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Preserving Sustainability Gains of the COVID-19 Pandemic: A Case Study of MIT Campus Commuting

Alex Berke[1], Ronan Doorley[1], Luis Alfonso[1], and Kent Larson[1]

Abstract

COVID-19 profoundly affected how communities live, work, and commute. In particular, reductions in commutes caused reductions in commuter-related emissions. The pandemic also prompted businesses and institutions to consider longer-term adjustments, including work-from-home policies that continue beyond pandemic protocols. If properly evaluated and implemented, these policies may have long-term beneficial impacts in reducing commuter-related emissions. This work presents a case study of the Massachusetts Institute of Technology campus community, using data from a prepandemic transportation survey with responses from approximately 50% of the community, as well as data on the academic groups and home locations of the broader population. These data were used to estimate car commuter miles by various academic groups and to model and evaluate interventions in relation to reducing car commuter miles. The interventions include staff work-from-home policies, changes that increase use of alternative transit, and improving access to housing. The analysis used differences in how groups commute to inform the potential interventions. For example, there was an estimated 16% reduction in car commuter miles if staff worked from home 1 day/week on average (excluding service staff whose work is on-site), and the same estimated reduction could be achieved were just one staff group that is well-suited to working from home allowed to do so 2 days/week. This analysis is intended to establish groundwork for further studies to assess how potential campus policies and land use might affect sustainable transportation use and parking demand, as well as to provide a case study for other institutions considering similar changes.

Keywords

data and data science, data analysis, sustainability and resilience, transportation and sustainability, air quality and greenhouse gas mitigation, greenhouse gas mitigation, policy analysis, transportation and economic development, economic development

COVID-19-related disruptions have had profound impacts on how communities live, work, and commute. In particular, work-from-home policies led to fewer vehicle miles traveled to and from work, reducing traffic, parking demand, and transportation-related greenhouse gas (GHG) emissions (*1–4*). At the same time, these changes have prompted businesses and institutions to consider longer-term adjustments to how their personnel live, work, and commute, such as work-from-home programs that continue beyond COVID-19 physical distancing protocols. If properly implemented, these potential policies could have long-term beneficial impacts, for example, reducing traffic congestion and parking demand, while also reducing emissions generated by commuters. However, the details of how to optimize the benefits of such changes while minimizing further disruption are often unclear.

This case study modeled and evaluated how various policy changes might reduce car commuter miles in the context of the Massachusetts Institute of Technology (MIT) campus and its surrounding community. Specifically, we focused on car commutes made by the institute's student and employee populations using prepandemic data.

[1]MIT Media Lab, Cambridge, MA

Corresponding Author:
Alex Berke, aberke@mit.edu

The study used 2018 transportation survey data that covered approximately 50% of the MIT community along with campus parking- and public road network data. The MIT community has various personnel groups, ranging from undergraduate and graduate students to a variety of categories of staff and faculty. These various groups differ in their propensity to drive as well as in their driving distances to and from campus, which in turn affect their car-related emissions. Our study approached these differences by simultaneously analyzing the community by personnel group and by residential distance from campus. By doing so, this work highlighted differences in how often and how far various groups commute by car and therefore how different intervention strategies might reduce car commuter miles.

We modeled and compared three primary intervention strategies to reduce car commuter miles: (a) work-from-home policies for staff, (b) changes that increase use of local alternative transit, and (c) improving affordable housing options close to campus.

The interventions we analyzed were grounded in what may be feasible. A challenge in modeling these changes with the information we had was that they may not lead to equitable interventions owing to the varied nature of responsibilities across the institute.

In what follows we present the background and context for this work, as well as for related research that has analyzed similar questions and employed comparable methods. We then describe our data sources and analysis methods, followed by the results. We model the community's baseline daily car commuter miles as a proxy for related emissions, and then model the change according to various interventions. We conclude with a summary and discussion of our findings.

Background and Related Work

Research preceding COVID-19 disruptions have highlighted universities as ideal places to make policy changes that improve sustainable travel, as they are often equipped with comprehensive policy options that affect commutes to their campuses (*5*). MIT has long-term goals to improve access to sustainable and equitable transportation, and to reduce congestion, parking demand, and commuter-related emissions. In this vein, the MIT Office of Sustainability, established in 2013, supports the development and integration of sustainable practices and policies across all levels of the MIT campus.

The MIT community consists of roughly 24,000 people (in the 2019/2020 academic year there were approximately 12,852 employees, including faculty; 6,990 graduate students; and 4,530 undergraduate students [*6*]). In March of 2020, most of the community transitioned to working from home as a result of the COVID-19 pandemic, and this new way of studying and working continued for the remainder of the year (*7*, *8*). These short-term changes drastically affected the MIT community's daily commuter patterns, and therefore the commuter-related emissions, and instigated this work to explore how longer-term changes might reduce commuter miles beyond COVID-19-related disruptions, and contribute to a part of the MIT Office of Sustainability goals. We note that although the 2020 disruptions affected both the student and staff campus communities, this work considers work-from-home policies targeted at staff, given that MIT focused on bringing students back to in-person learning.

