Title
Parking, Working from Home, and Travel Behavior

Authors
Ding, Hao
Manville, Michael

Publication Date
2024-07-01

DOI
10.7922/G24X5641

RESEARCH REPORT

Institute of Transportation Studies | UNIVERSITY OF CALIFORNIA

Parking, Working from Home, and Travel Behavior

Hao Ding, PhD Candidate, Department of Urban Planning, UCLA
Michael Manville, Professor of Urban Planning, UCLA

July 2024

California Resilient and Innovative Mobility Initiative

Report No.: UC-ITS-RIMI-4L-01 | DOI: 10.7922/G24X5641

Technical Report Documentation Page

1. Report No.
UC-ITS-RIMI-4L-01

2. Government Accession No.
N/A

3. Recipient's Catalog No.
N/A

4. Title and Subtitle
Parking, Working from Home, and Travel Behavior

5. Report Date
July 2024

6. Performing Organization Code
UCLA ITS

7. Author(s)
Hao Ding, orcid.org/0000-0001-5286-3367; Michael Manville, orcid.org/0000-0002-4218-6427

8. Performing Organization Report No.
N/A

9. Performing Organization Name and Address
Institute of Transportation Studies, UCLA
3320 Public Affairs Building
Los Angeles, CA 90095-1656

10. Work Unit No.
N/A

11. Contract or Grant No.
UC-ITS-RIMI-4L-01

12. Sponsoring Agency Name and Address
The University of California Institute of Transportation Studies
www.ucits.org

13. Type of Report and Period Covered
Final Report (July 2022 – December 2023)

14. Sponsoring Agency Code
UC ITS

15. Supplementary Notes
DOI:10.7922/G24X5641

16. Abstract
Drawing on the California Household Travel Survey, we demonstrate strong associations between choosing to drive and having free parking at work or home. We find that the median household vehicle in California spends 22 hours a day parked, and that households with parking included in the rent or purchase price of their homes are more likely to drive, and less likely to use transit. We further find that employees with free parking at work are more likely to drive for their commutes. We estimate regressions that analyze the decision to work from home. Largely for data reasons, these regressions are less conclusive.

17. Key Words
Travel behavior, mode choice, commuting, workplaces, residential location, parking, parking fees

18. Distribution Statement
No restrictions.

19. Security Classification (of this report)
Unclassified

20. Security Classification (of this page)
Unclassified

21. No. of Pages
57

22. Price
N/A

Form Dot F 1700.7 (8-72)

About the UC Institute of Transportation Studies

The University of California Institute of Transportation Studies (UC ITS) is a network of faculty, research and administrative staff, and students dedicated to advancing the state of the art in transportation engineering, planning, and policy for the people of California. Established by the Legislature in 1947, ITS has branches at UC Berkeley, UC Davis, UC Irvine, and UCLA.

The California Resilient and Innovative Mobility Initiative

The California Resilient and Innovative Mobility Initiative (RIMI) serves as a living laboratory—bringing together university experts from across the four UC ITS campuses, policymakers, public agencies, industry stakeholders, and community leaders—to inform the state transportation system's immediate COVID-19 response and recovery needs, while establishing a long-term vision and pathway for directing innovative mobility to develop sustainable and resilient transportation in California. RIMI is organized around three core research pillars: Carbon Neutral Transportation, Emerging Transportation Technology, and Public Transit and Shared Mobility. Equity and high-road jobs serve as cross-cutting themes that are integrated across the three pillars.

Acknowledgments

This study was made possible with funding received by the University of California Institute of Transportation Studies from the State of California through a one-time General Fund allocation in the 2021 State Budget Act for the Resilient and Innovative Mobility Initiative. The authors would like to thank the State of California for its support of university-based research, and especially for the funding received for this project.

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the State of California in the interest of information exchange. The State of California assumes no liability for the contents or use thereof. Nor does the content necessarily reflect the official views or policies of the State of California. This report does not constitute a standard, specification, or regulation.

Parking, Working from Home, and Travel Behavior

Hao Ding, PhD Candidate, Department of Urban Planning, UCLA
Michael Manville, Professor of Urban Planning, UCLA

July 2024

California Resilient and Innovative Mobility Initiative

Report No.: UC-ITS-RIMI-4L-01 | DOI: 10.7922/G24X5641

Table of Contents

Table of Contents

Executive Summary 1

I. Introduction 4

II. Background 7

Parking, Travel Behavior and the Built Environment 7

Parking and Remote Work 8

III. Data and Method 13

Dependent variables 14

Independent variables of interest – parking availability 14

Control variables 16

IV. Results 19

Descriptive results 19

Regression Results 22

V. Discussion and Conclusion 29

References 30

Appendix 33

Complete regression models 34

List of Tables

Table 1. Variables used in analysis 18

Table 2. Summary of daily household (HH) trips (source: CHTS) 19

Table 3. Summary of household (HH) commute trips (source: CHTS) 20

Table 4. Descriptive statistics on parking (source: CHTS & AHS) 21

Table 5. Commute modes for individuals with and without free parking at work (source: CHTS) 21

Table 6. Association between Parking and Vehicle Ownership (Negative Binomial Regression) 22

Table 7. Association between Parking and Transit Trips (Negative Binomial Regression) 23

Table 8. Association between Parking and Commuting by Transit (Logistic Regression) 24

Table 9. Association between Parking and Commuting by Driving (Logistic Regression) 25

Table 10. Association between Parking and VMT (Tobit Regression) 26

Table 11. Association between Parking and Car Trips (Negative Binomial Regression) 27

Table 12. Association between Parking and Working from Home (Logistic Regression) 28

Executive Summary

Executive Summary

California has a strong interest in reducing the externalities of vehicle travel. How can it do so? Parking policy offers one possible lever. When parking is abundant and free, theory and evidence both suggest that driving will be more attractive, and transit use less so. Taking steps to make free parking less prevalent, therefore, could nudge travel behavior in a more desirable direction. In the wake of the COVID-19 pandemic, moreover, the state is interested in the future of telework. Here too, parking could play a role, although its influence is more ambiguous a priori.

In this report we use the California Household Travel Survey (CHTS) to examine parking's role in travel behavior. The CHTS is unique in providing detailed parking data and allows us to paint a much more detailed picture of parking use and payment in California than any data set before or since. What we find confirms expectations: parking, and particularly free parking, dominates California's surface transportation system. The vast majority of trips are by automobile, the vast majority of automobile trips end in a parking space (usually an off-street space), and most parking spaces are free to the driver. Almost 80 percent of employees in the state have free parking at work. Indeed, the typical California automobile spends over 22 hours per day parked, typically without the driver making a direct payment.

We then show, both descriptively and in a series of regression equations, that this availability of free parking is powerfully associated with more driving and less transit use, both overall and for the commute. The regressions show, moreover, that these associations remain strong in the presence of statistical controls for differences in vehicle ownership, drivers licensure, and an array of factors related to the neighborhood built environment and socioeconomic status. While we do not explicitly control for self-selection in our models, for example, those wanting to drive and not take transit seeking out jobs with free parking, the existing research suggests that, at worst, self-selection controls would only modestly reduce the magnitude of our findings and might even increase them. At a broad level, our results highlight parking's role as an important intermediary in the relationship between transportation and travel behavior.

First, we find that most trips are by automobile, most automobile trips end in a parking space, and most parking is free. Indeed, the typical California automobile spends over 22 hours per day parked, and virtually none of this time or space results in a direct cost for the driver. Where parking *is* priced, in contrast, driving is less common.

Second, the massive consumption of unpriced land and time implies a large subsidy for automobile use, and our regressions show that households with bundled parking are more likely to drive and less likely to use transit and these households drive more miles than other households. We find, similarly, that households whose members with jobs have free parking at work will be more likely to drive to work, less likely to use transit, and more likely to drive more miles.

We do not find a strong association between parking provision and working from home, but some of this null finding may stem from our imprecise controls for employment and occupation. The report discusses why this may be the case. While working from home is likely to remain a larger option in California than it was before the pandemic, its relationship to the built environment is conceptually more complex than other forms of commuting, and measuring it correctly is harder given the structure of most data sets on commuting. Future research should seek to merge detailed parking data with more fine-grained data on work tasks and responsibilities.

Contents

I. Introduction: How Parking Affects Working from Home, and Other Travel Behavior

Driving stands out among transport modes for its high terminal costs: the time and space needed to park. The promise of automobility is to go where one wants, when one wants, but fulfilling that promise requires having a place to store the vehicle when one arrives. This requirement makes driving different. The typical train or bus spends most of its life in motion. The typical automobile spends most of its life parked.

In an unregulated market, or one where land values are high, parking's large temporal and spatial demands could make owning and using a vehicle expensive. Most of the United States, however, doesn't fit this description: in many places land values are low, and in almost all places the market for parking is not just highly regulated, but regulated in a way that depresses parking's price. Cities keep most of their curb spaces free and require almost all new developments to provide ample off-street parking. This combination of a price ceiling on the street and a quantity floor off it shields most drivers from parking's full cost. Because parking is a complement to driving, policies that hold its price down and force its supply up make driving less expensive (Shoup 2011).

The implied subsidy here is large and has both academic and policy relevance. From an academic perspective, regulations that keep parking abundant and cheap help clarify some stylized facts about transportation and land use that might otherwise be puzzling. Off-street parking, for example, is a low-value land use—it generates little revenue or employment—and for that reason it is often prevalent in declining cities. More surprising is how common it also is in economically vibrant places where land values are high (e.g. San Jose). Parking requirements, which mandate parking's presence regardless of its opportunity costs, resolve this paradox (Gabbe et al. 2020). Required parking also helps explain the emergence, in the late twentieth century, of "dense sprawl" or "car-oriented density" (Eidlin 2012): the phenomenon by which urban areas become denser while remaining deeply inhospitable to non-auto modes. Relative to other U.S. metropolitan areas, for example, Los Angeles and New York are quite dense. But Los Angeles has more vehicle ownership and driving than its density alone would predict, while New York has less. The difference lies, in part, with the availability of parking. Almost every housing unit in LA comes with a parking space, while about 70 percent of units in New York City do not (Shoup 2011; Manville and Shoup 2005; Manville et al. 2014; Manville 2017).

Regulation's role in these situations gives parking a strong policy valence. While parking is unlikely to be the largest determinant of whether and how much a household drives—income and family size are probably larger predictors—parking, unlike these other factors, lends itself to government action. Policymakers have neither a ready means nor (hopefully) a strong motivation to reduce family size or household income. But cities already regulate parking and could with relative ease change the manner of that regulation. They could require less parking (or none), charge more for their curb parking, and allow development in places that are currently parking lots.

While this reasoning isn't new, the COVID-19 pandemic and its aftermath have endowed it with renewed urgency. The pandemic and its associated lockdown demonstrated the benefits of reduced private vehicle travel, showed the importance as well as the vulnerability of public transit, and helped reveal the opportunity costs of abundant parking. At the pandemic's onset, large amounts of work immediately became remote and large amounts also simply stopped. The economic costs of lockdown were immense, but they also offered a window into the potential environmental benefits associated with less internal combustion driving. Vehicle travel plunged, and this caused congestion and air pollution to steeply decline (Bao and Zhang 2020; Laughner et al. 2021; Pishue 2020; Mueller et al. 2022). On the other hand, the stay-at-home orders also sent public transit systems, many of them struggling even before the coronavirus, into further distress. Then, as the pandemic persisted businesses, particularly restaurants, battled to stay afloat, cities began repurposing parking spaces, relaxing requirements and allowing restaurants to operate in parking lots and curb parking spaces.[1]

COVID's retreat has reversed some of these trends but not others. Remote work is not as common as it was at the pandemic's peak but remains far more common than it was pre-COVID. Driving, congestion, and pollution have also returned, rivaling and in some cases exceeding pre-pandemic levels. Transit ridership, however, has not recovered—in part because remote work has persisted disproportionately among educated workers employed by large firms (Barrero et al. 2023). While most of these workers do not commute by transit, those that do make up a disproportionate share of transit riders in the center cities that themselves hold a disproportionate share of U.S. transit. Finally, local governments seem ambivalent about the future of curbs and parking spaces. Some have continued to allow open-air dining in parking spaces, while others have returned these spaces to exclusive use for vehicles.

