. In their review (2001) and meta-analysis of literature to date (2010), Ewing and Cevero also conclude that distance and mode are more affected by the built environment, while frequency is relatively inelastic.

Seasonal affects and day of the week. People engage in a different mix of activities on weekends and weekdays, with overall less trip-making on weekends on average (e.g. Yamamoto & Kitamura, 1999). There may be additional differences on Saturday versus Sunday relating to religious activities or availability of opportunities such as shopping. On weekdays, there is greater volumes of activity midweek versus at the beginning and end of the week.

Taste and culture. Taste variation can be a catch-all for any unexplained variation in consumer behavior. In travel behavior research, when efforts have been made to capture factors such as lifestyle and attitudes, they appear to be important determinants (e.g. Kitamura, 1988; Choo et al., 2004; Ory & Mokhtarian, 2005). In addition, the role of prior experience and habit affects choices such as auto ownership (e.g. Weinberger,2010) and travel more generally (e.g. Gärling & Axhausen, 2003, and other articles in that issue). While not measured directly in the NHTS dataset, differing cultural experiences may correlate with available variables such as race, ethnicity, foreign-born status, and region of the country.

Table 26 summarizes factors measures available in the NHTS to capture factors influencing overall trip volumes.

Table 26. Available measures to serve as predictors of mobility demand

Factors theoretically affecting mobility demand	Related measures in the NHTS dataset
Economic status	• Household income • Home-ownership status • Educational attainment • Occupation of household workers • Vehicle ownership
Activity types	• Employment status • Occupation category • Factors relating to household roles
Household roles	• Household size • Presence, number, and ages of any children • Gender
Lifecycle stage	• Age • Presence of children or spouse • Employment status
Cultural factors	• Race • Hispanic • Foreign-born status and years since immigrating • Community type (town/country, suburban, urban, second city) • Region of the country
Physical ability and mobility resources	• Number of vehicles owned • Number of drivers in the household • Limiting medication conditions • Conditions resulting in particular outcomes • Age
Opportunity for activity in the built environment	• Density (people, housing units, employees) • Community type (town/country, suburban, urban, second city) • Home type (detached single house, etc.)
Opportunity for mobility in the built environment	• Transit score for home MSA • Community type (town/country, suburban, urban, second city) • Home type (detached single house, etc.)
Day of the week	• Day of the week

4.4 Distributional form of the dependent variable

Focusing on net trips (the green dashed line in Figure 10), about 15% of the sample made zero net trips, meaning they stayed in the same place all day (or, in very rare cases, made only a return-home and/or return-work trip without having gone to home and/or work within the same 24-hour reference period; this rare situation is just 0.3% of those with zero net trips and 0.05% of the overall sample). About 22% made one net trip, with a decaying incidence of people making successively higher numbers of trips.

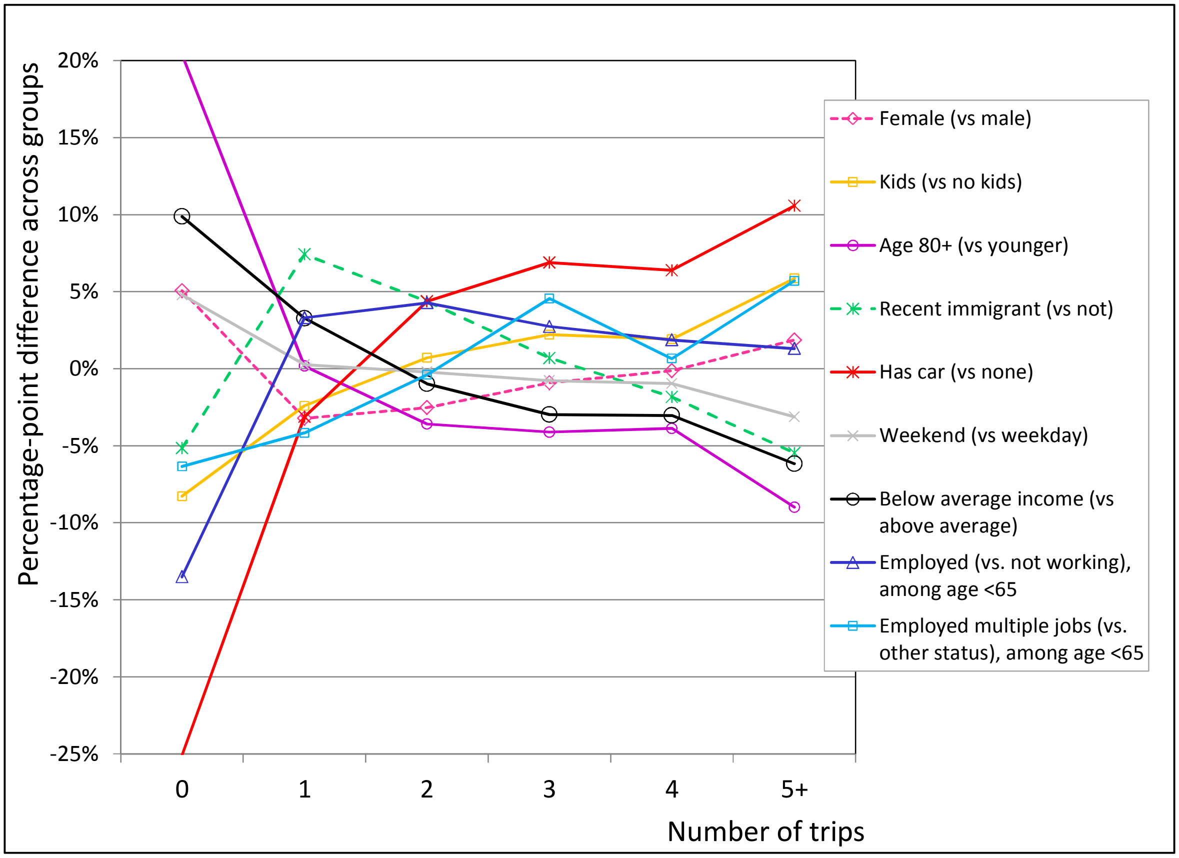
In considering the form of the dependent variable, and what sort of process it represents, there may be an important distinction between the phenomena of any trips (versus zero) and the phenomena of successively higher numbers of trips. This is for several reasons. First, once out of the house, there may be increased propensity to make additional trips along the way. (That is, crossing the threshold from 0 to 1 might be more difficult, psychologically or logistically, than increasing from 1 to 2 or from 2 to 3, given 1.) Second, the sorts of activities that tend to draw someone out of the house at all, such as work, school, and household maintenance activities, are likely to generate even more activity. (So, those engaging in any travel at all are those most likely to make higher numbers of trips, again resulting in a perhaps discontinuous continuum from 0 to 1 trip, versus successively higher numbers of trips.) Finally, certain personal attributes and circumstances may differently influence the probability of making any trips versus the proclivity for successively higher numbers of trips. For instance, on average, women are less likely to get out of the house, but when they do, they are more likely to make more trips (that is, move between more addresses) than are men. This would be difficult to capture in a single model, since it essentially implies there is a different effect of being female (for instance) at different levels of the dependent variable.

For a heuristic, visual representation for a handful of attributes that may influence trip-making, Figure 11 shows the difference of the apparent effect of each attribute on the dependent variable between 0 and 1, versus successively higher values. (Note that these only capture the bivariate relationship between a given variable and number of trips — not controlling for other explanatory variables or capturing any interaction effects that might indeed matter.) The y-axis measures the percentage-point difference across groups (for instance, females versus males) for each level of trip-making (on the x-axis). If a factor were consistently associated with more trip-making, there would be a straight line with a positive slope (the percent of 0's would less and the percent of 4's and 5's would be more).

There are relatively straight lines for some variables. For instance, having children is consistently associated with more travel: Among those with kids, the percent making 0 trips is about 8 percentage-points fewer; making 1 trip is 2 points fewer, making 4 trips is 2 points more, and making 5+ trips is 6 points more. Similarly, lower incomes are associated with less travel: Among those with below-average income (those whose household income per adult household member is less than the sample average), the percent making 0 trips is about 10 points more, making just 1 trip is 3 points more, making 4 trips is 3 points less, and making 5+ trips is 6 points less.

By contrast, for other variables, there are unusal elbows at 1, in some cases reversing the slope of the curve altogether, such as for females (versus males), recent immigrants (who arrived with the last 5 years versus longer ago or native-born), and employment (versus not working). Females are more likely to make 0 trips than are men, but then less likely to make 1 trip, and more likely to make successively higher numbers of trips above 1. Recent immigrants are much less likely to make 0 trips, but then less likely to make successively higher numbers of trips above 1. Employed people are much less likely to make 0 trips, but then not successively higher numbers of trips, perhaps less likely to do so. By contrast, those employed with multiple jobs are both less likely to make 0 trips *and* to make successively higher numbers of trips.

Figure 11. Difference in trip-making by select attributes across trip-count levels



Another consideration is whether there are any differences in the distributional form across vehicle-access groups. In general, trip volumes are lower among those with lower access, with more people making zero trips and the average volume of trips above zero also being less (see Table 27). Figure 12 and Figure 13 show how the distribution of trips differs most (across groups) at 0, with the decay of trip counts 1 and above more similar across each of the access groups.

Table 27. Distribution of net daily trips, by vehicle-access group

	Overall	Vehicle-access group		
		Low	Medium	High
% of people with:				
0	15.3%	39.4%	23.5%	12.2%
1	22.1%	24.9%	22.6%	21.9%
2	20.3%	16.1%	19.1%	20.8%
3+	42.2%	19.6%	34.8%	45.1%
Average number	2.50	1.37	2.13	2.64
Average, excluding 0's	2.95	2.26	2.78	3.01
N	146,347	7,113	22,837	116,397

Source: 2009 NHTS version 2.1. Among respondents age 18 and over, unweighted, with one person randomly selected from each household, excluding respondents who were out of town on the survey day.

Figure 12. Distribution of net trips, by vehicle-access level

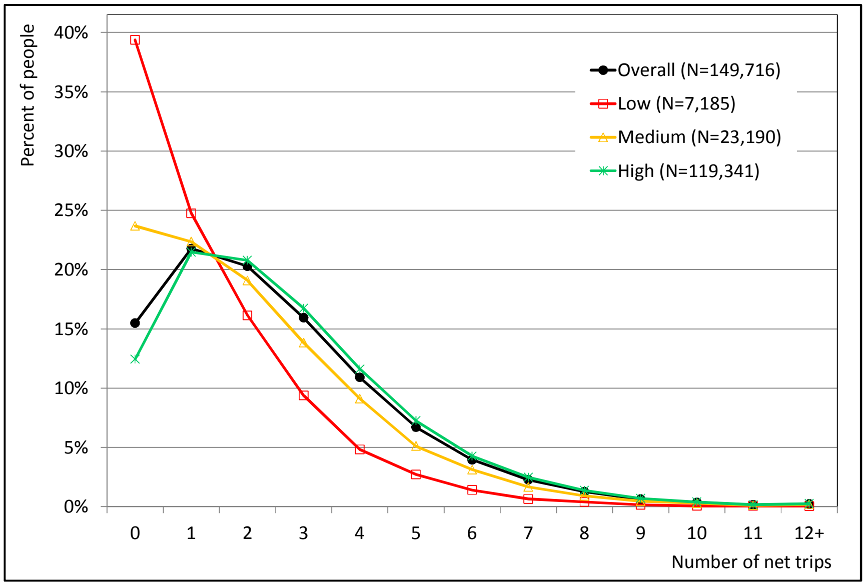
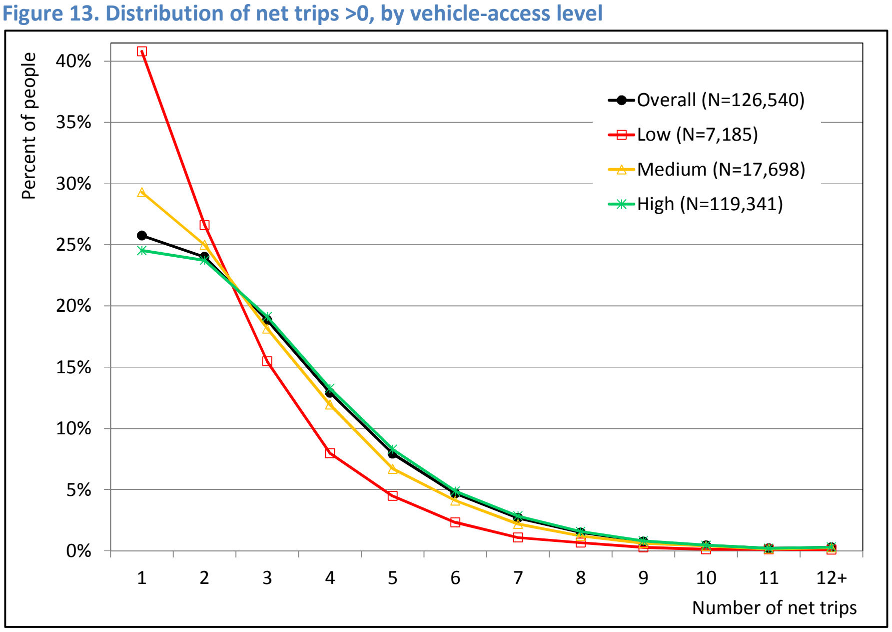


Figure 13. Distribution of net trips >0, by vehicle-access level



Given the nature of trip-making counts, I explore several different modeling frameworks to capture these patterns most meaningfully.

4.5 Comparison of four different model structures

I compare results for several types of models, in order to evaluate the importance of accounting for zero-versus-any trips separately from successively higher counts above one, and to better understand the influence of different predictors at these different levels of trip-making. Accordingly, I consider four different model types that each focus on a different range of values of the dependent variable, as follows:

(1) A single model for all values;
(2) A single model for the binary outcome, zero versus any trips;
(3) A single model for the counts 1 and above (excluding cases with zero trips); and
(4) A two-part hurdle model, jointly estimating separate coefficients for the prediction of zero-versus-any and for counts 1 and above.

The hurdle model (4) presumes that there are two different processes generating the first and second set of value ranges (0 versus any and 1 and higher) and partitions the prediction of each set of outcomes accordingly. The first part is predicted as a binary model, and the second as a truncated count, in which zeros are considered impossible (and the distribution of predictions adjusted accordingly). See the appendix section 4.8 for details. If there are important differences in the two parts, then the hurdle model is a way to combine two otherwise separate models more efficiently by accounting for the conditional probability of traveling at all (modeled in the first part). This type of model was found to be best in other contexts with large numbers of zeros as well as over-dispersion, as we have here, for instance in modeling the volume of recreational boating trips (Gurmu & Trivedi, 1996). It ultimately generates for each individual a single predicted number of trips (continuously valued), from 0 or higher, based on the outcome of the two component pieces.

Table 28. Summary of the four types of models considered

Short name:	Description:	Values of the observed y making up the dependent variable for each model:	Can be estimated for:	Model predicts:
(1) NB_{0+}	Single negative binomial model of total trip volume	All values of y with no transformations, so = 0, 1, 2, …	All respondents	Mean number of trips (continuously valued) for each respondent i, or the probability that respondent i makes any given number of trips, including zero
(2) BL	Single binary logit model of any trips	All values y, transformed to a binary outcome, so $=\begin{cases}0, \text{if } y = 0\\1, \text{if } y > 1\end{cases}$	All respondents	The probability that respondent i makes any trips (versus no trips)
(3) NB_{1+}	Single negative binomial model of trips excluding 0's	For $y > 0$ only, transform as $y - 1$, so = 0, 1, 2, …	Only respondents with $y > 0$	Mean number of trips (continuously valued) for each respondent i, or the probability that respondent i makes any given number of trips above one
(4) H	Conjoint hurdle model, with a binary logit and a zero-truncated negative binomial component part	All values of y with no transformations, so = 0, 1, 2, …	All respondents	Mean number of trips (continuously valued) for each respondent i, or the probability that respondent i makes any given number of trips, including zero

With respect to distributional forms, I use a binary logit model for (2) and for the binary portion of (4). For (1), (3), and the count portion of (4), I use a negative binomial model. Negative binomial models presume that the dependent variable can take on count values zero and higher. Thus, for model (3), which excludes cases with no trips, I model (y – 1) instead of y. That is, all of the response values are shifted down by 1 unit so that 0's represent one trip (or "0 trips above one") and 1's represent two trips (or "1 trip above one"), but the distribution itself is not truncated. For the count portion of (4), I use a truncated negative binomial, which adjusts the probability of counts 1 and above (upward) to account for the exclusion of zeros. (See the appendix section 4.8 for more details, including a review of alternative count distributions and a rationale for and implications of using negative binomial.)

In each model, a linear set of predictors ($\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k$) is linked to the outcome through some function, which varies depending on the presumed distributional form of the dependent variable. Model estimation consists of coming up with β coefficients that maximize the likelihood of observing the actual y's in the data, given the x's and the assumed distributional form of the model. Table 28 provides an overview of the four types of models compared in this analysis.In order to compare how the four different types of models compare in explaining behavior across vehicle-ownership segments, I estimated each of the four types of models several times, using different segments of the sample (as defined in Table 24): (a) the low-access segment, (b the medium-access segment, (c) the high-access segment, and (d) the entire sample. In total, this comprises sixteen separate estimations, for the four different model types (1 through 4), each estimated four different times for the different segments of the sample (a through d).

For the purposes of this comparison, I use the same specification (that is, the same set of explanatory variables) for all versions of all model types, including both parts of the hurdle model.[9] However, variables relating to vehicle ownership and driver status do not vary within some of the segments (the low- and high-access segments, respectively), and so only because of these, the number of predictors varies slightly across segments (between 33 and 36 explanatory variables). I selected the predictors to include in this specification based on theoretical influence on travel (see Table 26), on evidence of a relationship with trip-making in exploring descriptive statistics, and on their statistical significance when included in one or most of the models. In exploring different specifications, it became clear that adjustments to the exact combination of predictors made very little difference in overall model performance. Further, no one specification seemed best for all four types of models. Thus, the specification presented for the purposes of comparing the four models is not necessarily best, but good enough to give a sense

[9] In theory, the two parts of the hurdle model can have different explanatory variables. For this initial exercise comparing the different model types, I use the same explanatory variables in both parts. The hurdle model then estimates two coefficients for each explanatory variable, one for the part explaining zero versus any trips and then one for the explaining counts of trips one and above.

of what each model might be able to predict using the available set of explanatory variables. (However, a final best specification is presented in section 4.6.)

Table 29, Table 30, Table 31, and Table 32 show the estimated beta coefficients and overall fit statistics for the four versions of each type of model. As noted above, all of the explanatory variables listed were included in all versions of all types of models. However, only coefficients significant at $p < 0.10$ are shown in these tables. Coefficients with $p > 0.10$ are indicated with a "." symbol. Conclusions are discussed below.

Table 29. Results for four versions of model (1), a single negative binomial model of total trip volume: using the entire sample (d) and then each vehicle-access segment (a-c)

	Segment of the sample used:			
Dependent variable: Y = number of trips	Entire (1d)	Low (1a)	Medium (1b)	High (1c)
Beta coefficients ($\hat{\beta}_x$) for explanatory variables:				
Intercept	+ 0.269	+ 0.188	+ 0.377	+ 0.733
Female (vs. male)	+ 0.044	.	+ 0.066	+ 0.043
HH income per adult member	+ 0.005	+ 0.005	+ 0.007	+ 0.005
Age in 60s (vs. 18-59)	+ 0.043	.	.	+ 0.049
Age in 70s (vs. 18-59)	– 0.033	.	.	– 0.043
Age in 80s (vs. 18-59)	– 0.163	– 0.356	– 0.173	– 0.145
HH size	+ 0.008	.	.	+ 0.014
Presence of any kids (vs. none)	+ 0.056	.	+ 0.067	+ 0.049
Single-parent (vs. any other HH type)	+ 0.107	.	.	+ 0.113
Drives (vs. does not)	+ 0.480	+ 0.475	+ 0.432	n/a
Owns no vehicles (vs. 1+ / person)	– 0.097	n/a	n/a	n/a
Owns fewer vehicles (vs. 1+/person)	+ 0.033	n/a	n/a	n/a
Number of vehicles/person	+ 0.015	n/a	– 0.117	+ 0.024
Has limiting medical condition (vs. none)	– 0.219	– 0.279	– 0.204	– 0.217
Condition results in giving up driving (vs. not)	– 0.277	.	– 0.232	– 0.627
Employed (vs. not working)	.	.	+ 0.054	– 0.017
Emp part-time or multiple jobs (vs. any other)	+ 0.105	+ 0.136	+ 0.103	+ 0.101
Emp in manuf, construct, maint, or farming	– 0.059	.	– 0.076	– 0.058
Survey day = Monday (vs. Tues-Thurs)	– 0.045	– 0.135	– 0.047	– 0.042
Survey day = Friday (vs. Tues-Thurs)	+ 0.062	.	+ 0.071	+ 0.061
Survey day = Saturday (vs. Tues-Thurs)	– 0.108	– 0.090	– 0.068	– 0.120
Survey day = Sunday (vs. Tues-Thurs)	– 0.251	– 0.125	– 0.175	– 0.276
Born outside the U.S.	– 0.058	.	– 0.052	– 0.049
Recentness of immigration	– 0.282	.	.	– 0.538
“Second city” nbhd (vs. TC)	+ 0.042	+ 0.073	+ 0.038	+ 0.044
“Suburban” nbhd (vs. TC)	+ 0.029	.	+ 0.050	+ 0.028
“Urban” nbhd (vs. TC)	+ 0.020	+ 0.127	.	.
Residential units / sq mile in Census tract	+ 0.000	.	.	+ 0.000
Employees/ sq mile in Census tract	+ 0.000	.	.	+ 0.000
Female AND age 60s	– 0.028	.	.	– 0.025
Female AND age 70s	– 0.071	– 0.186	– 0.158	– 0.047
Female AND age 80s	– 0.130	.	– 0.174	– 0.108
Female AND has children	+ 0.074	.	.	+ 0.080
Employed AND survey day = Saturday	+ 0.151	.	+ 0.087	+ 0.167
Employed AND survey day = Sunday	+ 0.072	.	.	+ 0.097
NB dispersion parameter	+ 0.214	+ 0.408	+ 0.290	+ 0.198
Model statistics				
N	144,923	6,801	22,385	115,737
K	36	33	34	33
$\mathcal{L}_R$	-290,468.5	-11,009.1	-43,099.2	-233,935.4
$\mathcal{L}_F$	-282,321.2	-10,372.8	-41,214.2	-230,402.9
R^2_{MF}	0.028	0.058	0.044	0.015
$R^2_{MF\ adj}$	0.028	0.055	0.043	0.015
AIC	3.897	3.060	3.685	3.982
BIC	3.899	3.093	3.698	3.985
CAIC	3.899	3.098	3.699	3.985
QIC	3.898	3.084	3.693	3.983
χ^2-statistic = -2*($\mathcal{L}_R - \mathcal{L}_F$)	16,294.5	1,272.5	3,770.0	7,065.0
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)

All predictors were included in all four versions, but coefficients are only shown for those statistically significant at p<0.10. Insignificant coefficients are indicated with “.”Formulas for fit measures are listed in appendix section 4.8.4.

Table 30. Results for four versions of model (2), a single binary logit model of any trips: using the entire sample (d) and then each vehicle-access segment (a-c)

	Segment of the sample used:			
Dependent variable: binary, y = 0 (none) or 1 (any)	Entire (2d)	Low (2a)	Medium (2b)	High (2c)
Beta coefficients ($\hat{\beta}_x$) for explanatory variables:				
Intercept	+ 0.447	+ 0.390	+ 0.474	+ 1.276
Female (vs. male)	– 0.143	.	.	– 0.179
HH income per adult member	+ 0.012	+ 0.009	+ 0.012	+ 0.012
Age in 60s (vs. 18-59)	+ 0.084	.	.	+ 0.121
Age in 70s (vs. 18-59)	– 0.080	.	.	– 0.100
Age in 80s (vs. 18-59)	– 0.333	– 0.580	– 0.332	– 0.249
HH size	+ 0.023	.	.	+ 0.049
Presence of any kids (vs. none)	+ 0.101	.	+ 0.216	.
Single-parent (vs. any other HH type)	.	.	+ 0.820	.
Drives (vs. does not)	+ 0.887	+ 1.008	+ 0.851	n/a
Owns no vehicles (vs. 1+ / person)	– 0.077	n/a	n/a	n/a
Owns fewer vehicles (vs. 1+/person)	.	n/a	n/a	n/a
Number of vehicles/person	.	n/a	– 0.177	.
Has limiting medical condition (vs. none)	– 0.675	– 0.547	– 0.600	– 0.702
Condition results in giving up driving (vs. not)	– 0.337	.	– 0.280	– 1.202
Employed (vs. not working)	+ 1.234	+ 1.010	+ 1.289	+ 1.233
Emp part-time or multiple jobs (vs. any other)	– 0.106	.	.	– 0.138
Emp in manuf, construct, maint, or farming	– 0.143	.	– 0.195	– 0.148
Survey day = Monday (vs. Tues-Thurs)	– 0.119	– 0.267	.	– 0.125
Survey day = Friday (vs. Tues-Thurs)	.	.	.	.
Survey day = Saturday (vs. Tues-Thurs)	– 0.190	– 0.164	.	– 0.236
Survey day = Sunday (vs. Tues-Thurs)	– 0.238	.	– 0.125	– 0.307
Born outside the U.S.	.	.	.	.
Recentness of immigration	+ 1.420	.	+ 1.274	.
“Second city” nbhd (vs. TC)	+ 0.143	+ 0.197	+ 0.178	+ 0.129
“Suburban” nbhd (vs. TC)	+ 0.203	.	+ 0.301	+ 0.183
“Urban” nbhd (vs. TC)	+ 0.136	+ 0.356	+ 0.184	.
Residential units / sq mile in Census tract	+ 0.000	.	.	+ 0.000
Employees/ sq mile in Census tract	+ 0.000	.	.	+ 0.000
Female AND age 60s	– 0.112	.	– 0.211	.
Female AND age 70s	.	– 0.373	.	.
Female AND age 80s	.	.	.	.
Female AND has children	.	.	.	+ 0.140
Employed AND survey day = Saturday	– 0.537	.	– 0.531	– 0.518
Employed AND survey day = Sunday	– 0.909	– 0.633	– 0.875	– 0.875
NB dispersion parameter	n/a	n/a	n/a	n/a
Model statistics				
N	144,923	6,801	22,385	115,737
K	35	32	33	32
$\mathcal{L}_R$	-64,519.4	-4,816.8	-12,694.1	-44,842.1
$\mathcal{L}_F$	-47,634.7	-3,690.0	-9,766.7	-33,538.3
R^2_{MF}	0.262	0.234	0.231	0.252
$R^2_{MF\ adj}$	0.261	0.227	0.228	0.251
AIC	0.658	1.095	0.876	0.580
BIC	0.660	1.127	0.887	0.583
CAIC	0.660	1.131	0.889	0.583
QIC	0.659	1.118	0.883	0.581
χ^2-statistic = -2*($\mathcal{L}_R - \mathcal{L}_F$)	33,769.4	2,253.6	5,854.6	22,607.6
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)

All predictors were included in all four versions, but coefficients are only shown for those statistically significant at p<0.10. Insignificant coefficients are indicated with “.”Formulas for fit measures are listed in appendix section 4.8.4.