Within the United States, the Environmental Protection Agency estimates that the transportation sector is one of the largest contributors to GHG emissions and that the largest source of these emissions is light-duty vehicles such as passenger cars. Even as vehicles continue to become more fuel efficient, emissions continue to trend upwards owing to increased travel demand and vehicle miles traveled (VMT) (*9*).

Social scientists have long recognized disruptive events as catalysts of societal change (*10*), and recent research has highlighted such disruptions, including the COVID-19 pandemic, as opportunities for changes that could affect transportation-related emissions (*11*, *12*). These works have also suggested that policy makers must broaden the scope of interventions when considering ways to reduce emissions, such as interventions that accelerate existing trends for less mobility and therefore less carbon-intensive lives (*12*).

One such intervention that has been studied is "telecommuting," or "teleworking," which has been more broadly recognized through work-from-home policies as a result of the COVID-19 pandemic. However, studying the environmental impacts of telecommuting is complicated. Although energy is saved by reduced commuting (*13–16*), some argue that the reductions in GHG emissions are partially offset by increases in noncommute trips and energy consumption in the home (*17–19*). However, a 2020 systematic review of 39 empirical studies on the energy impacts of teleworking suggested that teleworking leads to a net reduction in economywide energy consumption (*20*).

Another important and more generally accepted strategy to reduce car commutes is to improve alternative transit options. The MIT campus is located in a city with public subway and bus networks and a public bike-share system. In addition to these networks, MIT operates a shuttle service that is free for students and staff, within a limited radius of the campus (*21*). In 2016 MIT launched the "Access MIT" program to provide free access to the public bus and subway networks to all benefit-eligible employees and postdocs at MIT. This contributed to a nearly 15% reduction in parking demand and yearly increases in employee public transportation use (*22*). Part of our analysis involves a scenario that further shifts the MIT community from car commutes to alternative transit. This might be achieved by expanding MIT shuttle service routes and increasing their frequency, or improving bikeable access through infrastructure improvements. Another increasingly recognized intervention to reduce car commutes is to promote a more "walkable city" (*23*), or "20-minute city" (*24*). This can be done by increasing local access to housing, services, and amenities near the workplace (*25*) and such interventions have previously been proposed for the urban area surrounding the MIT campus (*26*).

To empirically evaluate the various intervention strategies explored in this analysis, this work used data from the MIT 2018 transportation survey (*27*). MIT conducts a transportation survey every 2 years. (We note that the 2020 transportation survey was disrupted by COVID-19.)

Distributing detailed commuter surveys to individuals is a common approach for universities to obtain comprehensive overviews of community travel behaviors and to identify opportunities for change (*28–30*). Related research has used such surveys to estimate university GHG emissions and evaluate methods to reduce them. It is worth mentioning the 2011 travel survey distributed by researchers at McGill University to estimate GHG emissions generated by commuters to the university's downtown campus (*28*). The survey was designed to uncover mode split and travel distance by age, gender, and job category to reveal the greatest polluting groups and where they were coming from. In addition, the study authors used the collected data to estimate baseline commuter emissions to compare with alternative scenarios they had modeled. For example, they modeled a scenario in which anyone whose commute was within a distance they deemed reasonable for walking, biking, or public transit, used that option instead of driving, and compared the resulting estimated commuter emissions with the baseline. Like the McGill researchers, the current work also used transportation survey data to both identify groups whose commutes most greatly affect emissions, and to develop and compare baseline emissions estimates with alternative scenarios; the scenarios include increasing the use of alternative transit for commutes within a reasonable distance of campus. This study also used information about groups' relative impacts on commuter emissions to inform the analysis of other modeled scenarios (e.g., targeted work-from-home policies).

A similar study used survey data to estimate transportation-associated GHG emissions for faculty, staff, and students at San Diego State University (*5*). They too modeled and evaluated alternative scenarios, including telecommuting (i.e., work from home) and housing interventions. In particular, their research provided evidence that offering better and affordable housing options close to campus could dramatically reduce emissions. Likewise, the current study models the impacts of work from home and accessible housing interventions.

Other campus case studies have used travel surveys to inform recommendations to reduce single-occupancy vehicle travel (*31*) and approach parking problems (*32*).

Compared with these works, the response rate for the MIT Transportation Survey was quite high. It was roughly 50% in 2018; comparable case studies commonly have response rates in the range from 20% to 30% (*29, 33–35*). Furthermore, the MIT Transportation Survey was distributed to the entire campus community versus a small targeted sample (e.g., the McGill researchers distributed surveys with the goal of capturing responses from 5% of the student population [*28*]). Unlike other survey data, the MIT Transportation Survey data contain demographic information for the entire campus community, including those who did not respond. This allowed us to extend the survey responses to model the entire community in our analysis.