It is in this context that we revisit the potential of parking policy to influence travel behavior. We do so by drawing on the 2010-2012 California Household Travel Survey (CHTS). The CHTS is a large, representative travel diary from the U.S.'s largest state, and unique among travel large diaries for offering fine-grained data on the use and price of parking spaces away from home. Across thousands of users and a broad spectrum of built environments, the CHTS records if a given trip used parking, if the driver paid for it and (if they did) its price, if the parking was on or off-street, and so on. We match these data to measures of the built environment, and household and individual characteristics, and estimate the association between parking availability and the decision to travel (or not) in different ways.

Specifically, we estimate the associations between parking availability and decisions to work from home, drive, and use public transportation. Our first major result is descriptive; we use these data to confirm something that has long been anecdotally intuitive, but never empirically verified. The vast majority of California vehicle trips end in a parking space, and the vast majority of those spaces, both on- and off-street, are unpriced. We then estimate regressions demonstrating that, even controlling for a host of other factors, the presence of free parking is strongly associated with more vehicle ownership, more driving, and less transit use.

---

[1] Examples in Los Angeles include the city's Al Fresco Dining Ordinance (LA City Planning 2023) and its Curbside Dining Program (LA Department of Transportation nd). Grabar (2023) discusses programs nationwide.

Our final set of regressions measures the association between free parking and working from home. For reasons we discuss, we anticipate this relationship to be weaker, and it is. Nevertheless, we do see that employees who must pay to park at work are more likely to work from home. Consistent with other research, however, we cannot say with certainty that working from home results in less total driving.

In the next section we review some relevant studies on parking, travel behavior, and remote work. We pay particular attention to the determinants of telework, since this is the area where the least is known. Section III describes our data and empirical approach. Section IV presents our results, and Section V concludes.

II. Background: What We Know (or Don't Know) About Parking and Work

We draw on and contribute to two research literatures: one examining transportation and land use (and specifically transportation and parking) and the other that studies the determinants of remote work. Both literatures are large: the first is legitimately vast, and the second is growing rapidly as a result of COVID-19. We review each in turn.

Parking, Travel Behavior, and the Built Environment

Parking occupies a relatively small portion of the transport and land use literature, because parking was for a long time a neglected aspect of the transport and land use connection. Parking's time in the academic wilderness, however, has ended, and it is now not controversial to suggest that the ease and expense of storing a car influence the decision to own one, or to use it for any given trip. A diverse body of evidence now suggests that when parking's price is low, people are more likely to own vehicles, more likely to use them, and less likely to ride transit (Weinberger et al. 2009; Shoup 2011; Weinberger 2012; Chatman 2013; Manville 2017; Manville and Pinski 2019; Millard-Ball et al. 2022).

At the same time, our understanding of parking's influence on travel is limited compared with other aspects of transportation and land use, such as the relationship between driving and population density. This is so because most data sets still lack measures of parking. Large social science surveys and administrative data sets offer detailed information, over time and for the entire United States, on commuting behavior, the quantity of overall travel, the supply of roads, the count of vehicles, and the density of jobs, people and housing. In contrast, almost no systematic data sheds light on the supply, price and availability of parking, particularly outside the home. For example, the 1995 National Personal Transportation Survey (NPTS) asked respondents dozens of questions, and had them fill out a detailed travel diary, however, it asked only one question about parking: Did employed respondents pay to park at work? Three subsequent versions of the NPTS—in 2001, 2009 and 2017—were longer than the 1995 survey, but did not ask about parking at all. Currans et al. (2022), for example. used the 2017 NHTS to argue that housing developments with less than one parking space per unit are associated with less car ownership and vehicle travel. Because the NHTS has no data on parking, however, they had to infer its presence using secondary methods.

One result of these data limitations is that the empirical literature on parking is characterized by a combination of detailed data from limited contexts, and limited data from more general contexts. An example of the former is Millard-Ball et al. (2022) who administered a travel survey to residents of affordable housing in San Francisco and showed that compared to households assigned units with parking, households without parking drove less and rode transit more. Because affordable housing tenants in San Francisco are assigned their units by lottery, these findings avoid self-selection problems and are thus plausibly causal. They are, however, drawn from a particular subset of housing in one city, so a skeptic might question their generalizability.[2]

An example of the latter is Manville (2017), which uses data from the American Housing Survey (AHS) to show that households with bundled parking—parking included in the unit's rent or purchase price—were more likely to own vehicles and drive to work. This finding was robust to tests for self-selection and drew on more general data (the AHS is a representative sample of the U.S. housing stock). The data were, however, less detailed. The AHS contains few travel behavior variables, and its parking measure only shows if the household has bundled parking, it does not show the number of spaces a household has, nor indicate the price or availability of parking at different destinations away from the home.

Parking and Remote Work

The Determinants of Telework

Data limitations notwithstanding, the hypothesized relationship between parking availability and the decision to drive is straightforward: the ease or price of parking influences the total cost (in time, money, or stress) of using a car, and as that cost rises the likelihood of driving falls. Data limitations constrain our ability to measure the relationship between parking and remote work, or telework, but measuring this relationship is further compounded because it is conceptually more complicated. The availability of parking could, depending on the circumstances, encourage or discourage teleworking.

The data constraint affecting remote work arises because work location is rarely tracked directly; we learn about it instead as a byproduct of questions about commuting. The Census, for example, only mentions working from home when it asks respondents about how they travel to work. The trouble is that not all home-based work is telework, at least in the sense it is commonly used, which involves a job that does have a fixed location outside the home, but that the employee performs from the home instead, all or part of the time. It was telework that increased dramatically during COVID-19; lawyers, bankers and other people who were normally in offices were suddenly working from their kitchen tables. It was the spike in telework, alongside mass unemployment, that dramatically reduced personal travel.

Much work from home, however, is *not* telework, and instead involves people working or running businesses from their housing units, without any fixed location elsewhere. Examples can include freelance writers and artists, accountants who work from home offices, and people who give piano lessons or haircuts in their houses. Data sets that ask only if someone works from home, as most large data sets do, are accurate insofar as

[2] A point in the paper's defense is that housing in San Francisco is by now so expensive that families with incomes over $100,000 can qualify for subsidized units. So the inhabitants of subsidized housing are not automatically poor. Many have vehicles, or at least have income sufficient to get vehicles if they want them.

they capture the absence of a commute, but make it difficult to differentiate within that absence, and distinguish between telework and home-based work.[3]

Distinguishing between these categories is important, however, because they have different implications for travel, and for how the built environment might influence it. A telecommuter represents a foregone work trip. A work-from-home business owner or entrepreneur may not. Telecommuters, moreover, may be more likely to stay home if parking near the home is hard to find; going to work might invite the hassle of searching for parking when they return. Piano teachers, in contrast, might be more likely to teach at home if parking near the home is *easy* to find—the ease of parking might help attract and keep customers.

More broadly, the different forms of home-based work are characterized by different requirements surrounding in-person interaction. Telework is, by definition, work that doesn't require face-to-face proximity. Work from home is work that can be done in the house. These categories only sometimes overlap. There are times when computer programmers need to be in proximity to customers or coworkers, but many situations where they can work alone. Barbers, in contrast, always need to be with their customers. And yet while the barber and the customer need to be in the same place, that place needn't be a traditional barber shop. It could be the barber's or the customer's home.

The COVID stay-at-home orders increased telework (e.g., computer programmers began working from home), *decreased* some forms of home-based work (it became illegal to patronize home-based barbers), and converted some home-based in-person work to telework (people who gave in-person piano lessons in their houses started giving lessons over Zoom).[4]

One implication of this reasoning is that the decision to work from home, unlike the decision about how to get to work if one commutes, will hinge primarily on the nature of the work itself. Retail clerks and grocery cashiers can, in principle, get to work any number of ways. They could drive, bike, walk, or take transit. Aspects of the built environment, including the availability of parking, could influence that decision. But these workers *cannot* work from home; by definition they must be physically present to help customers. Their decision to work from home or not has nothing to do with the built environment or their travel options, and more to do with the job itself.

The first condition for telework, then, is a job that can be flexibly executed outside the workplace. Technological progress has, over time, placed more jobs into this category. In the year 2000 only one percent of U.S. adults had broadband Internet; in 2019, 73 percent did (Pew Research nd). Even before the pandemic, moreover, substantial improvements had been made to online meeting platforms like Zoom.

---

[3] Some of these people may work outside the house (a writer might go to a coffee shop), but the Census would most likely still record them as working from home for commuting purposes.

[4] Some home-based work that had been in person became telework (a person who gave piano lessons in her house began giving them over Zoom), but some just ceased.

A job that can be done remotely, however, is not necessarily one that will. A second condition is that a firm *permits* its employees to telework and gives them that option. Prior to COVID, many employers were reluctant to allow teleworking, even for jobs where it was technologically feasible. This reluctance owed to a combination of three concerns: a fear that employee effort would fall; a fear that work quality would fall even if effort did not; and a fear that productivity would fall even if effort and quality were constant, because of declines in serendipity and unplanned interaction.

The first fear is intuitive; remote workers, being unsupervised, might shirk. The second fear relates to the nature of the work; some job output might be unavoidably worse if delivered remotely. Piano teachers offering remote instruction could try every bit as hard as they would in person, but the quality of instruction might still fall because they could not (for example) reach over and adjust a student's hand position.

The third concern is the most abstract and relates to Marshallian externalities. Marshall (1890) suggested that people learn and improve at their jobs by being close to others doing the same work. This process of mutual learning, in turn, fuels innovation, often through chance encounters, casual conversation and informal mentoring. Because innovation accounts for a disproportionate share of productivity growth, learning generates increasing returns, and is among the most valuable attributes of an industrial atmosphere (Romer 1986, 1990).

Diminished innovation, then, is arguably the largest but also hardest to measure concern associated with telework. The logic of Marshallian externalities suggests that innovation could fall in even idealized teleworking situations, where the effort and output of remote employees is equal to what would occur in the office. Even in such circumstances, falling levels of unplanned interaction would result in less innovation, and/or less transmission of informal knowledge from veteran workers to their younger colleagues. This lost knowledge could be costly, but the costs would be hard to detect, especially in the short term. A telling example of this concern is a memo sent by the CEO of the teleconferencing platform Zoom—arguably the company that has benefited most from telework—asking employees to return to the office and explaining that the company suffered when its operations were entirely remote: "We cannot have a great conversation. We cannot debate each other well" (Stewart 2023).

The validity of these concerns, however, has long been ambiguous. Home-based workers might shirk, but shirking is hardly unknown among office dwellers. Few office workers are constantly monitored, and it is hard from even a short distance to tell if employees are doing their jobs or scrolling social media. The quality declines associated with remote work, moreover, are real but probably vary substantially by job. Relative to in-person instruction, remote piano or swimming lessons probably leave much to be desired. Many modern office jobs, however, are a bundle of different tasks, some of which require proximity but others of which can be completed effectively anywhere (Barrero et al. 2023). A good deal of modern office work involves writing reports, or calling or emailing people elsewhere.

The costs of less unplanned interaction, perhaps unsurprisingly, are harder to pin down. Chen et al. (2022) use mobile phone data to follow tech workers in Silicon Valley and showed that increased face-to-face interaction is associated with increased patent activity—a reasonable proxy for innovation. Consistent with the fears of Zoom's CEO, Gibbs et al. (2023) show that when Indian workers went remote during COVID, they did "narrow their networks" and encounter fewer people.

At the same time, however, at least some of this damage can be mitigated via hybrid working—people coming to the office for two or three days a week. On top of that, moreover, telework offers some benefits to firms as well as costs. Commutes are a burden, and one that employees already essentially consider work time. Some people who begin teleworking might start working earlier and finish later, increasing rather than decreasing productivity (Gibbs et al. 2023). A further point is that telework could slow nominal wage growth. If employees value working from home, they should be willing to forego some pay in exchange for doing so, and the savings to firms could be large because the highest-income workers (who have space for home offices and whose marginal earnings are most highly taxed) may be most willing to make this trade (Barrero et al. 2023).

None of these potential costs or benefits were unknown before COVID. Telework, nevertheless, was extremely uncommon. This reluctance to even experiment with telework may have arisen because for any *individual* employer, allowing remote work would entail large risks. These risks would be particularly large for first movers. Consider an employer that lets its employees telework while its competitors do not. A potential upside is that the firm will attract or retain more talent. A potential downside, however, is that teleworking does reduce effort, quality or innovation, and the decision is hard to reverse. The firm could now find itself locked in a competitive disadvantage. If firms understand these stakes, the result would be a prisoner's dilemma: most firms won't adopt large-scale teleworking unless most others do as well.