Table 31. Results for four versions of model (3), a negative binomial model of trips excluding 0's: using the entire sample (d) and then each vehicle-access segment (a-c)

	Segment of the sample used:			
Dependent variable: Counts 1+: y = (numb of trips – 1)	Entire (3d)	Low (3a)	Medium (3b)	High (3c)
Beta coefficients ($\hat{\beta}_x$) for explanatory variables:				
Intercept	+ 0.112	.	+ 0.205	+ 0.470
Female (vs. male)	+ 0.086	+ 0.135	+ 0.083	+ 0.088
HH income per adult member	+ 0.005	+ 0.005	+ 0.007	+ 0.005
Age in 60s (vs. 18-59)	+ 0.047	.	.	+ 0.051
Age in 70s (vs. 18-59)	– 0.039	.	.	– 0.052
Age in 80s (vs. 18-59)	– 0.172	– 0.255	– 0.149	– 0.172
HH size	.	.	.	+ 0.010
Presence of any kids (vs. none)	+ 0.087	.	+ 0.092	+ 0.083
Single-parent (vs. any other HH type)	+ 0.152	.	.	+ 0.162
Drives (vs. does not)	+ 0.373	+ 0.337	+ 0.363	n/a
Owns no vehicles (vs. 1+ / person)	– 0.135	n/a	n/a	n/a
Owns fewer vehicles (vs. 1+/person)	+ 0.048	n/a	n/a	n/a
Number of vehicles/person	+ 0.025	n/a	.	+ 0.035
Has limiting medical condition (vs. none)	– 0.112	– 0.164	– 0.087	– 0.113
Condition results in giving up driving (vs. not)	– 0.054	.	.	– 0.277
Employed (vs. not working)	– 0.168	.	– 0.101	– 0.179
Emp part-time or multiple jobs (vs. any other)	+ 0.152	.	+ 0.133	+ 0.155
Emp in manuf, construct, maint, or farming	– 0.092	– 0.166	– 0.129	– 0.085
Survey day = Monday (vs. Tues-Thurs)	– 0.047	– 0.100	– 0.062	– 0.043
Survey day = Friday (vs. Tues-Thurs)	+ 0.090	.	+ 0.088	+ 0.093
Survey day = Saturday (vs. Tues-Thurs)	– 0.108	.	– 0.074	– 0.120
Survey day = Sunday (vs. Tues-Thurs)	– 0.319	– 0.226	– 0.228	– 0.344
Born outside the U.S.	– 0.095	– 0.187	– 0.113	– 0.075
Recentness of immigration	– 0.751	.	– 0.569	– 0.951
"Second city" nbhd (vs. TC)	+ 0.033	.	.	+ 0.041
"Suburban" nbhd (vs. TC)	.	.	.	.
"Urban" nbhd (vs. TC)	.	.	.	.
Residential units / sq mile in Census tract	+ 0.000	.	.	+ 0.000
Employees/ sq mile in Census tract	+ 0.000	.	.	+ 0.000
Female AND age 60s	.	.	.	.
Female AND age 70s	– 0.070	.	– 0.170	– 0.051
Female AND age 80s	– 0.097	.	– 0.102	– 0.092
Female AND has children	+ 0.082	.	+ 0.075	+ 0.085
Employed AND survey day = Saturday	+ 0.248	.	+ 0.173	+ 0.266
Employed AND survey day = Sunday	+ 0.193	+ 0.327	.	+ 0.218
NB dispersion parameter	+ 0.436	+ 0.591	+ 0.480	+ 0.425
Model statistics				
N	122,940	4,156	17,164	101,620
K	36	33	34	33
$\mathcal{L}_R$	-228,830.3	-6,458.8	-30,913.8	-190,995.7
$\mathcal{L}_F$	-225,860.0	-6,304.9	-30,400.8	-189,066.1
R^2_{MF}	0.013	0.024	0.017	0.010
$R^2_{MF\ adj}$	0.013	0.019	0.015	0.010
AIC	3.675	3.050	3.546	3.722
BIC	3.678	3.100	3.562	3.725
CAIC	3.678	3.108	3.564	3.725
QIC	3.676	3.090	3.556	3.723
χ^2-statistic = -2*($\mathcal{L}_R - \mathcal{L}_F$)	5,940.6	307.7	1,026.0	3,859.2
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)

All predictors were included in all four versions, but coefficients are only shown for those statistically significant at p<0.10. Insignificant coefficients are indicated with "."Formulas for fit measures are listed in appendix section 4.8.4.

Table 32. Results for four versions of model (4), a conjoint hurdle model of total trip volume: using the entire sample (d) and then each vehicle-access segment (a-c)

Dependent variable: Count of trips (y=0, 1, 2…)	Segment of the sample used:							
	Entire (4d)		Low (4a)		Medium (4b)		High (4c)	
	Binary (0 vs. 1)	Counts (1+)	Binary (0 vs. 1)	Counts (1+)	Binary (0 vs. 1)	Counts (1+)	Binary (0 vs. 1)	Counts (1+)
Intercept	+ 0.439	.	+ 0.390	+ 0.319	+ 0.474	.	.	.
Female (vs. male)	– 0.144	.	.	+ 0.121	.	+ 0.075	– 0.179	+ 0.078
HH income per adult member	.	.	+ 0.009	+ 0.004	+ 0.012	.	.	.
Age in 60s (vs. 18-59)	+ 0.084	+ 0.041	.	.	.	.	+ 0.121	+ 0.045
Age in 70s (vs. 18-59)	– 0.079	– 0.034	.	.	.	.	– 0.100	– 0.045
Age in 80s (vs. 18-59)	– 0.331	.	– 0.580	– 0.238	– 0.332	– 0.133	– 0.249	– 0.152
HH size	+ 0.024	+ 0.006	.	.	.	.	+ 0.049	+ 0.010
Presence of any kids (vs. none)	+ 0.100	+ 0.076	.	.	+ 0.216	+ 0.081	.	+ 0.072
Single-parent (vs. any other HH type)	.	+ 0.130	.	.	+ 0.820	.	.	+ 0.142
Drives (vs. does not)	.	.	.	.	.	.	n/a	n/a
Owns no vehicles (vs. 1+ / person)	.	– 0.117	n/a	n/a	n/a	n/a	n/a	n/a
Owns fewer vehicles (vs. 1+/person)	.	+ 0.042	n/a	n/a	n/a	n/a	n/a	n/a
Number of vehicles/person	.	+ 0.027	n/a	n/a	– 0.177	.	.	+ 0.031
Has limiting medical condition (vs. none)	.	.	– 0.547	– 0.149	.	– 0.078	.	.
Condition results in giving up driving (vs. not)	.	– 0.051	.	.	– 0.280	.	.	– 0.245
Employed (vs. not working)	.	.	+ 1.010	.	.	– 0.089	.	.
Emp part-time or multiple jobs (vs. any other)	– 0.105	.	.	.	.	+ 0.118	– 0.138	.
Emp in manuf, construct, maint, or farming	– 0.144	– 0.082	.	– 0.153	– 0.195	– 0.114	– 0.148	– 0.075
Survey day = Monday (vs. Tues-Thurs)	– 0.119	– 0.041	– 0.267	– 0.090	.	– 0.055	– 0.125	– 0.038
Survey day = Friday (vs. Tues-Thurs)	.	.	.	.	.	+ 0.079	.	.
Survey day = Saturday (vs. Tues-Thurs)	– 0.190	.	– 0.164	.	.	– 0.067	– 0.236	.
Survey day = Sunday (vs. Tues-Thurs)	.	.	.	– 0.210	– 0.126	– 0.207	.	.
Born outside the U.S.	.	– 0.082	.	– 0.172	.	– 0.101	.	– 0.065
Recentness of immigration	+ 1.429	– 0.688	.	.	+ 1.274	– 0.519	.	– 0.850
“Second city” nbhd (vs. TC)	+ 0.144	+ 0.030	+ 0.198	.	+ 0.178	.	+ 0.129	+ 0.036
“Suburban” nbhd (vs. TC)	.	.	.	.	+ 0.301	.	+ 0.183	.
“Urban” nbhd (vs. TC)	+ 0.136	.	+ 0.356	.	+ 0.184	.	.	.
Residential units / sq mile in Census tract	.	.	.	.	.	.	.	.
Employees/ sq mile in	+ 0.000	.	.	.	.	.	+ 0.000	.

Dependent variable: Count of trips (y=0, 1, 2…)	Segment of the sample used: Entire (4d)		Low (4a)		Medium (4b)		High (4c)	
	Binary (0 vs. 1)	Counts (1+)	Binary (0 vs. 1)	Counts (1+)	Binary (0 vs. 1)	Counts (1+)	Binary (0 vs. 1)	Counts (1+)
Census tract								
Female AND age 60s	– 0.111	.	.	.	– 0.211	.	.	.
Female AND age 70s	.	– 0.062	– 0.373	.	.	– 0.154	.	– 0.045
Female AND age 80s	.	– 0.087	.	.	.	– 0.094	.	– 0.081
Female AND has children	.	+ 0.073	.	.	.	+ 0.067	+ 0.140	+ 0.075
Employed AND survey day = Saturday	.	.	.	.	– 0.531	+ 0.153	.	.
Employed AND survey day = Sunday	.	.	– 0.633	+ 0.305	– 0.875	.	.	.
NB dispersion parameter	n/a	.	n/a	+ 1.013	n/a	.	n/a	.
Conjoined model statistics								
N		144,923		6,801		22,385		115,737
K		71		65		67		65
$\mathcal{L}_R$		-290,468.5		-11,003.9		-43,071.3		-233,877.2
$\mathcal{L}_F$		-278,866.1		-10,142.8		-40,475.2		-227,985.5
R^2_{MF}		0.040		0.078		0.060		0.025
$R^2_{MF\ adj}$		0.040		0.072		0.059		0.025
AIC		3.849		3.002		3.622		3.941
BIC		3.854		3.067		3.646		3.946
CAIC		3.855		3.077		3.649		3.947
QIC		3.853		3.063		3.641		3.944
χ^2-statistic = -2*$(\mathcal{L}_R - \mathcal{L}_F)$		23,204.8		1,722.3		5,192.0		11,783.4
(p-value)		0.000		0.000		0.000		0.000

All predictors were included in all four versions, but coefficients are only shown for those statistically significant at p<0.10. Insignificant coefficients are indicated with "." Formulas for fit measures are listed in appendix section 4.8.4.

4.5.1 Overall model fit and predictive ability

Although the models have many variables with significant coefficients, the overall fit and predictive ability is weak. All of the models pass the low bar of performing better than an "intercept-only" model containing no explanatory variables. (A likelihood ratio test comparing $\mathcal{L}_F$, the log-likelihood value of the full model at convergence, to $\mathcal{L}_R$, the "restricted" log-likelihood for an intercepts-only model is significant at p<0.001 in each.) By design, almost all the variables included in the specification used in all of the models have significant coefficients when using the entire sample. Overall fit statistics such as pseudo-R^2 statistics, likelihood ratio tests comparing more- versus less-restricted models, and information-criteria-based statistics, are generally accepted as useful for distinguishing between the better of two different models estimated on the same data (or for the same model estimated on two different data sets), but unfortunately there is no consensus as to threshold values for these statistics that would indicate good or bad fit. That said, “very low [pseudo-R^2] values may indicate a lack of fit” (Hilbe, 2011, p. 67), as we have here, with pseudo-R^2 values of about 0.2 for the BL models (model 2) and values less than 0.1 for all the others.

Furthermore, there is a fair amount of dissonance between the values predicted by the models and their actual values in the data. First, the incidence of making no trips (zeros) is difficult to predict, especially among the high-access group among whom zeros are generally less likely. In particular, using the BL model calibrated to the entire sample (model 2d), and similarly using the H model (model 4d), since its binary portion is identical to the stand-alone BL model, the predicted probability of making zero trips among all the zero-trip-makers, or $\hat{\pi}(0)|(y{=}0)$, is 0.267, on average, meaning that the model estimates a 26.7% chance of making zero trips (or with repeated observation, that zero trips would be made 26.7% of the time), compared with a predicted probability of 0.131 for those making at least some trips (that is, $\hat{\pi}(0)|(y{=}1) = 0.131$; see Table 33). Of the zero-trip-makers, 14.0% are predicted to make zero trips with a probability over 0.500, using the entire-sample model (model 2d), or just 2.5% using the high-access model (model 2c), with an average predicted probability among them of 0.187.) There is more prediction of zero trips among the zero-trip-makers in the low-access segment (model 1a, with an average predicted probability of 0.503 and 59.2% of them with a predicted probability over 0.500), but there is also a higher incidence of zero trips in this segment.

As another perspective on the predictive contribution of the BL model (model 2), I can compare the portion of cases for which its predicted probabilities better match the observed outcomes than a naïve assumption that all respondents made a trip (since this is the dominant behavior). Since trip-making is dominant in all segments, the naïve assumption would be correct for most respondents, but more so in the high-access segment and less so in the low- and medium-access segments — which also means there is more room for improvement in low- and medium-access groups than in the high-access group. The measure lambda (λ) estimates the percent predicted "correctly" (that is, cases in which the predicted probability is greater than 0.500 for the observed outcome), after accounting for the "naïve" dominant outcome (from Veall and Zimmerman, 1996; see formulas in section 4.8.4). According to λ, none of the models provide much improvement among the high-access segment, with more improvement among the low- and medium-access segments. The most improvement is for the low-access model applied to the low-access segment, with 20.5-percent improvement after accounting for the naïve assumption. The measure sigma (σ) offers another measure based on the same principle, but designed to range between -1 and a positive value σ_{max} (which is at its greatest when the alternative outcomes are equally likely, when $p_i = p_j$ and $\sigma_{max} = 0.50$; σ_{max} decreases and approaches 0 as p_i=>1 and p_j =>0), with any value of σ above zero indicating any predictive power of the model (Veall and Zimmerman, 1996). By this measure, the high- and mid-access models (1b and 1c) provide *no* predictive power beyond the naïve assumption, though the low-access model provides some. (See Table 33.)

Table 33. Accuracy of the binary logit model for each segment in predicting observed values within that segment

	Model 1a	Model 1b	Model 1c	Model 1d
	Applied to segment:			
	Low (a)	Mid (b)	High (c)	Entire (d)
Observed % of y_i = 1	61.1%	76.5%	87.6%	84.7%
Overall % correct	69.1%	78.9%	87.7%	85.3%
Among observed 0's	59.2%	32.5%	2.5%	14.0%
Among observed 1's	75.4%	93.2%	99.7%	98.2%
Weighted sum of % correct	52.6%	69.7%	87.2%	82.1%
Measures based on the % correctly predicted*				
λ'	0.205	0.103	0.006	0.043
σ	0.163	0.013	-0.113	-0.077
$\sigma_{\max}$	0.472	0.224	0.011	0.070
$\sigma_n = \sigma/(\sigma_{\max})$	0.345	0.060	-10.557	-1.096
Average predicted probability of 0	0.389	0.233	0.122	0.152
Among observed 0's	0.503	0.377	0.187	0.267
Among observed 1's	0.316	0.189	0.113	0.131
Odds of 0's: among observed 0's vs. 1's	1.588	1.991	1.657	2.038
Average predicted probability of 1	0.611	0.767	0.878	0.848
Among observed 0's	0.497	0.623	0.813	0.733
Among observed 1's	0.684	0.811	0.887	0.869
Odds of 1's among observed 1's vs. 0's	1.375	1.301	1.091	1.186

* From Veall and Zimmerman (1996). See formulas in appendix section 4.8.4.

There is also considerable noise about the predictions of counts 1 and above. To illustrate, Table 34 shows various means of comparing the actual to predicted values based on each version of the hurdle model (model 4). Only about 20% of cases have predicted values that would round to the actual value (that is, is within 0.5 of the true number of trips), for all but the low-access segment. In general, lower counts tend to be underestimated, with an excess of cases assigned a predicted value near the observed mean (equal to 2.515 in the overall sample based on model 4d) – which would be the tendency the less predictive power the model provides. In all of the models, the prediction is higher than the actual number of trips made for more than half the cases, though varying to some degree across segments and models. (Although the model is designed so that the average discrepancy is zero for the segment used for estimation, it over-predicts for more cases than it under-predicts, in all vehicle-access segments. This is because the distribution of trip volumes is right-skewed, with a long, thin tail of relatively rare high values, and a disproportionately large share of 0’s and 1’s that the model has difficulty predicting.) And the *average* distance between the predicted and actual number of trips is greater than 1 for all of the models and segments, for instance about 1.455 trips, on average — either above or below the observed number — using the entire-sample model (model 1d; see Table 34).

Table 34. Accuracy of the hurdle model for each segment in predicting observed values within that segment

	Model 1a	Model 1b	Model 1c	Model 1d
	Applied to segment:			
	Low (a)	Mid (b)	High (c)	Entire (d)
Observed y_i				
$\bar{y}$	1.380	2.131	2.658	2.515
$\hat{\sigma}_y$	1.662	2.037	2.113	2.106
Predicted versus observed, $r_i = \hat{y}_i - y_i$:				
$\bar{r}$	0.000	-0.001	0.000	0.000
$\hat{\sigma}_r$	1.500	1.887	2.031	1.989
% with $r_i > 0$ (so $\hat{y}_i > y_i$)	60.7%	59.2%	56.9%	57.4%
Avg. $\|r_i\|$	1.104	1.433	1.568	1.528
(Avg. $\|r_i\|$) / $\bar{y}$	0.800	0.672	0.590	0.607
(Avg. $\|r_i\|$) / $\hat{\sigma}_y$	0.672	0.705	0.743	0.725
Avg. $\|r_i/\hat{\sigma}_{\hat{y}_i}\|$	0.787	0.789	0.778	0.780
% with $\|r_i\| < 0.5$	24.5%	19.6%	18.9%	19.3%
% with $\|r_i\| < 1$	58.6%	42.8%	38.0%	39.5%
% with $\|r_i\| < 1.5$	78.6%	62.7%	55.0%	57.1%
% with $\|r_i\| < 2$	87.7%	77.1%	72.2%	73.7%
% with $\|r_i\| < \|y_i - \bar{y}\|$	64.7%	55.5%	56.0%	56.3%
% with $\|r_i\| < \hat{\sigma}_y$	82.2%	78.0%	75.2%	76.0%
% with $\|r_i\| < 1$, among:				
$y_i = 0$	60.3%	28.3%	1.7%	13.8%
$y_i = 1$	77.4%	36.8%	10.5%	17.9%
$y_i = 2$	74.3%	83.4%	80.8%	81.3%
$y_i = 3$	37.2%	74.6%	92.2%	88.5%
$y_i = 4$	3.9%	16.9%	25.6%	23.7%
$y_i = 5$	0.5%	0.7%	0.9%	0.8%
$y_i = 6$	0.0%	0.0%	0.1%	0.1%
$y_i \geq 7$	0.0%	0.0%	0.0%	0.0%

In general, the results should be treated with caution due to lack of fit. However, better fit is difficult based only on the sort of demographic variables available in the dataset and possibly the idiosyncratic nature of trip-making. Next I discuss the contribution of the hurdle model in improving model performance, as well as differences in model performance across the different vehicle-access segments.

4.5.2 A single versus a two-part model

There are several pieces of evidence for assessing whether the two-part model is worthwhile. First, I consider the estimated coefficients for the explanatory variables — including their sign, magnitude, and significance levels. I compare the coefficients from the single BL and NB_{1+} models (models 2 and 3, Table 30 and Table 31), which capture the binary (zero versus any) and count (volume of trips 1 and above) in isolation. There are some differences in which explanatory variables have significant coefficients, in addition to some with significant coefficients in both models but with opposite signs. (The estimated coefficients for the binary and count portions of the H models (model 4, Table 32) are almost identical to those for the separate BL and NB_{1+} models and suggest the same conclusions.) This suggests that there may be some differences in what influences making any trips versus making successively higher numbers of trips. For instance, there is an *opposite* influence on making any trips versus a higher volume of trips for the following variables.

- Female versus male (– any, + volume, meaning an apparent negative impact on making any trips but a positive impact on the volume of trips). In addition, note the interaction effects involving gender: in each model, the observed direction of influence of being female is amplified for those with kids (for volume) and for older females (for both any and volume). The effect of female and older (–) seems to have a stronger effect on trip volume than the probability of any trips.
- Employment, in general, vs. not working (+ any , – volume).
- Employment part-time or with multiple jobs, vs. full-time or not working (– any, + volume). In both models, this serves to somewhat attenuate the effect of employment in general, among this sub-group.

- Recentness of immigration (+ any , – volume). Furthermore, note that foreign-born status only matters for making any trips once recentness is taken into account; by contrast a foreign-born dummy variable has a significant additional negative effect for volume only.
- Weekend days of the week, among those who are employed (– any, + volume). This serves to attenuate the otherwise positive influence of employment on the chances of any travel, and the otherwise negative effect on trip volume, among the employed on *weekdays*.

In addition, there is apparently more effect, that is, coefficients that are only significant, or more significant, in only one of the models, either the BL (model 2, modeling the probability of "any") or NB_{1+} (model 3, modeling only the volume of trips), for the following variables: Household size (+ , more impact on volume); Single-parent status (+, more impact on volume); Females with kids (+, more impact on volume); Older females (–, more on volume, perhaps); Suburban and urban built environments, vs. town/country (+, more impact on volume); Friday (+, more impact on volume); Number of cars (while having any cars, versus none, has a significant positive effect in both models, the number of cars is not significant in the BL (any) model, and has a seemingly complicated relationship with volume of trips in the NB models, discussed more below).

Comparing the coefficients from the separate BL and NB_{1+} models (models 2 and 3 in Table 30 and Table 31), which account for "any" and "volume" separately, to the single NB_{0+} model (model 1, Table 29), which treats all counts together, we see that estimates for all the above variables show a weaker effect and in some cases are not significant in the single model (model 1). For instance, while models 2 and 3 suggest that employment increases the chance of any trips but decreases trip volume, the coefficient in the single model is negative but not quite significant (with p=0.139), for the model with the entire sample), is even less significant for the low-access segment (p=0.512), and is significant but with opposite signs in the medium- and high-access segments, respectively. Separating the effect on any trips versus on the volume of trips offers more clarity on the influence of employment on activity. These sorts of differences would seem a justification for handling the phenomena of any trips versus successively higher numbers of trips separately, especially for the purposes of drawing conclusions about the role of particular explanatory variables.

Another consideration is whether separating the “any” and “volume” portions of the model improves the overall performance of the model. Considering various goodness of fit measures as well as the accuracy of the predicted values, the hurdle model is no worse than the single model, and may be slightly better, but it is unclear if the improvement is substantial. In particular, the information criteria statistics (AIC and BIC) are lower using the two-part hurdle model (model 4) than the single NB_{0+} model (model 1) for all of the segments, but only at the first decimal place (for instance reduced from 3.897 to 3.849 in model 4a versus 1a; see a consolidated side-by-side comparison in Table 35). The pseudo-R^2 values for the hurdle models (model 4) are also higher than for the single NB_{0+} models (model 1), but only by about 0.01 unit. However, with such low pseudo-R^2 values overall, these increases are substantial on a percentage basis. For instance, the increase from 0.028 to 0.040 between models 1d and 4d, respectively, comprises a 42-percent improvement (see Table 35).

Table 35 also shows some measures based on the accuracy of the predicted values generated by the models. These are also barely improved in the hurdle model compared to the ordinary negative binomial model (models 1 and 4, respectively). For instance, for the versions estimated using the high-access segment, the average absolute difference between the actual and predicted value decreases just 0.001 units (or 0.03%), from 1.569 to 1.568 trips difference. The percent of cases for which the average distance is less than 1 trip increases slightly from 37.8% to 38.0%. However, additional gains in accuracy, though still small, are achieved in model 5, which uses the final specification (discussed in 4.6 and shown in Table 37). Perhaps an important aspect to this final specification is that the explanatory variables for the binary and count components of the model differ somewhat. Forcing them to be identical, as done in models 1 through 4 for the purposes of comparison may have undermined the main theoretical advantage of the hurdle model framework.

I conclude that there are probably differences in the factors influencing "any" versus "volume" of trips, but that we are not able to model either that well. As a result, the hurdle model is only slightly better than the alternative, but it is theoretically superior, as well as measurably superior, even if just barely. I use it for the remainder of the analysis.

Table 35. Comparison of model performance of the single negative binomial model versus the joint hurdle model

	Desired value for measure	Model estimated using:				
		Entire sample (d)		High-access segment only (c)		
		Model 1d (Table 29) NB_{0+}	Model 4d (Table 32) H	Model 1c (Table 29) NB_{0+}	Model 4c (Table 32) H	Model 5* (Table 37) Best H
Model statistics						
K		36	71	33	65	101
$\mathcal{L}_R$		-290,468.5	-290,468.5	-233,935.4	-233,877.2	-232,137.7
$\mathcal{L}_F$	0	-282,321.2	-278,866.1	-230,402.9	-227,985.5	-225,598.6
R^2_{MF}	High	0.028	0.040	0.015	0.025	0.028
$R^2_{MF\ adj}$	High	0.028	0.040	0.015	0.025	0.028
AIC	Low	3.897	3.849	3.982	3.941	3.929
BIC	Low	3.899	3.854	3.985	3.946	3.938
CAIC	Low	3.899	3.855	3.985	3.947	3.939
QIC	Low	3.898	3.853	3.983	3.944	3.936
$\chi^2 = -2*(\mathcal{L}_R - \mathcal{L}_F)$	High	16,294.5	23,204.8	7,065.0	11,783.4	13,078.2
(p-value)	Low	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
For $r_i = \hat{y}_i - y_i$:						
Avg. $\lvert r_i \rvert$	Low	1.528	1.528	1.569	1.568	1.529
% with $\lvert r_i \rvert < 0.5$	High	19.2%	19.3%	18.9%	18.9%	19.3%
% with $\lvert r_i \rvert < 1$	High	39.3%	39.5%	37.8%	38.0%	39.1%
% with $\lvert r_i \rvert < 1.5$	High	57.2%	57.1%	55.1%	55.0%	57.1%
% with $\lvert r_i \rvert < 2$	High	73.6%	73.7%	72.0%	72.2%	73.4%
% with $\lvert r_i \rvert < \lvert y_i - \bar{y} \rvert$	High	56.3%	56.3%	56.0%	56.0%	56.1%
% with $\lvert r_i \rvert < \hat{\sigma}_y$	High	75.2%	75.2%	75.1%	75.2%	75.3%
Segment statistics						
N		144,923	144,923	115,737	115,737	115,737
$\bar{y}$		2.515	2.515	2.644	2.644	2.644
$\hat{\sigma}_y$		2.106	2.106	2.090	2.090	2.090

* Uses a different specification. See section 4.6 and Table 37.

4.5.3 Differences in model fit and the accuracy of predictions within different segments

I am ultimately interested in creating a most accurate predictive model using the high-access segment only. However, it is notable that the model performance is generally worst for this segment. This is the case despite the fact that it has more significant coefficients (perhaps due to the much larger sample size within this segment compared with the low- and mid- segments). Across all model types, the low-access segment has the highest pseudo-R^2 values and lowest information criteria values, followed by the mid-access model, then the entire-sample model, and lastly for the high-access model (see Table 29 through Table 32). In addition, the average differences between the predicted and actual values are less for those in the low-access group and higher for the high-access group (for instance 1.104 versus 1.568 for Models 4a and 4c, respectively; see Table 34), however this would be the tendency given the lower mean and variance of the observed trip counts among the low-access group.

To explore the extent that the greater discrepancy between actual and predicted values in the high-access segment might be accounted for by more variation in that group, I scale the raw difference (between actual and predicted) by measures of the mean and variance in y. In particular, I considered scaling the raw difference (1) by the mean value of the (observed) y within each segment (that is, (avg.$|r_i|$) / $\bar{y}$); (2) by the standard deviation of the (observed) y within each segment (that is, (avg. $|r_i|$) / $\hat{\sigma}_y$); and (3) at the disaggregate level, by the standard deviation of the predicted y for each respondent ($\bar{y}$) (so calculating the average of $\left|r_i/\hat{\sigma}_{\hat{y}_i}\right|$). (The latter is dictated by the theoretical distribution used for the model, and varies for different levels of $\hat{y}$.) Each is shown in Table 34.

Relative to the within-segment $\bar{y}$ (method (1)), the discrepancy is actually least in the high-access segment (at 0.590, versus 0.800 for the low-access segment; see Table 34). Relative to the within-segment $\hat{\sigma}_y$ (method (2)), the discrepancies are much more equal across segments, though still appear least in the low-access segment (at 0.672, versus 0.743 for the high-access segment). Relative to $\hat{\sigma}_{\hat{y}_i}$(method (3)), the discrepancies again appear much more equal, but the high-access segment is least (at 0.778, versus 0.787 for the low-access segment).

This suggests that much of the apparently different precision of the predictions across segments can be accounted for by less variation in observed y in the low-access group; and much or all can be accounted for by variation implied by the model assumptions at different levels of the predicted y. Thus, it is not so much that the model is inherently better at predicting trip-making among those in the low- versus high-access segments, but that by having less trip-making, those in the low-access segment tend to be situated in the more predictable spectrum (lower-variance range) of the dependent variable. However, the fact that those in the no-car and low-access segments do make fewer trips — that is, that they *are* statistically situated in the more predictable, lower-variance range of the dependent variable — is still interesting. An intention of this research is to understand the extent that less vehicle-access is a *cause* of less trip-making in these segments versus something concomitant to other circumstances.

4.5.4 Making predictions across segments

Another consideration is how well the version of the model that is estimated using data from one segment can predict the trip-making in *another* segment. This tells us something about whether the models are different — that is, though using the same specification, if the magnitudes of the estimated coefficients capture differently weighted set of influences – as well as differences across segments that are not accounted for in the model.

A first piece of evidence as to whether the versions of the model for each segment differ is in examining the coefficients. In general, there are fewer variables with significant coefficients in the low-access models, which could be in part due to a substantially smaller sample size for this segment, making it harder to capture small effects with statistical significance. Comparing the three segments (a vs. b vs. c), there are no instances of variables with significant oppositely signed coefficients; if significant, they are all appear to be influencing trip-making in the same direction, though there may be differences in the relative magnitude of each. A coarse piece of evidence suggesting that there may be significant differences is the likelihood ratio test for whether the segmented models (collectively) outperform the unsegmented model on the entire sample, which is significant for all model types.