Data and Methods

This analysis primarily used data from the MIT 2018 transportation survey. It also used daily parking transactions data from the same period to validate the analysis methods. Publicly available road network data were used to estimate driving distances, and therefore car commuter miles. Analysis was carried out in Python and is available at https://github.com/CityScope/CS_MITOS_Public.

Survey Description

The MIT Transportation Survey collects information about respondents' daily commuting methods, including how they get to campus, how often they do so, and whether they use MIT parking facilities. The 2018 survey was conducted with a web-based tool, which incentivized respondents by entering them into a lottery for cash prizes (Figure 1). Data were provided for 20,077 survey recipients with a response rate of 49%. MIT publishes aggregate statistics about their responses, however individual-level responses are private data (*27*). This research used the complete and individual-level responses data. All the researchers given access to this data followed strict guidelines to respect respondents' privacy. Therefore, only aggregate-level statistics are published in this report.

Survey Data Collected and Used

Many survey recipients only partially responded or did not respond at all. However, whether or not they

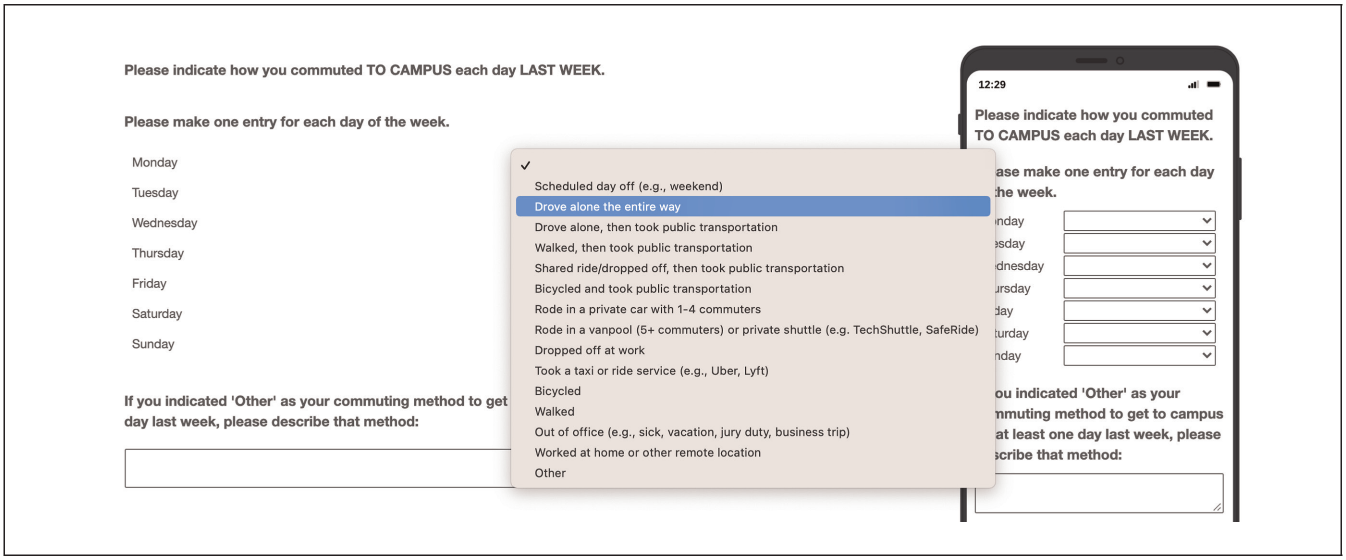

Figure 1. The MIT 2018 transportation survey, conducted with a web-based tool, asked questions about daily commuting.

responded, MIT already had on file their academic group, census block group of residence, and whether they were an on-campus resident. This information was provided to us for each survey recipient, along with their response to each survey question. The data for academic groups and residence allowed for the analysis to be based on the completed responses from each group, and then fit the analysis to the larger population. More information about academic groups is provided in the Supplemental Appendix.

The most important survey question used in the analysis was about daily commuting. Respondents were asked how they had commuted to campus each day in the week before the survey, and could select different answers for each day of the week from a range of options (see Figure 1). These responses were used with the assumption that answers about the week immediately before the survey represented respondents' overall commuting behaviors. The other questions used for analysis were about whether they drove to campus and where they parked. Respondents could answer that they used MIT parking facilities. These responses were used to quantify the daily parking facility users estimated by our analysis, and compare the results with parking facility usage data to validate our methodology. The variables and questions used in the analysis are summarized in Table 1.