The COVID-19 stay-at-home orders were designed to control the pandemic. But they also, as a side effect, broke this prisoner's dilemma. Every firm simultaneously went remote, mitigating fears of competitive disadvantage. The length of the lockdown also reduced any stigma that may have surrounded telework, and led both workers and firms to invest in equipment and skills that made teleworking more feasible.

Telework and Travel

As COVID recedes, two questions loom. First is the extent to which work locations will revert to their pre-COVID means. Firms thus far have been only moderately successful in getting employees back to work, meaning that many more workers will likely have at least the option of working from home. Once a worker has permission to telework, the built environment may become more relevant. Our expectation is that, controlling for occupations that allow remote work, the availability of parking will be associated with the decision to work remotely.

The second question is the extent to which teleworking actually reduces travel, and especially vehicle travel. Travel plunged during COVID, but COVID was marked by economy-wide contractions; not only did much work go remote, many other establishments closed as well (stores, gyms, restaurants, concert halls), and people were warned not to socialize. In less restrictive circumstances, the existing evidence about telework and travel is mixed. Teleworking undeniably reduces *commute* driving (see, e.g. Hook et al. 2020) and that can be important, given that commute hours suffer from the most congestion and pollution. It is less clear, however, that it reduces driving overall, and indeed some evidence suggests that among teleworkers driving *rises* (see, e.g. Caldarola and Sorrell 2022).

The reasons for this are varied. Telecommuting is sometimes associated with a greater distance from work, so on days when teleworkers do drive in, their longer trips fully offset their not driving on other days. (The causality of this association with longer distances is probably bidirectional: people are more likely to telework if they live far away, but also more likely to live further out if they have the option to telework.) This logic does imply that total reductions in driving are more likely if someone teleworks every day, and some evidence suggests as much (Caldorola and Sorrell 2022). Recall, however, that teleworking every day also raises the risk of productivity losses.

Less frequent but longer commutes, moreover, are not the only reason that telework might be associated with more driving. For one, teleworking in some instances might replace a transit commute, not a drive commute. If teleworkers then make some non-work car trips (errands or dropping kids at school) their vehicle mileage travelled (VMT) might rise. More generally, teleworking could increase non-work driving. This might occur because the teleworker gets "cabin fever" or wants to replace the lost social interaction that results from home-based work, or because having a vehicle at home (as opposed to parked at work all day) allows *other* members of the household to drive more (LaChapelle et al. 2018; Kim et al. 2015). The evidence, in summary, suggests that teleworking can reduce commute VMT, but will likely increase non-work VMT, although not always by enough to swamp the effect of reduced commuting.

III. Data and Research Methods: Factors Influencing Work from Home

Our primary hypothesis is that the price and availability of parking will influence people's travel behavior, including whether they telework, their modes of transport, and how much they travel. Specifically, we expect that people with free parking available at home or work will be more likely to drive (and drive more miles) and less likely to use transit, than people who do not. Our expectations surrounding the decision to work from home are more tempered: we anticipate that a lack of free parking at work will be associated with more remote work, but do not see a clear relationship between free residential parking and the decision to work from home. We expect occupational categories to explain more of the variance in working from home.

Our primary data source is the 2010-2012 CHTS. As we discussed in the introduction, the CHTS is a large travel diary, carried out on behalf of the California Department of Transportation and designed to be representative of California households. Its advantage, for our purposes, is the extent of its non-residential parking data. Alone among travel surveys, the CHTS records where a person parked for almost every trip away from home, and also records how much (if any) the traveler paid to do so. It also differentiates between on- and off-street parking. The presence of these detailed parking data, matched to both a travel diary and extensive socioeconomic information, is unique among transportation data sets.

The CHTS has two potential drawbacks. The first, which we will discuss more below, is a lack of reliable data on residential parking. The second, which we will discuss now, is that the data are by now rather old. For two reasons, we are not overly concerned with this fact. The first reason is that with one exception (telework), neither California's overall travel behavior nor its built environment have changed much since the CHTS was administered. The automobile and the single-family home remain dominant, and most neighborhoods, particularly in the expensive coastal metros where most people live and most economic activity occurs, have not seen their development densities change. The *demographics* of some coastal MSA neighborhoods have changed substantially, often because housing prices have sharply risen, but these rising prices are due in many ways to the built environment remaining unchanged. Demand for housing rose but new housing was slow to be developed, so demographics changed rather than density.

The exception to this overall pattern of stability is the aforementioned surge in working from home. Census ACS commuting data show that in 2011, across California counties, 4.4 percent of workers worked from home. In 2022 that figure had more than quadrupled, to 17.3 percent. It seems probable however, as discussed in Section II, that this change is almost entirely a product of COVID and its impact on workplace norms, not a result of California's changing built environment. The ACS also shows, for example, that in 2019, only 6 percent of workers worked from home. The CHTS obviously does not capture the change in workplace norms that helped unleash teleworking, but norms are also not one of our variables of interest. Our questions revolve around the built environment's impact, controlling for norms, and the built environment (again) has not changed much.

Our second reason for not worrying much about the age of CHTS data is more general. Our goal here is a test of a general principle—when people have less access to parking they will, all else equal, be less likely to drive. It is a truism in research that a good test with older data is better than a bad test with newer data. As the research we undertook here demonstrates that parking availability and price were strongly associated with travel behavior in California in 2010-2012, that finding will have academic and policy relevance so long as Californians in those years were responding to their built environment in the way that most people will, in most places at most times. We have no reason to believe this is not the case.

Dependent Variables

Our research focused on the association between parking availability and three main travel behaviors: the decision to work from home, the choice of commute mode, and the amount of overall travel by car and transit. We measured these at both the individual and household level.

Our ability to measure these variables differed somewhat by question. For employees who travel to work, the CHTS reports data on 29 different commute modes. We collapsed and then built two variables for the travel we were interested in: commuting by transit and commuting by driving. To create VMT variables, we used CHTS data on the mode and distance of individual trips. We summed car and transit trips at the individual and household levels, and then summed car trip distances to compute total VMT. The variables themselves are twofold: a binary variable indicating whether an individual drove, took transit, etc., and then a proportional variable showing the share of workers in the household who did so.

Our most problematic variable is the one measuring telework. For employed respondents, the CHTS provides data on work location. These data are coarse: they show if an individual's job location was fixed (such as at an office), if it was at home, or if it varied (e.g., a salesperson who travels, or a construction worker who goes to different job sites). Given this breakdown, we cannot know if people working from home were working *at* home in a home-based business or working remotely *from* home for an office job. As a result, our work from home variables are highly imperfect proxies for telework; they capture not just telework but also other forms of home-based employment. As our discussion in Section II suggests, these two forms of home-based work may have very different determinants with respect to the built environment. As with our other dependent variables, we constructed work from home variables for both individuals and households.

Independent Variables of Interest – Parking Availability

We constructed binary variables indicating whether a household had bundled parking at home and whether an individual employee had free parking at work. We built the work parking variable from CHTS data about the price and availability of parking at various trip destinations. We identified trips ending at the respondents' workplace, and then coded that commute as having free parking if the parking was either unpriced, or if it was priced but employees were reimbursed by employers.

The home parking variable is more complex. As we mentioned briefly above, the CHTS, somewhat surprisingly, does not contain usable information about residential parking. We overcame this problem by combining CHTS data with data from the American Housing Survey (AHS). The AHS reports the presence of bundled residential parking, and the 2011 AHS overlaps the CHTS in both time and geography. As such, we were thus able to use the AHS to estimate the probability that a housing unit in the CHTS had bundled parking.[5]

Our procedure for doing so was as follows. The AHS shows if a housing unit has off-street parking included in its rent or purchase price, with off-street parking defined as a garage or carport, driveway, or other off-street parking. We defined housing units that include one of these options as having bundled parking. We then used this tabulation as the dependent variable in a series of logistic regressions and estimated the presence of bundled parking with independent variables that were available in both the AHS and CHTS. These included the structure type (e.g. apartment, detached single family home), household size, tenure, and center city location, and—for units in metropolitan areas—MSA fixed effects (a dummy variable assigned to each MSA). The regression took the following form:

$$\text{Bundled parking} = \alpha + \beta 1 * \text{central city} + \beta 2 * \text{MSA} + \beta 3 * \text{household size} + \beta 4 * \text{housing structure type} + \beta 5 * \text{owner occupied} + \varepsilon$$

We estimated separate regressions for units inside and outside metropolitan statistical areas (MSAs). For units within larger MSAs, the AHS metropolitan surveys offer representative samples of the housing stock. For units in smaller MSAs, the AHS national surveys have smaller samples. For units outside MSAs, we estimated bundled parking from the Pacific and Mountain West regional sample of the national AHS data (there were no MSA variables in this model).[6] Our estimates were thus the most representative in the largest MSAs where most Californians live (and where travel behavior is most varied) and least representative in rural areas.

We use the estimated parameters from these models to predict the probability that households in the CHTS had bundled residential parking. For simplicity, in most cases we converted the predicted probability into a binary variable (1= bundled parking present, 0 = otherwise) and did so using cutoff values that yielded roughly

[5] This general approach of predicting a variable in one data set based on a model constricted in another, is similar to the procedure described in Manville et al. (2022) for inferring transit use from the U.S. Census.

[6] To be more precise, the AHS metropolitan sample offers representative detail of some core California MSAs, including Los Angeles-Long Beach, San Diego, San Francisco, Oakland, San Jose, Sacramento, Anaheim-Santa Ana, and Riverside-San Bernardino. The AHS national sample contains these major MSAs and nine additional California MSAs: Bakersfield, Fresno, Modesto, Oxnard-Ventura, Salinas-Seaside-Monterey, Santa Barbara-Santa Maria, Santa Rosa-Petaluma, Stockton, and Vallejo-Fairfield-Napa. We aggregated these into a California MSA sample and generated a parking probability for units in these MSAs, and then used regional data from the national sample to generate probabilities for housing units outside metropolitan areas.

equal rates of false positives and false negatives when we examined the AHS data.[7] A drawback of the AHS variable is that it does not indicate how many spaces are present at the housing unit, only that there is at least one. The AHS also has a measure of *bundled* parking. It tells us whether the price of the housing unit includes a parking space, but it does not indicate if parking is available on-site for an additional fee.

Having constructed this variable, we now had binary variables measuring both parking at home and parking at work. We then tested the association between parking availability on people's travel behavior. We regressed bundled parking at home on the dependent variables—working from home, commuting by transit, commuting by driving, total number of transit trips, total number of car trips, and total VMT, and in addition, free parking at work on the two commuting variables. We estimated all the models at both individual and household levels and, for total number of car trips and total VMT, we also estimated the models for households with employed workers only. The functional form of our regressions varied with our dependent variables. For binary variables such as teleworking, commuting by transit, and commuting by driving and the fractions computed for household level analysis of these variables, we fitted logistic models. For count variables like total number of transit trips and total number of car trips we fitted negative binomial models. For total VMT, which is left censored, we fitted a Tobit model.

Control Variables

We controlled for an array of factors likely to influence travel behavior. Perhaps the largest of these is vehicle access. Parking availability can influence travel behavior directly, by increasing the probability that a person drives for any given trip, but also indirectly, by influencing the probability that they have an automobile. The second aspect is likely larger than the first; previous research strongly suggests a causal relationship between residential parking and the decision to own a vehicle (Manville 2017; Millard-Ball et al. 2022). We document this relationship in an initial regression that used vehicle ownership as a dependent variable, but our primary interest is in the first aspect, the relationship between parking changes and travel behavior among those who have cars. We also controlled, in a similar vein, for the number of licensed drivers in the household.[8]

---

[7] We experimented with different cutoff values to define the binary variable and compared them to the observed bundled parking variable from AHS data. We chose the values (one for inside an MSA and one for outside) that generated similar rates of false positives and false negatives to balance between the possibility of over- and under-estimating parking availability for the CHTS sample.

[8] Arguably both household vehicle access and licensure are endogenous to travel decisions. This endogeneity threat is larger, however, at larger scales of spatial and temporal aggregation. Measuring the prevalence of vehicles and licenses at a neighborhood scale and associating that prevalence with driving raises obvious issues of simultaneity. Similarly, examining a person's travel habits over a year and then correlating that licensure and vehicle ownership does the same. Examining the factors within a daily travel diary, in contrast, poses fewer problems, particularly when they are controls. A person's decision between modes for a given trip hinges in part on the ability to access some of those modes, and isolating the association between this decision and parking without capturing the presence of cars or licensure would likely bias the parking coefficient.