Comparing predicted values across segments using the hurdle models, the low-access model (model 4a) underestimates trips for the high-access group, and the high-access model (model 4c) overestimates trips for the low-access group (see the original results in Table 32 and a consolidated summary of comparisons in Table 36). In particular, using the high-access model to predict trips in the low-access group (model 4c, estimated on a), actual trips are 0.437 fewer than predicted, on average (with an average absolute difference of 1.318 trips predicted above or below the actual value); using the low-access model to predict trips in the high-access group (model 4a, estimated on c), actual trips are 0.332 greater than predicted, on average (with an average absolute difference of 1.561 trips above or below the actual value).

The *direction* of this finding is to be expected, given important variables left out from each of these specifications: The high-access model (model 4c) excludes driver status (as well as the dummy variables for no cars and fewer cars, though including the continuous variable for number of vehicles); and the low-access model (model 4a) excludes *all* of the vehicle ownership variables, since there is no variation in these variables within the segment. It seems likely that these variables would account for at least some of the discrepancy across models. The fact that there is a discrepancy across models in their absence may be evidence that these factors, and their underlying causes, matter for mobility; that is, that driver status matters for non-owner mobility; and vehicle-ownership level matters for owner mobility. (See related discussion in Chapter5.)

Even without these variables, however, the models account for a good share of the average differences in mobility across segments. In particular, the average trip volume (that is, observed $\bar{y}$) in the low-access segment is 1.388, versus 2.644 in the high-access segment, a 1.255-trip shortfall, on average (see Table 36). The model (calibrated to the high-access group, model 4d) predicts that the low-access group *would* have a shortfall, however, predicting an average trip volume of 1.826. This means that much of the observed differences across segments can be accounted for by the sorts of demographic variables included in the model, common to all segments. In particular, in the case of the high-access model explaining behavior of the low-access segment, about 34.8% of the observed gap in behavior is explained by this model. A remaining 65.2%, or 0.818 trips, is unexplained, perhaps having to do with excluded variables (so that the model is failing to fully capture variations in latent demand for activity) or offering evidence of a barrier to mobility unique to the low-access segment (explored more in Chapter 5).

Finally, it seems notable that the comparative performance of how well the low-access model predicts behavior in the high-access segment versus how well the high-access model predicts behavior in the low-access segment is not symmetric. In particular, the high-access model overestimates by a bit more than the low-access model underestimates (by 0.437 trips versus 0.332 trips; or 34.8% versus 26.4% of the observed gap). If this difference is indeed large enough to be meaningful, it suggests one of two things: (1) either the variables omitted from the high-access model are more important for explaining low-access-segment behavior than the variables omitted from the low-access model for explaining high-access-segment behavior; or (2) the proclivity to make trips is generally lower in the low-access segment than in the high-access segment, even after accounting for the explanatory variables in the model. As discussed elsewhere, and in detail in the next chapter, this could have to do with either preferences or ability: It could be evidence of underlying systematic differences in the two groups in the desire to get around to different addresses, or of constraints the low-access group suffers, limiting their ability to fulfill their latent demand for trip-making. Before drawing further conclusions based on this preliminary modeling, first I develop a final best specification of a hurdle model using the high-access sample, for most accurate estimate of the expected trip volume for a given demographic profile.

Table 36. Cross-segment predictions, using the hurdle model (model 4) estimated for each segment

	Observed and predicted numbers of trips in each vehicle-access segment		
	Low (b)	Medium (c)	High (d)
Average observed value ($\bar{y}$)	1.388	2.139	2.644
Average predicted value			
from low-access H model ($\bar{\hat{y}}_{4b}$)	1.388	1.830	2.312
from mid-access H model ($\bar{\hat{y}}_{4c}$)	1.698	2.139	2.645
from high-access H model ($\bar{\hat{y}}_{4d}$)	1.826	2.209	2.644
Average difference, actual versus predicted value			
from low-access H model ($\bar{y} - \bar{\hat{y}}_{4b}$)	0	0.309	0.332
from low-access H model ($\bar{y} - \bar{\hat{y}}_{4c}$)	-0.309	0	-0.002
from low-access H model ($\bar{y} - \bar{\hat{y}}_{4d}$)	-0.437	-0.069	0
Difference in average observed value across segments			
compared to low-segment average ($\bar{y} - \bar{y}_b$)	n/a	0.751	1.255
compared to mid-segment average ($\bar{y} - \bar{y}_c$)	-0.751	n/a	0.504
compared to high-segment average ($\bar{y} - \bar{y}_d$)	-1.255	-0.504	n/a
Gap in prediction as percent of gap in observed values			
based on low-access H model ($\bar{y} - \bar{\hat{y}}_{4b}$) / ($\bar{y} - \bar{y}_b$)	n/a	41.2%	26.4%
based on mid-access H model ($\bar{y} - \bar{\hat{y}}_{4c}$) / ($\bar{y} - \bar{y}_c$)	41.2%	n/a	-0.4%
based on high-access H model ($\bar{y} - \bar{\hat{y}}_{4d}$) / ($\bar{y} - \bar{y}_d$)	34.8%	13.8%	n/a

4.6 Specification of a final “best” model

I develop a final model (Model 5) using the hurdle framework (as in Model 4), but differing from Model 4 in the exact mix of explanatory variables included. This version differs importantly from Model 4 in that it allows different explanatory variables for the binary and count portions of the hurdle model, and that only the high-access segment of sample was considered in experimenting with alternative specifications. As such, it designed to be a best predictive model for that segment of the data.

After experimenting with many variations of instrumenting the predictors in Table 26, I opted to retain variables in either the "any" or "volume" parts of the model only if their coefficient had a statistical significance at $p<0.10$. Given comparably significant alternatives, I opted for versions of variables (or combinations of variables) that were theoretically meaningful or easier to interpret. I retained a few variables whose main effects were not significant but interaction effects were, as well as some that were close to significant and theoretically meaningful and/or part of a set of dummy variables that belonged together.

In general, when a variable is included as a predictor in both the any and count parts of the model, two different coefficients are estimated to capture that variable's influence on the probability of making any trips, on the hand, and on the probability of making successively higher volumes of trips above one, on the other; together, and with the other variables in the model, the two effects contribute to the overall expected volume of trips for a given individual. When a variable is only included in one part of the model and not the other, it means that the factor only contributes to whether the individual makes any trips and not the volume of trips, or vice versa.

Table 37 shows the final specification. With respect to various performance measures, this version is improved only slightly over Model 4c, previously shown in Table 35: McFadden's (adjusted) pseudo-R^2 increases by 0.003 (from 0.025 to 0.028); information-criteria type measures such as the AIC decrease by 0.012 (from 3.941 to 3.929); the average absolute difference between predicted and actual values decreases by 0.039 trips (from 1.568 to 1.529); and the percent of cases whose prediction is within 1 trip of their actual increases by 1.1 percentage points (from 38.0% to 39.1%). In the final specification, the categories of predictors from Table 26 are operationalized as follows and have the following estimated effects. Recall that the model was estimated only using the segment of the sample with "unlimited" vehicle access, as defined in Table 24, and therefore these effects apply specifically to that subgroup.

***Built environment**:* Dummy variables for each community type (urban, second city, and suburban) all have a positive effect on both the probability of any trips and higher volumes of trips, relative to town/country areas, which was omitted as the reference group (where the largest portion of households lives, 39.8% of the weighted sample). Of the three types, suburban environments contribute most to making any trips but not as much to the volume of trips (though still more than town/country areas). Urban and second city types contribute more to the volume of trips than do suburban areas, but not as much to the probability of making any trips (with the urban coefficient only significant at p=0.179). Transit score for the MSA, continuously valued (but taking on only 26 unique values) has a negative effect on both the probability of any trips and higher volumes of trips. This may be serving as an indicator for major urban area rather than a reflection of the effect of transit service per se. Density of employees per square mile and housing units per square mile for the Census tract of the home residence, valued at the midpoint of eight categories and treated as continuous variables in the model, have a positive effect on the probability of any trips only (and housing units only with significance at p=0.112 in the presence of the other measures of the built environment).

***Economic status**:* Dummy variables for each level of household income per adult household member, in $5,000 increments, have an increasingly larger effect on both any trips and the volume of trips, but especially the former (in part due to different reference groups used for the any and volume components of the model: <$7,500 per adult for making any trips and <$17,500 per adult for the volume of trips). Dummy variables for educational attainment affect both any trips and volume of trips, with a seemingly larger effect on the probability of making any trips. Relative to the reference group of those with either a high school diploma and/or some college but less than a four-year degree (these were grouped together because of no significant difference between their effects), those with less than high school make fewer trips and those with graduate degrees make more, and those with college degrees but not graduate degrees make the most, all else equal. Homeownership, reflecting economic status (but likely also correlated with residence in a detached single-family homes, which did not have a significant coefficient in either part of the model in the presence of the other built-environment measures) significantly and positively affects only the probability of any trips but not volume of trips. As another indication of economic status, having a household member in a manufacturing/construction/maintenance/farming occupation has a negative effect on both the probability of any trips and volume of trips, while having a household member in a professional/managerial/technical occupation has a negative effect on making any trips. (Note additional effects for those personally employed in certain occupational categories, described below.)

Vehicles and driving: Among this segment including only drivers in households with high-ownership levels, the number of *additional* drivers in the household was not significant. Higher numbers of vehicles (instrumented as a continuous measure of the number of vehicles per household member excluding non-driving children —so number of vehicles divided by the number of all adults plus any minors who drive) has a significant effect on the volume of trips only, and positively. This is potentially endogenous (those with greater mobility needs or more diverse mobility needs, may be more inclined to own more cars, such as specific types of vehicles for different activities). Having a limiting medical condition has a negative effect on making any trips and on trip volume, and having one specifically affecting driving has an additional negative effect on both.

Lifecycle stage: Age is instrumented as a series of dummy variables for each decade, retaining in each part of the model only those with significant coefficients. Among those making any trips, peak trip-making occurs among those in their 50s and 60s, with those both younger and older making fewer trips, with significant additional negative effect among older females. Age effects (on their own) are less pronounced for the probability of making any trips, though with decreased probability among those in their 80s and 30s, all else equal (and no significant interaction with gender).

Children, employment, and household roles: Those in households with (more) children have a greater probability of making any trips and more trips (instrumented as a continuous variable for total number of children), an effect that is even greater for females with children (instrumented as the interaction of female and dummy variable for any children). However, the effect on making any trips (but not volume, given any) is attenuated for those with very young children (age 0 to 5), again even more so among females. People in multi-adult households (three or more adults) are more likely to make any trips but fewer trips, perhaps reflecting more sharing of household duties, more time spent at home with multiple adults for companions, or less need for travel among the type of people in this living situation (e.g. young people living with roommates, or households including an elderly parent). Relative those living with one or more other adults, lone adults make a higher volume of trips, an effect that is even greater among those with children (who are also mostly female), perhaps reflecting the need to single-handedly perform household-maintenance duties. In general, people who are employed (versus not working) have a greater probability of making any trips but fewer trips. Those with multiple jobs have an even greater probability of making any trips, but those with only part-time with less. Additionally, the effect on trip volume is attenuated (that is, less negative) among those employed part-time, in multiple jobs, and/or in certain occupation categories: sales/service, clerical/admin support, professional/managerial/technical (but not manufacturing/construction/maintenance/farming or other). This may have to do with the nature of the work, the opportunities for trip-chaining to and from work, or the likelihood of these jobs being located in certain built environments, such as more urban areas. Interactions between employment and gender, or employment and presence of children were not significant. The overall effect of gender is that females have a less probability of making any trips but a more probability of making a higher volume of trips, consonant with their frequent role in performing more childcare and household maintenance duties in and outside of the home, regardless of employment status.

Race, ethnicity, and foreign-born status: Hispanics of any race have a greater probability of making any and more trips, while Blacks (African-American and mixed African-Americans) have a greater probability of making any trips (relative to non-Blacks of any other race), and Asians have a greater probability of making more trips (relative to non-Asians of any other race). These may reflect cultural differences, patterns in the types of the built environments where they live, or be compensating for some other effect in the model that affects these groups differently, such as income (that is, these groups may make more trips with less income). Recent immigrants are more likely than less-recent immigrants and the native-born to make any trips, but also a lesser volume of trips. The effect on volume diminishes with time spent in the United States (shown by the diminishing magnitude of the coefficients for immigrating less than 6 years ago, 6-10 years, and 11 or more years ago, relative to the native-born).

Day of the week: Weekday trip-making is somewhat reduced on Mondays and somewhat greater on Fridays (in volume), with no significant differences among those who are working versus not working. The probability of weekend trip-making differs by employment status. Among non-workers, the probability of any trips and the volume of trips is less on weekends than on weekdays; among workers, the probability of any trips is even less on weekends versus weekdays than among those who do not work, but if they do make any trips, they are somewhat more likely to make more trips than are non-workers, especially on Saturdays.

Table 37. Results for model (5), a final best hurdle model of total trip volume, using only the high-access segment

Explanatory variable	Hurdle model coefficients: Zero-vs-one	Hurdle model coefficients: Counts above 1
HH income per adult		
<$7.5	(ref)	(ref)
$7.5-12.5	0.114 **	(ref)
$12.5-17.5	0.114 **	(ref)
$17.5-22.5	0.248 ***	0.060 ***
$22.5-27.5	0.314 ***	0.077 ***
$27.5-32.5	0.364 ***	0.089 ***
$32.5-37.5	0.215 ***	0.056 ***
$37.5-42.5	0.480 ***	0.086 ***
$42.5-47.5	0.401 ***	0.112 ***
$47.5-$50	0.486 ***	0.139 ***
>$50	0.503 ***	0.146 ***
Homeowner (vs. rents)	0.094 **	
Vehicles per person (excluding non-driving minors)		0.034 ***
Has HH member in manuf/farm/const/maint	-0.184 ***	-0.029 *
Has HH member in prof/mang	-0.076 *	0.015 *
Female (vs. male)	-0.201 ***	0.071 ***
Age		
18-24	(ref)	-0.125 ***
25-29	(ref)	-0.105 ***
30s	-0.140 ***	-0.075 ***
40s	(ref)	-0.024 **
50s	(ref)	(ref)
60s	0.057 *	(ref)
70s	(ref)	-0.035 **
70s and female		-0.055 ***
80s	-0.133 **	-0.141 ***
80s and female		-0.095 ***
Limiting medical condition (vs. none)	-0.678 ***	-0.099 ***
Condition results in giving up driving (vs. no condition or not this result)	-1.219 ***	-0.250 ***
Employed (vs. not working)	1.208 ***	-0.206 ***
with multiple-jobs	0.549 *	0.167 ***
with part-time job	-0.150 ***	0.133 ***
in admin/clerical role		0.048 ***
in prof/managerial role		0.032 **
in service/sales role		0.072 ***
Educational attainment (vs HS diploma or some college)		
Less than HS	-0.271 ***	-0.139 ***
Bachelor's degree	0.244 ***	0.092 ***
Graduate degree	0.147 ***	0.052 ***
Hispanic of any race (vs non-Hispanic)	0.090 .	0.018
Black (vs any other)	0.098 *	
Asian (vs any other)		-0.093 ***

Explanatory variable	Hurdle model coefficients: Zero-vs-one	Hurdle model coefficients: Counts above 1
Years in US		
<6 yrs	0.486 .	-0.236 ***
6-10 yrs	(ref)	-0.128 ***
11+ yrs	(ref)	-0.080 ***
Native born	(ref)	(ref)
Number of adults		
1 adult	(ref)	0.060 ***
2 adults	(ref)	(ref)
3+ adults	0.101 **	-0.032 **
Number of kids (continuous var.)	0.108 ***	0.064 ***
Has any kids	-0.038	-0.022
Female and has any kids	0.316 ***	0.090 ***
Has any kids age 0-5	-0.020	
Female and has any kids age 0-5	-0.226 *	
Has any kids and only 1 adult		0.126 ***
Metro-level transit-score	-0.001 **	-0.001 ***
Community type (vs. town/country)		
Second city	0.107 **	0.046 ***
Suburban	0.158 ***	0.019 **
Urban	0.070	0.051 ***
Housing density in home CT	0.00002	
Density of employees in home CT	0.00003 **	
Day of the week		
Mon	-0.139 ***	-0.038 ***
Tues-Wed	(ref)	(ref)
Thurs	-0.067 *	(ref)
Fri	(ref)	0.080 ***
Sat	-0.253 ***	-0.104 ***
Sat and employed	-0.519 ***	0.227 ***
Sun	-0.321 ***	-0.304 ***
Sun and employed	-0.875 ***	0.192 ***
Intercept	1.363 ***	0.842 ***

Model statistics	
N	114,882
K	101
$\mathcal{L}_R$	-232,137.7
$\mathcal{L}_F$	-225,598.6
R^2_{MF}	0.028
$R^2_{MF\ adj}$	0.028
AIC	3.929
BIC	3.938
CAIC	3.939
QIC	3.936
χ^2-statistic = $-2*(L_R - L)$	13,078.2 ***
Avg $\lvert y-\hat{y}\rvert$	1.557
% with $\lvert y-\hat{y}\rvert < 0.5$	19.2%
% with $\lvert y-\hat{y}\rvert < 1.0$	38.2%
% with $\lvert y-\hat{y}\rvert < \hat{\sigma}_y$	75.3%

Significant at p <0.20 (.), < 0.10 (-), <0.05 (*), <0.01 (**), or <0.001 (***).

4.7 Summary and conclusions

This chapter describes the development of a model for estimating benchmark mobility levels, for a given demographic profile. Mobility is measured as the number of trips made in a day (defined as anytime someone moves between addresses, except for returning to home or work), as a proxy for the overall volume of out-of-home activities in which someone engages. This is a coarse way to capture activity-participation, treating all types of activity (outside the home) the same, when in reality some sorts of activities may be more important than others in their contribution to (or detraction from) the overall welfare of individuals.

Using this measure of activity, there are apparently meaningful differences in the sorts of factors influencing whether someone makes any trips (versus staying in the same place all day) and those influencing the volume of activity on a given day. I account for these by using a two-part hurdle model that allows different explanatory variables (with separately estimated coefficients) for each part. However, because both parts are difficult to predict with a high level of precision, the two-part hurdle model is only slightly improved over a simpler single-equation count model, such as the Negative Binomial.

The sorts of factors used as predictors of trip volume are those available in the NHTS dataset, including: household attributes such as income, household size, homeownership, occupations of household workers; individual attributes such as gender, employment, occupation type, education level, immigrant status, and race/ethnicity; attributes of the built environment such as community type (e.g. urban, suburban), density, and MSA-level transit availability; and day of the week. A potential limitation of the model is the overarching difficulty in predicting individual activity levels on any given day deterministically based solely on these sorts of predictors. That is, actual behavior appears idiosyncratic, and model fit is poor, though not necessarily worse than other disaggregate models of travel behavior. Even with noise in the model (only 38.2% of cases have predicted values within +/-1 trip of the actual value), there may be meaningful patterns at the aggregate level. That is, aggregating will help cancel out some of the noise evident at the individual level, allowing for overall comparisons of outcomes among groups.

The group of people used as the basis for benchmark mobility levels are those whose vehicle access is “unlimited,” defined as adults over age 18, who drive, and who live in a household with at least as many cars as people excluding non-driving minors (so including driving teens plus all adults, whether or not they drive). (It also includes a small minority who experience medical conditions or handicaps making travel outside the home difficult, and even a very few who report giving up driving as a result of the condition, but who apparently still drive.)

A consideration in light of poor model fit is what might be omitted from the model, especially if it is something that might have a different role among the high-access owners used to calibrate the model versus the low-car households to whom the model will be applied. For instance, Ory and Mokhtarian (2005) have examined the role of overall travel liking. If travel liking were an important predictor of trip volume, and differed — for instance, is generally greater — among the high-access owners, then the benchmark model might systematically overestimate trip volumes for those in low-car households. This sort of bias would be less important if it impacted the entire group of low-car households equally. However, if impacting some more than others, it could potentially bias the sorts of subgroup comparisons explored in Chapter 5, whose focus is to evaluate mobility fulfillment among members of no-car and low-car households.

4.8 Appendix: Methodological details

4.8.1 Idea of using a two-part "hurdle" model

I need a way to account for the possibility that the effect of a variable on 0-versus-1 trips may be different from its influence on successively higher numbers of trips: either different in magnitude or in some cases in the opposite direction. A method that is well suited to handling this circumstance is a hurdle (or two-part) model, which "relaxes the assumption that the zeroes and the positives come from the same data generating process" (Cameron & Trivedi, 2001). In particular, a hurdle model partitions the model into two parts, one for zero versus positive counts and another for only positive counts (see Cameron & Trivedi, 1998; Winklemann, 2008; Hilbe, 2011). In the application at hand, the first part would model the propensity to make zero versus any trips, and the second part would model the propensity to make successively higher numbers of trips.

Specifically, we assume the probability of zeros is determined by some density function f_1, such that $\Pr(Y=0) = f_1(0)$. The probability of positives is therefore $\Pr(Y>0) = (1 - f_1(0))$. Specific values greater than zero come from a truncated density function f_2, conditioned on Y being positive, so $\Pr(Y=y_i \mid Y>0) = f_2(y) / (1 - f_2(0))$, which we then multiply times the probability of positives to form the overall density function, $g(y)$ (from Cameron & Trivedi, 2001):

$$\Pr(Y=y_i) = g(y) = \begin{cases} f_1(0), & \text{if } y = 0, \\ \frac{f_2(y)}{1-f_2(0)} \cdot \left(1 - f_1(0)\right), & \text{if } y \geq 1. \end{cases}$$

A conjoined likelihood functions is then formulated as $L = f_1(0) \cdot \frac{f_2(y)}{1-f_2(0)} \cdot \left(1 - f_1(0)\right)$,

and taking logs, the log-likelihood function is: $\mathcal{L} = \ln\left(f_1(0)\right) + \ln\left(\frac{f_2(y)}{1-f_2(0)}\right) + \ln\left(1 - f_1(0)\right)$, which can be easily formulated depending on the assumed distributions of f_1 and f_2 (Hilbe, 2011). To model the expected value of Y, I find the set of β_{f_1}'s and β_{f_2}'s that maximize $\mathcal{L}$.

4.8.2 Selecting the appropriate distribution for net trips for each type of model

For f_1, it is logical to represent the binary outcome of no versus any trips as a binomial random variable and model it as a binary logit (mathematically equivalent to logistic regression). For f_2, there are more choices. As a discretely valued positive count, Poisson or negative binomial are logical choices. Poisson is the simplest and most common, representing the number of events occurring in a fixed interval of time. However, a Poisson distribution presumes that all counts are independent of each other and that the mean is always equal to the variance (so, the greater the mean, the greater the variability in the data; and if the mean is low, so must be the variance). In practice, real life data often depart from this assumption. If substantially so, an alternative method may be warranted. There are a variety of alternatives, either amended versions of a Poisson distribution (adjusting the estimated standard errors) or other models relying on different distributions altogether.

The negative binomial distribution can be thought of as a family of distributions for count variables that incorporate an additional parameter, α, capturing dispersion in excess of the mean. The dispersion parameter α can take on any value greater than zero. As α approaches 0, the negative binomial becomes equivalent to the Poisson distribution (so Poisson can be thought of as the special case of negative binomial where α=0). The geometric distribution, the discrete corollary to the negative exponential distribution for continuous variables, is the special case of negative binomial when α=1.

Gamma distributions are also sometimes used for counts, attractive because of the flexibility in shape afforded by its two input parameters. The shape of the gamma distribution varies substantially depending on the values of a shape and scale parameter, and thus can be tailored to fit may different datasets.

For each of these options, I compare the distribution of the actual trip data to the form of the theoretical distribution, based on visual plots as well as a χ^2-test. Treated as a single variable, taking on count values 0 and above, the form of Y (for the entire sample) has somewhat of a bell shape but is right-skewed, with 15% of cases valued at 0, another 22% at Y=1, and 20% at Y=2. This means there are many low counts of 0, 1, 2 (58% cumulatively) relative to the long thin tail of cases with higher counts (see Figure 14). The overall skewness is 1.25. Trip counts are even more right-skewed among the low-access group, among whom 39% of cases are valued at 0 and 80% are valued at 0, 1, or 2 (with an overall mean of 1.37 net trips and skewness of 1.77). In all vehicle-access groups, though especially the high-access group, the sample variance is greater than the mean, perhaps suggesting excess dispersion for Poisson (with $\bar{Y}$=2.51 and σ^2=4.46 in the overall sample).

Removing the zero's, the form of the data Y>0 is a curve that decays from Y=1, which includes about 26% of truncated cases (that is, among those with trips greater than zero), with another 24% at Y=2, and 19% at Y=3 (see Figure 15). About 94% of cases have 6 or fewer trips. This means that the data are still relatively right-skewed; that is, there are a lot of low counts of 1, 2, and 3 relative to the long thin tail of higher counts. Indeed, the sample variance is still greater than the mean, perhaps suggesting excess dispersion for Poisson (with $\bar{Y}$= 2.98 and σ^2 =3.88, among those with Y>0 in the overall sample).