For our analysis, we only used data from respondents who completely answered about their daily commuting for all 5 weekdays (Monday through Friday) and answered about driving to campus and parking. With these criteria, 9,173 of 20,077 survey recipients completed the survey (i.e., a response rate of 46%). Response rates varied by academic group and demographics. When comparing the number of residents and completed survey responses from each census block group, there was a Pearson correlation coefficient of 0.992. (See the Supplemental Appendix for more details about data representativeness.)

Analysis Methodology

We considered the set of all survey recipients ($N = 20{,}077$) as the study population and the recipients who sufficiently completed the survey as the sample ($n = 9{,}173$).

Distances. For each recipient, we computed their line distance to MIT as the distance between the MIT campus and the centroid of their residential census block group. These distances were used to partition the population in the analysis described below. Recipients' driving distances to the MIT campus were estimated as the shortest possible path on the road network by using data from Open Street Maps (*36*). Similar methods have been used to estimate transit time using GoogleMaps in related university transportation case studies (*28*).

Preprocessing. Each member of the survey recipient population was assigned to a distance bucket corresponding to their line distance to MIT. Distance buckets were in increments of 1 mile. Conceptually this corresponds to increasing concentric distance radii from MIT. Note that people with the same distance bucket did not necessarily have the same driving distance (see Figure 2).

Below, we refer to the driving distance for individuals, i, as $drivingDistance_i$. Respondents in the sample were also assigned the following variables. Car commuter weights, $WcarCommuter_i$, were computed as the fraction

Table 1. Key Variables and Questions From the MIT Transportation Survey Data Used in the Analysis

Variable	Options
Academic group	Graduate student Undergraduate student Support staff Administrative staff Faculty Sponsored research staff Service staff Other academic group
Census block group	GEOID
On-campus	On-campus Off-campus
Question	**Response options**
Please indicate how you commuted to campus each day last week (Asked separately for each day of the week.)	Worked at home or other remote location Walked Dropped off at work Bicycled Drove alone, then took public transportation Walked, then took public transportation Took a taxi or ride service (e.g., Uber, Lyft) Scheduled day off (e.g., weekend) Shared ride/dropped off, then took public transportation Out of office (e.g., sick, vacation, jury duty, business trip) Rode in a private car with 1–4 commuters Drove alone the entire way Rode in a vanpool (5 + commuters) or private shuttle Bicycled and took public transportation Other
In the last year, have you driven to campus for work or study?	Yes No
Where is your motor vehicle usually parked? (Only shown if respondent answered "Yes" they had driven to campus in the past year.)	MIT parking facility On-street parking (meter, unrestricted) Other paid parking lot or garage On-street resident permit parking Other

Note: Further description of the academic groups is provided in the Supplemental Appendix.
GEOIDs are numeric codes that uniquely identify all administrative/legal and statistical geographic areas for which the Census Bureau tabulates data.

of weekdays (Monday through Friday) that respondents said they commuted by driving alone. Parking weights, $Wparking_i$, were assigned equal to respondents' car commuter weights if they answered that they use MIT parking facilities, and zero otherwise

$$W\,parking_i = \begin{cases} WcarCommuter_i & \text{if use MIT parking} \\ 0 & \text{otherwise} \end{cases}$$

Respondents' daily car commuter miles, $carMiles_i$, were estimated as twice their driving distance multiplied by their car commuter weight,

$$car\,Miles_i = 2 \times driving\,Distance_i \times Wcar\,Commuter_i$$

This represents their average daily miles driving alone to and from MIT.

Analysis by Group. The number of car commuters greatly varied by both academic group and residential distance from campus (see Figure 3). Furthermore, the estimation of car commuter miles was dependent on distance. For these reasons we used a survey sample weighting method (*37*) that partitioned the population by academic group, and these partitions were further partitioned by distance buckets. Each resulting partition was then defined by academic group and distance bucket. For each partition, weights were computed as the inverse of the partition's sampling fraction,

N_j = partition j population size,
n_j = partition j sample size, and
$\frac{N_j}{n_j}$ = partition j weight.

These weights were used to expand the sample data from respondents within each partition to represent the

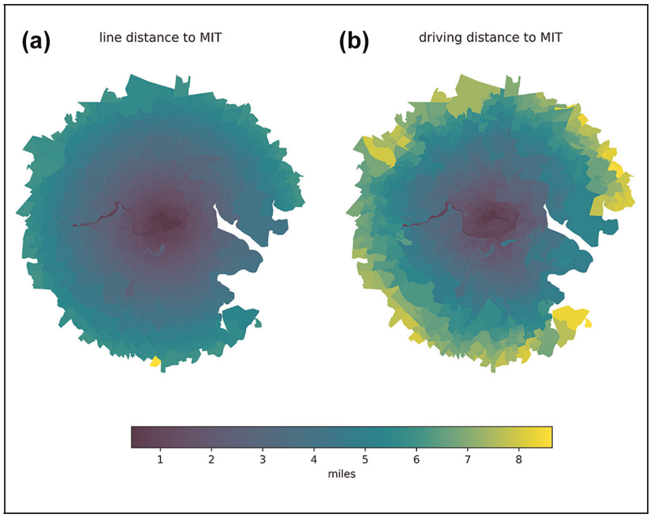

Figure 2. (*a*) Line distance and (*b*) driving distance from census block groups to MIT shown on maps to illustrate how these distances differ.
Note: To better visualize these differences by census block group, the maps were limited to a 5-miles radius from the MIT campus. This limitation applies only to this visualization, not to the analysis.

