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A Randomized Controlled Trial in Travel Demand Management

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Abstract

This paper presents a trial aimed at reducing parking demand at a large urban employer through an informational campaign and monetary incentives. A six-week randomized controlled trial was conducted with (N=2000) employee commuters at the Massachusetts Institute of Technology, all of whom frequently drove to campus. Split into four arms of five hundred each, one group received weekly informational emails highlighting MIT's various new transportation benefits; a second group received monetary rewards for reducing their frequency of parking; a third group received both interventions, while a control group was monitored with no intervention. The paper aims to examine how behavioral incentives, namely targeted information provision and monetary rewards, can be used independently or in combination to encourage alternatives to drive-alone commuting. Success was measured as the extent to which drivers decreased their frequency of parking and increased their use of alternative modes during and after the campaign. While the combined treatment group contained the highest number of top-performing participants, no statistically significant differences-in-differences were observed amongst the treatment arms compared to the control. A post-experiment survey indicated a widespread increase in awareness of employer transportation benefits, and a much larger stated shift from driving towards transit than was supported by passively-collected data. Survey results suggested that while intent to reduce car use existed, complaints of insufficient quality of transit service and relative convenience of driving suppressed modal shifts. Most importantly, the discrepancy between self-reported and actual behavior change highlights important limitations and biases of survey-based travel behavior research.

Keywords: Travel demand management, nudge, randomized controlled trial, behavior change

1. Introduction

Parking, specifically its availability and pricing, is well established as one of the largest determinants of car usage (Shoup, 2005). In urban centers across North America, the cost of providing parking has risen both in infrastructure expense and the opportunity cost of land, resulting in downward pressure on general parking supply. At the same time, drivers face increasing commute times as roadway congestion worsens. These combined forces incentivize workplaces to promote alternatives to driving through travel demand management (TDM) techniques. University campuses are especially opportune places for TDM programs, given their centralized planning, comprehensive commuter data, and their campus-wide transportation and land use plans (Cherry et al., 2018).

Motivated by an increasingly limited parking supply, MIT launched a sweeping reform of its employee commuting benefits program in 2016, branded as *AccessMIT*. It aims to reduce the need to construct underground parking (costing over \$100,000 per space (Gates, 2015)) as existing elevated structures reach

the end of their lifespan, while promoting flexible, affordable and low-carbon alternatives. In the first phase of *AccessMIT*, the Institute provided all eleven thousand benefits-eligible staff with a 100%-subsidized local transit pass built into their employee ID card, making it the largest known employer in Massachusetts to offer such a benefit. In addition, most annual parking permits were converted to daily, pay-as-you-park permits in order to remove the yearly sunk cost and provide the opportunity for commuters to save money on days in which they choose not to drive. A partial subsidy for parking at transit stations was also introduced alongside an increase to existing commuter rail subsidies. Among all staff, the program led to a decrease in drive-alone mode share from 30% to 25% between 2014 and 2016 (see Rosenfield et al. (2019) for further details).

As a second phase, and the subject of this paper, researchers at the MIT Transit Lab used the commuter benefits overhaul as an opportunity to examine how low-cost, targeted nudges and incentives could further the reach of the new campus-wide program. The core experiment was a randomized controlled trial (RCT) in which drivers received either informational nudges, monetary incentives or a combination of the two, and changes to parking frequency and transit ridership were monitored through a post-experiment survey and passive data sources (parking gates and fare cards) for several months before and after the trial. With a sample size of two thousand employees, this experiment is among the largest known workplace-based RCTs conducted in the TDM literature (Petrunoff et al., 2016; Graham-Rowe et al., 2011; Yang et al., 2010; Ogilvie et al., 2007). The paper seeks to examine how behavioral incentives, namely targeted information provision and monetary rewards, can be used independently or in combination to encourage alternatives to drive-alone commuting; and to what extent temporary incentives will retain their effectiveness beyond the duration of the program. It seeks to fill a gap of high-quality RCT studies that (a) engage a meaningfully large sample size, (b) target a population that has already been the recipient of substantial TDM measures (meaning that commuters who are most likely to switch modes have already done so), and (c) use passive data collection to augment (and compare with) survey-based self-reporting of behavior change. The research, which explores a divergence of self-reported findings from ground-truth results, is framed through the lens of behavioral science and the psychological theories of bias and predictable irrationality.

The paper is structured as follows: Section 2 provides a brief literature review; Sections 3 and 4 present the experimental methods and results, respectively; and Section 5 discusses the implications and limitations of the experiment, and documents lessons learned for TDM program design.

2. Literature Review

The origins of TDM in the United States stem largely from federal government initiatives introduced in the 1970s and 1980s aimed at reducing air pollution (Meyer, 1999). Framed as “Transportation Control Measures” (TCM), such approaches were centered around traffic management through a combination of supply-side interventions (e.g. increasing roadway capacity) and demand-side programs (e.g. early campaigns to encourage carpooling). Internationally, the ‘predict and provide’ paradigm used to justify continual road building continued without substantial critique through the 1980s (Goulden et al., 2014). The toolkit of TDM techniques available to program managers—whether government or private employers—has evolved since the TCMs of the 1970s, and can be applied from regional approaches down to individual workplaces or residential communities. This study focuses on site-based approaches implemented through employers.