Figure 14. Distribution of net trips, by vehicle-access level

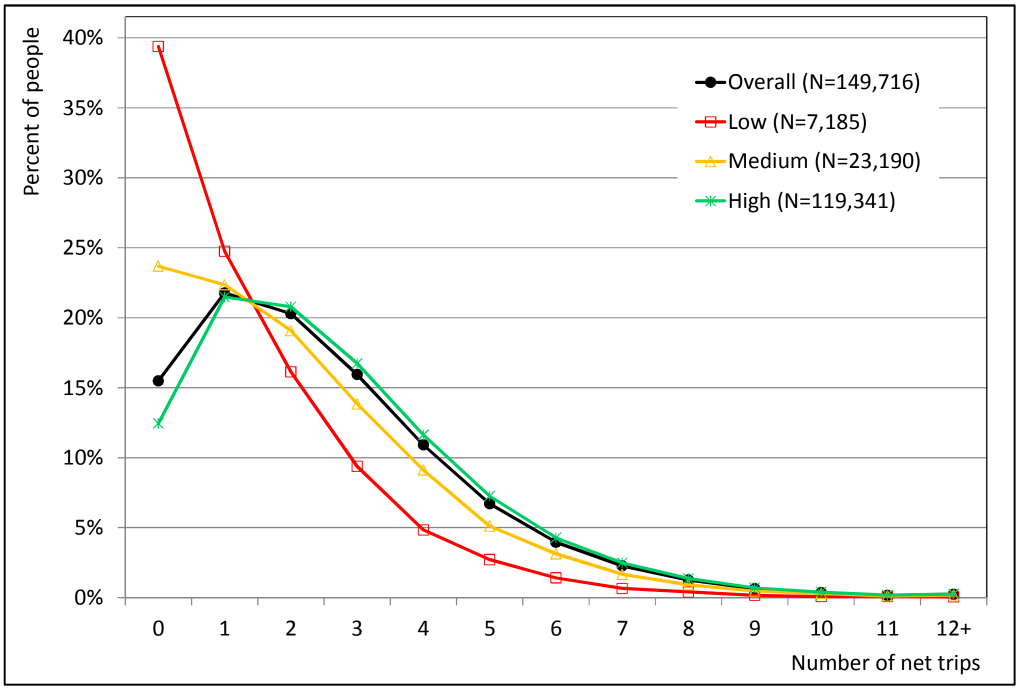


Figure 15. Distribution of net trips >0, by vehicle-access level

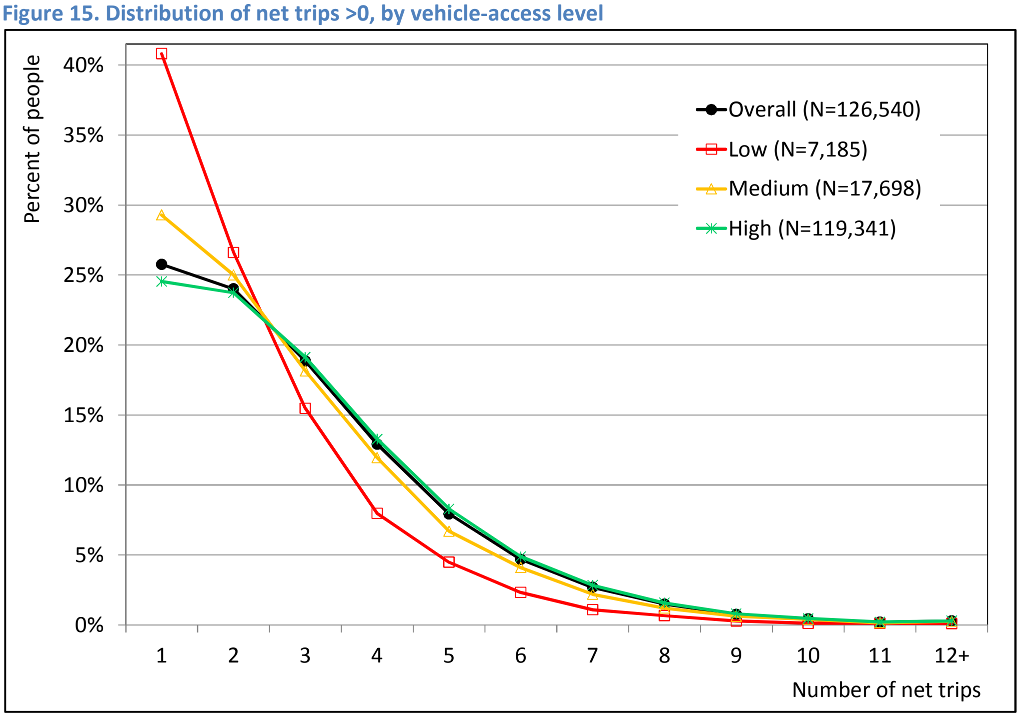
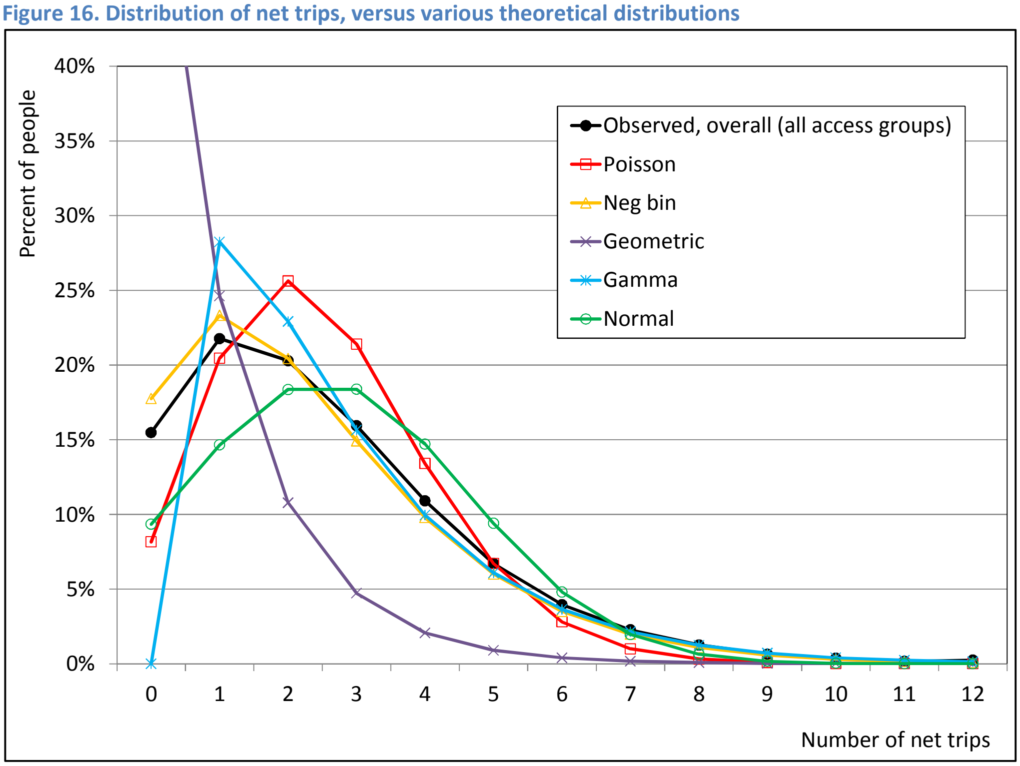


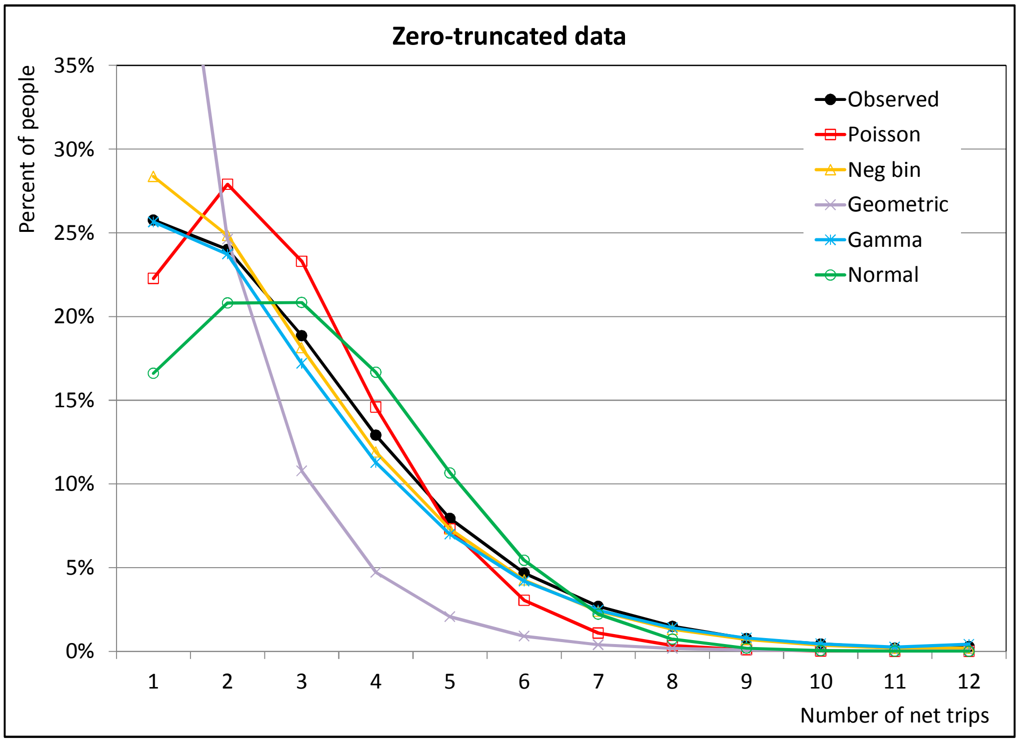
Figure 16 and Figure 17 show the distribution of net trip counts (in the overall sample) for the range of values including zeros and excluding them, respectively, overlaid with various theoretical distributions. In Figure 17 (showing the distribution of trip counts 1 and above from among those with non-zero trips), the theoretical distributions are zero-truncated to adjust for the impossibility of Y=0, that is, in the form of $f(y)$ / (1 – $F(0)$), so that the probability at each value Y >1 is proportionately inflated. In both contexts, the negative binomial performs well because of the ability to adjust the dispersion parameter based on the sample mean and variance. In particular, in the distribution including the cases with zeroes (Figure 16), using negative binomial with the dispersion parameter $\hat{\alpha}$ = 1/r = ($\sigma^2 - \bar{Y}$)/ $\bar{Y}^2$=0.311, fits the shape best, though somewhat overestimating values of 0 and 1. In Figure 17, we see that even truncated, the Poisson curve predicts a maximum frequency at Y = 2 trips, and so is somewhat off. The Negative binomial (with $\hat{\alpha}$ = ($\sigma^2 - \bar{Y}$)/ $\bar{Y}^2$=0.102) better captures the decay shape, though somewhat overestimating values of 1 and 2, and underestimating values 3 and above. The Gamma curve fits closely, with parameters α and β set to 1.85 and 1.50 for that purpose.

Figure 16. Distribution of net trips, versus various theoretical distributions



The theoretical distributions were generated in Excel with parameters based on the mean and standard deviation in the sample data, so $\bar{Y}$=2.505 and σ=2.111. In particular, the parameters were: Normal ($\bar{Y}$,σ), Poisson ($\bar{Y}$); Geometric (p) and Negative binomial (r, p), with $\hat{r} = \bar{Y}^2$ / ($\sigma^2 - \bar{Y}$) = 3.215 and $\hat{p} = \hat{r}/(\hat{r} + \bar{Y})$) = 0.562; and Gamma ($\alpha$, β), with α = β =1.60, selected through trial-and-error to make the Gamma curve look like the shape of the observed data.

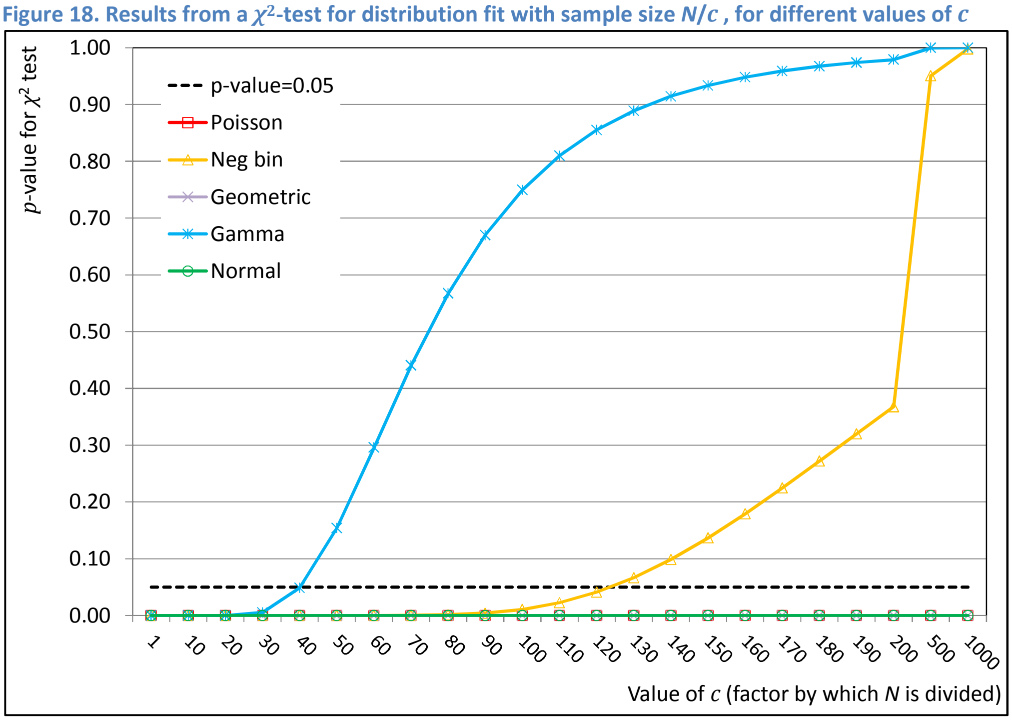
Figure 17. Observed distribution of trip volume >0 versus various zero-truncated theoretical distributions



The theoretical distributions were generated in Excel in the zero-truncated form of $f(y)/(1-f(0))$. The parameters for each are based on the mean and standard deviation in the sample data (from the full sample, that is, including zeroes), so $\bar{Y}$=2.976 and σ=1.969. In particular, the parameters were: Normal ($\bar{Y}$,σ), Poisson ($\bar{Y}$); Geometric (p) and Negative binomial (r, p), with $\hat{r} = \bar{Y}^2 / (\sigma^2 - \bar{Y})$ = 9.844 and $\hat{p} = \hat{r}/(\hat{r} + \bar{Y})$= 0.768; and Gamma ($\alpha$, β), with α=1.85 and β =1.50 selected through trial-and-error to make the Gamma curve look like the shape of the observed data.

One test to evaluate how well data fit a given distribution is a χ^2-test, comparing the observed frequency of data at each level of Y (O_{y_i}) to the expected frequency (E_{y_i}) for a given theoretical distribution. In particular, the test statistic, $\sum_{i=0}^{k} \frac{(O_{y_i} - E_{y_i})^2}{E_{y_i}}$, is χ^2-distributed with k+1 degrees of freedom. With the null hypothesis that the data fit, we fail to reject the null (suggesting the data may fit) with high p-values (e.g. $p > 0.050$) and reject the null (suggesting the data do not fit) with low p-values (e.g. $p < 0.050$). However, this test is sensitive to sample size; large sample sizes produce large χ^2-test statistics and low p-values (so we tend to conclude the data do not fit). Applied to the truncated set of data (excluding zeros) with n = 126,540, the significance is $p < 0.001$ for every distribution shown in Figure 17 (so we reject the null and conclude the data do not fit). However, the sample size is divided by a constant, c, of sufficient size, then the data appear close enough to both the Negative binomial and Gamma distributions such that we fail to reject the null (that is, conclude that the data may fit). Figure 18 plots the resulting p-values from tests with different values of c. The p-values are plotted on the vertical axis; for any below the dotted line, we would reject the null hypothesis that the distribution fits (that is, conclude that the data don't seem to fit) and for any above we fail to reject the null (that is, conclude the data may fit). The Gamma distribution "fails" by c=40 (so a theoretical N of about 3,160) and the Negative binomial by c=130 (so a theoretical N of about 970). The p-values for tests with the Normal, Poisson, and Geometric distributions remained less than 0.001 no matter how high a value of c. These results suggest that the Gamma and Negative binomial distributions fit best.

Figure 18. Results from a χ^2-test for distribution fit with sample size N/c , for different values of c



In summary, in considering use of Poisson, Negative binomial, Geometric (as a special case of the Negative binomial), Gamma, and Normal curves, it seems that negative binomial is best — based on eyeballing the shape of the plots, results of a χ^2-test for distribution fit, its availability in the procedures provided by off-the-shelf statistical software (the pscl package in

R), and its conceptual meaning as a Poisson count with excess dispersion captured in an extra dispersion parameter, which we can estimate from the data. Below is a review of the mechanics of negative binomial regression models.

4.8.3 The mechanics of negative binomial regression

If the dependent variable, Y, is negative binomially distributed, then the probability mass function of a Negative binomial variable predicts the probability that $Y = y_i$, for a given mean and dispersion parameter μ and α, so $f(y; \mu, \alpha)$.[10] In modeling, we flip this around to identify the parameters μ and α that maximize the likelihood of having the set of y_i's observed in our data, so $f(\mu, \alpha; y)$. It is customary to set α to a specific value and then treat it as a constant. We could impose any value, but having no theoretical reason to impose a particular value we can first estimate the maximum-likelihood value of α (from our data) as an initial step, and then thereafter treat it a constant (this is one of the built-in options in SPSS and other statistical packages), making the likelihood function $f(\mu; y, \hat{\alpha}_{\mathrm{ML}})$.

μ is not constant, but different for each person i, as a function of the linear predictors (the explanatory X variables), through some "link" function, g, where, $g(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p$. Different functions of g are used in different versions of the Negative binomial model (see an overview of the variety and their differences in Hilbe, 2011), which affects the interpretation the β coefficients. I use a log link, or $\ln(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p$ (what Hilbe, 2011 refers to as NB2), because it is the most common, along with some other advantages. Whatever link function is assumed, the likelihood function is then a function of the β's, so $f(\beta; y, \hat{\alpha}_{\mathrm{ML}})$. The point of the modeling process is to find the β's that maximize this likelihood function.

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[10] Note these two parameters are called different things and assigned different notation depending on how the pmf is expressed. Here I use the notation μ and α, where μ is the mean and α is the dispersion or heterogeneity parameter, distinguishing it from the Poisson, as discussed above. See Hilbe (2011, p. 189).

These sorts of models are usually estimated using either a maximum likelihood (ML, also known as Newton-Raphson type) or iteratively re-weighted least squares (IRLS) algorithm. The latter is more common because of its easy application to the gamut of generalized linear models, but can result in different set of estimated standard errors[11] for any $g(\mu)$ other than the "canonical"[12], especially in unbalanced (sparse) datasets or those with small *n* (Hilbe, 2011). Though these circumstances are not likely in this application, I opt to use ML[13].

Using the log link to parameterize the Negative binomial model, the estimated β coefficients represent the factor difference in the expected log-count of Y for X = true versus X = not true (for binary X) or for successively higher levels of X (for continuously valued X). (That is, the log-count increases or decreases by a factor of β.) Exponentiated β represents the factor difference (increase or decrease) in the expected count. (So the expected count increases or decreases by a factor of e^{β}.) Or alternatively, $e^{\beta} - 1$ represents the percent increase or decrease in the expected count. The following summarizes how to interpret the β coefficients:

Value	Interpretation
β	Factor by which the log-count of Y increases or decreases for different X
e^{β}	Factor by which the count of Y increases or decreases for different X
$e^{\beta} - 1$	Percent increase or decrease in the count of Y for different X

4.8.4 Measures for assessing model fit

I use three types of fit statistics for each model: information criterion measures, pseudo-R^2 measures, and measures based on the accuracy of predicted values.

[11] This is because IRLS estimates standard errors from the expected information matrix whereas ML estimates them from the observed information matrix, which is more complex (Hilbe, 2011).

[12] This is the parameterization that makes negative binomial one in the family of generalized linear models, and turns out to be $g(\mu) = \ln\left(\frac{\alpha\mu}{1+\alpha\mu}\right)$. See Hilbe (2011).

[13] To accomplish this using the GENLIN function in SPSS, we set METHOD=NEWTON in the CRITERIA subcommand.

4.8.4.1 Information criterion measures

The rule of thumb for information criterion is that low values are better, but there is no established guideline as to how low is "good enough" or how different two values might be to indicate a substantial difference in performance between two models (e.g. Hilbe, 2011; Cameron & Trivedi, 1998). There are a variety of formulations, all based on the log-likelihood value for the fitted model, with some penalty for the number of predictors included, and theoretic advantages to each for different contexts. Elsewhere in the literature, such measures are alternatively presented in raw form or divided by the sample size; I use the latter because of the very large sample size and very large differences in sample sizes across segments (and models) in this analysis. The formulas for the statistics presented in Table 29 through Table 32 are shown below, with $\mathcal{L}_F$ = the log-likelihood value of the full model at convergence, k = number of parameters in the model, n = sample size, from Hilbe (2011).

AIC = $\frac{-2(\mathcal{L}_F - k)}{n}$ = Aikaike information criterion.

BIC = $\frac{-2\mathcal{L}_F + k * \ln(n)}{n}$ = Bayesian information criterion, also referred to as the Schwarz criterion, and accordingly as SBC or SBIC, and BIC_L.

CAIC = $\frac{-2\mathcal{L}_F + k * (\ln(n) + 1)}{n}$ = Consistent AIC, which has an added penalty for higher numbers of predictors (k), and may be better when there are many (Hilbe, 2011; Nylund, Asparouhov, & Muthén, 2007), as we have here.

QIC = $\frac{-2(\mathcal{L}_F - k * \ln(k))}{n}$ = Hannan-Quinn information criterion, or HQC, sometimes referred to as a version of BIC in software such as Limdep and Stata.

4.8.4.2 Pseudo-R^2 measures

There are many variants of pseudo-R^2 measures, with none very clearly more meaningful than any other. Table 29 through Table 32 show results for two of the most basic formulations (from Ben-Akiva & Lerman, 1985, for instance):

$\mathrm{R}^2_{\mathrm{MF}} = 1 - \frac{\mathcal{L}_F}{\mathcal{L}_\mathrm{R}}$ = McFadden's pseudo-R^2, and

$\mathrm{R}^2_{\mathrm{MF}_{\mathrm{adj}}} = 1 - \frac{\mathcal{L}_F - \mathrm{k}}{\mathcal{L}_\mathrm{R}}$ = McFadden's adjusted pseudo-R^2,

where $\mathcal{L}_F$ = the log-likelihood value of the full model at convergence, $\mathcal{L}_R$ = is the log-likelihood value of a the "restricted" intercept-only model (that is, where all non-intercept coefficients are restricted to zero), and k = number of parameters in the model.

4.8.4.3 Accuracy of the predicted values

The following measures are based on a comparison of predicted values to actual values, from Veall and Zimmerman (1996). Using the notation that p_{ij} is the percent of cases with a true value of i and a predicted value of j, and $p_{i\bullet}$ as the percent of cases with a true value of i, and $p_{\bullet j}$ is the percent of cases with a predicted value j, and $p_{m\bullet}$ as the percent of cases where the most common outcome occurs, the following measures have an upper bound of one:

$\lambda' = \frac{p_{00} - p_{11} - p_{m\bullet}}{1 - p_{m\bullet}}$,

$\sigma = p_{00} + p_{11} - p^2_{\bullet 1} - p^2_{\bullet 2}$,

$\sigma_n = \sigma/(\sigma_{\mathrm{max}})$, as a normalized version of σ, where

$\sigma_{\mathrm{max}} = 1 - p^2_{\bullet 1} - p^2_{\bullet 2}$.

5 Evaluating relative mobility fulfillment among those in no-car and low-car households

The purpose of this chapter is to evaluate mobility fulfillment among members of no-car and low-car households. The implication of mobility fulfillment, as opposed to mere mobility levels, is that there is some expectation about what mobility levels *ought* to be. Fulfillment is the extent to which the expectation is met.

While there are a variety of ways to assess fulfillment, perhaps most typically through some type of subjective self-reporting, as an alternative method, in Chapter 4 I develop a benchmark level of mobility for a given demographic profile, based on mobility levels of those with "unlimited" vehicle access (see Chapter 4). In this chapter I consider, how well does the behavior of those in no-car and low-car households match the predictions of the benchmark model? If well matched, it suggests an ability to fulfill mobility needs, despite owning fewer cars.

This framework relies on the precision of the prediction in the benchmark model, as well as on the assumption that any unexplained differences across ownership segments can be attributed to ownership status, once other demographic and geographic attributes have been accounted for, which may be a leap. Because of the overall noise in the benchmarking model, and the possibility for other systematic differences between the ownership segments (high-car versus no- or low-car households), the chapter focuses more on variations *within* each segment: Relative to the segment average, which subgroups have more versus less mobility fulfillment? I present results for demographic and geographic subgroups, as well as among users of particular modes of transportation. The results show which types of people are better able to fulfill their apparent mobility needs, which types of environments are conducive to fulfill needs, and which modes of transportation are associated with more or less mobility fulfillment – within the no-car and low-car segments – all relative to the benchmark predictions.

5.1 Method of analysis

All of the analysis in this chapter is based on the discrepancy between individuals' actual trip volumes and that predicted by the benchmark-mobility model developed in Chapter 4.

To review, the purpose of the model in Chapter 4 is to predict the expected number of total daily trips (excluding return-home and return-work) as a proxy for latent demand for engaging in activities outside the home, in the absence of constraints relating to vehicle access. The premise is that demand for activity varies systematically by demographics, and that while actual behavior is an imperfect reflection of latent demand, the behavior of those with unlimited automobility reflects the level of activity desired and achievable if access to vehicles is unlimited. Thus, for a given demographic profile, the actual behavior of those with virtually unlimited access to vehicle transportation can serve as a proxy for the latent demand for out-of-home activity, or benchmark mobility level, in the population more broadly.

The benchmarking model generates a predicted volume of trips for each individual, valued continuously, based on demographic and geographic explanatory variables (see Chapter 4). Here I compare this predicted value to the actual volume of trips made by each individual as an indication of the extent to which their behavior matches the expected behavior for someone with a similar demographic profile with full vehicle access. I call this difference — the actual volume minus predicted volume — a mobility discrepancy. Positive values indicate a person made more trips than the model predicted, while negative values indicate a person made fewer trips than predicted. In this chapter, I consider patterns in these discrepancy values: where and for whom the discrepancy tends to be higher or lower.

The implication of low or high discrepancy values among a particular subgroup is that either the model was systematically incorrect — over- or under-estimating demand for activity participation (trip volume) among that group – and/or that this group has an easier or harder time fulfilling their desired activity level, as follows. My primary interest is in the latter. However, if there are any differences across segments other than the demographic and geographic attributes included in the model that would influence trip volumes, then they would contribute to the apparent gap. For instance, an attitudinal preference – enjoying travel itself or a more active lifestyle – might result in more trip-making, and might be more likely among those in the high-car ownership segment.

Discrepancy value ($d_i = y_i - \hat{y}_i$)	Meaning	Interpretation		
Negative ($y_i < \hat{y}_i$)	Person made fewer trips than predicted by the benchmarking model	Benchmarking model over-estimates demand for activity	and/or	Person has more difficulty fulfilling desired level of activity
Positive ($y_i > \hat{y}_i$)	Person made more trips than predicted by the benchmarking model	Benchmarking model under-estimates demand for activity	and/or	Person has easier time fulfilling desired level of activity

y represents total daily trip volume for person *i* (excluding return-home and return-to-work trips).

I consider two different angles of mobility fulfillment. First, without knowing *how* needs were fulfilled (either by which modes, or the extent of traveling at all), I consider which subgroups appear more versus less fulfilled. That is, I consider patterns among demographic and geographic subgroups of non-owners, using the following types of analysis:

(a) Descriptive statistics: the average discrepancy values for each subgroup. In particular, whether that subgroup has more or less mobility deficit (based on predictions of the benchmarking model) compared to other no-car or low-car households. I conduct *t*-tests for differences in averages across subgroups within segments.

(b) A linear regression model of the discrepancy value, as determined by demographics and geography, within the ownership segment. This is one way to evaluate the role of specific demographic attributes, after others are accounted for. If attributes are interrelated or overlapping, it can help show which ones dominate. However, because the direction of causality is not clear and the explanatory variables are not independent from one another, the results are more diagnostic than deterministic.

The variables considered for inclusion as explanatory variables in the regression are the same ones included in the benchmarking model (from Chapter 4, see Table 37), plus driver status, which was not included in the benchmark model, since all members of the "unlimited access" (high-car) segment were drivers. Variables were evaluated based on the magnitude and statistical significance of their coefficients and their apparent contribution to the variation explained (based on the adjusted R-squared), with note taken as to which variables seemed to conflict with one another.

For the no-car households, the best model has an adjusted-R^2 value of 0.106, and for the low-car households it is even lower, at 0.027, meaning that not much of the variation in the discrepancy values in either segment is explained by the regression (about 89.4% and 97.3% unexplained in each, respectively) (see Table 46). However to the extent that the estimated coefficients are accurate and unbiased, the results offer insight on the relative role of specific factors in accounting for the discrepancy in mobility among members of the each segment. All the variables included are binary dummy variables, meaning they have the same units and the magnitudes of the coefficients can be compared directly within a given regression. In each case, the coefficient represents the change in number of trips, on average, when the condition holds, all else equal.

Because the original benchmarking model included these variables as predictors of expected trip-making levels, a significant contribution in this regression means that a variable has a systematically different influence on trip volume among no-car (or low-car) households than among the high-car households, either adding to or attenuating effects captured in the benchmarking model.

Second, I also consider relative mobility fulfillment among users of different modes of transportation within the no-car and low-car segments. This shows more about how needs are fulfilled, and which types of modes are associated with choice versus constraint. Again, I conduct *t*-tests for differences in average across subgroups within segments.

5.2 Overall averages within each vehicle-access segment

As described above, the correct interpretation of the discrepancy values is rooted in the fact that they are generated by the benchmarking model, calibrated to the high-car-access group. This means that by design, within the high-car owner group, the average discrepancy (or average difference between actual and predicted trip volumes) is precisely zero. For all other groups, the average represents whether the members of the group made greater or fewer trips, on average, than predicted by the benchmarking model. One interpretation of the benchmarking model is that it determines how much of the shortfall in average trip volumes among no-car and low-car households can be explained by demographics and geography (the variables included in the benchmarking model). Any remaining gap between actual behavior and that predicted by the model is unexplained by demographics alone — either reflecting mobility constraints related to vehicle ownership or some other reason that their demand for activity might be less than for the high-access owners used to calibrate the model.

The results suggest that for those in no-car households, about 70.1% of the apparent shortfall (of 0.896 trips fewer relative to high-car owners) is accounted for by demographics, but a statistically significant portion of the difference is *not* accounted for, representing an average remaining shortfall of 0.376 trips, relative to what the benchmarking model would predict (see Table 38). For those in low-car households, all of the apparent shortfall (of 0.527 fewer trips relative to high-car owners) is accounted for by demographics, with an average remaining shortfall of 0.009 trips, on average, which is not statistically different from zero. This means that among the no-car households there is an unexplained gap, attributable to lack of vehicle access itself, or to other differences between the no-car and high-car segments that are not accounted for in the benchmarking model. Meanwhile, among the low-car segment, actual trip-making is no less than it would be with more plentiful vehicles, on average.

Is the 0.376-trip shortfall among non-owners a large or small amount? Relative to the overall noise in the benchmarking model, it might not be that much. (Recall that only 38.2% of cases in the benchmarking model were predicted within +/-1 trip of their actual value; see Table 37.) However, it is sizeable as a percent of overall trip-making among non-owners. If the benchmark prediction were accurate, then actual trip-making is only 78.3% of what it otherwise would be in the absence of vehicle-related constraints (or in the absence of whatever other attributes differentiate the non-owners that might reduce their trip-making), on average.