entire population as follows: values for daily car commuters, parking commuters, and car commuter miles for each partition population were estimated by summing the individual values over the partition sample and expanding the sum by the partition weight.

For example, for a given partition, j, in J partitions,

$$carCommuters_j = \frac{N_j}{n_j}\sum_{i}^{n_j} WcarCommuter_i$$

$$parkingCommuters_j = \frac{N_j}{n_j}\sum_{i}^{n_j} Wparking_i$$

$$carMiles_j = \frac{N_j}{n_j}\sum_{i}^{n_j} carMiles_i$$

The total population estimates were then computed by summing the estimates of each partition,

$$carCommuters = \sum_{j}^{J} carCommuters_j$$

$$parkingCommuters = \sum_{j}^{J} parkingCommuters_j$$

$$carMiles = \sum_{j}^{J} carMiles_j$$

These methods were used to compute baseline estimates as well as the differences between the baseline and alternative scenario estimates. Computing changes for various scenarios was done by modifying the corresponding partition weights. For example, in a scenario where a fraction, X, of some partition, j, (e.g., administrative staff in the 1 to 2 miles distance bucket) worked from home, and therefore did not drive, the estimated miles driven by that partition was computed by Equation 1,

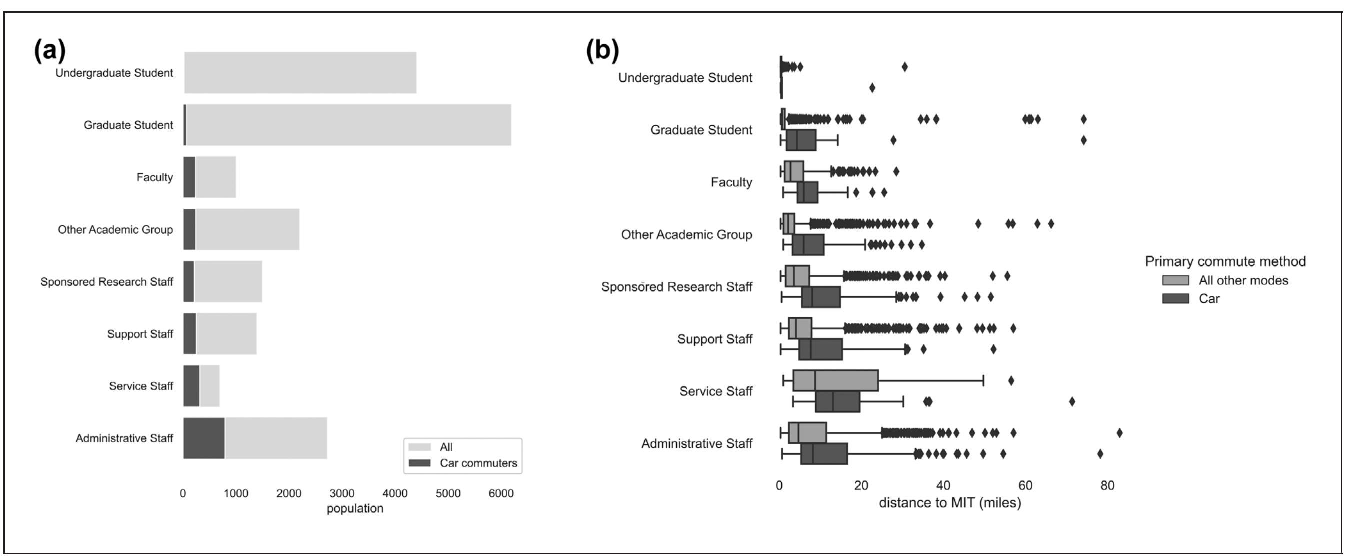

Figure 3. (*a*) Total number of car commuters compared with the entire community and (*b*) distribution of residential distances for car commuters versus commuters using other transit modes, by academic group. (Car commuters are counted as respondents who answered they drive alone at least 3 days/week.).