In addition, we controlled for built environment characteristics. Research on the so-called “Five Ds”—density, diversity, design, destination accessibility, and distance to transit—suggests that the built environment can affect people’s travel behavior, although the extent of their influence remains a source of debate (Stevens 2017; Ewing and Cervero 2011; 2017). We measured built environment attributes using neighborhood typology data developed by Voulgaris et al. (2017) who collected 2010 data on 20 different measures of census tract-level built environments, including measures of density, transit service, job access, and street layouts. They then used factor and cluster analysis to categorize census tracts into seven distinct neighborhood types. Of most relevance to our work is their finding that travel behavior typically differs little from one neighborhood type to another, but that one comparatively rare type, which they call “old urban” accounted for a highly disproportionate share of non-auto travel. Old urban neighborhoods are what they sound like: dense, largely multifamily census tracts with tight street grids and reliable transit supply. We expect such neighborhoods to have less off-street parking, but also hypothesized that parking would be associated with travel behavior even controlling for neighborhood typology. Because the CHTS has census tract identifiers for each respondent, we were able to merge the neighborhood typology with the CHTS data and used the neighborhood variable to control for built environment characteristics.

Lastly, we controlled for socioeconomic characteristics. All regressions included data on race, gender, age, disability status, nativity, income, and educational attainment. We did not include controls for tenure and the number of units in the housing structure, because these were the biggest predictors of residential parking, and including them created multicollinearity. All models included some form of county fixed effects.

Some models called for additional controls. The regressions analyzing people’s decision to work from home include CHTS variables indicating respondent occupation, as well as a binary variable indicating whether the respondent had a flexible work schedule (defined as being mostly free to adjust their schedule as they like). The occupation variables are not fine-grained (e.g., the “education” category cannot differentiate between a school teacher, a piano teacher, and a professor) but do let us control, albeit roughly, for the type of work a respondent does. The work from home regressions also included a rough proxy for broadband access. The CHTS does not include data on respondent access to high-speed Internet, so we used county-level data from the 2013 ACS on the proportion of working age population with access to broadband. In addition to measuring regional broadband access, these variables essentially function as county fixed effects, so in the work from home models we omitted explicit county fixed effects.[9]

Our commuting models controlled for distance to work. Arguably this variable is *endogenous*, meaning people might drive to work because they live far away, but they might take a job farther away because they know they can drive. Such endogeneity can make regression output hard to interpret. In this case most of the endogeneity, however, would relate to car ownership rather than parking availability. People who knew they

[9] In the work from home regressions, some of the standard control variables also take on additional meanings. The association of income with working from home is probably partly the result of greater income being a proxy for managerial or knowledge-work, partly being a proxy for having more living space, and partly a result of higher-income households, as a result of higher marginal tax rates, preferring the convenience of working from home to extra pay.

would live far from work would be more likely to buy a car, and people who buy cars may be more likely to take jobs far from work.

Lastly, for our models examining the total number of transit and car trips and total VMT, we included employment status as an additional control. Table 1 shows all our variables and their sources.

Table 1. Variables used in analysis

Dependent variables	Source
Work from home ^	CHTS
Commute by transit ^	CHTS
Commute by driving ^	CHTS
Total number of daily transit trips	CHTS
Total number of daily car trips	CHTS
Total daily VMT (distance traveled by car)	CHTS
Independent variables	
Bundled parking at home (binary)	AHS, CHTS
Free parking at work ^	CHTS
Controls	
Neighborhood typology	Voulgaris et al. (2017)
Distance to work	CHTS
Flexible work schedule ^	CHTS
Occupation	CHTS
Share of county population with broadband access	ACS
Number of household vehicles	CHTS
Number of licensed drivers in household	CHTS
Household income	CHTS
White ^	CHTS
Black ^	CHTS
Asian ^	CHTS
Latino ^	CHTS
Male ^	CHTS
65 or over ^	CHTS
Disabled ^	CHTS
Foreign born ^	CHTS
Employed ^	CHTS
Bachelor's degree or higher ^	CHTS
Less than high school ^	CHTS
County fixed effects	CHTS

^ These variables are expressed as binaries for regressions examining individual travel behavior and expressed as fractions of the household for regressions examining household travel. For variables that apply to employed individuals only, the fractions are out of the total number of household workers.

IV. Results: How Parking Influences Telework

Descriptive Results

Before turning to our regressions, we take advantage of the relatively rich data the CHTS offers and paint a picture of California's parking and travel landscape in 2010-2012. Table 2 shows that across the sample, driving by automobile was the predominant travel mode. Mean and median daily household VMT are only slightly lower than those of daily household person miles traveled (PMT), suggesting that travel is overwhelmingly by car.[10] The middle rows of the table examine VMT's relationship with work location. We see that the small share (about nine percent) of households with a worker who works from home do in fact average less daily driving than those who commute to a fixed work location. Daily VMT in these work from home households has a mean of about 40 miles, and a median of about 20 miles, compared to a mean and median of about 53 and 26 miles for households where workers had a fixed location. Households where at least one worker had a varying work location had VMT roughly equal to work-from-home households but were also very small in number (less than one percent of the sample).

The table's final rows illustrate the rarity of transit use in California. While the average household took over eight trips per travel day, it took only 0.3 trips by transit. The median number of daily transit trips and the median share of trips that used transit were both essentially zero.

Table 2. Summary of daily household (HH) trips (source: CHTS)

	N	mean	sd	median
Total VMT	42,421	66.4	136.7	30.1
Total PMT	42,421	86.9	385.1	34.1
Total VMT for HHs where a worker works from home	3047	40.4	112.1	19.9
Total VMT for HHs where a worker has a fixed work location	31950	52.6	89.6	26.0
Total VMT for HHs where a worker has a varied work location	376	39.6	66.2	17.5
Total trips	42,421	8.3	7.8	6
Total transit trips	42,421	0.30	1.3	0
Fraction of HH trips that are transit	36,735	0.03	0.09	0

[10] These VMT and PMT numbers differ only slightly from those from the California oversample of the 2017 NHTS, but not by much. Mean and median VMT for California in the 2017 NHTS are 45 and 24 miles and the mean and median PMT are 93 and 36 miles.

Table 3 turns more specifically to commuting, which—while important because of its association with congestion—accounts for a relatively small share of both household and individual travel. Driving remains the predominant mode. Commuting can be examined in two ways: by individual trips (e.g., what share of trips are commutes?) or individual travelers (e.g., how does the typical person commute?). Table 3 examines trips. We see that on average, only 16 percent of all household trips were commutes (this percentage rises slightly, to 19 percent, if the sample is restricted to households with at least one worker). Almost 88 percent of commute trips were completed by driving alone. Another 6.8 percent were by carpool, just over five percent were by non-motorized modes like walking and biking, and less than 0.3 percent were by transit. Commutes tend to be long; they reflect 16 percent of household trips but account for 22 percent of household VMT on average. The average driving commute trip was 29 miles,[11] and the median 17 miles.[12]

Table 3. Summary of household (HH) commute trips (source: CHTS)

	N	mean	sd	median
Fraction of HH trips that are commute	36,735	0.16	0.28	0
HH VMT for commute	15,070	29.1	37.3	18.1
HH PMT for commute	15,826	28.3	36.9	17.3
Fraction of HH VMT that is commuting	34,246	0.22	0.34	0
Fraction of HH PMT that is commuting	36,641	0.20	0.32	0

Note: VMT measures only count car trips and hence exclude households that only used non-auto modes. The latter households were included in PMT calculations. Because non-auto trips tend to be shorter, household PMT measures have slightly smaller means and medians than household VMT measures.

Table 4 turns to our main variable of interest: parking. Most households, by our estimate, had bundled parking using the method outlined above, and the estimates indicate that the vast majority of households (87.9%) would have bundled parking at home. Similarly, 79.2 percent of employed people had free parking at work. Away from home and work locations, parking is still abundant and often free or very inexpensive. Most trips in our sample required parking (only about eight percent of trips ended with the driver not leaving the vehicle, suggesting a dropoff, or a driver waiting while a passenger did an errand) and the vast majority of trips that required parking ended in free parking off street. For the average person in the sample, only about nine percent of daily trips that required parking used a street parking space. Fewer than one percent (0.37%) of these

[11] A large share of commutes involved a trip-chain. On average, 45 percent of a household's commute trips involved quick stops. The CHTS does not detail what these stops were; they could be visits to drive-through businesses or retail, dropping off passengers, or (for people on transit) transfers. The prevalence of trip chains could help explain the appeal of driving but driving—because of the flexibility it enables—could explain the prevalence of trip chaining. (If people did not drive, they would make the trip on its own.)

[12] If we examine travelers rather than trips, we see similar proportions: 83 percent of respondents reported driving alone as their mode of commuting, and only 6 percent reported transit as mode of commuting (4.7% for walking and biking, 5.3% for getting rides from other people).

people paid for that street parking. The rest of the sample that parked did so off-street. On average, over 60 percent of an individual's daily trips ended with free parking. The median person paid nothing for parking on a travel day.

Notably, among the minority of people who paid to park (less than one percent of the sample) the average daily payment wasn't trivial: $6.33. The median, however, was much lower, at $2.60, suggesting that parking costs are Pareto-distributed and highly concentrated.[13] A small proportion of the one percent of travelers who pay account for most of the payment. The table's final row, meanwhile, shows parking's enormous temporal demands. The average car in the sample was parked almost 23 hours per day.

Table 4. Descriptive statistics on parking (source: CHTS & AHS)

	N	mean/%	sd	median
Fraction of households w/bundled parking at home	38,679	87.9%		
Fraction of employees w/free parking at work	26,341	79.2%		
Fraction of trips that involve leaving the vehicle	73,406	0.92	0.21	1
Fraction of trips where parking was free	71,905	0.61	0.46	1
Fraction of parking that was on street	48,615	0.09	0.23	0
Amount paid to park on travel day	111,976	0.10	5.6	0
Amount paid to park (if > $0)	891	6.3	11.3	2.6
Total time a car is parked (hours)	48,150	22.6	1.4	23.0

Notes: Calculated from the CHTS & AHS. Calculations shown are averages for individuals. Household level calculations households show similar results.

The sheer amount of time vehicles were parked suggests parking's potential to influence travel decisions. Table 5 reinforces that impression. Almost 95 percent of employed people with free parking at work reported commuting by automobile, while just under 37 percent of people without free work parking did the same. Most people without free parking at work rode transit (27.6%), walked or biked (18.7%), or carpooled with others (15%).

Table 5. Commute modes for individuals with and without free parking at work (source: CHTS)

	N	Driving alone	Transit	Walk/bike	Get rides	Other
With free parking	17,906	94.5%	0.92%	1.4%	2.5%	0.71%
Without free parking	4,682	36.9%	27.6%	18.7%	15%	1.9%

[13] By way of comparison, a gallon of gas in California 2010-2012 averaged between $3.00 and $3.74 in nominal dollars, meaning the average daily parking price was close to double the average per gallon fuel cost.

Although not shown in the table, parking's prevalence is correlated with neighborhood typology. Parking is much scarcer in "old urban" neighborhoods described by Voulgaris et al. (2017). While only a small share of our respondents (6.5%) lived in old urban neighborhoods, these households accounted for 46 percent of units without bundled residential parking. They also accounted for 22 percent of total transit trips and over 24 percent of zero-vehicle households. Most of these neighborhoods are in Los Angeles and San Francisco counties, and they are notable for their high average tract density: almost 25,000 people per square mile. It should be noted, however, that even in these neighborhoods most households still had bundled parking at home (67%), and still owned cars (78.1%).

Regression Results

Our first regression shows, consistent with previous research, that the availability of bundled parking at home is associated with owning 0.23 more household vehicles, holding everything else constant (see Table 6, column #1). This relationship is robust to an array of controls, including household income and the presence of more licensed drivers.