Although the benchmarking model is designed so that the average discrepancy is zero for the segment used for estimation (the high-car segment), it over-predicts for more cases than it under-predicts, in all vehicle-access segments. This is because the distribution of trip volumes is right-skewed, with a long, thin tail of relatively rare high values, and a disproportionately large share of 0's and 1's that the model has difficulty predicting. If the distribution of trip volumes were symmetric, half of the predictions would be under and half over (at least in the high-access segment of the sample, used to estimate the model); in this instance, the prediction is higher than the actual for 58.3% of the cases in the high-car segment, resulting in negative discrepancy values (suggesting reality falls short of the predicted value); the prediction is lower than the actual for 42.7% percent of cases (reality exceeds the predicted value). This is a useful reference for then considering that these relative portions are even farther from 50%-50% among the no-car segment: 68.7% are negative values (reality falls short of the predicted value) and 31.3% are positive values (reality exceeded the predicted value) (see Table 38). Again, this offers evidence of either mobility limitations, or an over-estimate of their latent demand for out-of-home activity.

Table 38. Discrepancy values (actual minus predicted values) for each vehicle-access segment

	Unweighted data				Weighted data			
	Vehicle-access segment				Vehicle-access segment			
	No-car	Low	High	Overall	No-car	Low	High	Overall
Actual trip volume (y_i)								
valid N	7,185	23,190	119,341	149,716	11,628.4	28,126.3	99,396.4	139,151.1
Min	0	0	0	0	0	0	0	0
Max	17	20	25	25	17	20	25	25
Avg	1.380	2.131	2.658	2.515	1.716	2.246	2.757	2.567
s.d.	1.662	2.037	2.113	2.106	1.721	1.983	2.104	2.077
Apparent shortfall of avg (y) relative to high-car avg	-1.278	-0.527	n/a	n/a	-1.041	-0.512	n/a	n/a
Avg as % of high-car avg	78.6%	99.6%	n/a	n/a	62.2%	81.4%	n/a	n/a
Predicted trip volume ($\hat{y}_i$)								
valid N	6,719	22,200	114,882	143,801	10,760.0	26,877.5	95,754.4	133,391.9
Min	0.279	0.270	0.336	0.270	0.279	0.270	0.336	0.270
Max	4.842	5.291	6.888	6.888	4.842	5.291	6.888	6.888
Avg	1.763	2.148	2.643	2.526	1.995	2.251	2.695	2.549
s.d.	0.790	0.707	0.537	0.630	0.794	0.639	0.517	0.619
Actual versus (y_i) predicted ($\hat{y}_i$)								
% difference in average value	-21.7%	-0.8%	0.6%	-0.4%	-14.0%	-0.3%	2.3%	0.7%
Raw difference ($\mathrm{d_i = y_i - \hat{y}_i}$)								
Min	-4.284	-4.530	-5.102	-5.102	-4.284	-4.530	-5.102	-5.102
Max	14.730	16.905	22.108	22.108	14.730	16.905	22.108	22.108
Avg	-0.376	-0.009	0.000	-0.019	-0.295	0.005	0.056	0.018
s.d.	1.594	1.908	2.019	1.986	1.596	1.891	2.014	1.961
% of $\mathrm{d_i} > 0$	31.3%	40.8%	42.7%	41.9%	36.2%	41.3%	43.6%	42.6%
Actual avg (y) as % of predicted avg ($\hat{y}$)	78.3%	99.2%	100.6%	99.6%	86.0%	99.7%	102.3%	100.7%

5.3 Mobility fulfillment among demographic subgroups of the no-car and low-car segments

The discussion of results (below) is organized by categories of attributes, synthesizing findings based on the descriptive statistics (Table 40 through Table 45) and on the regression model (results shown in Table 46). Table 49 summarizes findings for each demographic attribute.

In Table 40 through Table 45, results are shown for all three vehicle-access segments, but the focus is on the extent of variation across subgroups within each. Consequently, the subgroup figures are expressed relative to the segment average (as the difference between the average for the subgroup and the overall segment average; e.g. the average among urban versus the average among all neighborhoods). Results for *t*-tests are shown for difference in average within a subgroup versus its opposite (e.g. the average among urban versus the average among *not* urban). Results for the no-car and low-car segments are discussed.

5.3.1 Economic status

If there were a clear difference in mobility outcomes among low-car households depending on whether their ownership decision was voluntary or involuntary (as in Delbosc and Currie, 2012), then measures relating to their purchasing power, or economic status, would be associated with the degree of mobility deficit: for instance, those with higher incomes would have more mobility (or less mobility deficit) than those with lower incomes. However, there is no clear association between income and mobility deficit within either the no-car or low-car segments, though there are weak relationships with educational attainment and home-ownership that may be related.

First with respect to household income level, mobility levels are slightly higher (that is, there is less mobility deficit, on average) among those in households with incomes above the median, but the difference is not statistically significant in either segment (Table 39). In a regression, a continuously valued version of household income is not significant, within either segment, regardless of what else is included in the model. A correlation coefficient between income and mobility is positive and significant, but barely different from zero (at 0.021, p=0.091 among non-owners; and 0.015, p=0.031 among fewer-car owners). There are some levels of income with statistically significantly different averages, but no consistent trend (see Table 39). That deficits are somewhat *less* in the second lowest income category ($7,500-$12,500 per adult) among no-car households and more in the lowest category (<$7,500 per adult) among low-car households may be because these two levels were not distinguished in the benchmarking model (since not significant among the high-access segment). In both the no-car and low-car segments there is also an apparent dip in mobility among those with incomes in the category \$17,500-\$22,500 per adult, with no clear explanation, though this category spans the mean and median level for each segment. It could be capturing an overall negative effect that would otherwise be part of the constant term, applying to the mid-level portion of the sample. Or it could be a particular level of income more commonly found among retirees or some other group with lower overall mobility levels not otherwise captured in the benchmarking model or the regression. There is generally higher mobility (less mobility deficit) among the higher income categories, but not statistically significantly in the no-car segment and only at one of the levels among the low-car segment (\$47,000-\$50,000 per adult).

Educational attainment may capture an aspect of opportunity or access to resources not reflected in household income levels. In both the non-owners and limited-owners segments, those with just a high school diploma have less mobility than average and those with some college or an associate's degree (less than a bachelor's) have more mobility than average, in addition to those with a bachelor's degree among the limited-owners (but not the non-owners) (Table 39). As with the lowest income categories, one reason for differences among those with associate's degrees is that this level was not included in the benchmarking model (since it was not significant for those in the high-access segment), in which they would have been grouped with those with just a high-school degree; the positive effect here captures the apparent difference between those levels, significant among the non-owners and limited-access owners. The negative effect of having just a high school degree suggests that this group faces greater mobility challenges, or alternatively have less need for travel, than comparably educated people in the high-car segment. This effect is significant in the regression models for both segments, as is the positive effect of the associate's degree in the non-owners' segment (but not quite among the limited-access owners, once other factors are included) (Table 46).

Home-ownership is another factor that reflects economic status and access to tangible resources. Perhaps counter-intuitively, home-owners have a greater mobility deficit, on average, relative to non-home-owners (Table 39). That is, there is a bigger gap between predicted and actual trip volumes for home-owners than for renters, among both the no-car and low-car households, though the average effect is much greater and more significant among the no-car households. This could be because home-ownership is correlated with a certain style of built environment, with lower density and more detached homes; this would mean that on average, those who are home-owners may also be living in environments where non-vehicle transportation is more difficult and so their greater mobility deficits reflect this circumstance rather than home-ownership per se. (When included in the regression, home-ownership does not have a significant coefficient in the non-owner regression, seemingly conflicting with the built environment measures, rather than with the (few) economic indicators, providing support for this theory. However, among the limited-access segment, it is still significant and negative, and the built environment measures are not.) Alternatively, home-ownership versus non-ownership may mean something different among the high-car-households versus the no- and low-car households. For instance, home-ownership without vehicle-ownership may reflect circumstances associated with overall less demand for activity (so the model would over-predict their demand, with a negative discrepancy value appearing as a mobility deficit). This seems plausible in the sense that if people own a home, probably they *could* afford an additional vehicle and so not owning one is a deliberate choice and indicative of their particular travel needs and preferences, or lack thereof – perhaps they are retired or have a preference for fewer out-of-home activities.

Table 39. Mobility fulfillment in each vehicle-access segment, by subgroups: Economic status

Subgroup	Average discrepancy value in each vehicle-access segment: No-car		Low		High		% > 0, in each vehicle-access segment: No-car	Low	High
	– 0.374		– 0.009		0.000		31.4%	40.8%	42.7%
	Difference within this subgroup relative to average in the entire segment:						%-point difference relative to entire segment:		
Household income per adult									
<$7,500	– 0.004		– 0.104	**	– 0.062	.	– 0.5%	– 3.2%	– 4.6%
$7,500-12,500	+ 0.170	***	– 0.024		+ 0.007		+ 3.9%	– 0.6%	– 2.0%
$12,500-17,500	+ 0.049		+ 0.073	**	+ 0.008		– 1.0%	+ 1.0%	– 1.1%
$17,500-22,500	– 0.254	***	– 0.067	**	– 0.003		– 6.2%	– 1.1%	– 0.5%
$22,500-27,500	+ 0.074		+ 0.101	**	– 0.003		+ 4.5%	+ 2.1%	+ 0.4%
$27,500-32,500	– 0.033		– 0.079	.	– 0.003		+ 2.9%	– 0.1%	+ 0.0%
$32,500-37,500	+ 0.185		+ 0.104	**	+ 0.001		+ 2.5%	+ 2.3%	+ 0.0%
$37,500-42,500	+ 0.033		– 0.032		+ 0.004		+ 3.3%	– 1.3%	+ 0.9%
$42,500-47,500	+ 0.250	.	– 0.084		– 0.000		+ 9.1%	– 1.3%	+ 0.9%
$47,500-$50,00	+ 0.068		+ 0.151	**	+ 0.004		+ 5.4%	+ 4.2%	+ 0.7%
>$50,000	+ 0.129		– 0.096		– 0.002		+ 4.3%	+ 0.4%	+ 0.8%
Household income per adult									
< median ($27,500)	– 0.002		– 0.003		– 0.014	-	– 0.5%	– 0.3%	– 1.1%
>= median ($27,500)	+ 0.010		+ 0.010		+ 0.009	-	+ 2.3%	+ 1.0%	+ 0.7%
Educational attainment									
Less than high school	– 0.045	.	– 0.043	.	– 0.003		– 3.0%	– 2.3%	– 3.4%
High school	– 0.103	***	– 0.121	***	– 0.107	***	– 1.5%	– 2.7%	– 2.8%
Some college / associates	+ 0.202	***	+ 0.146	***	+ 0.099	***	+ 5.2%	+ 3.2%	+ 2.3%
Bachelor's	+ 0.024		+ 0.068	**	+ 0.003		+ 2.3%	+ 2.0%	+ 0.8%
Graduate degree	– 0.017		+ 0.056	.	+ 0.001		– 0.2%	+ 2.9%	+ 0.6%
Home ownership									
Rents	+ 0.056	***	+ 0.040	.	+ 0.016		+ 1.7%	+ 0.3%	+ 0.3%
Owns	– 0.082	***	– 0.009	.	– 0.002		– 2.6%	– 0.1%	– 0.0%

Significance shown is for t-test of equivalence of means, indicated if the average within the row subgroup is significantly different from the average among the rest of the segment at p <0.20 (.), < 0.10 (-), <0.05 (*), <0.01 (**), or <0.001 (***).

5.3.2 Driving and physical ability

Measures of driving ability are more strongly associated with a low versus high discrepancy value (that is, how actual behavior compares to that predicted by the benchmarking model) than any other factor, among those in both the non-owner and low-car segments. This is somewhat surprising for the non-owners, since driving would seem to be less important for mobility in that context.

Driving ability (both current and/or former status) was not included in the benchmarking model, because all members of the benchmarking segment were current drivers, as a defining criterion. However this distinction apparently matters. Among the low-car households, those who drive have mobility levels that are no less than would be predicted by the benchmarking model (reflecting behavior of high-car households) – in fact they make even more trips than would be predicted (by 0.125 trips, on average). This suggests that this subgroup (72.0% of the weighted sample in low-car households) faces few mobility barriers, and perhaps even mobility advantages – or greater underlying demand for trip-making – compared with their counterparts in high-ownership households, after accounting for other attributes. That is, there is no evidence that their travel is limited by lack of access to household vehicles. By contrast, those who do not drive, who either formerly drove or never drove, have much lower mobility levels (on average 0.470 or 0.664 fewer trips, on average, than predicted by the benchmarking model), but not as low as non-drivers in no-car households.

Among non-owners, those that drive also have the lowest mobility deficit — that is, their trip volumes more closely resemble the predicted volumes for their demographic profile – than any other subgroup within their ownership segment, except for those with disabilities (discussed more below). On average, they make just 0.039 trips fewer than predicted (or, 0.337 trips closer to the predicted volume than the non-owners overall; see Table 40). By contrast, those who never drove made 0.664 fewer trips than predicted, on average (0.288 below the segment average), while those who do not currently drive but formerly drove make 0.470 fewer trips than predicted (0.094 below the segment average). (See Table 40.)

This suggests that among non-owners, drivers face fewer mobility barriers than non-drivers, either because they use their driving ability to get around (such as by borrowing or renting cars) or because driving ability is associated with access to other mobility resources – such as friends with cars who give them rides or cultural savvy that results in a greater ability to travel – or that *inability* to drive signifies a lack of these. Alternatively, it could also potentially indicate that drivers in non-owning households have a greater preference for travel than their other demographics alone would predict (that is, the model under-predicts their activity demand), perhaps an activity-oriented, busy lifestyle preference not otherwise captured in the model; conversely that non-drivers have *less* preference for travel than their other demographics alone would predict, or than anyone in the benchmarking group of high-access owners.

Two variables relating to limiting medical conditions (limiting his ability to travel, by any means[14]; and among those with such conditions, whether the condition results in giving up driving[15]) *were* included in the benchmarking model, where they contribute negatively to the expected volume of trips (see Table 37). However, among the no-car and low-car households, mobility levels are higher among these special populations. That is, those with limiting medical conditions make *more* trips than predicted by the benchmarking model, on average. While they make fewer trips than those in high-car households generally, and fewer trips than others in their ownership-segment without limitations, on average, once the benchmarking model takes into account their other demographic circumstances, it predicts that they would make even fewer trips than they reportedly do (see Table 40).[16]

On the face of it, this would suggest that these people (medically limited in no-car and low-car households) face *fewer* mobility barriers, and perhaps even mobility advantages,

[14] In particular, they report having a medical condition making it hard to travel, for some resulting in circumstances such as limiting driving to daytime, giving up driving, riding the subway less, asking others for rides, or reduced day-to-day travel).

[15] Giving up driving as the result of a medical condition is a subset of those with any sort of limiting medical condition, so these act like a main effect and an interaction effect. Giving up driving as a result of a medical condition and driver status have overlap but are not equivalent, since the former can be an incremental reduction but the person still reports being a driver. In total 85% of those who report giving up driving as a result of medical condition do not drive and 15% do; 40% of those who do not drive have a limiting medical condition, but 60% do not.

[16] To put these results in perspective, however, it should be noted that in all vehicle-access segments, those with limiting medical conditions make significantly fewer trips, on average, than their non-limited counterparts. Among those with limiting conditions, those in high-access households make significantly more trips than those in low-access (non-owning) households (1.93 versus 0.99 trips, on average). As a percent of the overall within-segment trip volume average, trip-making among the medically limited is also still higher among the high-access segment (at 71.1% versus 58.1%).

relative to their counterparts in car-owning households, after accounting for other attributes. This may be possible if the presence of vehicles and able drivers hampers travel by the non-driving (or limited) household member, whose desire to travel is less fulfilled. Alternatively, for those in vehicle-owning households, the non-driving (or limited) household member may opt to abdicate responsibilities to the able household members, making fewer trips by choice, while in non-owning households, the limited person may be forced to travel more than he or she would like, because there is no one else to call upon with easy use of a vehicle. In this case, what appears here as “mobility surplus” may actually be an undesirable experience, perhaps forced mobility, for those in non-owning households. Another explanation might relate to the fact that vehicle ownership is a longer-term decision, and that perhaps having a limiting condition and giving up a car is evidence of consonance between ownership and circumstances, achieved over time perhaps with any other lifestyle adjustments needed to maintain mobility despite disabilities; by contrast reporting a limiting condition while still owning a car might reveal situations in which a person has not yet adjusted to a relatively recent (or gradually emerging) circumstance of disability. Whatever the explanation, there seems clear evidence that the circumstances of disability in the context of a high-car versus no-car or low-car household are different and should be examined accordingly.

When included with other demographic variables in a regression model, the driving variables have significant coefficients, even in the presence of variables such as income (which are mostly not significant), education (again, mostly not significant), age, and attributes of the built environment – suggesting that they are not serving as a proxy for these attributes. Furthermore, they have the largest magnitudes of any other factor (see Table 46). According to the regression, drivers in no-car households make 0.631 more trips than non-drivers, all else equal, and drivers in low-car households make 0.698 more trips than non-drivers, all else equal.

Having a medical condition that makes it difficult to travel also results in more trip-making (relative to the level predicted by the benchmark model), by 0.114 trips among those in no-car households, and the specific circumstance of having a condition that results in giving up driving is associated with an additional 0.838 more trips among no-car and 0.702 more trips among low-car households, all else equal. With respect to these variables, the person who would have the least mobility (that is, most likely to make fewer trips relative to the level predicted by the benchmarking model) is someone who does not drive and has no medical reason for it – a person not well represented in the benchmarking segment of high-access owners.

Table 40. Mobility fulfillment in each vehicle-access segment, by subgroups: Driving and physical ability

	Average discrepancy value in each vehicle-access segment:						% > 0, in each vehicle-access segment:		
	No-car – 0.374		Low – 0.009		High 0.000		No-car 31.4%	Low 40.8%	High 42.7%
Subgroup	Difference within this subgroup relative to average in the entire segment:						%-point difference relative to entire segment:		
Driver status									
Never drove	– 0.290	***	– 0.470	***	n/a		– 7%	– 10.9%	n/a
Formerly drove	– 0.095	***	– 0.294	***	n/a		– 3.5%	– 9.7%	n/a
Currently drives	+ 0.336	***	+ 0.134	***	+ 0.000		+ 9.5%	+ 3.8%	+ 0.0%
Limiting medical conditions									
No limiting condition	– 0.234	***	– 0.009		+ 0.000		– 3.7%	+ 0.9%	+ 0.2%
Any condition making it hard to travel	+ 0.287	***	+ 0.024		– 0.003		+ 4.4%	– 2.6%	– 1.4%
Results in limiting driving to daytime	+ 0.359	***	+ 0.029		– 0.089	***	+ 7.8%	– 0.7%	– 3.6%
Results in using bus/subway less often	+ 0.439	***	– 0.008		+ 0.100	.	+ 11.4%	– 3.0%	+ 0.7%
Results in asking others for rides	+ 0.337	***	+ 0.029		– 0.019		+ 5.5%	– 3.2%	– 2.7%
Results in giving up driving	+ 0.476	***	+ 0.093	***	+ 0.002		+ 8.7%	– 3.5%	– 7.1%

Significance shown is for t-test of equivalence of means, indicated if the average within the row subgroup is significantly different from the average among the rest of the segment at *p* <0.20 (.), < 0.10 (-), <0.05 (*), <0.01 (**), or <0.001 (***).

5.3.3 Built environment

Whether because households without cars self-select into environments that are better suited to car-free living or whether households opt to give up a car once living in a place where it is not needed, it seems logical that low-car households would have easier mobility in such environments. However, the results suggest that it only matters for those in no-car households and makes little measurable difference to those in low-car households.

Among the no-car households, average deficits are generally greater in the lower-density areas and less in the higher density areas, but the difference is slight except for in the highest density category (see Table 41). At densities less than 4,000 housing units per square mile, the deficit is about 0.10 trips lower than the average deficit among all non-owners; at 4,000 to 24,999 units per square mile it is about the same as the average for the whole segment; at 25,000-999,999 units per square, it jumps to just 0.089 fewer trips made than predicted by the model, which is about 0.287 less than the average for the segment. Furthermore, the deficit is also significantly less in "urban" community types compared to any of the other three types: second city, suburban, and town/country, but not by as much as in the specific category of highest-density Census tracts (0.143 less versus 0.287 less, on average). There is no significant difference, on average, between the second city, suburban, and town/country areas. This suggests that those living without a car are no worse off, on average, in town/country and suburban areas than in second cities; or conversely, that those in second cities are no better off than in town/country areas, and the only type with a significant advantage is truly urban, especially in areas with the highest level of density. Corresponding to the different styles of development, those living in detached single-family homes also have significantly more deficit, on average, by about 0.167 trips, compared to non-owners in other styles of housing.

Meanwhile none of these distinctions matters much, on average, for those in low-car households, where there is also less range in fulfillment levels generally. However, if anything, members of low-car households are worse off in more urban neighborhoods, on average. Mobility fulfillment is slightly less, on average, among those in urban and second city neighborhoods, though only the latter is significant (with p=0.0355 and p=0.095, respectively) and more in suburban and town/country neighborhoods, though only the former is significant (*p*=0.092 and *p*=0.598, respectively). This could be an indication of residential/ownership dissonance, where as car-owners, more urban neighborhoods are inherently more constraining (as found in de Vos et al. 2012). While no similar pattern is apparent among the high-car households, perhaps this is dissonance with less ability to readjust (whereas the high-car owners may have more ability to self-select). Alternatively, perhaps neighborhood type correlates with other differences in life circumstances associated with more constraint or less demand for travel. Contrasting with the direction of these results by neighborhood type is that low-owners in detached homes have less mobility fulfillment, on average, as found among the no-car households, though only by about 0.063 trips. In this case, perhaps the circumstances of home-ownership, discussed above, are more prevalent than the circumstances of built environment.

Table 41. Mobility fulfillment in each vehicle-access segment, by subgroups: Built environment

	Average discrepancy value in each vehicle-access segment:						% > 0, in each vehicle-access segment:		
	No-car		Low		High		No-car	Low	High
	– 0.374		– 0.009		0.000		31.4%	40.8%	42.7%
Subgroup	Difference within this subgroup relative to average in the entire segment:						%-point difference relative to entire segment:		
PRIZM group									
Urban	+ 0.141	***	– 0.027		+ 0.002		+ 4.3%	– 0.9%	+ 0.8%
Second city	– 0.078	**	– 0.043	-	+ 0.001		– 2.0%	– 0.4%	+ 0.0%
Suburban	– 0.063	.	+ 0.039	-	+ 0.002		– 1.7%	+ 1.7%	+ 0.7%
Town/country	– 0.048	.	+ 0.009		– 0.002		– 1.9%	– 0.4%	– 0.5%
Density of housing in home Census Tract (units per square mile)									
0-99	– 0.114	**	– 0.022		– 0.041	***	– 4.6%	– 2.1%	– 1.6%
100-499	+ 0.004		+ 0.027		+ 0.022	**	+ 0.6%	+ 0.8%	+ 0.5%
500-999	– 0.092	-	+ 0.038		+ 0.002		– 2.8%	+ 1.6%	+ 0.3%
1,000-1,999	– 0.103	**	+ 0.007		+ 0.019	.	– 2.6%	+ 0.9%	+ 0.8%
2,000-3,999	+ 0.092	**	– 0.028		+ 0.01		+ 3.1%	– 0.7%	+ 0.6%
4,000-9,999	+ 0.088	.	– 0.019		+ 0.026		+ 3.7%	– 0.2%	+ 1.3%
10,000-24,999	+ 0.019		– 0.152	.	+ 0.100		– 2.5%	– 1.9%	+ 2.5%
25,000-999,999	+ 0.285	**	+ 0.011		+ 0.044		+ 8.7%	+ 1%	– 0.8%
Home type									
Detached single-family home	– 0.110	***	– 0.018	**	+ 0.002		– 3.8%	– 0.5%	+ 0.0%
Other type of unit	+ 0.057		+ 0.045		– 0.006		+ 2.0%	+ 1.3%	– 0.1%

Significance shown is for t-test of equivalence of means, indicated if the average within the row subgroup is significantly different from the average among the rest of the segment at *p* <0.20 (.), < 0.10 (-), <0.05 (*), <0.01 (**), or <0.001 (***).

Transit availability — though only measured at the MSA level (and only for respondents in MSAs over a million people for which "transitscore" data are available) — appears significantly associated with less mobility deficit, but notably also in the no-car segment only. Grouping transit scores into quintiles, there is incrementally less deficit for those in the low-access group for each increasing level of transit — except for the highest category, which includes only New York City (see Table 42). Valued continuously (though taking on only 26 unique values), transit score is somewhat weakly but positively and significantly correlated with discrepancy value, but again only among the low-access group, where the correlation coefficient is 0.052 (p=0.000).

When included together in a regression, no combination of built environment measures is significant for the low-car households. Among the no-car households, of the four community-type indicators, the urban community type has the most robust effect. When included on its own in lieu of the other three indicators it has a significant positive coefficient, indicating 0.109 more trips, on average, among no-car households living in an urban area, all else equal. However, including the three other indicators, for town/country, suburban, and second-city (omitting the urban as reference) proves informative (see Table 46). As expected, all three coefficients are negative, greatest for suburban, then for second city, and least for town/country, which is only marginally statistically significant. It is somewhat surprising that town/country doesn't have the biggest effect. An explanation might be that travel volumes are generally less for everyone in town/country areas (owners and non-owners alike, as indicated in the original predictive model), and the additional reduction among non-car-owners is small and possibly not significant. By contrast, there is more of a disadvantage among no-car households in suburban areas, where car-owners are more active than in town/country areas. Notably, there is still a disadvantage in second city areas, only slightly less than in suburban areas (0.111

fewer versus 0.154 fewer trips in second city and suburban areas, respectively, relative to what the benchmark model otherwise would have predicted).

Even among the no-car households, neither the measures of housing-unit density nor employee density are significant in the regression in the presence of the community-type indicators. However a dummy variable for the highest density of housing units is significant, associated with 0.193 more trips than the benchmarking model would have predicted. The indicator for living in a detached home has a significant coefficient if included, but conflicts with the community-type indicators without providing clear improvement. (It is omitted from the specification in Table 46, assuming its effect is captured as part of the community type.) Transit score is significant only if none of the other built environment measures is included, and clearly conflicts with them. (Again, it is omitted from the specification in Table 46, assuming the community type and density factors capture its effect.)

Table 42. Mobility fulfillment in each vehicle-access segment, by subgroups: Transit availability

Transit score range	MSAs in this range	Average discrepancy value in each vehicle-access segment:			% > 0, in each vehicle-access segment:		
		No-car – 0.374	Low – 0.009	High 0.000	No-car 31.4%	Low 40.8%	High 42.7%
		Difference within this subgroup relative to average in the entire segment:			%-point difference relative to entire segment:		
0-20	MSAs <1 million and MSAs with missing transit data	– 0.07 ***	– 0.006	+ 0	– 2%	– 0.1%	– 0.2%
21-40	Austin, Baltimore, Columbus, Dallas, Houston, Kansas City, Las Vegas, Miami, Pittsburgh, Portland, Raleigh, Sacramento, San Antonio, San Diego, Seattle, Tampa	+ 0.048	+ 0.01	– 0.03 **	+ 1.9%	– 0.6%	– 0.2%
41-60	Buffalo, Cleveland, Denver, Los Angeles, Milwaukee, Salt Lake City, San Jose, St. Louis	+ 0.119 **	+ 0.008	+ 0.03 .	+ 3.8%	+ 0.5%	+ 1.3%
61-80	Boston, Chicago , Minneapolis, Philadelphia, San Francisco, Washington DC	+ 0.248 **	+ 0.071	+ 0.036 .	+ 6.2%	+ 1.8%	+ 1.3%
81-100	New York	+ 0.082 .	– 0.034	+ 0.044	+ 1.8%	+ 0.8%	+ 1.6%

Significance shown is for t-test of equivalence of means, indicated if the average within the row subgroup is significantly different from the average among the rest of the segment at p < 0.10 (.), <0.05 (*), <0.01 (**), or <0.001 (***).

While sample sizes are small, I also consider averages within specific MSAs. If the average discrepancy is positive (or a smaller negative value), it would provide evidence of one of two possibilities: that there is something about that MSA that enables more mobility than is captured in the model, or that there are cultural or demographic attributes of the population that differ from elsewhere (resulting in systematically more or less demand for travel, or more or less ability/proclivity to realize that demand, not captured in the model).

Table 43 lists the average discrepancy for the available cases from each MSA, sorted from greatest to least (from surplus mobility to most deficit, relative to the level predicted by the benchmarking model) among the no-car segment. The significance result shown is for a t-test of the equivalence of the within-MSA mean to the mean for all other cases excluding that MSA, within a given segment. In most MSAs, sample sizes are too small for statistical significance and the results should be treated with caution. However, mobility levels are statistically significantly higher than the no-car segment average in Boston and Pittsburgh (where there is actually surplus mobility) and in Portland and Los Angeles (where there is less mobility deficit than in the segment overall). These might be places where mobility is easier, relative to their transit scores – such as if the transit score underrates the availability of transit or if there are walking and biking opportunities (such as in Portland) not captured in the transit score — and/or where the population is especially active and/or attitudinally oriented to alternative modes. This might be the case in Boston, where there are many college students as well as a strong transit culture, and in Portland, where there are both young people and a strong bicycle culture.