Table 2. Baseline Estimates for the Number of Car Commuters and Miles Driven by Car Commuters for Each of the Academic Groups

Academic group	*N*	Population, %	Car commuters	Total, %	Car commuter miles	Total, %
Administrative staff	2,719	13.54	794	37.09	22,628	39.74
Service staff	691	3.44	309	14.43	10,228	17.96
Support staff	1,391	6.93	253	11.82	6,540	11.49
Sponsored research staff	1,494	7.44	215	10.04	5,986	10.51
Other academic group	2,196	10.94	247	11.54	5,528	9.71
Faculty	998	4.97	237	11.07	4,361	7.66
Graduate student	6,187	30.82	67	3.13	1,567	2.75
Undergraduate student	4,401	21.92	19	0.89	98	0.17

Note: Estimates shown are mean values computed with bootstrap sampling (10,000 iterations).

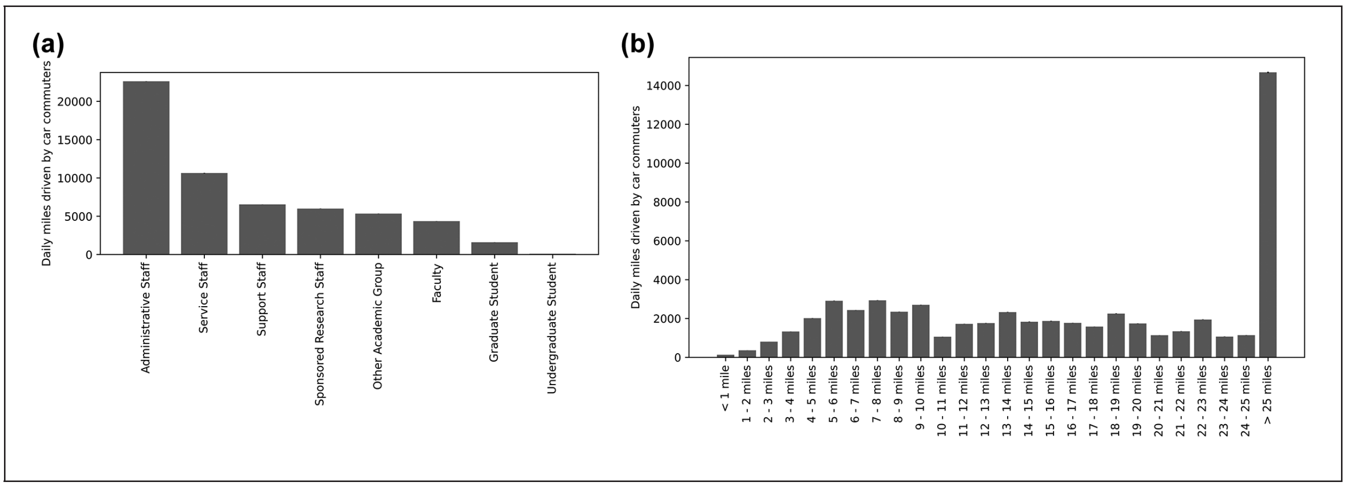

Figure 4. (*a*) Estimated daily miles driven by car commutes by academic group and (*b*) residential distance from campus.

$$carMiles_{j'} = (1 - X)\frac{N_j}{n_j}\sum_{i}^{n_j} carMiles_i \tag{1}$$

Total population estimates for the scenario were again computed by summing the scenario estimates of each partition. The estimated changes between the baseline and the alternative scenarios were the differences in these values.

For each scenario, the estimated daily miles driven by car commuters, *carMiles*, were considered a proxy for emissions generated by car commutes.

Scenario Analysis and Results

This analysis estimated daily car commuters, daily commuters using MIT parking facilities, and daily miles driven by car commuters, for baseline and alternative scenarios. The baseline results were used to understand differences in how the groups contribute to daily car commuter miles. The baseline estimates were then compared with the modeled estimates for the alternative scenarios to estimate the change in car commuter miles that could result from policy interventions that would create such scenarios.

Baseline

We used the previously described methods with bootstrap sampling (10,000 iterations) to compute the baseline estimates with confidence intervals (CIs) (*38*). Our results were 2146.09, 95% CI (2144.74, 2147.45) average total daily car commuters; 1752.66, 95% CI (1751.45, 1753.87) average total daily car commuters using MIT parking facilities; and 56934.59, 95% CI (56889.37, 56979.81) total daily miles driven by the population commuting by car to MIT.

For these baseline values, we also estimated the contributions to daily miles driven by each of the academic groups and by how far people lived from the MIT campus. The results are summarized in Figure 4 and Table 2.