Table 6. Association between Parking and Vehicle Ownership (Negative Binomial Regression)

	Number of household vehicles	Number of household vehicles
Bundled parking at home	0.23 ***	
	(0.02)	
No. of licensed drivers	0.30 ***	0.31 ***
	(0.00)	(0.00)
Household income:	0.19 ***	0.20 ***
10,000 – 24,999	(0.03)	(0.03)
Household income:	0.33 ***	0.36 ***
25,000 – 34,999	(0.03)	(0.03)
Household income:	0.38 ***	0.42 ***
35,000 – 49,999	(0.03)	(0.03)
Household income:	0.46 ***	0.50 ***
50,000 – 74,999	(0.03)	(0.03)
Household income:	0.49 ***	0.53 ***
75,000 – 99,999	(0.03)	(0.03)
Household income:	0.52 ***	0.56 ***
100,000 – 149,999	(0.03)	(0.03)
Household income:	0.54 ***	0.59 ***
150,000 – 199,999	(0.03)	(0.03)
Household income:	0.57 ***	0.62 ***
200,000 – 249,999	(0.04)	(0.04)
Household income:	0.60 ***	0.65 ***
250,000+	(0.04)	(0.04)

	Number of household vehicles	Number of household vehicles
Socioeconomic status controls	Y	Y
Neighborhood controls	Y	Y
County fixed effects	Y	Y
Constant	-0.86 ***	-0.74 ***
	(0.04)	(0.04)
Observations	35,716	35,800

Notes: Significance codes: ***p < 0.001,**p < 0.01, *p < 0.05; Standard errors in parentheses.
Socioeconomic status controls include race (Asian, Black, Latino), male, 65 or older, foreign born, disabled, employed, household income, Bachelor's degree or higher, less than high school;
Neighborhood controls are neighborhood typologies from Voulgaris et al. (2017), only neighborhoods of home locations used; County fixed effects are counties of home location.

To put the size of this association into perspective, households with bundled parking at home have 0.42 more household vehicles, slightly smaller than the effect of having an additional licensed drivers in the household (0.56), but note that licensure is arguably more endogenous to the decision to acquire a vehicle than the presence of parking. Both effects are substantially larger than the differences from moving from one household income category to another (about $15,000 per jump) which is associated with having only 0.05 to 0.25 more vehicles. While this relationship is not causal, the reported magnitudes of the association between the two are similar to those found in instrumental variable approaches (Manville 2017) and quasi-experimental approaches (Manville 2017; Millard-Ball et al. 2022) which adds support to our findings.

Recall that we predicted whether a household had bundled parking using variables like household size, structure type, and home tenure, which may correlate with household income to a limited extent. The second regression (Table 6, column #2) shows that if we predict vehicle ownership without our parking variable, the effect of the income variables is stronger, but only slightly. Of course, this result could also arise because housing with bundled parking, which tends to be more expensive (Gabbe and Pierce 2017; Manville 2013), is one way that income influences vehicle ownership.

Table 7. Association between Parking and Transit Trips (Negative Binomial Regression)

	Total no. of transit trips on travel day	
	Individual	Household
Bundled parking at home	-0.55 ***	-0.45 ***
	(0.07)	(0.08)
No. of household vehicles	-0.56 ***	-0.53 ***
	(0.03)	(0.04)
No. of licensed drivers		0.32 ***
		(0.04)
Employed	0.04	0.05
	(0.05)	(0.07)

	Total no. of transit trips on travel day	
	Individual	Household
Socioeconomic status controls	Y	Y
Neighborhood controls	Y	Y
County fixed effects	Y	Y
Constant	0.69 ***	0.22
	(0.17)	(0.18)
Observations	79,554	35,716

Note: See Table 6 notes for significance codes and controls.

In our second set of regressions we turn to travel mode choice (Table 7). We see that bundled parking at home is associated with fewer daily transit trips, for both individuals and households. Specifically, having free parking at home is associated with 0.55 fewer daily transit trips for individuals and 0.45 fewer for households, all else equal. This association is robust to controlling for an array of demographic and built environment factors, including household vehicles, neighborhood typology, and licensed drivers. The magnitude of the association is comparable to that of the relationship between transit use and adding an additional household vehicle (0.56 fewer daily transit trips for individuals and 0.53 for households). If we compute average marginal effects for the regression, the estimated effect of having bundled parking at home is 0.07 fewer daily transit trips for individuals, comparable to that of having one additional household vehicle (0.07). For households, the average marginal effect of having bundled parking at home is 0.16 fewer daily transit trips, slightly smaller than that of having one additional vehicle (0.19).[14]

Table 8. Association between Parking and Commuting by Transit (Logistic Regression)

	Using transit to commute			
	Individual		Household	
	Logit	Odds ratio	Logit	Odds ratio
Bundled parking at home	0.07	1.1	-0.03	0.97
	(0.21)		(0.18)	
Free parking at work	-2.0 ***	0.13	-1.7 ***	0.18
	(0.14)		(0.13)	
No. of household vehicles	-0.41 ***	0.67	-0.64 ***	0.53
	(0.08)		(0.09)	
Stopped during the commute	-1.4 ***	0.24	-0.36 *	0.70
	(0.18)		(0.15)	

[14] The positive association between number of licensed drivers and total daily transit trips may seem odd, but since the regression also controls for vehicles the coefficient reflects the number of licenses net of the number of cars, meaning that more of it reflects circumstances where there are more drivers than cars in a household. In this case transit use would become more likely.

	Using transit to commute			
	Individual		Household	
	Logit	Odds ratio	Logit	Odds ratio
Distance to work	0.00	1.0		
	(0.00)			
No. of licensed drivers			0.23 **	1.3
			(0.08)	
Socioeconomic status controls	Y		Y	
Neighborhood controls	Y		Y	
County fixed effects	Y		Y	
Constant	0.34	1.4	-0.30	0.74
	(0.53)		(0.47)	
Observations	17,608		12,165	

Notes: See Table 6 for significance codes and controls. Neighborhood controls in these regressions include neighborhoods of both home and work locations.

Our third and fourth sets of regressions (Tables 8 and 9) examine commute modes. What matters in these regressions, perhaps unsurprisingly, is having free parking at work. The coefficients on bundled parking at home are small and statistically insignificant. In all specifications, in contrast, free work parking is statistically and economically associated with commuting. Specifically, individuals having free parking at work are about 87 percent less likely to commute by transit, and 22 times more likely to commute by driving; household level effects have the same direction but smaller magnitudes. These associations are substantially larger than those associated with having one additional vehicle in the household—individuals with one additional vehicle in their households are about 33 percent less likely to commute by transit and 40 percent more likely to commute by driving. The household level associations have the same direction but larger magnitudes.

Table 9. Association between Parking and Commuting by Driving (Logistic Regression)

	Driving to commute			
	Individual		Household	
	Logit	Odds ratio	Logit	Odds ratio
Bundled parking at home	0.00	1.0	-0.04	0.96
	(0.10)		(0.11)	
Free parking at work	3.1 ***	22.5	2.6 ***	12.8
	(0.06)		(0.07)	
No. of household vehicles	0.31 ***	1.4	0.51 ***	1.7
	(0.03)		(0.05)	
Stopped during the commute	0.13	1.1	-0.29**	0.75
	(0.13)		(0.09)	
Distance to work	0.01 ***	1.0		
	(0.00)			
No. of licensed drivers			-0.26 ***	0.77

	Driving to commute			
	Individual		Household	
	Logit	Odds ratio	Logit	Odds ratio
			(0.04)	
Socioeconomic status controls	Y		Y	
Neighborhood controls	Y		Y	
County fixed effects	Y		Y	
Constant	-2.3 ***	0.11	-1.38 *	0.25
	(0.39)		(0.29)	
Observations	17,608		12,165	

Notes: See Table 6 for significance codes and controls. Neighborhood controls in these regressions included neighborhoods of both home and work locations.

Our fifth and sixth sets of regressions examine overall auto travel—the fifth examines VMT and the sixth the number of daily car trips (Tables 10 and 11). Results from both sets of regressions show that parking availability is associated with more auto travel. Specifically, Table 10 shows that having free parking at home is associated with 6.6 more daily vehicle miles traveled by individuals, all else equal, 14.6 more by households, and 12 more by households with employed workers. Free parking at home is also associated with 0.08 more car trips per day taken by individuals, 0.14 more by households, and 0.13 more by households with employed workers. Moreover, having free parking at work is associated with 10.4 more vehicle miles traveled and 0.1 more car trips taken by households with employed workers, all else equal.

Table 10. Association between Parking and VMT (Tobit Regression)

	Total VMT (by car) on travel day			
	Individual	Household	Employed individuals	Household with employed workers
Bundled parking at home	6.6 ***	14.6 ***	6.9 ***	12.0 **
	(1.1)	(3.3)	(1.4)	(3.9)
Working from home			5.6 ***	10.4 *
			(1.4)	(4.9)
No. of household vehicles	3.2 ***	9.4 ***	1.9 ***	7.8 ***
	(0.3)	(1.3)	(0.4)	(1.5)
No. of licensed drivers		30.4 ***		26.9 ***
		(1.4)		(1.6)
Employed	18.5 ***	20.6 ***		
	(0.65)	(2.8)		
Socioeconomic status controls	Y	Y	Y	Y
Neighborhood controls	Y	Y	Y	Y
County fixed effects	Y	Y	Y	Y
Constant	-42.2 ***	-140.0 ***	-27.1 ***	-118.7 ***
	(2.7)	(8.3)	(3.8)	(10.7)

	Total VMT (by car) on travel day			
	Individual	Household	Employed individuals	Household with employed workers
Observations	79,554	35,716	47,450	27,853
Note: See Table 6 for significance codes and controls.				

These magnitudes are, again, substantial; they are greater than those associated with having an additional household vehicle. On average having bundled parking at home increases VMT by 4.6 vehicle miles for individuals, 11 miles for households, and 10.4 miles for households with employed workers, while the effects on travel of having an additional vehicle are 2.4, 7.5, and 7.0 miles respectively. Similarly, the average marginal effects of bundled parking at home on the number of daily car trips is 0.23 trips for individuals, 0.94 for households, and 0.97 for households with employed workers, while the effect of an additional vehicle are 0.12, 0.44, and 0.3 more trips respectively.

Table 11. Association between Parking and Car Trips (Negative Binomial Regression)

	Total daily car trips			
	Individual	Household	Employed individual	Household with employed workers
Bundled parking at home	0.08 ***	0.14 ***	0.07 ***	0.13 ***
	(0.02)	(0.02)	(0.02)	(0.02)
Working from home			0.11 ***	0.10 ***
			(0.02)	(0.03)
No. of household vehicles	0.04 ***	0.06 ***	0.02 ***	0.04 ***
	(0.00)	(0.01)	(0.00)	(0.01)
No. of licensed drivers		0.37 ***		0.34 ***
		(0.01)		(0.01)
Employed	0.22 ***	0.08 ***		
	(0.01)	(0.02)		
SES Controls	Y	Y	Y	Y
Neighborhood controls	Y	Y	Y	Y
County fixed effects	Y	Y	Y	Y
Constant	0.52 ***	0.22 ***	0.76 ***	0.43 ***
	(0.04)	(0.05)	(0.04)	(0.05)
Observations	79,554	35,716	47,450	27,853
Note: See Table 6 for significance codes and controls.				

Our final set of regressions examines the decision to work from home. The results (Table 12) indicate that parking availability may have limited influence over decisions on working from home. As the models show, individuals that have free parking at home are about 14 percent less likely to work from home. In comparison, individuals with one additional vehicle in the household are slightly more likely (about 10%) to work from home. Stronger predictors of working from home are flexible working schedule, broadband access, and education level.

As discussed above, readers should be cautious about interpreting these results as associations with teleworking. Our working from home variable, again, includes both people who work *at* home-based businesses and those who work remotely *from* home for an office job. The relationship between parking and travel for these two groups may be quite different. It is possible that people who work *from* home would be more likely to benefit from giving up a car and hence a parking space, because they would no longer need to commute, or that (from the other direction) people with the option of teleworking will be more likely to use it if they lack parking at home. In contrast, those who work *at* home would probably still benefit from having a car and hence a parking space for work related travel, or because they have customers come to their homes. These opposite tendencies mean that treating the working from home variable as a proxy for teleworking will likely underestimate the true association between parking availability and people's decision to telework.