By contrast, mobility levels are statistically significantly lower among no-car households in San Jose and in Memphis. These might be places where mobility is more difficult relative to their transit score, and/or where the population is less active. With the caveat of dubious statistical significance, I note the position of some other major cities (focusing on those with at least 100 respondents): more mobility (less deficit) in Tampa, San Francisco, Phoenix, Washington, San Diego, and New York; and less mobility (more deficit) in Miami, Houston, Dallas, and MSAs with less than 1 million people (identity unknown and grouped collectively).

Table 43. Average mobility discrepancy by vehicle-access group in individual MSAs

MSA name	Average discrepancy value by vehicle-access segment:			N		
	No-car	Low-car	High-car	No-car	Low	High
Boston-Cambridge-Quincy, MA-NH	0.754 **	0.024	-0.085	28	52	235
Birmingham-Hoover, AL	0.510	-0.151	-0.209	2	6	59
Pittsburgh, PA	0.475 -	0.209	0.021	12	36	118
Baltimore-Towson, MD	0.448 .	-1.054 **	-0.150	8	17	133
Kansas City, MO-KS	0.307	0.395	0.044	3	16	113
Milwaukee-Waukesha-West Allis, WI	0.060	0.349 .	0.097	21	59	296
Jacksonville, FL	0.029 .	-0.019	-0.049	47	162	933
Oklahoma City, OK	0.010 .	0.363	-0.137	2	8	64
Tampa-St. Petersburg-Clearwater, FL	-0.071	0.175	0.000 **	117	483	1487
Portland-Vancouver-Hillsboro, OR-WA	-0.114 -	0.397	-0.052	8	27	115
San Francisco-Oakland-Fremont, CA	-0.136	-0.014	0.140	138	341	1693
Los Angeles-Long Beach-Santa Ana, CA	-0.152 **	-0.025	-0.048 .	248	833	3339
Indianapolis-Carmel, IN	-0.158	-0.028	-0.050	38	91	653
Phoenix-Mesa-Glendale, AZ	-0.159	-0.060 -	-0.029 .	164	860	3490
Austin-Round Rock-San Marcos, TX	-0.190	-0.030	-0.104 -	41	206	1214
Washington-Arlington-Alexandria, DC-VA-MD-WV	-0.196	0.027 .	-0.076 **	105	326	1666
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	-0.242	0.395	0.187 **	23	78	303
San Diego-Carlsbad-San Marcos, CA	-0.261	0.025 -	-0.008	259	908	4511
New York-Northern NJ-Long Island, NY-NJ-PA	-0.292	-0.043	0.044 **	834	1052	2995
Sacramento—Arden-Arcade—Roseville, CA	-0.293	-0.242	-0.043	41	160	972
San Antonio-New Braunfels, TX	-0.303	0.201	0.059	72	343	1547
Chicago-Joliet-Naperville, IL-IN-WI	-0.336	0.119	0.035	43	154	648
Buffalo-Niagara Falls, NY	-0.337	0.171	-0.031	36	138	472
Virginia Beach-Norfolk-Newport News, VA-NC	-0.349 **	-0.139 **	-0.091	115	414	2508
Riverside-San Bernardino-Ontario, CA	-0.355 ***	-0.003 .	-0.119 -	53	285	1141
Overall average	-0.376	-0.009	0.000	6719	22200	114882
Rochester, NY	-0.380	0.199	-0.009 **	38	104	563
Miami-Fort Lauderdale-Pompano Beach, FL	-0.390	-0.004	0.165 ***	250	847	2668
Salt Lake City, UT	-0.392	-0.311	-0.287	5	19	79
Houston-Sugar Land-Baytown, TX	-0.415	-0.060	-0.133 ***	166	613	3071
Atlanta-Sandy Springs-Marietta, GA	-0.441	-0.136	-0.159 **	36	173	989
New Orleans-Metairie-Kenner, LA	-0.449	-0.527	0.628	6	15	50
unknown (blocked) MSA < 1 million	-0.451	-0.010	0.016 .	3281	11531	65384
Columbus, OH	-0.479	0.020	0.054	4	11	81
Dallas-Fort Worth-Arlington, TX	-0.496	-0.101 .	-0.007	167	769	4666

MSA name	Average discrepancy value by vehicle-access segment:			N		
Minneapolis-St. Paul-Bloomington, MN-WI	-0.503	0.176	0.016	12	37	175
Orlando-Kissimmee-Sanford, FL	-0.529	0.056	-0.174	42	213	841
Detroit-Warren-Livonia, MI	-0.546	0.325	-0.025	11	49	178
St. Louis, MO-IL	-0.558	-0.242 .	0.086	8	29	148
Cleveland-Elyria-Mentor, OH	-0.592	0.217	0.004	7	14	111
Hartford-West Hartford-East Hartford, CT	-0.657	0.736	0.079	7	9	72
Nashville-Davidson—Murfreesboro—Franklin, TN	-0.671	-0.170	-0.026	19	49	531
San Jose-Sunnyvale-Santa Clara, CA	-0.688 -	0.048	-0.071 **	24	109	682
Seattle-Tacoma-Bellevue, WA	-0.707	-0.325	-0.410	7	25	150
Denver-Aurora-Broomfield, CO	-0.729	-0.782	0.321 -	5	7	114
Louisville-Jefferson County, KY-IN	-0.806	0.389	0.301 -	8	22	158
Providence-New Bedford-Fall River, RI-MA	-0.823	0.231	0.092	18	54	200
Charlotte-Gastonia-Rock Hill, NC-SC	-0.882	0.059	-0.037	14	78	454
Richmond, VA	-0.882	-0.178 **	-0.074	84	242	2015
Cincinnati-Middletown, OH-KY-IN	-0.936	-0.172	-0.120	9	22	135
Las Vegas-Paradise, NV	-0.940	-0.090	0.064	3	24	107
Memphis, TN-MS-AR	-0.946 **	0.427	-0.170 .	25	43	251
Raleigh-Cary, NC	-0.953	-0.652	0.074	5	37	304

Significance shown is for t-test of equivalence of means, indicated if the MSA average is significantly different from the average among the rest of the segment at p <0.20 (.), < 0.10 (-), <0.05 (*), <0.01 (**), or <0.001 (***).

5.3.4 Lifecycle stage, gender, and household roles

On average, mobility deficits are higher than the segment average among those in their 70s and 80s, and less for everyone else, with a greater spread among those in no-car households than in low-car households (see Table 44). When included in the regression, mobility shortfalls are apparent in the no-car households among those in their 50s and increase from there: 0.160 fewer trips among those in their 50s, growing to 0.310 fewer among those in their 60s, 0.396 fewer in their 70s, and 0.390 fewer among those 80 and older, all else equal, according to the regression in Table 46. By contrast, the shortfall is only significant for those in their 70s and 80s for those in low-car households (and for those in their 70s, only significant among women), and less than among no-car households. (In both the no-car and low-car segments, the coefficients for those in their 70s and 80s are even higher without including the income-level variables, which end up overlapping with age. Older people are likely to suffer from the combined effects captured by both the age and income variables included in this regression.) In general, the finding that older people in no-car and low-car households experience increasing mobility shortfalls relative to the benchmarking models implies that they either have less demand for travel than similarly aged adults in high-car households, or face greater mobility barriers that prevent them from fulfilling their desired level of activity as well. Both seem plausible possibilities.

Among no-car households, presence of children is also associated with greater mobility deficit, though with marginal statistical significance; and among low-car households with less mobility for those with young children (age 0 to 5) and more mobility otherwise. This means that although the benchmarking model accounts for having children, parents in no-car households make 0.487 fewer trips than the model predicts and parents of (young) children in low-car households make 0.107 fewer trips than the model predicts, on average. This suggests that these parents either face mobility barriers preventing them from making as many trips as they otherwise would, or as with other factors, that as a group, they have different preferences and/or demand for activity than their car-owning counterparts.

On average, females have a significantly greater mobility deficit than males – that is, they make fewer trips than the benchmarking model would predict, with a greater spread among those in no-car households (0.177 fewer trips) than in low-car households (0.099 fewer trips; see Table 44). This could mean that females face more mobility limitations for some reason directly related to their gender, or that female gender is associated with other circumstances resulting in greater mobility limitations, such as age, parenting, or other circumstances.

When included together in the regression with other demographic variables, there is no significant difference among females in general, but significant effects among certain subgroups of women: women in their 70s and women with children (among low-car households) and single parents, 92% of whom are female (among no-car households). Because the original benchmarking model included positive coefficients for females with children (for both the probability of making any trips and the successive volume above one, though the former was attenuated for females with children age 0-5) as well as a positive coefficient for the volume of trips among single parents, the findings here suggest that these effects are attenuated or reversed among mothers without cars. Perhaps notably, there were no additional gender differences among elderly in no-car households (more than the gender gap already captured in the benchmarking model), but an additional gap among elderly in low-car households, with a spread of 0.393 *additionally fewer* trips among women versus men in their 70s in low-car households, on average.

There are also some differences by the number of household adults. There is a slightly greater mobility deficit, on average, among lone adults (see Table 44). Lack of others could directly influence mobility levels if other household members are a source of mobility, as companion or chaperone. Alternatively, single-adult households may be associated with other circumstances resulting in (in this case, only slightly) greater mobility limitations, on average. By contrast, among no-car households there is much less of a deficit (more mobility) among those living with three or more adults. This may be an indicator for a lifecycle stage in which they are active, young, and living with roommates, perhaps in a more urban environment. When included in the regression, measures of household size can have significant coefficients, depending on what else is included in the model. For instance a dummy variable for having three or more adults is sometimes positive and significant in the no-car regression, and most notably conflicts with the built environment measures indicating a higher-density urban area, suggesting that these circumstances are overlapping. By excluding it from the regression, some of the effects unique to these sorts of households may be reflected in the coefficients for "urban" community type (see Table 46).

Employment status, which could be both an economic indicator as well as a household role, is not clearly associated with any particular mobility deficit or advantage, on average. The one exception is those working part-time, who have greater mobility deficits, on average, suggesting that part-time workers in non-vehicle-owning households face greater mobility barriers (or have less demand for trip-making, which doesn't seem particularly likely) than their counterparts in car-owning households. There is also some evidence the difference in employment status matters more for women than men. Working women have less mobility fulfillment among no-car households and more among low-car households.

Table 44. Mobility fulfillment in each vehicle-access segment, by subgroups: Lifecycle stage, gender, and household roles

	Average discrepancy value in each vehicle-access segment:						% > 0, in each vehicle-access segment:		
	No-car		Low		High		No-car	Low	High
	– 0.374		– 0.009		0.000		31.4%	40.8%	42.7%
Subgroup	Difference within this subgroup relative to average in the entire segment:						%-point difference relative to entire segment:		
Age									
18-24	+ 0.175	.	– 0.033		+ 0.042		+ 3.0%	– 1.1%	– 1.4%
25-29	– 0.145		+ 0.048		– 0.009		– 1.0%	– 0.1%	– 0.8%
30s	+ 0.132	.	+ 0.061	.	+ 0.001		+ 8.1%	+ 1.9%	+ 0.2%
40s	+ 0.211	**	+ 0.080	**	+ 0.010		+ 7.2%	+ 1.3%	– 0.1%
50s	+ 0.228	***	+ 0.068	**	– 0.013		+ 6.4%	+ 1.2%	– 0.6%
60s	+ 0.022		+ 0.003		+ 0.009		+ 0.7%	+ 1.0%	+ 0.4%
70s	– 0.147	***	– 0.009		– 0.008		– 3.3%	+ 1.2%	+ 0.5%
80s+	– 0.136	***	– 0.145	***	– 0.003		– 5.7%	– 4.8%	+ 0.1%
Gender									
Male	+ 0.127	***	+ 0.056	***	– 0.000		+ 4.8%	+ 0.9%	– 0.4%
Female	– 0.052	***	– 0.043	***	+ 0.000		– 1.9%	– 0.7%	+ 0.3%
Number of adults									
1 adult	– 0.031	**	n/a		+ 0.002		– 1.1%	– 10.2%	+ 0.8%
2 adults	+ 0.052	.	+ 0.029	**	– 0.001		+ 1.4%	+ 1.2%	– 0.2%
3+ adults	+ 0.219	**	– 0.027	.	– 0.002		+ 10.0%	– 1.7%	– 1.4%
Presence of children									
No children	+ 0.012	-	– 0.006		– 0.001		– 0.1%	– 0.1%	– 0.1%
Some children, any age	– 0.113	-	+ 0.016		+ 0.002		+ 0.5%	+ 0.2%	+ 0.3%
Youngest child is 0 to 5 years	– 0.084		– 0.098	**	– 0.023	.	+ 0.9%	– 2.2%	+ 0.2%
Youngest child is 6 to 17 years	– 0.146	.	+ 0.097	**	+ 0.024	.	+ 0.1%	+ 2.0%	+ 0.5%
Single parent	– 0.293	**	+ 0.090		– 0.001		– 0.7%	+ 0.1%	+ 2.6%
Number of adults									
<65, overall	+ 0.165		+ 0.039		– 0.000		+ 5.1%	+ 0.8%	– 0.3%
1 adult	+ 0.158		– 0.200	-	+ 0.030	-	+ 4.5%	– 5.3%	+ 1.2%
2 adults	+ 0.155		+ 0.054		– 0.012	**	+ 5.0%	+ 1.5%	– 0.6%

Subgroup	Average discrepancy value in each vehicle-access segment:						% > 0, in each vehicle-access segment:		
	No-car		Low		High		No-car	Low	High
	– 0.374		– 0.009		0.000		31.4%	40.8%	42.7%
	Difference within this subgroup relative to average in the entire segment:						%-point difference relative to entire segment:		
3+ adults	+ 0.260		+ 0.028		+ 0.020		+ 9.7%	+ 0.0%	– 1.1%
65+, overall	– 0.129		– 0.048		+ 0.001		– 4.0%	– 1.0%	+ 0.6%
1 adult	– 0.130		– 0.461	***	– 0.021	**	– 4.0%	– 12.5%	+ 0.5%
2 adults	– 0.136		+ 0.006	***	+ 0.029	**	– 5.3%	+ 0.9%	+ 0.9%
3+ adults	+ 0.023		– 0.191	***	– 0.166	**	+ 11.2%	– 6.7%	– 3.5%
Age, among males vs. female									
Among males, overall	+ 0.127		+ 0.056		– 0.000		+ 4.8%	+ 0.9%	– 0.4%
18-24	+ 0.399	.	– 0.025		+ 0.043		+ 10.4%	– 3.4%	– 2.2%
25-29	+ 0.121		+ 0.124		– 0.049		+ 3.6%	– 0.2%	– 3.5%
30s	+ 0.27		+ 0.052		– 0.007		+ 10.4%	+ 1.2%	– 0.5%
40s	+ 0.256	.	+ 0.005		– 0.004		+ 10.1%	+ 0.3%	– 0.5%
50s	+ 0.219	.	+ 0.146	**	– 0.012		+ 9.1%	+ 2.3%	– 1.3%
60s	+ 0.115		+ 0.046		+ 0.019		+ 2.5%	+ 0.7%	+ 0.3%
70s	+ 0.046		+ 0.159	**	– 0.002		+ 3.1%	+ 5.1%	+ 0.5%
80s+	– 0.157	***	– 0.073	***	– 0.002		– 5.5%	– 2.4%	+ 0.9%
Among females, overall	– 0.052		– 0.043		+ 0.000		– 1.9%	– 0.7%	+ 0.3%
18-24	+ 0.022		– 0.042		+ 0.041		– 2.1%	+ 1.4%	– 0.6%
25-29	– 0.322	-	– 0.011		+ 0.019		– 4.0%	+ 0.0%	+ 1.1%
30s	+ 0.051		+ 0.067	-	+ 0.008		+ 6.7%	+ 2.5%	+ 0.8%
40s	+ 0.179	**	+ 0.134	***	+ 0.021		+ 5.1%	+ 2.0%	+ 0.1%
50s	+ 0.235	***	+ 0.008		– 0.014		+ 4.4%	+ 0.3%	– 0.1%
60s	– 0.016		– 0.026		+ 0.001		– 0.1%	+ 1.1%	+ 0.5%
70s	– 0.201	***	– 0.134	**	– 0.013		– 5.1%	– 1.7%	+ 0.6%
80s+	– 0.132	**	– 0.199	***	– 0.003		– 5.8%	– 6.6%	– 0.3%
Presence of children by gender									
Among males									
No children	+ 0.122		+ 0.044		– 0.001		+ 4.8%	+ 0.8%	– 0.4%
Some children, any age	+ 0.181		+ 0.091		– 0.000		+ 5.2%	+ 1.2%	– 0.2%
Youngest child is 0 to 5 years	+ 0.157		+ 0.049		– 0.037	.	+ 3.6%	– 0.1%	– 0.6%
Youngest child is 6 to 17 years	+ 0.213		+ 0.117	.	+ 0.032	.	+ 7.3%	+ 2.0%	+ 0.2%
Among females									
No children	– 0.032	**	– 0.045		– 0.001		– 2.1%	– 0.8%	+ 0.1%
Some children, any age	– 0.206	**	– 0.036		+ 0.003		– 0.9%	– 0.4%	+ 0.8%
Youngest child is 0 to 5 years	– 0.167		– 0.190	**	– 0.012		+ 0.0%	– 3.5%	+ 0.8%
Youngest child is 6 to 17 years	– 0.252	-	+ 0.081	**	+ 0.017		– 2.1%	+ 1.9%	+ 0.7%
Employment by gender (among <65 only)									
Among males <65	+ 0.226		+ 0.052		– 0.007		+ 8.1%	+ 0.4%	– 0.9%
Employed, any hours	+ 0.263		+ 0.090	**	+ 0.004	**	+ 8.1%	+ 0.8%	– 0.8%
Employed FT	+ 0.343	.	+ 0.100	**	+ 0.004	-	+ 12.7%	+ 1.2%	– 0.8%
Employed PT	+ 0.092		+ 0.077		+ 0.006		– 1.6%	– 0.6%	– 0.7%
Not working	+ 0.201		– 0.019	**	– 0.050	**	+ 8.1%	– 0.3%	– 1.4%
Among females <65	+ 0.125		+ 0.029		+ 0.005		+ 3.1%	+ 1.1%	+ 0.2%
Employed, any hours	+ 0.020	-	+ 0.134	***	– 0.011	**	+ 0.9%	+ 3.6%	– 0.2%
Employed FT	+ 0.051		+ 0.156	***	– 0.012	-	+ 0.1%	+ 3.7%	– 0.3%
Employed PT	– 0.076	.	+ 0.088		– 0.007		+ 1.3%	+ 3.3%	+ 0.1%
Not working	+ 0.178	-	– 0.077	***	+ 0.039	**	+ 4.2%	– 1.4%	+ 1.1%

Significance shown is for t-test of equivalence of means, indicated if the average within the row subgroup is significantly different from the average among the rest of the segment at p <0.20 (.), < 0.10 (-), <0.05 (*), <0.01 (**), or <0.001 (***).

5.3.5 Race, ethnicity, and foreign-born status

Within no-car households, the foreign-born have more mobility (less deficit) than the native-born, even more so among more recent immigrants, but the difference is not statistically significant. (The sample size is also rather small for the recently immigrated, at just n=67 for those who immigrated within the last five years and own no car, making statistical significance more difficult.) If the difference were significant, then it would suggest that the non-owning foreign-born either face fewer mobility barriers than their native-born non-owning counterparts, or that they have more demand for travel than their vehicle-owning foreign-born counterparts. Either seems plausible: they may face fewer mobility barriers if they are more likely to live in urban areas with more opportunity for alternative transportation; they may have access to more informal ride sharing through ethnic enclaves; and they may have greater demand for travel (than their also foreign-born but vehicle-owning counterparts) if working hard to save money for a car or establish themselves. Interestingly, and by contrast, the average mobility deficit is significantly greater among the foreign-born versus native-born in the low-car households, though only slightly, suggesting that these face more mobility barriers than their high-access foreign-born counterparts. This could indicate a dissonant ownership level specific to immigrants that only affects those who have decided they need at least one car: that is, among foreign-born, vehicle-ownership level may be low relative to their income level (and other attributes in the benchmarking model) compared with the native-born, among those who own at all. By contrast, those who have not bought a car may be situated in environments of car-free travel, and less disadvantaged.

There are few significant differences in the average discrepancy value by racial group or Hispanic ethnicity, though whites have slightly more mobility compared with all other racial groups within the low-car segment. This suggests that other groups face constraints not otherwise captured in the benchmarking model, and/or that their vehicle-ownership level is low relative to their income level (and other attributes in the benchmarking model). None of the variables measuring foreign-born status (overall or among more recent immigrants), race, or ethnicity were significant in the regressions (Table 46), suggesting that the differences are too small to be significant relative to the sample size, or that underlying (or concomitant) factors such as residential location can account for some or all of the differences among these subgroups.

Table 45. Mobility fulfillment in each vehicle-access segment, by subgroups: Lifecycle stage, gender, and household roles

	Average discrepancy value in each vehicle-access segment:				% > 0, in each vehicle-access segment:		
	No-car	Low		High	No-car	Low	High
	− 0.374	− 0.009		0.000	31.4%	40.8%	42.7%
Subgroup	Difference within this subgroup relative to average in the entire segment:				%-point difference relative to entire segment:		
Foreign-born							
Native-born	− 0.008	+ 0.011	-	− 0.001	− 0.2%	+ 0.3%	+ 0.0%
Foreign-born, all	+ 0.039	− 0.057	-	+ 0.008	+ 1.1%	− 1.5%	− 0.1%
Immigrated 0-5 years ago	+ 0.115	− 0.128	.	− 0.049	+ 3.0%	− 5.3%	+ 0.0%
Race							
White	+ 0.006	+ 0.017	**	− 0.001	− 0.2%	+ 0.5%	− 0.0%
Black	− 0.059	− 0.076	.	+ 0.012	− 0.1%	− 1.7%	+ 0.3%
Asian	+ 0.173	− 0.102	.	− 0.002	+ 1.6%	− 4.6%	+ 1%
Other	+ 0.046	− 0.048		+ 0.004	+ 0.9%	− 0.9%	+ 0.2%
Hispanic							
Not Hispanic	− 0.006	− 0.001		+ 0.000	− 0.3%	− 0.0%	− 0.0%
Hispanic (any race)	+ 0.030	+ 0.008		− 0.003	+ 1.7%	+ 0.2%	+ 0.5%

Significance shown is for t-test of equivalence of means, indicated if the average within the row subgroup is significantly different from the average among the rest of the segment at p <0.20 (.), < 0.10 (-), <0.05 (*), <0.01 (**), or <0.001 (***).

Table 46. Linear regression model of the discrepancy value, for the non-owner and limited-access segments

Explanatory variable	Estimated coefficients for each model: No-car		Low-car	
Constant	-0.587	***	-0.440	***
Drives	0.637	***	0.698	***
Vehicles/person*			-0.179	**
Has limiting medical condition	0.123	**		
Condition results in giving up driving	0.836	***	0.702	***
Owns home (vs. rents)			-0.076	**
HH income /adult $7,500-12,500	0.131	**	-0.061	-
HH income /adult $17,500-22,500	-0.199	***		
Female	0.046		0.019	
Age in 50s	-0.140	**		
Age in 60s	-0.289	***		
Age in 70s	-0.378	***	0.086	.
Age in 70s+ and female			-0.194	**
Age in 80s+	-0.372	***	-0.117	**
Has children	-0.161	**	0.077	.
and female			-0.125	**
and single parent	-0.276	**		
and kids are 0 to 5			-0.134	**
High school degree (vs < HS or > bachelor's)	-0.076	-	-0.145	***
Some college or associate's (vs < HS or > bachelor's)	0.116	**		
Employed	0.170	**	-0.005	
and female	-0.259	**	0.121	**
White			0.068	**
Hispanic			0.093	**
Community type town/country	-0.082	.		
Community type second city	-0.112	**		
Community type suburban	-0.156	**		
Census tract 25,000+ housing units/square mile	0.181	**		
Model statistics				
N	6,716		22,186	
Mean Y ($\bar{d}$)	-0.376		-0.009	
s.d. Y ($\hat{\sigma}_d$)	1.594		1.908	
R	0.329		0.165	
R Square	0.108		0.027	
Adjusted R Square	0.106		0.027	
Std. Error of the Estimate	1.508		1.883	
Akaike Information Criterion	5,538.4		28,092.6	
Amemiya Prediction Criterion	0.897		0.974	
Mallows' Prediction Criterion	21		18	
Schwarz Bayesian Criterion	5,681.5		28,236.8	
AIC/N	0.825		1.266	
BIC/N	0.846		1.273	

Beta coefficients shown are significant at $p < 0.10$ (-), <0.05 (*), <0.01 (**), or <0.001 (***).

5.4 Mobility fulfillment among users of different modes of transportation

Use of a particular means of transportation is inherent evidence that the mode is helping fulfill mobility needs. However, use of modes dissonant with ownership status (e.g. vehicle use among non-owning households) might be evidence of constrained choices. If that is the case, it might also be associated with less mobility fulfillment (greater mobility deficit values). In general, the average discrepancy value (extent that trip-making matches level predicted by the benchmarking model) among users of a particular mode of transportation offer a characterization of whether users of that mode are able to fulfill their needs (as estimated by the benchmarking model). As with the demographic subgroups, greater deficits among a subgroup of users means that members of that subgroup tend to make fewer trips than predicted by the benchmarking model, indicating that they face mobility constraints or that the model over-estimates their demand for activity.

For this assessment, I limit the analysis to respondents who made at least one trip on the survey day. Among these, I identified those making *any* trips by various modes of transportation: any vehicle, as driver, as passenger, any non-vehicle mode (including bike, walk, and transit), or any biking, any walking, and any transit. I also identified those making *all* of their trips by vehicle, *all* their trips by a non-vehicle mode (any of bike, walk, or transit), or some of each (at least one vehicle trip, as driver or passenger, plus at least one trip by any of biking, walking, or transit). Table 47 shows the average discrepancy value within each of these modal subgroups, relative to two different baseline averages: the upper panel shows the average for a given subgroup versus the average among its opposite (essentially the spread in averages associated with the subgroup; for instance any vehicle trips versus not any vehicle trips), along with significance levels for *t*-tests of equivalence of these two averages; the lower panel shows the average for a given subgroup relative to the overall segment average, among those making any trips. (This is different from the baseline average used in Table 39 through Table 45 since it excludes those who made no trips, whose averages tend to be negative.[17]) In both panels, the

[17] Because the model tends to predict that people make at least some trips, the discrepancy value is negative (that is, actual trip-making falls short of the predicted level) for anyone who made no trips, which comprises a substantial portion of the sample in all three segments (see Table 48). This means that

raw differences in averages are shown, as well as the raw difference divided by the standard deviation of trip volume within each segment. This helps standardize comparisons of magnitudes across segments. For instance a one-trip difference is bigger relative to overall variation in trip volumes in the no-car segment than in the low- or high-access owning segments. For context, Table 48 shows the overall mode split in each segment.