Analyzing these numbers by the various groups highlighted their differences in residential distances and propensity to drive. As expected, car commuters tended to live further from campus, and staff tended to live further

Table 3. A Summary of the Alternative Scenarios Analyzed and Their Estimated Impact on Emissions From Car Commutes Compared with the Baseline

Intervention strategy	Scenario description	Estimated reduction in car commuter miles, %
A. Work-from-home policy	20% of staff (excluding service staff) stay home. i.e., work from home 1 day/week	16
	20% of the administrative staff stay home. i.e., work from home 1 day/week	8
	40% of the administrative staff stay home. i.e., work from home 2 days/week	16
B. Improved alternative transit	20% of car commuters living within a 5-miles radius switch to alternative transit	2
C. Accessible housing	20% of the community living more than 1 mile from campus moves to within a 1 mile radius	20

from campus and drive than students (see Figure 4). Large disparities were shown as well. For example, administrative staff make up 13.5% of the total MIT community, but 37% of the daily car commuters, versus graduate students who make up 31% of the community but only 3% of daily car commuters.

To check whether the analysis methods produced reasonable estimates, the estimated number of daily MIT parking facilities users was compared with MIT parking lots data from the same period. The transportation survey was sent out in October 2018. The number of unique daily MIT parking lots users counted on weekdays in October (excluding holidays) ranged from 1,881 to 2,406, with a mean of 2,236. In addition to commuters, MIT parking lots are used by on-campus residents as well as people not counted in the 2018 transportation survey (e.g., temporary workers and visitors). Using the 2018 transportation survey data, our analysis estimated 1,748 daily car commuters using MIT parking lots and 382 vehicles owned by on-campus residents. The combined estimate (2,130), was within the range of daily parking lots users counted in the October 2018 parking lots data. Further details can be found in the Supplemental Appendix.

Alternative Scenarios

The following analysis explores alternative scenarios created by policy interventions, and their impact on car commuter miles. The analyzed scenarios were those considered most feasible for policy-change implemention and success.

The policy intervention strategies were,

A. work-from-home policies,
B. improved access to alternative transit, and
C. accessible housing.

The scenarios and analysis results are summarized in Table 3.

Work-From-Home Policies. The baseline analysis showed that staff contribute more to car commuter miles than students, as they tend to live further from campus and drive more often, and certain staff groups contribute more than others. Many staff, excluding "service staff," could work from home. A variety of work-from-home policies that exclude service staff were modeled. In particular, administrative staff were the focus of some of the scenarios owing to their disproportionately large impact on car commuter miles and the administrative nature of their work. The described scenarios were set to affect 20% (or 40%) of targeted groups because 20% corresponds to working from home on 1 out of 5 weekdays and may therefore be easier to communicate or implement.

Scenario: 20% of Staff (Excluding Service Staff) Stay Home Each Day. In this scenario, a random 20% of all staff, excluding service staff, stay home each day. This is the same as them working from home 1 day/week on average. This was modeled by setting the value of X in Equation 1 to 0.2 for the affected partitions.

There was an estimated 16% reduction in car commuter miles.

Scenario: 20% of Administrative Staff Stay Home Each Day. This scenario was modeled similarly to the previous one, but in this case only the administrative staff were affected: a random 20% of only administrative staff stay home each day. This is the same as them working from home 1 day/week on average. This was modeled by setting the value of X in Equation 1 to 0.2 for all partitions with this academic group.

There was an estimated 8% reduction in car commuter miles.

Scenario: 40% of Administrative Staff Stay Home Each Day. In this scenario, a random 40% of administrative staff stay home each day. This is the same as them working from home 2 days/week on average. This was modeled similarly to the former scenario, this time setting X in Equation 1 to 0.4.

There was an estimated 16% reduction in car commuter miles.

Improved Access to Alternative Transit. Policy interventions that improve the access, convenience, safety, and affordability of alternative transit options can reduce car commutes. This was demonstrated by the success of the aforementioned "Access MIT" program. The following scenario assumes further policy changes are made that increase the use of alternative transit options. The assumed mode shift may seem relatively large, however the intention of this scenario description was to show that, even with a large mode shift, the impact was relatively small compared with the other intervention strategies explored.

Scenario: 20% of Car Commuters Who Live Within 5 miles of Campus Switch to Alternative Transit Modes. This was modeled by setting the value of X in Equation 1 to 0.2 for all partitions with distance bucket values within 5 miles

There was an estimated 2% reduction in car commuter miles.

Accessible Housing. In the following scenario, we assume a long-term policy intervention that improves the supply and affordability of housing for MIT community members near campus. In the baseline scenario, 48% of the MIT community lived within a 1-mile radius of campus. This portion of the community was the least likely to commute by car and contributed less than 0.24% of daily emissions from car commutes to campus. Much of this population was undergraduate students. The following analysis considers the propensity to drive for the different academic groups, such as undergraduates, separately. (Supplemental Appendix Figure A.5 provides intuition for this scenario.)