Table 12. Association between Parking and Working from Home (Logistic Regression)

	Working from home			
	Individuals		Household	
	Logit	Odds ratio	Logit	Odds ratio
Bundled parking at home	-0.15 *	0.86	-0.13	0.87
	(0.07)		(0.08)	
No. of household vehicles	0.11 ***	1.1	0.12 ***	1.1
	(0.02)		(0.03)	
Flexible work schedule	0.35 ***	1.4	0.19 **	1.2
	(0.05)		(0.07)	
Broadband access	1.6 ***	4.7	1.3 **	3.6
	(0.34)		(0.43)	
Bachelor's degree or higher	0.22 **	1.2	0.31 ***	1.4
	(0.05)		(0.08)	
Less than high school	-0.45 ***	0.64	-0.19 ^	0.82
	(0.13)		(0.12)	
Occupations	Y		Y	
Socioeconomic status	Y		Y	
Neighborhood type	Y		Y	
Constant	-4.8***	0.01	-3.7 ***	0.03
	(0.38)		(0.43)	
Observations	42,334		27,423	

Notes: ^p<0.1.See Table 6 for other significance codes and controls; Flexible work schedule, broadband access, and occupations are added to working from home models as additional controls.

V. Discussion and Conclusion

California has a strong interest in reducing the externalities of vehicle travel. One way to accomplish this goal is by encouraging those people who can drive less to do so. In the aftermath of the COVID-19 pandemic, moreover, the state has expressed an interest in rejuvenating its moribund public transportation systems. It has also expressed interest in the potential for continued telework.

In this report, we use the CHTS to make two contributions. First, we use the survey's detailed parking data to present a heretofore unseen picture of how thoroughly parking, and particularly free parking, dominates California's surface transportation system. Most trips are by automobile, most automobile trips end in a parking space, and most parking is free. Indeed, the typical California automobile spends over 22 hours per day parked, and virtually none of this time or space results in a direct cost for the driver. Where parking *is* priced, in contrast, driving is less common.

The massive consumption of unpriced land and time implies a large subsidy for automobile use, and estimating the magnitude of its effect is our second contribution. Our regressions show that households with bundled parking are more likely to drive and less likely to use transit, both overall and particularly for commuting. We also show that these households drive more miles than other households. We find, similarly, that households whose members with jobs have free parking at work will be more likely to drive to work, less likely to use transit, and more likely to drive more miles. All these relationships are robust to controls for vehicle ownership, driver's licensure, and an array of controls for neighborhood built environment and socioeconomic status. While we did not explicitly control for self-selection in our models, the existing literature suggests that, at worst, self-selection controls would only modestly reduce the magnitude of our findings and might even increase them. At a broad level, our results highlight parking's role as an important intermediary in the relationship between transportation and travel behavior.

We do not find a strong association between parking provision and working from home, but some of this null finding may stem from our imprecise controls for employment and occupation. Future research should seek to merge detailed parking data with more fine-grained data on work tasks and responsibilities. Future work should also address two questions we discuss but did not directly examine: whether teleworking reduces productivity, and the extent to which teleworkers drive less than other employees. Both of those questions speak to important tradeoffs embedded in the goal of promoting teleworking.

References

Atkin, David, M. Keith Chen, and Anton Popov. 2022. The returns to face-to-face interactions: Knowledge spillovers in Silicon Valley. NBER Working Papers 30147. National Bureau of Economic Research, Inc.

Bao Rui, and Acheng Zhang. 2020. Does lockdown reduce air pollution? Evidence from 44 cities in northern China. Sci Total Environ. 731:139052.

Barrero, Jose Maria, Nicholas Bloom, and Steven Davis. 2023. The evolution of work from home. Journal Economic Perspectives 37(4): 23-50.

Caldarola, Bernardo, and Steve Sorrell. 2022. Do teleworkers travel less? Transportation Research Part A. 159:282-303.

Cervero, Robert, and Reid Ewing. 2010. Travel and the built environment: A meta-analysis. Journal of the American Planning Association 76(3): 265–94.

Chatman, Daniel. 2013. Does TOD need the T? Journal of the American Planning Association 79(1): 17–31.

Currans, Kristina, Gabriella Abou-Zeid, Chris McCahill, Nicole Iroz-Elardo, Kelly J. Clifton, Susan L. Handy, and Irene Pineda. 2022. Households with constrained off-street parking drive fewer miles. Transportation 50(6): 2227-2252.

Eidlin, Eric. 2010. What density doesn't tell us about sprawl. Access. 37(Fall): 2-9.

Gabbe, CJ, and Gregory Pierce. 2017. Hidden costs and deadweight losses: Bundled parking and residential rents in the metropolitan United States. Housing Policy Debate 27(2): 217-229.

Gabbe, CJ, Michael Manville, and Taner Osman. The opportunity cost of parking requirements. Journal of Transport and Land Use 14(1): 277–301.

Gibbs, Michael, Fredereike Mengel, and Christoph Siemroth. 2023. Work from Home and Productivity: Evidence from Personnel and Analytics Data on Information Technology Professionals. Journal of Political Economy Microeconomics 1(1): 7-41.

Grabar, Henry. 2023. Paved Paradise. New York: Penguin.

Guo, Zhan. 2013. Does residential parking supply affect household car ownership? A case of New York City. Journal of Transport Geography 26: 18–28.

Hook, Andrew, Victor Court, Benjamin L. Sovacool, and Steve Sorrell. 2020. A systematic review of the energy and climate impacts of teleworking. Environmental Research Letters 15(9).

Los Angeles Department of City Planning. 2023. Al Fresco Dining Ordinance. https://planning.lacity.org/plans-policies/outdoor-dining

Los Angeles Department of Transportation. 2023. Curbside Dining Ordinance. https://ladot.lacity.org/sites/default/files/documents/alfresco_curbside_dining_en.pdf

LaChapelle, Ugo, Georges A. Tanguay, and Léa. Neumark-Guadet. 2018. Telecommuting and sustainable travel. Urban Studies. 55(10): 2226-2244.

Laughner, Joshua, Jessica L. Neu, David Schimel, Zhao-Cheng Zeng, and others. 2021. Societal shifts due to COVID-19 reveal large-scale complexities and feedbacks between atmospheric chemistry and climate change. Proceedings of the National Academy of Sciences vol. 118, no. 46. https://orcid.org/0000-0002-0008-6508

Manville, Michael. 2013. Parking requirements and housing development: Regulation and reform in Los Angeles. Journal of the American Planning Association 79(1): 49–63.

Manville, Michael, Alex Beata, and Donald Shoup. 2013. Turning housing into driving: Parking requirements and 53 Bundled parking and vehicle ownership: Evidence from the American Housing Survey density in Los Angeles and New York. Housing Policy Debate 23(2): 350–375.

Manville, Michael, and Donald Shoup. 2005. People, parking and cities. Journal of Urban Planning and Development 131(4): 233–253.

Manville, Michael, and Miriam Pinski. 2020. Parking Behaviour: Bundled Parking and Travel Behaviour in American Cities. Land Use Policy. 91(2): 103853

Marshall, Alfred. 1890. Principles of economics. New York: Macmillan

Millard-Ball, Adam, Jeremy West, Nazanin Rezaei, N., and Garima Desai. 2022. What do residential lotteries show us about transportation choices? Urban Studies 59(2): 434-452.

McCahill, Chriss, and Norman Garrick. 2010. Influence of parking policy on built environment and travel behavior in two New England cities, 1960–2007. Transportation Research Record 2187: 123–130.

Pew Research. No date. Internet/Broadband Fact Sheet. https://www.pewresearch.org/internet/fact-sheet/internet-broadband/

Pishue, Bob. 2020. Inrix Traffic Scorecard 2020. March. Inrix Research.

Rietveld, Piet. 2011. Telework and the transition to lower energy use in transport: On the relevance of rebound effects. Environmental Innovations and Societal Transition 1(1): 146-151.

Romer, Paul. 1986. Increasing returns and long-run growth. Journal of Political Economy 98(5): 71-102.

Romer, Paul. 1990. Endogenous technological change. Journal of Political Economy 95(5): 1002-1037.

Shoup, Donald. 2011. The high cost of free parking. Chicago: Planner's Press.

Stevens, Mark R. 2017. Does compact development make people drive less? Journal of the American Planning Association 83 (1): 7-18 .

Stewart, Ashley. 2023. Leaked Zoom all-hands: CEO says employees must return to offices because they can't be as innovative or get to know each other on Zoom. Business Insider. August 23.

Voulgaris, Carole T., Brian D. Taylor, Evelyn Blumenberg, Anne Brown, and Kelcie Ralph. 2016. Synergistic neighborhood relationships with travel behavior: An analysis of travel in 30,000 US neighborhoods. Journal of Transport and Land Use 10(1): 437–461.

Weinberger, Rachael, Mark Seaman, and Carolyn Johnson. 2009. Residential off-street parking impacts on car ownership, vehicle miles traveled, and related carbon emissions: New York City case study. Transportation Research Record 2118: 24–30.

Weinberger, Rachael. 2012. Death by a thousand curb cuts. Transport Policy 20: 93–102.

Appendix

Table A1. Distribution and density of neighborhood types (source: CHTS, ACS)

Neighborhood type	No. of HH	Share of HH	Average tract density
Old urban	2,744	6.47%	24,853
Mixed use	2,096	4.94%	7,455
Urban residential	7,704	18.16%	9,991
Established suburb	8,215	19.37%	8,028
Patchwork	6,051	14.26%	4,206
New development	10,058	23.71%	3,749
Rural	5,552	13.09%	210
Overall	**42,420**	**-**	**8,236**

Complete regression models

Table A2. Association between Parking and Vehicle Ownership (Negative Binomial Regression)

	Number of household vehicles	Number of household vehicles
Bundled parking at home	0.23 ***	
	(0.02)	
No. of licensed drivers	0.30 ***	0.31 ***
	(0.00)	(0.00)
Household income:	0.19 ***	0.20 ***
10,000 – 24,999	(0.03)	(0.03)
Household income:	0.33 ***	0.36 ***
25,000 – 34,999	(0.03)	(0.03)
Household income:	0.38 ***	0.42 ***
35,000 – 49,999	(0.03)	(0.03)
Household income:	0.46 ***	0.50 ***
50,000 – 74,999	(0.03)	(0.03)
Household income:	0.49 ***	0.53 ***
75,000 – 99,999	(0.03)	(0.03)
Household income:	0.52 ***	0.56 ***
100,000 – 149,999	(0.03)	(0.03)
Household income:	0.54 ***	0.59 ***
150,000 – 199,999	(0.03)	(0.03)
Household income:	0.57 ***	0.62 ***
200,000 – 249,999	(0.04)	(0.04)
Household income:	0.60 ***	0.65 ***
250,000+	(0.04)	(0.04)
Socioeconomic status controls		
Asian	0.00	0.01
	(0.02)	(0.02)
Black	-0.07 **	-0.09 ***
	(0.03)	(0.03)
Latino	0.01	0.01
	(0.01)	(0.01)
Other race	0.00	-0.01
	(0.02)	(0.02)
Male	0.11 ***	0.11 ***
	(0.02)	(0.02)
Over 65 years old	-0.01	0.00
	(0.01)	(0.01)
Foreign born	-0.01	-0.02
	(0.02)	(0.02)
Disabled	-0.15 ***	-0.16 ***
	(0.02)	(0.02)

	Number of household vehicles	Number of household vehicles
Employed	0.05 ***	0.04 ***
	(0.01)	(0.01)
Bachelor's degree or higher	-0.06 ***	-0.06 ***
	(0.01)	(0.01)
Less than high school	-0.04 *	-0.03 ^
	(0.02)	(0.02)
Neighborhood controls		
Old urban	-0.02	-0.04
	(0.03)	(0.03)
Urban residential	0.07 **	0.09 ***
	(0.02)	(0.02)
Established suburb	0.10 ***	0.13 ***
	(0.02)	(0.02)
Patchwork	0.09 ***	0.12 ***
	(0.02)	(0.02)
New development	0.11 ***	0.14 ***
	(0.02)	(0.02)
Rural	0.17 ***	0.20 ***
	(0.02)	(0.02)
County fixed effects	Y	Y
Constant	-0.86 ***	-0.74 ***
	(0.04)	(0.04)
Observations	35,716	35,800

Notes: Significance codes: ***p < 0.001,**p < 0.01, *p < 0.05, ^p < 0.1; Standard errors in parentheses.