Table 47. Average discrepancy values among users of different modes of transportation, by vehicle-access segment

	Among those making at least one trip, in each vehicle-access segment:								
	No-car			Low-access			High-access		
Avg. actual trip volume ($\bar{y}$)	2.380			2.783			3.047		
s.d. of of y ($\hat{\sigma}_y$)	1.589			1.838			2.003		
Avg. discrepancy value ($\bar{d}$)	0.305			0.498			0.323		
	Difference between average discrepancy value for this subgroup versus for its opposite (spread):								
	Diff.	Diff. $/\hat{\sigma}_{y_{no}}$		Diff.	Diff. $/\hat{\sigma}_{y_{low}}$		Diff.	Diff. $/\hat{\sigma}_{y_{high}}$	
With *any* trips by:									
Vehicle (private or taxi)	+ 0.601	+ 0.378	***	+ 1.121	+ 0.61	***	+ 1.372	+ 0.685	***
As driver	+ 0.332	+ 0.209	**	+ 0.347	+ 0.189	***	+ 0.476	+ 0.238	***
As passenger	+ 0.600	+ 0.378	***	+ 0.400	+ 0.218	***	+ 0.631	+ 0.315	***
Any non-vehicle mode	– 0.020	– 0.013		+ 0.276	+ 0.15	***	+ 0.857	+ 0.428	***
Walking	+ 0.359	+ 0.226	***	+ 0.456	+ 0.248	***	+ 0.887	+ 0.443	***
Transit	+ 0.118	+ 0.074	**	– 0.246	– 0.134	***	+ 0.759	+ 0.379	***
With trips:									
All by vehicle	+ 0.053	+ 0.033	***	– 0.242	– 0.131	***	– 0.832	– 0.416	***
Some of each	+ 1.160	+ 0.730	***	+ 1.099	+ 0.598	***	+ 1.264	+ 0.631	***
All by non-vehicle modes	– 1.292	– 0.813	***	– 1.967	– 1.070	***	– 2.420	– 1.209	***
	Difference between average discrepancy value for this subgroup versus for the overall segment average:								
	Diff.	Diff. $/\hat{\sigma}_{y_{no}}$		Diff.	Diff. $/\hat{\sigma}_{y_{low}}$		Diff.	Diff. $/\hat{\sigma}_{y_{high}}$	
With *any* trips by:									
Vehicle (private or taxi)	+ 0.302	+ 0.190		+ 0.098	+ 0.053		+ 0.036	+ 0.018	+ 0.302
As driver	+ 0.291	+ 0.183		+ 0.132	+ 0.072		+ 0.054	+ 0.027	+ 0.291
As passenger	+ 0.346	+ 0.218		+ 0.249	+ 0.136		+ 0.511	+ 0.255	+ 0.346
Any non-vehicle mode	– 0.014	– 0.009		+ 0.214	+ 0.116		+ 0.714	+ 0.356	– 0.014
Walking	+ 0.193	+ 0.121		+ 0.372	+ 0.202		+ 0.750	+ 0.375	+ 0.193
Transit	+ 0.075	+ 0.047		– 0.236	– 0.129		+ 0.751	+ 0.375	+ 0.075
With trips:									
All by vehicle	+ 0.028	+ 0.017		– 0.056	– 0.03		– 0.141	– 0.07	+ 0.028
Some of each	+ 0.992	+ 0.624		+ 0.944	+ 0.514		+ 1.085	+ 0.542	+ 0.992
All by non-vehicle modes	– 0.299	– 0.188		– 1.023	– 0.556		– 1.335	– 0.667	– 0.299

Significance levels: p <0.20 (.), < 0.10 (-), <0.05 (*), <0.01 (**), or <0.001 (***), for t-test of equivalence of means of the average mobility fulfillment (discrepancy value) among those in a given subgroup of users versus its opposite (e.g. those using any vehicles versus not using any vehicles), within each ownership segment. Non-vehicle modes include walking, biking, and all types of public transit.

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it tends to be positive for anyone who made at least some trips. That is, removing those who made zero trips, among the remaining cases, people tended to make more trips, on average, than predicted by the model, in all three segments and by comparable amounts in all three segments, though significantly more, on average, within the medium-access segment (at 0.498 trips more than predicted, versus 0.305 among the non-owners and 0.323 among the high-access owners).

The most revealing results in Table 47 are the differences among those making all, none, or some of their trips by vehicle versus alternative modes. Relative to others making at least one trip within each ownership segment, people using a mix of modes make the most trips – about 1 additional trip per day – in all three of the ownership groups (see Table 47, upper panel)[18]. Among both the owner segments (low-car and high-car owners), those who make *all* their trips by car have lower-than-average mobility levels, as do those making *none* of their trips by car. This suggests that both circumstances reflect more constraint (or other disinclination to travel) relative to the mixed-mode users than is captured in the benchmarking model — perhaps there is a lack of sidewalks or transit, or few destinations reachable by a mode other than a car, or the person has physical disability or disinclination to use modes other than a car — or conversely, that the mixed-mode users have *less* constraint (or are more inclined to travel) than is captured in the benchmarking model – perhaps they have an especially active lifestyle or the very nature of using a mix of modes lends itself to making more stops (which in this study would be measured as more activity).

In both car-owning segments, the spread is much greater for *no* car trips than for *all car* trips. For instance, low-car owners with no car trips (versus some) make 1.967 fewer trips (relative to the predicted benchmark values) while those with all car trips (versus none) make 0.242 fewer, on average (Table 47, upper panel). This suggests that for car-owners, while both extremes (using only cars or no cars) imply some sort of constraint, on average, using *no* cars is more aberrant. In addition, the all-car "extreme" actually comprises the majority of owners in both segments (70.3% of those in low-car households and 82.0% in high-car households; see Table 48). By contrast, the no-car "extreme" comprises 13.2% and 3.2% of those in low- and

[18] Though one trip is a bigger relative to the standard deviation of trip volumes in the no-car group.

high-car households, respectively. Meanwhile, the greatest capability for mobility (or greatest demand for travel relative to the level predicted by the benchmarking model, on average) is among those using a mix of modes, comprising about 15% of those in car-owning households.

Among the zero-car households, those using a mix of modes also have the highest mobility levels relative to others in their ownership category. In contrast to the car-owners, however, non-owners who make *all* their trips by car also have higher-than-average mobility levels rather than a shortfall, but only by a small amount (about 0.028 trips, see Table 47). This suggests that despite the seemingly dissonant circumstance of relying on cars but not owning one, this group is no less constrained, at least relative to the others in their segment, which may be a low bar. Alternatively, it could reflect the mix of different circumstances that on average balance out in the group average: those with disabilities or other conditions restricting their use of alternative modes and those where use of a car is an additional freedom enabling greater mobility than for other non-owners.

Also interestingly, non-owners using *no* cars make significantly fewer trips than average, as found among the owners. This suggests that even among non-owners, the circumstance of using *no* cars is associated with more constraint (or less inclination to travel) relative to others in this segment than is reflected in the benchmarking model. The spread among car-users versus non-users is not as great as among the owners, however, and a much greater share of the segment (59.3%) falls into the non-user category (Table 48).

These results also show how using vehicles for *any* trips is more of a distinguishing characteristic among non-owners than owners. Relative to others making at least one trip, those using a vehicle for any trips have higher mobility levels, on average, in all segments, but the difference is greater among the low-access segment, for whom it is associated with 0.302 boost in the average volume of trips (or a 0.601-trip spread between users), compared with 0.098

among the medium-access group and 0.036 among the low-access group.[19] In all of the segments, there is higher average mobility among those with at least one trip as a passenger versus at least one trip as a driver. This may reflect other circumstances associated with riding as a passenger that might be associated with more mobility, such as socializing or having a family.

Similarly, the use of modes *other than* a vehicle is more of a distinguishing characteristic among the vehicle-owners than the non-owners. Among non-owners, there is no significant difference among those using a non-vehicle mode. Among low-car owners, the average trip volume is 0.214 trips greater than the segment average among those using some non-vehicle mode (or a 0.276 spread among users versus non-users), and 0.714 trips greater among high-access owners. Making any trips by walking is more of a distinguishing characteristic at increasing levels of vehicle ownership: walking is associated with a mobility boost of 0.193 trips among non-owners (or a 0.118-trip spread), 0.372 trips among low-car owners (a 0.456-trip spread), and 0.750 trips among high-car owners (a 0.887-trip spread).

Transit seems to have an interestingly different effect in all three segments. Among non-owners, anyone using transit for at least one trip makes slightly (statistically significantly) more trips than those reporting no transit use (0.075 more trips, on average, or a 0.118-trip spread); among high-car owners, transit-users make substantially more trips on average than non-users (0.751 more trips, on average, or 0.759-trip spread); and for low-car owners, transit-users make significantly fewer trips than non-users (0.236 fewer trips, on average, a 0.246-trip spread). This may tell us something about circumstances with which the members of each segment tend to use transit. Among the high-access segment, use of transit is more likely a choice, therefore representing an added mobility benefit, on average, among those who end up using it. It also comprises only 1.7% of the segment (see Table 48). By contrast, in the medium-access segment

[19] Standardizing by the standard deviation within each segment would make these differences appear even greater, as is the case for all the results in the next several paragraphs.

(consisting of individuals in households that divide the use of a car(s) among themselves), transit may be more likely to be chosen out of necessity due to lack of access to a household vehicle (comprising 8.4% of the sample). Among non-owners, it is simply not a very distinguishing characteristic (users and non-users are not systematically very different, in needs or mobility levels, but for a small boost in mobility among users, who comprise 41.7% of the sample).

In general, what might be thought of as a dissonant mode – that is, one opposite from ownership group – boosts mobility for walking and driving/riding in a vehicle. That is mobility is higher among high-car owners who walk, on average, as well as among non-owners and low-car owners who drive/ride in vehicles. But for transit, the effects are mixed effects. For high-car owners, for whom transit is likely more of a choice than necessity, use of transit is associated with a mobility boost. For low-car owners, however, it is associated with constraint. Perhaps owning at all is an indicator that cars are indeed needed, but owning so few and using transit tends to be a circumstance with constraint. Meanwhile, transit use is more mainstream among non-owners and therefore there is no distinguishable trend.

Table 48. Mode split and average trip volume by mode, among weighted sample in each segment

	Percent of people in the weighted sample				Average volume of trips for this group			
	In each vehicle-access segment				In each vehicle-access segment			
	No-car	Low-car	High-car	Overall	No-car	Low-car	High-car	Overall
Trip-making level:								
Made no trips	27.8%	19.2%	9.5%	13.0%	0	0	0	0
Made at least one	72.2%	80.8%	90.5%	87.0%	2.380	2.783	3.047	2.380
Total	100.0%	100.0%	100.0%	100.0%	1.716	2.246	2.757	1.716
Among those with any trips:								
% with any by:								
Any vehicle	40.7%	86.8%	96.8%	91.1%	2.530	2.895	3.084	2.530
As driver	6.8%	57.7%	89.2%	77.8%	2.852	3.088	3.117	2.852
As passenger	33.9%	37.9%	17.2%	22.2%	2.567	2.865	3.543	2.567
Any non-vehicle	73.0%	29.0%	17.8%	23.7%	2.473	2.944	3.875	2.473
Biking	3.4%	2.1%	1.1%	1.4%				
Walking	52.2%	22.6%	16.3%	19.9%	2.801	3.184	3.950	2.801
Transit	41.7%	8.4%	1.7%	5.7%	2.592	2.621	3.577	2.592
% with:								
All by vehicle	25.6%	70.3%	82.0%	75.9%	2.069	2.714	2.868	2.823
Some of each	15.1%	16.5%	14.8%	15.2%	3.312	3.663	4.279	4.087
All by non-vehicle	59.3%	13.2%	3.2%	8.9%	2.250	2.042	1.895	2.098
Total	100.0%	100.0%	100.0%	100.0%	2.364	2.783	3.046	2.950

Table 49. Summary of findings on relative mobility fulfillment among subgroups of the no- and low-car segments

Attribute	Less mobility than segment average (more deficit)	Same as average for the segment (no significant difference)	More mobility than segment average (less deficit or surplus)
Household income per adult	<$7,500 (low-car only) $17,500-$22,500 level (both)	Most income levels (both)	$7,500-$12,500 (no-car only)
Educational attainment	High-school grads (both)	All other levels (both)	Associate's degrees (both) Bachelor's (low-car only)
Home-ownership	Home-owners (both)		Renters (both)
Driver status	Never drove (both) Formerly drove (both)		Currently drives (both)
Limiting medical condition		Other conditions (low-car)	Any condition (no-car only) Results in giving up driving (both)
Community type	Second city (both) Suburban (no-car only) Town-country (no-car only)	Urban (low-car only) Town/country (low-car only)	Urban (no-car only) Suburban (low-car only)
Housing unit density in home Census tract	Densities < 2,000 units/square mile (no-car only)	Any level (low-car only)	Densities 2,000 units/square mile and above, especially 25,000+ (no-car only)
Transit score for metro area	Scores < 20 (no-car only)	Scores 21-40, and 81+ (no-car) Any level (low-car only)	Transit scores 41-80 (no-car only)
Home type	Other home type (both)		Detached single-family home (both)
Specific MSAs	Memphis, TN; San Jose, CA (no-car); Baltimore, MD; Virginia Beach, VA; Phoenix, AZ; San Diego, CA; Richmond, VA (low-car)	All other MSAs	Boston, MA; Pittsburgh, PA; Portland, OR ; Los, Angeles, CA (no-car)
Gender	Females (both), especially with kids, single-parents (both), and in their 70s (low-car)		Males (both)
Age	50s, 60s (no-car); 70s, 80s (both)		Most other ages
Children	Any children (no-car) Children age 0-5 (low-car)		Children age 6-17 (low-car)
Employment status	Not working, especially among women (low-car)	Any status (no-car)	Employed, especially full-time and among women (low-car)
Number of adults	One (no-car)		Two (both) Three or more (no-car)
Foreign born	Foreign-born, especially among recent immigrants (low-car)	Any status (no-car)	Native-born (low-car)
Race/ethnicity	Other than white (low-car)	Any race (no-car) Hispanic (both)	White (low-car)

Note on interpretation: More deficit than average means that the model over-estimates activity demand, and/or group faces greater mobility barriers. Less deficit than average means that the model more accurately estimates activity demand than for other non-owners, and/or group faces fewer mobility barriers than other non-owners, on average. Surplus means that the model under-estimates activity demand, and/or group enjoys mobility advantages (or the burden of having to travel) relative to high-car owners. No difference is indicated when there is no statistically significant difference, relative to the average within the rest of the ownership segment.

5.5 Summary and conclusions

In this chapter I evaluate relative mobility fulfillment, focusing on two groups with limited vehicle ownership: no cars and low-access, with mobility fulfillment defined as the extent that actual trip volume matches the volume predicted for each respondent by the benchmarking model developed in Chapter 4. One interpretation of these results is that it shows how much of the apparent shortfall in trip-making among those in households with fewer vehicles versus more vehicles can be accounted for by demographic attributes alone, on average. The results show that among those who do own at least one car, but fewer than one per autonomous person[20], all of the apparent differences in mobility are accounted for by demographics. That is, there is no evidence of constrained mobility as a result of owning fewer cars, on average, as defined here. By contrast, among no-car households, about 70.1% of the apparent difference is accounted for by demographics, but there is a significant shortfall still unexplained — of about 0.376 trips per person per day. This means that actual trip-making among non-owners is just 78.3% of the predicted levels. This shortfall can be attributed to lack of vehicle access, as the defining difference in this segment, or other differences between non-owners versus those in high-ownership households that are not captured in the benchmarking model.

Variations within each ownership segment show attributes associated with more or less mobility fulfillment relative to others of the same ownership level. As with the overall segment averages, whatever patterns are observed among subgroups could potentially reflect either (or a mix of) attributes associated with mobility constraint, or attributes associated with more (or less) underlying demand for travel not captured by the variables in the benchmarking model. In some cases it is difficult to identify which one is likely to dominate.

[20] Defined as all adults (age 18+) whether or not they drive, plus driving teens, but excluding non-driving minors.

I had hypothesized more mobility fulfillment, on average, among those whose circumstance is voluntary, in particular who were not financially constrained and could purchase additional vehicles, if desired. However, though there are small differences corresponding to some attributes related to economic status, there is almost no apparent relationship between household income and mobility deficit, on average. This suggests that whether ownership is voluntary is apparently not related to mobility fulfillment, or at least not very strongly, on average. In other words, those less likely to be able to afford a car are as likely to fulfill their mobility needs (as predicted by the benchmarking model) as those with more purchasing power — in the right circumstances. And the circumstances that are better and worse for low-car households are found among low- and high-income alike, for the most part.

What are the circumstances that are better or worse for households with fewer cars? The built environment seems to make a difference, but only for those in no-car households. For them, mobility fulfillment is higher in urban neighborhoods and with highest density levels, as hypothesized, but notably no different among any of the other types of neighborhoods, with second city, suburban, and town/country areas no different from one another in enabling mobility fulfillment among no-car households, on average. None of the built-environment measures seem to matter much for those in low-car households, where mobility fulfillment is no higher in neighborhoods with theoretically more opportunity for non-vehicle travel, on average, but where there is also less of a range in fulfillment levels (and on average, no difference from high-car households).

Among those in both the no-car and low-car segments, mobility shortfalls are greater among older people, starting with those in their 50s (among no-car households), but especially among those in their 70s and 80s (among no-car and low-car households). Among low-car households, elderly women have greater mobility shortfalls than men, suggesting that among couples that share, women get out less relative to their counterparts in high-car households, who in turn get out less than men in general. In addition, people in households with children, and especially those with young children and mothers (versus fathers), also have less mobility fulfillment. Collectively, these results mean that women have less mobility fulfillment than men, on average, despite greater vehicle use, as indicated in Chapter 3. In general, these differences in mobility fulfillment may reflect either constraint or differing levels of demand among these subgroups relative to their counterparts in high-car households. For instance, elderly may go out less than desired because they have no car, or give up a car because they have less need or desire to go out.

One of the most distinguishing characteristics of relative mobility fulfillment is driver status, among those in car-owning and non-owning households: Drivers have no less mobility fulfillment, and even surplus fulfillment (among low-car households) relative to their high-car owning counterparts, while non-drivers have substantially less mobility fulfillment. Among the low-car-owning households, this suggests a shift of trip-making from non-drivers to drivers within the household. Among no-car households, driver status has a less obvious role in how it would enable mobility. There is little evidence that it is because they are themselves driving. While non-owners sometimes themselves drive, it is not prevalent: only 6.8% make any trips as drivers (see Table 48). Furthermore, average mobility fulfillment is actually greater on average among those riding (at least once) as passengers than those traveling (at least once) as drivers (see Table 47). Rather, driver status is likely serving as an indicator for access to other mobility resources and/or a preference for more trip-making, relative to non-drivers. In general, the group whose behavior is “unexplainably” low – relative to the benchmark model — is non-drivers who have no medical reason for not driving. It is unclear if these are an excluded minority, suffering from lack of access to automobility, or a type of person with different travel preferences than represented in the rest of the population.

With respect to the modes of transportation used, I hypothesized more mobility fulfillment among those using modes consonant with their ownership status, but find substantial asymmetry that underscores the importance of cars for all ownership segments. Among owners, not using a car is a major constraint, as would be expected: There is much less mobility among non-users, among both low- and high-ownership segments, perhaps more so among high-car households, which makes sense as a dissonant circumstance. But the converse does not hold among non-owners. That is, not using a car is *also* apparently a constraint among no-car households, and using the dissonant choice, cars, is not associated with mobility shortfall (and in fact is associated with an advantage, relative to others in the segment). Furthermore, using *only* the non-vehicle modes, which would be logically consonant for non-owners, is associated with more apparent constraint, on average. If the sort of discrepancies captured by this modeling truly reflect constraint, these results suggest that cars are necessary for mobility parity among the non-owning segment, on average. However, among all ownership segments, those with the highest mobility levels are those using a mix of modes. Using either only vehicles or only non-vehicles apparently reflects circumstances with relatively more constraint and/or less demand for trip-making (relative to the predictions in the benchmarking model).

A limitation of this analysis is the inability to distinguish between constraint and lower demand, due to factors other than the demographic and geographic variables included in the benchmarking model (from Chapter 4).

6 The practice of getting rides and borrowing vehicles through social networks: Experiences of recent Mexican immigrants in California

The purpose of this chapter is to offer a qualitative examination of vehicle use in a non-owning context. As established in Chapter 2, travel by private vehicle makes up a substantial share of trips made by members of no-car and low-car households, with variations in the share of these that are rides from outside the household among demographic subgroups and trip types, as shown in Chapter 3. Results in Chapter 5 show that the use of vehicles is strongly associated with mobility fulfillment, even among those in non-owning households. However there has been little research on the *process* of accessing rides and cars through informal channels, likely to be different from other modes of transportation because it is mediated through social exchange, as reviewed in Chapter0.

Toward that end, this chapter presents qualitative findings from ten focus group discussions with Mexican immigrants to California,[21] the largest immigrant group in the state, comprising 44 percent of the state's foreign-born population and 12 percent of its overall population (U.S. Census Bureau, 2007). Mexican immigrants, especially recent immigrants, have particularly low auto-ownership rates (Casas, Arce, & Frye, 2004; Heisz & Schellenberg, 2004; Tal & Handy, 2005), making their perspectives on the use and acquisition of cars well suited to this study, although potentially with additional considerations unique to their cultural experience and legal status. Although these were originally conducted as a part of a broader exploratory study of the transportation needs of diverse populations in the state, the experiences of recent Mexican immigrants are useful for this topic because of their limited access to cars. Finding varying degrees of vehicle access and use among the focus group participants — not always corresponding with ownership — I review the experiences they describe in finding rides,

[21] Related results are presented in Lovejoy and Handy (2007, 2008, and 2011).

highlighting the unique aspects of informal access to cars, drawing on social exchange theory and related research to characterize the procurement process and likely levels of exchange. I identify the circumstances – attributes of individuals, their environments, and their social networks – that might help predict the extent to which rides and borrowed vehicles are likely to be available to a given individual, based on the experiences of the focus group participants.

6.1 Source of the data

The focus group discussions referenced in this chapter were conducted as a part of a grant from the California Department of Transportation to study the travel of diverse populations in California. The goal of the focus groups was exploratory research on the general transportation needs of Mexican immigrants. The topic for this chapter emerged after data was collected, when it became clear that participants' limited access to cars was associated with extensive borrowing of cars and ridesharing.

Participants were recruited from six different California cities with high numbers or concentrations of Mexican immigrants, ranging from settings that are urban with diversified economies and relatively good transit service to exurban or small urban areas with limited transit service and agriculturally oriented economies. To better tailor the conversation to the likely experiences of the participants, we held separate sessions for participants in households with a vehicle and for those in households with no vehicles, as determined by the screening question, "Do you or does someone in your household have a car?" – although the distinction between the two categories was sometimes ambiguous (see Lovejoy & Handy, 2008). There were a total of five sessions of each type, including sessions in Fresno, Los Angeles, Riverside, San Jose, Stockton (car-owning only), and Sacramento (car-less only). Sessions were held on Saturdays between June and August of 2006 in centrally located, transit-accessible, formal focus group facilities (with the exception of the Stockton session; due to concerns about accessibility to the site and the recruitment of car-less participants, a session in Sacramento was added to replace the session with car-less participants in Stockton).

Participants were recruited over the phone in Spanish from lists of phone numbers corresponding to Hispanic last names in each area.[22] Potential participants were offered a $75 incentive to participate, after being screened by whether they were Mexican, immigrated in the last 10 years, were between the ages of 20 and 40 (to avoid confounding issues unique to younger and older travelers), and whether someone in their household owned a car ("yes" for five groups, "no" for five groups). While we wanted "average" people from the target population as participants, we made no effort to recruit a representative sample, since the sample size was too small for statistical significance and because the format of the study was designed as a qualitative exploration rather than quantitative investigation. In the end, there were a total of 102 focus-group participants, with 49 and 53 in the five car-owning and car-less groups, respectively. The groups ranged in size from 8 to 13 participants in each session. Most groups were evenly split with male and female participants, but three groups (two in Riverside and one in Stockton) disproportionately consisted of women. About three-quarters of both the car-owning and car-less participants had children under the age of 18. About 70 percent of car-owning participants and 90 percent of car-less participants reported household incomes lower than $25,000. About 15 percent reported speaking English, a share that seemed to be evenly distributed among the car-owning and car-less groups. (See Table 50.)

The sessions were held in Spanish, led by a bilingual professional facilitator[22] who followed a protocol (originally developed in English but translated into Spanish) that included questions about various transportation modes (including getting rides and borrowing cars from

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[22] TMDgroup, Inc. of Sacramento conducted the recruitment, facilitated the focus group sessions, and provided translations of session transcripts. The sessions and recruitment phone calls were conducted in Spanish.

those outside their households), such as which they used, how often, for what purposes, and what they perceived to be good and bad about each. Audio and video recordings of the proceedings in Spanish as well as an audio recording of a live translation in English were retained for each session. We used textual transcriptions of the translations as the primary content for analysis, referring to the videos as needed to clear up ambiguities. A report of the results, including a copy of the protocol used for the interviews, is available in Lovejoy and Handy (2007).

Table 50. Demographic attributes of focus group participants, by group location and ownership status

	Percent of participants							
Group	In the U.S. <5 years	In the U.S. <10 years	Female	Have any children	Household earns <$25,000	Speak English	Know how to drive	Total number of participants
Car-owning	14%	85%	63%	79%	71%	18%	88%	49
Fresno	25%	100%	50%	89%	100%	n/a	75%	8
Los Angeles	n/a	n/a	46%	77%	69%	8%	100%	13
Riverside	30%	100%	100%	100%	70%	20%	90%	10
San Jose	0%	89%	40%	60%	50%	30%	100%	10
Stockton	0%	50%	88%	73%	n/a	38%	n/a	8
Car-less	42%	98%	60%	62%	89%	13%	25%	53
Fresno	11%	78%	40%	100%	90%	n/a	40%	10
Los Angeles	63%	100%	67%	50%	100%	0%	0%	12
Riverside	33%	100%	89%	44%	89%	33%	56%	9
San Jose	55%	100%	54%	57%	79%	31%	15%	13
Sacramento	50%	100%	n/a	n/a	n/a	n/a	n/a	9
Total	30%	92%	62%	72%	80%	16%	56%	102

6.2 Vehicle use and mobility fulfillment among focus group participants

Participants relied on vehicles to varying degrees. While for some participants this variation was likely related to the availability of alternative modes of transportation in their area, many participants felt they could not get by without utilizing vehicles, and chose to do so even when it was difficult. Not surprisingly, the car-owning participants described using vehicles more than the car-less participants, on average, with correspondingly more transit use and walking among the car-less participants. The car-less participants described employing a wider range of solutions in order to get around, identified more places that were "hard to get to," spent more time getting to work, and described more overall transportation challenges and foregone opportunities as a result of transportation-related limitations (see Lovejoy & Handy, 2007).

However, there was a range in participants' use of vehicles and access to rides in both the car-owning and car-less groups (see Lovejoy & Handy, 2008). As a part of this variation, reliance on getting rides and borrowing cars was extensive in all of the groups. Although systematic counts were not collected, almost every participant (both car-owning and car-less) reported getting rides at least sometimes. Only a few indicated that it was rare. Many reported getting frequent rides, such as regular arrangements for getting to school or work, and as often as daily rides to shopping, errands, church, or social outings. Those offering rides included friends, neighbors, family (cousins, siblings, parents, children, in-laws), significant others, ex-spouses, co-workers, and even strangers. Many participants expressed more reluctance to borrow cars than to get a ride, but there were still some regular borrowers in all of the groups. The most frequently cited destinations for which participants would borrow cars was to reach medical services, whether for an emergency trip or for a scheduled doctor's appointments, followed by grocery stores, far-away destinations (whether errands or recreation), taking laundry to a Laundromat, recreational outings, transporting particular passengers, and going to church. Thus even if participants' transportation needs were not always met, especially those from car-less households, a mix of getting rides and borrowing cars seemed to go a long way to fill gaps. This suggests that sometimes—but not always, and in varying degrees—social networks represent a valuable source of private-vehicle transportation.

6.3 Factors affecting the social exchange of rides and borrowed cars

The focus groups made clear that some participants enjoyed more access to private-vehicle transportation through their social networks than others. What factors shaped these outcomes?

In this section, I propose a list of determinants, adapting existing theories of social exchange (reviewed in Chapter 0) to the exchange of transportation resources in particular based on findings from the focus groups. I start by examining factors affecting the likelihood of *offering* rides or vehicles, then factors affecting the likelihood of *receiving* them.

6.3.1 Factors affecting the likelihood of offering rides or vehicles

Clearly, an important factor determining an individual's likelihood of offering resources to friends and contacts is whether he possesses them in the first place. The types of resources that proved valuable to participants in this study included knowing how to drive and having a driver's license; being able to teach someone how to drive, how to buy a car, maintain a car, or obtain a license or insurance; having the time to give rides or to teach someone how to drive; as well as owning a vehicle or multiple vehicles, and further having a vehicle that is in good working order, safe, insured, and with sufficient capacity for extra passengers or other cargo.

These resources were not taken for granted among participants in this study. The general trend was to have no vehicle (and no ability to buy a vehicle) upon arriving from Mexico. Some might know how to drive or have a Mexican driver's license, but many would be unlicensed and/or have never learned to drive prior to immigrating. Over time, they would save for a vehicle and learn to drive, whether or not they ever became licensed. In particular, about three-quarters of the participants from car-owning households had acquired a car within the first three years after immigrating (Lovejoy & Handy, 2007). However, not all the participants from even the car-owning households drove, either because they had not learned how or did not have access to the household vehicle(s). About 16 percent of participants from car-owning households and 75 percent of those from car-less households reported that they did not drive (see Lovejoy & Handy, 2008). Participants in both the car-owning and car-less groups explained that they were unable to obtain California driver's licenses due to their legal status, although some were legal and licensed and others were driving with Mexican licenses. In addition to driving without licenses, many participants reported driving without any or without good auto insurance, and that they could only afford junky cars that frequently broke down (Lovejoy and Handy, 2008).