Scenario: The Number of Community Members Living Within 1 mi of Campus Increases by 20%. In this intervention, 20% of the population in each academic group living more than 1 mile from campus moved to within 1 mile of campus. This was modeled by recomputing the population partition sizes and weights. For each partition with a distance more than 1 mile from MIT, and for each academic group, 20% of the partition sample was subtracted from that partition and then added to the partition with the same academic group living within 1 mile of campus. All else was kept the same. It was then assumed that the rate at which each academic group commutes by car would be the same as that academic group's population already living in the area.

There was an estimated 20% reduction in car commuter miles.

Summary and Discussion

Universities are uniquely equipped with policy tools to make sweeping changes to how their communities live, work, and commute, to promote sustainable travel and produce long-term environmental impacts. In addition to the environmental benefits, more flexible policies around working from home can be seen as a benefit for employees. Research has shown that most employees who have been working remotely during the pandemic would prefer to continue to do so for part of the working week (*39*, *40*). The disruptions caused by the COVID-19 pandemic set a new precedent and showed that such changes are possible. However, for changes to be made in ways that maximize their benefits while minimizing disruption, alternative scenarios should be modeled, evaluated, and compared, using quality data.

In this case study of the MIT campus community, we compared how various groups contribute to car commuter miles, which can be considered a proxy for the emissions caused by car commutes. We used these findings to evaluate various intervention strategies to reduce car commuter miles.

For example, we found that graduate students make up 31% of the community but only 3% of daily car commuters. In contrast, there is a staff group that makes up only 13.5% of the total MIT community, but 37% of the daily car commuters, and contributes about 40% of the daily car commuter miles. We estimated that if this one staff group opted to work from home 2 days/week on average, car commuter miles could be reduced by 16%, and that this same reduction would be achieved if all staff (excluding service staff) worked from home just 1 day/week on average.

These work-from-home scenarios were evaluated alongside interventions that improve alternative transit and access to housing near campus.

An estimated 2% reduction in car commuter miles could be achieved if alternative transit interventions shifted 20% of car commuters living within a 5-miles radius to alternative transit. These reductions might seem modest in comparison to those from work-from-home scenarios. This is because commuters who live near campus are already less likely to commute by car, and when they do, their commutes are shorter and therefore contribute less to commuter miles traveled. Despite these modest reductions, improvements to alternative transit are important elements of larger, long-term sustainability policies, as they can decrease dependence on cars, which will further influence travel behaviors and the resulting emissions. This might also be said for policy interventions that increase access to housing near the workplace. We estimated a 20% reduction in car commuter miles if accessible housing interventions shifted 20% of the community living more than 1 mile from campus to within a 1-mile radius.

A limitation of this work is that it only estimated and evaluated changes in car commuter miles. It did not account for traffic congestion and emissions resulting from other modes of commuter transport, nor for non-commuter travel. Nor did it account for the difference in energy consumed by working in offices versus residences. Although working from home reduces the energy needed for commutes, it increases energy use in the home; the extent to which energy reductions from commutes outweigh the increases in energy consumed in the home is debated. However, it should be noted that the intervention strategy that increases housing availability near the workplace circumvents these caveats, as workers can presumably commute to work by other modes such as walking or cycling and avoid contributing to traffic congestion or commuter-related emissions.

Future work could incorporate estimates for building energy usage to help account for these differences. Future work could also analyze how and where to improve alternative transit and housing accessibility to have a greater impact.

Work-from-home policies may seem the easiest and least expensive interventions to implement in the short term to reduce commuter-related emissions, traffic congestion, and parking demand. However, the other intervention strategies present additional long-term benefits. For example, improved alternative transit options could involve more walking and cycling, which can have health benefits. In addition, shared alternative transit options and housing interventions that bring communities closer together could increase the potential for community interactions that stimulate innovation, which are of particular interest to institutions like universities.

The analysis presented in this work is intended to establish the groundwork for further studies that assess potential campus policies and land use in relation to their impact on parking demand and energy usage, as well as commuter-related emissions. This work is also intended to provide a case study for other institutions considering similar changes.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: A. Berke, R. Doorley; analysis and interpretation of results: A. Berke, R. Doorley, K. Larson; draft manuscript preparation: A. Berke, L. Alfonso, R. Doorley. All authors reviewed the results and approved the final version of the manuscript.

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ORCID iDs

Alex Berke https://orcid.org/0000-0001-5996-0557
Ronan Doorley https://orcid.org/0000-0001-7166-8815
Kent Larson https://orcid.org/0000-0003-4581-7500

Data Accessibility Statement

This research used parking transactions data provided by the MIT Office of Sustainability, and transportation survey response data provided by the MIT Office of Institutional Research. The data may be made available on request from the respective MIT offices. The data are privacy-sensitive, and the researchers given access to the data followed strict guidelines to respect respondents' privacy. The code that processed the data in the reported analyses, as well as the aggregate-level statistics, have been made available by the authors via an open source repository: https://github.com/CityScope/CS_MITOS_Public.

Supplemental Material

Supplemental material for this article is available online.

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