Table A3. Association between Parking and Transit Trips (Negative Binomial Regression)

	Total no. of transit trips on travel day	
	Individual	Household
Bundled parking at home	-0.55 ***	-0.45 ***
	(0.07)	(0.08)
No. of household vehicles	-0.56 ***	-0.53 ***
	(0.03)	(0.04)
No. of licensed drivers		0.32 ***
		(0.04)
Employed	0.04	0.05
	(0.05)	(0.07)
Socioeconomic status controls		
Household income:	-0.30 **	-0.11
10,000 – 24,999	(0.11)	(0.11)
Household income:	-0.55 ***	-0.35 **
25,000 – 34,999	(0.12)	(0.12)
Household income:	-0.58 ***	-0.39 **
35,000 – 49,999	(0.12)	(0.12)
Household income:	-0.71 ***	-0.55 ***
50,000 – 74,999	(0.12)	(0.12)
Household income:	-0.91 ***	-0.60 ***
75,000 – 99,999	(0.12)	(0.13)
Household income:	-0.63 ***	-0.38 **
100,000 – 149,999	(0.12)	(0.13)
Household income:	-0.47 ***	-0.40 **
150,000 – 199,999	(0.14)	(0.15)
Household income:	-0.72 ***	-0.47 *
200,000 – 249,999	(0.17)	(0.18)
Household income:	-0.45 **	-0.08
250,000+	(0.16)	(0.17)
Asian	0.39 ***	0.32 **
	(0.09)	(0.11)
Black	0.86 ***	0.89 ***
	(0.11)	(0.12)
Latino	0.52 ***	0.62 ***
	(0.06)	(0.07)
Other race	0.39 ***	0.39 **
	(0.11)	(0.17)
Male	0.02	0.02
	(0.04)	(0.08)
Over 65 years old	-0.86 ***	-1.09 ***
	(0.07)	(0.09)

	Total no. of transit trips on travel day	
	Individual	**Household**
Foreign born	0.04	0.34 ***
	(0.06)	(0.09)
Disabled	0.39 ***	0.51 ***
	(0.08)	(0.10)
Bachelor’s degree or higher	0.07	0.05
	(0.05)	(0.07)
Less than high school	0.64 ***	1.55 ***
	(0.07)	(0.09)
Neighborhood controls		
Old urban	0.14	0.15
	(0.12)	(0.13)
Urban residential	-0.26 *	-0.27 *
	(0.11)	(0.11)
Established suburb	-0.15	-0.18
	(0.11)	(0.11)
Patchwork	-0.29 **	-0.29 *
	(0.11)	(0.12)
New development	-0.43 ***	-0.41 ***
	(0.11)	(0.11)
Rural	-0.62 ***	-0.37 **
	(0.13)	(0.13)
County fixed effects	Y	Y
Constant	0.69 ***	0.22
	(0.17)	(0.18)
Observations	79,554	35,716

Note: See Table A2 notes for significance codes.

Table A4. Association between Parking and Commuting by Transit (Logistic Regression)

	Using transit to commute			
	Individual		Household	
	Logit	Odds ratio	Logit	Odds ratio
Bundled parking at home	0.07 (0.21)	1.1	-0.03 (0.18)	0.97
Free parking at work	-2.0 *** (0.14)	0.13	-1.7 *** (0.13)	0.18
No. of household vehicles	-0.41 *** (0.08)	0.67	-0.64 *** (0.09)	0.53
Stopped during the commute	-1.4 *** (0.18)	0.24	-0.36 * (0.15)	0.70
Distance to work	0.00 (0.00)	1.0		
No. of licensed drivers			0.23 ** (0.08)	1.3
Socioeconomic status controls				
Household income: 10,000 – 24,999	-0.45 (0.34)	0.64	-0.30 (0.32)	0.74
Household income: 25,000 – 34,999	-0.16 (0.36)	0.86	-0.31 (0.33)	0.73
Household income: 35,000 – 49,999	-0.70 ^ (0.37)	0.49	-0.46 (0.34)	0.63
Household income: 50,000 – 74,999	-0.84 * (0.37)	0.43	-0.59 ^ (0.34)	0.56
Household income: 75,000 – 99,999	-0.47 (0.36)	0.63	-0.22 (0.34)	0.80
Household income: 100,000 – 149,999	-0.69 ^ (0.38)	0.50	-0.18 (0.35)	0.83
Household income: 150,000 – 199,999	-1.1 ** (0.43)	0.32	-0.26 (0.38)	0.77
Household income: 200,000 – 249,999	-0.42 (0.44)	0.66	0.28 (0.41)	1.3
Household income: 250,000+	-1.2 * (0.54)	0.29	-0.04 (0.43)	0.97
Asian	0.28 (0.27)	1.3	0.10 (0.26)	1.1
Black	1.1 *** (0.29)	2.9	0.98 *** (0.28)	2.7
Latino	0.65 *** (0.18)	1.9	0.74 *** (0.19)	2.1
Other race	-0.07 (0.38)	0.93	-0.03 (0.37)	0.97
Male	-0.17	0.84	-0.18	0.84

	Using transit to commute			
	Individual		Household	
	Logit	Odds ratio	Logit	Odds ratio
	(0.13)		(0.22)	
Over 65 years old	-0.81 *	0.44	-0.59 ^	0.55
	(0.41)		(0.32)	
Foreign born	-0.28	0.75	0.22	1.2
	(0.18)		(0.20)	
Disabled	1.6 ***	4.9	1.3 ***	3.8
	(0.24)		(0.31)	
Bachelor's degree or higher	-0.25	0.78	0.04	1.0
	(0.16)		(0.20)	
Less than high school	0.32	1.4	-0.31	0.73
	(0.24)		(0.24)	
Neighborhood controls				
Home location: Old urban	0.22	1.2	0.10	1.1
	(0.31)		(0.28)	
Home location: Urban residential	-0.03	0.97	-0.13	0.88
	(0.28)		(0.25)	
Home location: Established suburb	-0.41	1.5	0.07	1.1
	(0.28)		(0.25)	
Home location: Patchwork	-0.23	0.80	-0.33	0.72
	(0.32)		(0.28)	
Home location: New development	0.09	1.1	-0.15	0.86
	(0.31)		(0.27)	
Home location: Rural	-0.38	0.68	-0.74	0.48
	(0.46)		(0.41)	
Work location: Old urban	-0.61 *	0.54		
	(0.28)			
Work location: Urban residential	-0.33 ^	0.72		
	(0.20)			
Work location: Established suburb	-1.0 ***	0.35		
	(0.28)			
Work location: Patchwork	-0.84 ***	0.43		
	(0.19)			
Work location: New development	-0.52 ^	0.60		
	(0.29)			
Work location: Rural	-0.52	0.59		
	(0.37)			
County fixed effects	Y		Y	
Constant	0.34	1.4	-0.30	0.74
	(0.53)		(0.47)	
Observations	17,608		12,165	

Notes: See Table A2 notes for significance codes.

Table A5. Association between Parking and Commuting by Driving (Logistic Regression)

	Driving to commute			
	Individual		Household	
	Logit	Odds ratio	Logit	Odds ratio
Bundled parking at home	0.00	1.0	-0.04	0.96
	(0.10)		(0.11)	
Free parking at work	3.1 ***	22.5	2.6 ***	12.8
	(0.06)		(0.07)	
No. of household vehicles	0.31 ***	1.4	0.51 ***	1.7
	(0.03)		(0.05)	
Stopped during the commute	0.13	1.1	-0.29**	0.75
	(0.13)		(0.09)	
Distance to work	0.01 ***	1.0		
	(0.00)			
No. of licensed drivers			-0.26 ***	0.77
			(0.04)	
Socioeconomic status controls				
Household income:	0.09	1.1	0.33 ^	1.4
10,000 – 24,999	(0.21)		(0.20)	
Household income:	0.19	1.2	0.42 *	1.5
25,000 – 34,999	(0.22)		(0.21)	
Household income:	0.51 *	1.7	0.70 ***	2.0
35,000 – 49,999	(0.21)		(0.20)	
Household income:	0.48 *	1.6	0.76 ***	2.1
50,000 – 74,999	(0.21)		(0.20)	
Household income:	0.58 **	1.8	0.71 ***	2.0
75,000 – 99,999	(0.21)		(0.21)	
Household income:	0.42 ^	1.7	0.77 ***	2.2
100,000 – 149,999	(0.22)		(0.21)	
Household income:	0.34	1.5	0.56 *	1.8
150,000 – 199,999	(0.24)		(0.22)	
Household income:	0.26	1.4	0.42 ^	1.5
200,000 – 249,999	(0.25)		(0.25)	
Household income:	0.29 ^	1.3	0.55 *	1.7
250,000+	(0.17)		(0.25)	
Asian	0.12	1.1	0.20	1.2
	(0.13)		(0.15)	
Black	0.17	1.2	0.06	1.1
	(0.20)		(0.21)	
Latino	-0.13	0.87	-0.17 ^	0.84
	(0.09)		(0.10)	
Other race	0.07	1.1	0.02	1.0
	(0.16)		(0.19)	
Male	-0.30 ***	0.74	-0.14	0.87

	Driving to commute			
	Individual		Household	
	Logit	Odds ratio	Logit	Odds ratio
	(0.06)		(0.13)	
Over 65 years old	0.36 *	1.4	0.44 **	1.6
	(0.15)		(0.16)	
Foreign born	0.03	1.0	-0.14	0.87
	(0.09)		(0.12)	
Disabled	-0.81 ***	0.45	-0.58 **	0.56
	(0.16)		(0.20)	
Bachelor's degree or higher	0.06	1.1	-0.12	0.89
	(0.07)		(0.10)	
Less than high school	-0.29 *	0.75	-0.05	0.95
	(0.12)		(0.13)	
Neighborhood controls				
Home location:	0.29 ^	1.3	0.25	1.3
Old urban	(0.17)		(0.18)	
Home location:	0.14	1.2	0.15	1.2
Urban residential	(0.13)		(0.14)	
Home location:	0.20	1.2	0.27 ^	1.3
Established suburb	(0.13)		(0.15)	
Home location:	0.31 *	1.4	0.17	1.2
Patchwork	(0.14)		(0.15)	
Home location:	0.47 ***	1.6	0.38 *	1.5
New development	(0.14)		(0.15)	
Home location:	0.47 **	1.6	0.64 ***	1.9
Rural	(0.16)		(0.17)	
Work location:	-0.09	0.91		
Old urban	(0.15)			
Work location:	0.03	1.0		
Urban residential	(0.10)			
Work location:	0.29 *	1.3		
Established suburb	(0.11)			
Work location:	0.21 *	1.2		
Patchwork	(0.08)			
Work location:	-0.01	0.99		
New development	(0.12)			
Work location:	-0.11	0.90		
Rural	(0.13)			
County fixed effects	Y		Y	
Constant	-2.3 ***	0.11	-1.38 *	0.25
	(0.39)		(0.29)	
Observations	17,608		12,165	

Notes: See Table A2 notes for significance codes.

Table A6. Association between Parking and VMT (Tobit Regression)

	Total VMT (by car) on travel day			
	Individual	Household	Employed individuals	Household with employed workers
Bundled parking at home	6.6 ***	14.6 ***	6.9 ***	12.0 **
	(1.1)	(3.3)	(1.4)	(3.9)
Working from home			5.6 ***	10.4 *
			(1.4)	(4.9)
No. of household vehicles	3.2 ***	9.4 ***	1.9 ***	7.8 ***
	(0.3)	(1.3)	(0.4)	(1.5)
No. of licensed drivers		30.4 ***		26.9 ***
		(1.4)		(1.6)
Employed	18.5 ***	20.6 ***		
	(0.65)	(2.8)		
Socioeconomic status controls				
Household income: 10,000 – 24,999	8.6 ***	24.2 ***	12.6 ***	31.2 ***
	(1.8)	(5.2)	(3.0)	(7.6)
Household income: 25,000 – 34,999	11.2 ***	32.7 ***	14.3 ***	31.5 ***
	(1.9)	(5.5)	(3.1)	(7.9)
Household income: 35,000 – 49,999	13.2 ***	37.3 ***	15.8 ***	37.7 ***
	(1.9)	(5.4)	(3.0)	(7.6)
Household income: 50,000 – 74,999	18.9 ***	51.7 ***	22.4 ***	51.8 ***
	(1.8)	(5.3)	(2.9)	(7.5)
Household income: 75,000 – 99,999	20.2 ***	53.4 ***	22.8 ***	56.1 ***
	(1.9)	(5.5)	(2.9)	(7.6)
Household income: 100,000 – 149,999	23.5 ***	61.8 ***	26.9 ***	65.5 ***
	(1.9)	(5.6)	(2.9)	(7.7)
Household income: 150,000 – 199,999	22.6 ***	59.4 ***	26.6 ***	65.3 ***
	(2.0)	(6.2)	(3.1)	(8.2)
Household income: 200,000 – 249,999	23.7 ***	65.6 ***	27.6 ***	71.7 ***
	(2.3)	(7.4)	(3.3)	(9.2)
Household income: 250,000+	22.7 ***	67.9 ***	26.5 ***	74.7 ***
	(2.3)	(7.2)	(3.3)	(9.1)
Asian	-3.5 **	2.9	-2.0	3.9
	(1.3)	(4.7)	(1.6)	(5.3)
Black	-2.0	3.6	2.4	6.8
	(1.7)	(5.3)	(2.2)	(6.6)
Latino	2.9 ***	12.9 ***	3.9 ***	11.7 ***
	(0.82)	(3.0)	(1.0)	(3.5)
Other race	-2.6 ^	-1.4	-2.7	2.2
	(1.4)	(5.2)	(1.9)	(6.3)
Male	2.0 ***	-4.9	4.2 ***	-4.1
	(0.55)	(3.2)	(0.70)	(4.1)
Over 65 years old	-6.2 ***	-18.9 ***	-1.3	-17.4 ***