These sorts of issues affected both willingness to do someone a favor and the quality of the transportation provided. In particular, having no license meant that drivers risked being stopped by the police and having their vehicle seized, to be recovered for a fee that was prohibitively large for many in the groups. It also meant driving without auto insurance (with no license), or with expensive limited-coverage insurance (for those with Mexican licenses). By asking for a ride, the passenger put the license-less driver at additional risk. For instance, a Fresno participant identified his greatest challenge in getting to work as the following:

> The people that give me a ride don't have a license either and whenever they go and pick me up or take me back home they have to be thinking about the police, if they get stopped. So that's hard on them too. They're out watching and they're careful, you know? Because they can lose the car if they get stopped and then it's going to be a lot of money to get it out.

One explained, "I really don't like to ask for rides…he doesn't have a license and he's risking getting stopped" and another advised, "Never borrow a car, because if it breaks down, then you are the one that's responsible."

In this way, license, insurance, and maintenance issues amplified the cost to would-be donors, perhaps making members of this community less likely to give rides and lend cars than they otherwise might be. Thus anyone who was actually licensed, insured, and with a more reliable vehicle might be more likely to offer rides. Because these things tend to come with time spent in the United States, those who have been here longer might be more likely to have resources to offer to those in need. In addition, because women participants seemed somewhat more likely than men to not know how to drive, or to have taken more time to learn how to drive after immigrating, males also might be more likely to have resources to offer those in need. As tentative support for this theory, participants seemed to reference male relatives (such as cousins, brothers, and in-laws) more often as sources of rides and as car-owners. (However, participants also indicated that women would acquire a license and/or learn to drive when possible or needed. A Stockton participant explained, “Usually, regularly, women learn [to drive] because we have to…necessity, because the husbands work all day.”)

6.3.2 Factors affecting the likelihood of receiving rides or cars

A first set of factors affects the likelihood of receiving rides or cars by affecting the size of the favor demanded of the other party. In particular, a participant who could contribute some portion of the resources—that is, who either *knows how to drive or has a car on hand*—was more versatile, able to either borrow a driver or borrow a car on a given occasion. By contrast, those who couldn’t drive were relegated to using cars only as passengers, having to secure not only an available vehicle but also a willing driver for any given trip. For instance, one participant described wanting to go the hospital with a sick child, and having access to a car but no driver, and finally going to a neighbor for help: “I asked her, ‘Please take me.’ She said, ‘I know how to drive, but I don’t have a car.’ I said, ‘I have keys and let’s go!’”

Another consideration affecting the size of the favor relates to the fact that giving rides and lending cars is embedded geographically, spatially, and temporally in the two parties’ lives, as noted in Schwanen’s (2008) study of parents arranging for their children’s pickup from school and daycare. It is easier to complete the exchange *if the two parties are spatially and temporally compatible*. In particular, when getting rides, it is more convenient when there is spatial overlap between the driver’s and passenger’s origin and/or destination, when their schedules are concordant, and when the driver has to forego fewer activities on the passenger’s behalf. For instance, participants indicated that it was easier to find rides if they knew drivers who were going to the same place they were going at the same time, or who were coming from the same place they were coming from, or both. A Sacramento participant explained, “I go with my girlfriends because they live over where I live and we work at the same place and we live in the same neighborhood.” In contrast, a Fresno man’s ride to work was more difficult to secure, “because the guy that I’m working with lives [farther away]…so sometimes it’s inconvenient. He has to go and get me and then double back in the mornings…I don’t feel comfortable.”

Similarly, when borrowing cars, it is more convenient if the owner’s and borrower’s scheduling needs are non-overlapping, if the owner has alternative means of transportation, and if there is spatial overlap at the origin. Among participants, these considerations seemed relevant both for borrowing cars from outsiders and for sharing cars with household members. For instance, a Riverside woman explained that because her husband had a good back-up plan, she enjoyed more access to the family car. In contrast, another Riverside woman described resorting to using a taxi to get to a doctor’s appointment since using the family car would have required her husband to miss an entire day of work.

A second set of factors relates to some of the intangible considerations unique to social exchange. In particular, participants’ experiences supported the theory that *friendly relationships* enable small favors without explicit compensation. For instance, being friendly with co-workers helped a Riverside participant find rides: “If you get along with a person, she’ll take you or bring you.” Another described being in a hospital waiting room at 2 AM and chatting up some of the other patients in order to find a ride home; after approaching about 20 different people, she listened to a woman gripe about her spouse for longer than she would have wanted to in order to get a ride with her later: “She would talk and talk and talk about how the husband drank and smoked. And I would say, ‘Yes, ma’am…Take care of him.’ And that’s the way we got a ride all the way from [that part of town].” Similarly, women seeking companionship from one another offered their friends rides to shopping:

> "I have a neighbor, a good friend, and sometimes she will call me and say, 'I'm going to Wal-Mart. Would you like to go?' 'Yeah, okay, I do need something. Let's go…'"
>
> "I also have a very good neighbor that she takes me all over, Costco, Albertsons. She loves to go out, and she invites me: 'Let's go [name].' 'Where are you going?' 'Let's go to Albertsons…'"

Participants' experiences also supported to some extent the theory that *closer ties* foster more supportive relationships, consisting of higher-value or repeated exchanges. Favors considered to be large, such as borrowing a car, could only come from close friends or relatives. One participant explained, "I don't try to borrow a car from just anyone, only if it's my brother or a good friend." Another attested, "My father and my brothers and I get along really well. We have a very good relationship and I don't mind borrowing a car from them or vice versa." However, for some participants neither friendship nor kinship guaranteed access to a ride or a car. Sometimes this reflected the magnitude of the favors, such as for these participants:

> My brother loaned me his car a few years ago and I almost had an accident. The car wasn't mine so I got frightened. So I decided to solve my problem by other means.
>
> When I recently got here, I would get off work, the restaurant would close about two in the morning and we'd stay, washing the pots…and we wouldn't get out until three in the morning. So then my brother had to go pick me up and he was very sleepy…he said everything would be dandy, but afterwards it wasn't.

Aside from friendship and closeness, the results also point to several other circumstances that might help a recipient receive rides or vehicles, presumably as a result of other intangible social rewards shared in the exchange. In particular, the results are not inconsistent with the theory that participants in this study as *members of an ethnic community* would enjoy easier exchange of resources through that network. However, we have no explicit evidence to support it, since the topic was not discussed in any of the sessions, and because all of our participants were from the same group. The only common-group effect that participants referenced explicitly was *women being more likely to help other women*, as one attested, "Sometimes they don't even know me, but since they're women they'll say, 'Yes, where are you going?'" This may alternatively be interpreted as a gender effect, with women more likely to give and/or receive support. This would corroborate the finding from Chapter 3 that women are more likely than men to get rides outside their households. The discussions also offered some support for the theory that charity is offered *when the recipient is especially needy*. This was made clear when participants described sharing resources in emergency situations, such as, "a coworker of mine, his wife was going into labor and I needed to lend my vehicle and he needed a vehicle so I lent him my vehicle to take his wife to the emergency room," or even in just emergency-like situations, such as getting a ride after missing the bus or when it's raining.

A third set of factors relates to the *recipients' ability to offer somewhat explicit reciprocity, either with money or other instrumental favors*. As with Burkhardt's (1999) seniors, participants in this study made clear that explicit compensation was a common and necessary practice. For instance, a Riverside participant explained, "Every day I would ask her [for a ride] and she would get annoyed… [but] then when you would give her $5 or $20, then she was happy…she was not as annoyed at having to give a ride." Participants mentioned giving cash, buying gas, and offering other types of favors in exchange for rides and cars. They described offering both in-kind favors—such as having a car to offer as a trade when borrowing someone else's or offering to alternate who drives a carpool—and un-related favors, such as babysitting or lending a television. Several participants reported submitting regular financial contributions for a work carpool; one had his contribution deducted from each paycheck, since his boss provided the ride. Some participants even reported that they had bought a car because it ended up costing less than what was required to compensate someone who had lent a car. In general, however, it seems that if a recipient is able to offer explicit compensation that is attractive to the potential donors in his network, he is more likely to enjoy access to rides and vehicles.

A fourth factor is the general extent of a recipients' social network. Participants made several comments supporting the hypothesis that *larger social networks offer more potential sources of support* and therefore a higher level of overall support. For instance, the following illustrates the array of contacts that might combine to support a family's mobility needs: "My husband takes the car usually, because my sister-in-law gives [my children] a ride to school. But should I need the car, then he has a friend that works with him and he lives close by, and his friend will give him a ride." Another participant demonstrated the value of network size by explaining that he avoided having to use public transit by having "a lot of friends" and another explained "Everybody liked me, so I always got a ride," while another lamented rarely getting rides "because I've been alone, completely alone, for three years now." However, it is difficult to establish whether the network size itself matters, or if something like an extroverted personality results in both a larger network and finding rides more easily.

A final factor that is difficult to otherwise categorize but seemed especially important in determining the level of access to rides/vehicles relates to the recipients' *attitude toward seeking help.* Like Burkhardt's (1999) elderly, many participants in this study disliked the process of requesting favors, describing feelings of embarrassment, guilt, and dread in approaching others. A Fresno participant explained, "Sometimes people make you feel like you're bothering them, so you feel bad. Sometimes they don't answer the phone. 'Oh, gosh, here he comes again. He's calling for a ride.'" Another explained, "It's so embarrassing…you feel so bad and you think to yourself, 'I'm not coming back to ask ever again,'" and "You really feel bad. So I'd rather not. I'm one of those individuals…I am independent. I'd rather do it on my own than ask for a ride." By contrast, a bold or brazen orientation helped some participants secure resources. One reflected,

> They're frightened of me, because if I see someone that has a car I right away ask for a ride…I go with my brother and he says, 'You're already looking around to see who's going to give you a ride

> home!' …I'm very good at asking for rides… Sometimes when you have the need, then you have to overcome the shame of asking for a ride.

This demonstrates that what constitutes a fair social exchange is subjective, relevant for those who cannot (or prefer not to) offer explicit compensation, but do not enjoy an easy social rapport with potential givers/lenders. Those with a higher tolerance for unilateral flows of resources, or perhaps an extroverted personality, are more likely to seek and accept favors.

It was difficult to draw general conclusions on the process of intra-household resource allocation from the focus groups. Because some women did not know how to drive, some were dependent, or had been in the past, on (often male) relatives for rides. For instance, one reported that after immigrating, "My husband had a car, but he wouldn't lend it to me…until about a year later." For those who did drive, it seemed that gender roles sometimes continued to limit vehicle access. For instance, "I give my husband priority, so usually it's not decided by the need, but by the one that has the say-so," and a male attested, "I'm the only one who drives the vehicle." However, several husbands reported giving their wives priority over the car. Other families described taking care of one another's needs such that "no one is stopped from doing something because they didn't have a chance at the car." For many, the allocation of vehicles was dictated by who was perceived to have the greater need, resulting in a range of solutions of how to prioritize vehicle use and juggle schedules. Thus cultural norms and household roles could be a factor, but with varying outcomes in different families.

6.4 Summary and conclusions

In this chapter I presented a qualitative analysis of access to private-vehicle transportation acquired through social networks, based on focus groups with recent Mexican immigrants living in six different California communities. I highlighted the extent to which participants in both car-owning and non-car-owning groups relied on rides and borrowed cars to fill mobility gaps. I find that some participants exchanged rides and cars in the context of informal favors from friends (nonnegotiated), enabling unilateral conferral of transportation resources (as theorized by Molm 2003) but also sometimes accompanied by feelings of guilt or dread, which were sometimes prohibitive (as with Burkhardt 1999). Aid without explicit compensation seemed most likely from friends, from closer ties, from larger social networks, between women, for smaller favors, to those attitudinally predisposed to seek help, and in urgent or emergency-like situations.

Other participants exchanged rides and cars as part of a negotiated exchange—that is, with explicit payment or reciprocation. While this seemed a stable temporary solution for some, most participants indicated having a long-term goal of obtaining their own car—perhaps unique to this population (especially upwardly mobile and evolving) relative to other transportation-disadvantaged populations such as elderly, disabled, or poor. There was some evidence of overpayment in these negotiated exchanges, offering support for Molm's (2003) theory that power disparities have greater impact in negotiated exchanges where disadvantaged members face the risk of exclusion.

In both types of exchange (with and without explicit compensation), spatial proximity and logistical or technical considerations more broadly, seemed prominent considerations, as in Schwanen (2008). Schwanen's description of individuals operating within the context of an assemblage—consisting of both human and non-human agents rooted in space and time—seems apt, and is also consistent with Urry's concept of network capital (2007). The findings show that in the face of limited network capital (in particular, limited access to cars in a society where cars are a practical necessity), participants did tap social capital to compensate, but that in many cases their friends and relatives had limited ability to help. In particular, the prevalence of discussion among the participants of this study about unlicensed drivers and uninsured or poorly maintained cars as liabilities for those offering rides indicates that participants largely drew support from within the community of recent immigrants, who offered a limited stock of resources (corroborating Portes & Zhou, 1993). This suggests that participants would benefit from establishing more ties beyond this community (e.g. Granovetter's (1973) weak ties or Putnam's (2000) bridging capital). On the other hand, the bonds of common group membership — or enclave membership in particular — may have facilitated the exchanges happening at all. Participants did seem willing, and frequently did, rely on less-intimate contacts for rides, such as co-workers, recent acquaintances, and sometimes strangers, as well as to make payments for rides.

A limitation of this analysis and a direction for future research is to understand the extent to which these findings apply to other population groups, such as the elderly, children, or the general population. Immigrant communities may be uniquely well poised to foster this sort of informal resource-sharing due to a cascading cycle of assistance that is received and then offered, as new immigrants quickly assimilate and are then well positioned to help others. By contrast, elderly are at the mercy of younger generations who might not yet empathize with their plight. Members of the general population may be richer in network capital, such as the relatively tech-savvy early adopters of both carsharing and dynamic livery cabs, and some may be more likely to engage in equal or symmetric exchanges (people that can both give and receive rides), a potentially important aspect of peer-to-peer ridesharing and carsharing. It remains to be seen if these sorts of solutions might be adopted in the mainstream and effectively displace vehicle use through ownership, and/or be adapted to serve transportation-disadvantaged populations, to offset hardship and social exclusion.

7 Conclusions

There is growing interest among policymakers in reducing carbon emissions, vehicle-miles traveled, and auto dependence. A logical means of doing so is through incremental reductions in vehicle use. It is unlikely and probably not desirable to get rid of cars altogether, but using them more selectively may be feasible, achieving emission reductions in combination with cleaner vehicle technologies. A key to incremental reductions may be new paradigms for using cars only sometimes, by sharing cars and sharing rides, perhaps aided by technological advancements facilitating exchange, real-time arrangements, geo-located matching of rides and passengers, and incremental pricing. Better understanding of the ways of using cars *other than* the conventional U.S. model of saturated ownership and ubiquitous use is helpful for informing this potential – with respect to practical logistics, social context, and mobility outcomes.

This dissertation contributes by examining the existing practices of using cars for travel outside of ownership, specifically, the nature and extent of vehicle use among those in non-owning and low-car households. Results from a review of statistics from the nationwide NHTS survey as well as focus groups with recent immigrants living in California underscore the difficulty in determining, based on behavior alone, what is evidence of successful coping or of a dissonant ownership-access circumstance. To help evaluate welfare, I developed a model that measures mobility fulfillment relative to a benchmark level for a given demographic profile. Differences among subgroups illustrate who among them is better or worse off. This is useful not only for identifying groups at risk, but also for identifying how to improve the potential non-owner experience so that it is sufficiently attractive to entice owners to shed one or more of their household vehicles. Findings and policy implications are summarized below.

7.1 Who and where

First, fulfillment is greater among those in households with at least one car but still fewer cars than adults compared to those with no cars. Their lower average trip-making levels than households with more cars are accounted for entirely by other demographic differences, such as age and residential location, on average, suggesting that this group is able to fulfill their needs despite owning fewer cars. By contrast, about 70% of the diminished trip-making observed among those in no-car households can be accounted for by demographics, but the rest is unexplained. This potentially reflects unfulfilled desire to engage in activities outside the home, though it may also be related to unmeasured preferences for fewer activities that are not reflected in demographics.

- **Policy implication:** People still need cars, but lower ownership levels may be able to provide sufficient mobility.

Among non-owners, fulfillment is generally greatest among those living in environments consonant with a car-free lifestyle: "urban" community types and the highest-density Census tracts, where (though not measured explicitly) alternatives such as walking and transit and proximate destinations are likely to be richest. This is expected. Interestingly, however, there is little difference in fulfillment between any of the other community types: suburban areas, second cities (which have densities similar to suburban areas but distinctly function as a population and/or employment center within the local area), and truly low-density town/country areas. This suggests that all of these places are failing (or succeeding) to the same degree as one another in accommodating no-car households. Vehicle use is no less, and actually slightly greater, on average, among non-car-owners living in second cities than in suburban areas (though it is even greater among those in town/country areas).

- **Policy implication**: More places with more of the features of the higher density urban areas are needed in order to make car-free lifestyles truly feasible. Although which "urban" features would make a difference is beyond the scope of this research, “second city” community types appear to offer no meaningful improvement over suburban areas for non-car-owners.

- **Policy implication**: The potential importance of vehicle-sharing in enabling incremental reduction in vehicle dependence may be greatest *outside* of the highest-density urban areas.

As a group, the elderly appear most at risk for transportation-related hardship, with low measures of mobility fulfillment and greater vehicle use — seemingly dissonant from their ownership status. Women also have lower fulfillment, but seemingly only among the elderly and those with children.

- **Policy implication:** Services or policies targeting the mobility of the elderly and children could have particular social benefit.

Vehicle sharing is also especially high among the very young (age 18-24), among whom mobility fulfillment is also high. This suggests successful use of vehicles outside of the traditional model of vehicle ownership, perhaps specific to the typical activities, sociability, technology-use, or cultural orientation of this age group. This is particularly interesting in light of the overall trend toward decreased licensing, ownership, and use among the younger generation (Davis, Dutzik, & Baxandall, 2012).

- **Policy implication**: The habits of non-owning youth (and perhaps all youth) may serve as a model of the future. Some aspects of their current practices may help inform the design of innovative sharing-enabling services, whether targeting the young or old.
- **Policy implication**: The young may be the most likely early adopters of some types of innovative services, though they might also have access to the greatest array of alternative sources of rides through informal channels and therefore more discriminating about services offered.

Some of the surprising results may reflect people whose living situations or other life circumstances have not yet adjusted to their vehicle-ownership (or driver) status, or vice versa. For instance, among non-vehicle-owners, home-ownership is associated with more vehicle use, even after taking into account the residential environment, housing type, ages, and income levels of the occupants, on the face of it suggesting more access to tangible resources (apparently leading to rides in cars) than their other demographic attributes would predict. But this group also has less fulfillment, on average, perhaps an indication that ownership (and reluctance to move) have resulted in a living situation that is no longer consonant with their transportation needs. Conversely non-car-owners with limiting medical conditions apparently enjoy greater mobility than expected, perhaps reflecting longer-term adjustment to their circumstances, compared with medically limited car-owners.

- **Policy implication:** Policies designed to ease or accelerate adjustment to car-free living, such as financial incentives that favor leaving a detached single-family home in a low-density environment and moving to a more accommodating environment, are needed.
- **Policy implication**: Policies designed to help elderly "age in place" may be at odds with this approach, though they could also ameliorate the consequences of living in an otherwise dissonant situation.

Despite the hypothesis that income itself would be an indicator of choice, both for vehicle-ownership level and complementary life circumstances, the results suggest that within ownership strata (which are already related to income but have heterogeneity within them), income has little correspondence to either vehicle use or mobility fulfillment, once residential environment (and other relevant demographic attributes such as age) have been accounted for. This suggests an equalizing effect of car-free lifestyles for those who are able to live in consonant built environments. However, other factors emerged as potential indicators of choice versus necessity: Non-car-owners with less educational attainment use vehicles *more* (seemingly dissonant with their ownership status) and those who cannot drive also use vehicles *more* with *less* mobility fulfillment (even after accounting for factors such as age, disability, income, and residential location). This suggests that although not reflected in income per se, there may be other constraints among non-driving non-owners that affect mobility, which may be an equity concern.

- **Policy implication:** Educational attainment and driving ability are the best indicators of "choice" (versus necessity) among non-owners. Highly educated drivers might be the most likely early adopters of any innovative sharing-enabling services — whether or not they require driving.

Table 51. Summary of the correlates of vehicle use and fulfillment among non-owners

Attribute	Vehicle use	Mobility fulfillment
Household income	Less as income increases, on average, but no difference after accounting for residential location	No difference
Educational attainment	Less	No difference
Home-ownership	More	Less
Driver status	Less	More
Limiting medical conditions	More	More
Female gender	More	Less
Age	More among 18-24 and 60+	Diminishing with age among 50+
Children	No difference	Less
Employment	No difference	No difference
Household size	No difference	Less if alone, More if 3+ adults
Density	Less as increases	More as increases
Community type		
Urban	Less	More
Second city	No different from Suburban	No difference between any others
Suburban	No different from Second city	
Town/country	More	
MSA-level transit score	Less	More
Modes used		
No vehicles (all alternatives)	(n/a)	Less
All vehicles (no alternatives)		More
Some of each		Most

7.2 What and how

Results regarding the extent and nature of the vehicle-sharing and ride-sharing that is already occurring provide two types of conclusions for policy and marketing. On the one hand, the types of occasions in which vehicle-sharing already occurs point to the circumstances most ripe for innovative services or policies designed to further promote sharing. On the other hand, the types of occasions in which vehicle-sharing is absent point to circumstances in which services or policies might contribute the most value — with potential for profit (if a willing market exists) and/or a social benefit, by accommodating disadvantaged subgroups as well as making car-free living more enticing to those that have more choice.

The NHTS data show that non-owner vehicle use is highest for activities that are most social, all else equal, including trips during the evening hours (7pm-midnight), on weekends, for social/recreational outings, and to religious activities. This suggests that in these contexts sharing is most natural and successful. By contrast, there is evidence of hardship in completing shopping and medical visits. The focus group participants explained that these sorts of destinations were some of the hardest to get to, as well as the ones for which they are most likely to try to find a ride. In the vehicle-use modeling (using NHTS data), trips for these purposes showed the biggest differences between owners and non-owners. Among owners, the baseline level of vehicle use is already high, and the probability of using a vehicle was even higher for shopping/errands and for medical/dental visits. By contrast, among non-owners, the baseline level of vehicle use is very low, and the probability of using a vehicle for those trip types was elevated by significantly smaller amount.

- **Policy implication:** Services designed to accommodate shopping and medical visits may provide the greatest social value for those with limited choice, and may be occasions in which choice users are the most willing to pay.
- **Policy implication**: Social and recreational outings are a natural fit for sharing, and therefore may be the easiest context in which to introduce a sharing-oriented service but could provide less added value.

Turning to the logistics of sharing, the focus group participants revealed that people are willing and do seek rides from people they don't know. While participants mentioned being more comfortable asking larger favors from close contacts, they also revealed relying on mere acquaintances, and in some cases strangers, for rides and resources.

- **Policy implication**: Peer-to-peer ride-sharing or shared taxis or shuttles that would require individuals to rely strangers or more distant contacts have potential for success.

The discussions suggested that being from a common group helped enable trust and lubricate social exchange, and that women were more comfortable with these exchanges than men. The NHTS data corroborated a gender difference, showing that non-owning women are substantially more likely to find rides outside their households than non-owning men (except among the elderly, for whom there is little difference), making a greater share of their trips by car, and perhaps as a result, making more trips overall.

- **Policy implication**: Sharing-enabling services rooted within community organizations, or tacked onto existing social networks, such as through social-networking sites, seem promising.
- **Policy implication**: However, more diverse (rather than narrow or close knit) networks may provide access to a broader array of mobility resources than would be available from a familiar community already tapped informally.

The results also help inform some of the different types of sharing suited to different contexts, to fit either the particulars of geography or of market-segment preferences. For instance, non-owner driving trips (versus passenger trips) are much more common outside of the urban areas, and most common in the lowest-density town/country areas. This might mean these areas could most benefit from services that facilitate sharing (or alternatively, that services offering more autonomy would be more likely to succeed). Meanwhile, suburbanites appear to engage in less travel with people outside their households. Again, this might mean that such connections are waiting to be made, or that services are more likely to succeed if designed to operate within family units. This might take the form of an educational behavior-change tool, such as the “travel blending” campaigns pioneered in Australia (Goulias, Broeg, James, & Graham, 2002; Rose & Ampt, 2001). As another example, the apparent differences by gender could have implications for the design of a sharing-enabling service. Based on the fact that non-owning women get more rides (and use cars more), while men use cars less but drive more, we might conclude that women would be more likely to take advantage of ridesharing and socially embedded services, while men more likely to take advantage of programs that allow them to drive, or that are less mediated through social exchange. On the other hand, if not naturally inclined to tap social networks for rides, perhaps males would be a better market for services facilitate the process; similarly, if women face barriers or reluctance to driving, programs that reduce the barriers might make more of a difference for their mobility.

Payment is also an important issue. The focus groups made clear that the affective dimensions of giving and receiving rides, including guilt and willingness to ask for help, play an important role. To the extent that these are barriers to finding rides, a possible advantage to a more organized sort of service is the opportunity for explicit payment. For those less willing or able to pay money, an opportunity to offer some other service in exchange, such as meals or babysitting in exchange for rides, might help assuage feelings of guilt and facilitate finding rides. On the other hand, even among the low-income immigrants in the focus groups, there was willingness to pay. Participants reported paying friends and associates for rides, as well as using taxis. In the NHTS data, the elevated use of taxis for certain trip types, such as medical visits, supports a willingness to pay in those circumstances. “Choice” users may be willing to pay even more, as demonstrated by those paying large amounts for reliable taxi service that is priced dynamically in response to demand (Bilton, 2012).

- **Policy implication:** Even the poor are willing and sometimes eager to pay, suggesting the existence of a market for more fare-based, possibly for-profit, services.
- **Policy implication**: A greater range in types of services and price points has the potential to capture more users. This could manifest as product differentiation, or as different types of pricing for a given product (such as pricing based on a sliding scale, demand-responsively, or negotiated informally).
- **Policy implication**: Service attributes that will likely hold different appeal for different market segments (likely correlating with gender, age, and community type, among others) include: whether prices are explicit or implicit, whether price is negotiated or fixed, extent that it is mediated through social exchange,

extent of autonomy versus dependence, whether driving or riding, and the requisite degree of trust.

7.3 Directions for future research

A new contribution in this dissertation is the method of developing a model for benchmark mobility levels based on the behavior of theoretically unconstrained high-access vehicle-owners. The framework proves useful for comparing mobility fulfillment within groups, relative to the benchmarking model, but an important limitation is the inability to distinguish between constraint and lower demand — due to factors other than the demographic and geographic variables included in the benchmarking model, such as attitudinal differences or other orientation toward travel. This underscores the value of measuring factors such as attitudes and preferences likely to affect activity levels (even in the absence of constraints, such as travel-liking or being highly active), or subjective assessments of fulfillment and satisfaction, through self-reporting on surveys.

In addition, with respect to demographics and geography, the measures used in this analysis are necessarily coarse, limited to those available in the NHTS dataset. More nuanced measures of opportunities for walking/biking, availability of transit at a more local level, and attributes not just of home environments but work and other important destinations might also be important for evaluating mobility fulfillment. By glossing over these, models such as those in this dissertation are noisier and there is less opportunity for evaluating how such factors contribute to mobility fulfillment. A direction for future research might be to replicate this overall modeling framework using data with more detailed measures of the transportation environment, and if possible, also with subjective measures of self-reported fulfillment, to help validate the overall premise of using a benchmarking model based on the behavior of one portion of the sample.

Another direction for future research is to further evaluate the sorts of ridesharing and car-sharing that are feasible – either as a part of an organized program or service (either high-tech or low-tech) or ad hoc within existing social circles. In particular, how socially distant can contacts be and still be trusted to provide a ride? How important is common group membership in fostering exchange? How much are participants willing to pay for a ride? How are non-owning young people orchestrating so much of their travel in cars? How do different types of potential users perceive issues of trust, payment, technology, privacy, and autonomy? From an equity perspective, another question relates to the best way to form bridges from those with transportation resources to those without.

With widespread interest in reducing vehicle dependence, today's no-car and low-car households have an important role for researchers, both as the object of concern and as the avant-garde. The processes by which they use vehicles demonstrate the circumstances most conducive to vehicle-sharing, and gaps in mobility fulfillment point to circumstances in which innovative services could best play a role in making car-free lifestyles more attractive. The fact that mobility fulfillment is highest — across all vehicle-ownership segments — among those using a mix of modes, both in vehicles and by alternatives means, suggests that increased sharing of cars and rides holds promise as a key to incremental vehicle reduction in the broader population, complementing other policy strategies such as investments in transit and complementary land use changes.

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