	Total VMT (by car) on travel day			
	Individual	Household	Employed individuals	Household with employed workers
	(0.83)	(3.0)	(1.5)	(4.4)
Foreign born	-0.06	-13.8 ***	0.32	-17.3 ***
	(0.84)	(3.6)	(1.1)	(4.3)
Disabled	-18.6 ***	-27.7 ***	-10.8 ***	-26.4 ***
	(1.1)	(4.1)	(2.2)	(6.2)
Bachelor's degree or higher	6.5 ***	9.4 ***	3.7 ***	6.9 *
	(0.64)	(2.6)	(0.79)	(3.2)
Less than high school	-6.8 ***	72.7 ***	-4.8 **	78.4 ***
	(1.0)	(3.7)	(1.7)	(4.4)
Neighborhood controls				
Old urban	-2.3	-3.7	-2.2	-3.4
	(1.9)	(5.6)	(2.3)	(6.6)
Urban residential	2.6 ^	6.8	2.2	6.1
	(1.9)	(4.5)	(1.8)	(5.4)
Established suburb	2.3	7.8 ^	2.4	8.0
	(1.5)	(4.6)	(1.8)	(5.4)
Patchwork	4.2 **	10.4 *	3.0	7.9
	(1.5)	(4.7)	(1.9)	(5.6)
New development	9.5 ***	21.0 ***	10.0 ***	22.2 ***
	(1.5)	(4.6)	(1.8)	(5.4)
Rural	9.6 **	19.5 ***	10.3 ***	20.0 ***
	(1.6)	(5.0)	(2.0)	(6.0)
County fixed effects	Y	Y	Y	Y
Constant	-42.2 ***	-140.0 ***	-27.1 ***	-118.7 ***
	(2.7)	(8.3)	(3.8)	(10.7)
Observations	79,554	35,716	47,450	27,853

Note: See Table A2 notes for significance codes.

Table A7. Association between Parking and Car Trips (Negative Binomial Regression)

	Total daily car trips			
	Individual	Household	Employed individual	Household with employed workers
Bundled parking at home	0.08 *** (0.02)	0.14 *** (0.02)	0.07 *** (0.02)	0.13 *** (0.02)
Working from home			0.11 *** (0.02)	0.10 *** (0.03)
No. of household vehicles	0.04 *** (0.00)	0.06 *** (0.01)	0.02 *** (0.00)	0.04 *** (0.01)
No. of licensed drivers		0.37 *** (0.01)		0.34 *** (0.01)
Employed	0.22 *** (0.01)	0.08 *** (0.02)		
Socioeconomic status controls				
Household income: 10,000 – 24,999	0.12 *** (0.03)	0.22 *** (0.03)	0.15 *** (0.04)	0.21 *** (0.04)
Household income: 25,000 – 34,999	0.18 *** (0.03)	0.31 *** (0.03)	0.20 *** (0.04)	0.24*** (0.04)
Household income: 35,000 – 49,999	0.26 *** (0.03)	0.39 *** (0.03)	0.27 *** (0.04)	0.33 *** (0.04)
Household income: 50,000 – 74,999	0.27 *** (0.02)	0.43 *** (0.03)	0.25 *** (0.04)	0.36 *** (0.04)
Household income: 75,000 – 99,999	0.29 *** (0.03)	0.47 *** (0.03)	0.29 *** (0.04)	0.41 *** (0.04)
Household income: 100,000 – 149,999	0.31 *** (0.03)	0.49 *** (0.03)	0.29 *** (0.04)	0.45 *** (0.04)
Household income: 150,000 – 199,999	0.29 *** (0.03)	0.48 *** (0.04)	0.27 *** (0.04)	0.44 *** (0.04)
Household income: 200,000 – 249,999	0.26 *** (0.03)	0.42 *** (0.04)	0.26 *** (0.04)	0.40 *** (0.05)
Household income: 250,000+	0.29 *** (0.03)	0.46 *** (0.04)	0.24 *** (0.04)	0.44 *** (0.05)
Asian	-0.12 *** (0.02)	0.08 ** (0.03)	-0.07 *** (0.02)	0.09 ** (0.03)
Black	-0.12 *** (0.02)	-0.08 ** (0.03)	-0.09 *** (0.03)	-0.07 ^ (0.03)
Latino	0.0 (0.01)	0.06 *** (0.02)	-0.01 (0.01)	0.02 0.02
Other race	-0.09 *** (0.02)	-0.02 (0.03)	-0.08 *** (0.02)	0.01 0.03
Male	-0.08 *** (0.01)	-0.09 *** (0.02)	-0.07 *** (0.01)	-0.09 *** (0.02)

	Total daily car trips			
	Individual	Household	Employed individual	Household with employed workers
Over 65 years old	-0.14 ***	-0.19 ***	-0.04 *	-0.14 ***
	(0.01)	(0.02)	(0.02)	(0.02)
Foreign born	-0.02	-0.23 ***	-0.03 *	-0.25 ***
	(0.01)	(0.02)	(0.01)	(0.02)
Disabled	-0.34 ***	-0.28 ***	-0.17 ***	-0.19 ***
	(0.01)	(0.02)	(0.03)	(0.03)
Bachelor's degree or higher	0.14 ***	0.11 ***	0.10 ***	0.08 ***
	(0.01)	(0.02)	(0.01)	(0.02)
Less than high school	-0.18 ***	1.2 ***	-0.14 ***	1.2 ***
	(0.01)	(0.02)	(0.02)	(0.02)
Neighborhood controls				
Old urban	-0.05 ^	-0.07 *	-0.04	-0.06 ^
	(0.02)	(0.03)	(0.03)	(0.03)
Urban residential	0.08 ***	0.07 **	0.08 ***	0.06 *
	(0.02)	(0.03)	(0.02)	(0.03)
Established suburb	0.07 ***	0.08 **	0.08 ***	0.08 **
	(0.02)	(0.03)	(0.02)	(0.03)
Patchwork	0.07 ***	0.07 *	0.06 **	0.04
	(0.02)	(0.03)	(0.02)	(0.03)
New development	0.07 ***	0.07 **	0.05 *	0.06 *
	(0.02)	(0.03)	(0.02)	(0.03)
Rural	-0.01	-0.01	0.0	-0.01
	(0.02)	(0.03)	(0.02)	(0.03)
County fixed effects	Y	Y	Y	Y
Constant	0.52 ***	0.22 ***	0.76 ***	0.43 ***
	(0.04)	(0.05)	(0.04)	(0.05)
Observations	79,554	35,716	47,450	27,853

Note: See Table A2 notes for significance codes.

Table A8. Association between Parking and Working from Home (Logistic Regression)

	Working from home			
	Individuals		Household	
	Logit	Odds ratio	Logit	Odds ratio
Bundled parking at home	-0.15 *	0.86	-0.13	0.87
	(0.07)		(0.08)	
No. of household vehicles	0.11 ***	1.1	0.12 ***	1.1
	(0.02)		(0.03)	
Flexible work schedule	0.35 ***	1.4	0.19 **	1.2
	(0.05)		(0.07)	
Broadband access	1.6 ***	4.7	1.3 **	3.6
	(0.34)		(0.43)	
Bachelor's degree or higher	0.22 **	1.2	0.31 ***	1.4
	(0.05)		(0.08)	
Less than high school	-0.45 ***	0.64	-0.19 ^	0.82
	(0.13)		(0.12)	
Occupations				
Arts/Entertainment	0.99 ***	2.7		
	(0.17)			
Business/Financial	0.47 **	1.6		
	(0.16)			
Cleaning/Grounds Keeping	0.92 ***	2.5		
	(0.19)			
Community/Social Services	0.98 ***	2.7		
	(0.18)			
Computer/Math	0.42 *	1.5		
	(0.17)			
Construction	0.26	1.3		
	(0.20)			
Education	1.1 ***	3.0		
	(0.15)			
Farm./Fish./Forestry	0.64 **	1.9		
	(0.23)			
Food Prep./Serving	1.3 ***	3.5		
	(0.17)			
Healthcare Practitioners	1.1 ***	2.9		
	(0.16)			
Healthcare Support	1.2 ***	3.4		
	(0.17)			
Install./Maint./Repair	0.52 **	1.7		
	(0.19)			
Legal	0.59 **	1.8		
	(0.20)			

	Working from home			
	Individuals		Household	
	Logit	Odds ratio	Logit	Odds ratio
Management	0.34 *	1.4		
	(0.15)			
Military	0.40	1.5		
	(0.39)			
Office/Administrative	0.54 ***	1.7		
	(0.16)			
Personal Care	1.1 ***	3.1		
	(0.18)			
Production	0.55 **	1.7		
	(0.21)			
Protective Service	1.0 ***	2.8		
	(0.19)			
Sales	0.77 ***	2.2		
	(0.15)			
Science	0.53 **	1.7		
	(0.20)			
Transportation	0.72 ***	2.1		
	(0.18)			
Socioeconomic status controls				
Household income:	0.24	1.3	0.14	1.2
10,000 – 24,999	(0.19)		(0.21)	
Household income:	0.27	1.3	0.22	1.2
25,000 – 34,999	(0.19)		(0.21)	
Household income:	0.35 ^	1.4	0.26	1.3
35,000 – 49,999	(0.18)		(0.20)	
Household income:	0.18	1.2	0.02	1.0
50,000 – 74,999	(0.18)		(0.20)	
Household income:	0.07	1.1	-0.08	0.92
75,000 – 99,999	(0.18)		(0.20)	
Household income:	0.04	1.0	-0.15	0.86
100,000 – 149,999	(0.18)		(0.21)	
Household income:	-0.18	0.84	-0.37 ^	0.69
150,000 – 199,999	(0.19)		(0.22)	
Household income:	-0.19	0.83	-0.48 ^	0.62
200,000 – 249,999	(0.21)		(0.25)	
Household income:	-0.3	0.74	-0.60 *	0.55
250,000+	(0.2)		(0.25)	
Asian	-0.14	0.87	-0.14	0.87
	(0.10)		(0.14)	
Black	-0.05	0.96	0.14	1.1
	(0.12)		(0.14)	

	Working from home			
	Individuals		Household	
	Logit	Odds ratio	Logit	Odds ratio
Latino	-0.11 ^	0.89	-0.15 ^	0.86
	(0.06)		(0.09)	
Other race	0.19 ^	1.2	0.21	1.2
	(0.10)		(0.15)	
Male	-0.06	0.94	-0.26 **	0.77
	(0.04)		(0.09)	
Over 65 years old	-0.30 ***	0.74	-0.22 **	0.80
	(0.09)		(0.11)	
Foreign born	-0.34 ***	0.71	-0.46 ***	0.63
	(0.09)		(0.11)	
Disabled	-0.22 ^	0.80	-0.06	0.95
	(0.13)		(0.15)	
Neighborhood controls				
Old urban	0.10	1.1	0.14	1.2
	(0.11)		(0.14)	
Urban residential	-0.16	0.85	-0.12	0.89
	(0.10)		(0.12)	
Established suburb	-0.12	0.88	-0.12	0.89
	(0.10)		(0.12)	
Patchwork	-0.11	0.90	-0.07	0.94
	(0.10)		(0.13)	
New development	-0.20 *	0.82	-0.14	0.87
	(0.10)		(0.12)	
Rural	-0.04	0.96	-0.02	0.98
	(0.11)		(0.14)	
Constant	-4.8***	0.01	-3.7 ***	0.03
	(0.38)		(0.43)	
Observations	42,334		27,423	

Note: See Table A2 notes for significance codes.