2.1. Employer-based TDM Interventions

TDM initiatives are often most effectively administered via the workplace, given employers' unique ability to influence the travel behavior of large numbers of commuters. Employers comprise an ideal venue for TDM programs for four reasons: first, they typically represent a geographic nexus of activity, wherein commuters dispersed across a region travel to a singular location at similar times (Dill & Wardell, 2007); second, they have the administrative resources to centrally manage a coordinated series of benefits and policies (ICF & CUTR, 2005); third, their employee population represents a community of potentially like-minded individuals who may influence each other's travel decisions, helping ensure a TDM program to be self-sustaining (Hendricks, 2005); and fourth, employers must pay for parking, either directly or via employees, so they have a built-in incentive to reduce parking demand (Meyer, 1999). The U.S. Federal Highway Administration funds the Value Pricing Pilot Program (through which this study was sponsored), investigating the ability for transportation pricing to influence travel demand, and leverages the fourth aspect as a key economic incentive.

Given the strategic position of employers, there are a number of ways in which workplaces can encourage a reduction in car use. Most fundamentally is through the location and multimodal accessibility of the workplace. Regardless of convenient alternatives to driving, however, Shoup (1997) describes the crucial role that parking provision plays in an individual's decision to drive. He demonstrates the effectiveness of adequately pricing parking to manage demand.

2.2. Soft TDM Approaches

Attributes above, such as workplace location and transportation pricing, are examples of 'hard' TDM, or direct measures that affect the utility of a commuting option. Many other approaches, involving a modification of the perceptions of choice or nudging, fall under the category of 'soft' TDM. Informed by behavioral science, these measures do not change the economic costs and benefits of a travel option, but rather acknowledge human irrationality and the sociological nuance of travel behavior.

For example, research in behavioral economics has shown a distinction between social norms and market norms (Ariely, 2010), reflecting that a desire to be liked, to conform, or to impress others (i.e. peer pressure) can easily supersede a desire to spend less money. Workplace culture has a key role in determining the success of TDM programs. Wen et al. (2010) show that simply the perception of a workplace as being encouraging of non-single-occupancy vehicle (SOV) commuting is associated with a lower SOV mode share. Travel awareness campaigns, such as informational kits sent to households, have been shown to be successful in Australia (Rose & Ampt, 2001), while workplace travel plans common in the United Kingdom often include a series of soft measures targeted at commuters (UK Ministry of Housing, Communities & Local Government, 2014). These can include personal travel planning, an individualized approach to TDM, which originated in Australia in the 1980s (UK Department for Transport, 2008).

Changing the way costs are interpreted by commuters can dramatically alter travel behavior. Shoup, in his advocacy for the parking "cash-out", shows that employers who seek to offer parking as a benefit can still do so, but by offering cash in lieu of parking for non-drivers, the playing field can be leveled for all commuters wherein non-parkers can cash-out their benefit (Shoup, 1997). Related is the idea of daily parking pricing as an alternative to monthly or annual permits. In this paradigm, the sunk cost of a permit purchase is removed so that even if the maximum monthly cost is the same, there remains a daily incentive to not drive.

2.3. TDM Evaluation

Despite the proliferation of employer and government-based TDM programs, there is often relatively little analysis of the effects of such programs, particularly regarding the extent to which changes in travel behavior can be causally attributed to the TDM initiative. Arnott et al. (2014) find that across an array of behavioral interventions, no conclusive evidence exists to suggest the causal efficacy of such programs. Programs that encourage non-SOV commuting are often paired with more expensive and restricted parking, and it can be difficult to discern whether ensuing reductions in parking are simply the result of pricing or a more nuanced behavioral process. It can be argued that even in the presence of a forced shift in travel patterns (e.g. with the closing of a parking facility), a TDM program's value can be in 'softening the blow' and making travelers feel the change in their travel routine was because of their own conscious decision (such as an appeal to environmentalism) rather than frustrated deference to a new policy.

A technique best known for clinical trials in medical research, the randomized controlled trial (RCT) experimental design allows researchers to control for selection bias, temporal effects and other confounding factors by randomizing a population sample and providing an intervention to one subset while passively monitoring another (the control). The theory of RCT design advanced through agricultural trials beginning in the 1920s by Ronald Fisher (1937), and grew in the social sciences towards the latter half of the twentieth century with experiments on income tax (Hausman & Wise, 1985) and development economics (Duflo et al., 2007). Today, the RCT is generally considered the "gold standard" of experimental design. That said, some challenge the implied methodological hierarchy that places the RCT on top, given that this experimental design may exaggerate quantitative precision and make overreaching claims on generalizability (Melia, 2015). Bamberg & Rees (2017) note that transportation research tends to rely on large-scale quasi-experimental designs, while research from the public health domain more commonly applies an RCT framework.

2.4. RCTs in Transportation

In the transportation literature, a sparse number of truly randomized *and* controlled experiments have been conducted, mostly on small samples of commuters or households, given the difficulty of producing such an experimental environment. Yang et al. (2010) identified twenty-five studies of interventions to promote cycling, two of which were RCTs, while Ogilvie et al. (2007) identified nineteen RCTs studying interventions to promote walking, generally from a public health perspective, and noted a dearth of similar research from the transportation sector. Graham-Rowe et al. (2011) reviewed 77 studies specifically on car use reduction, finding that most used relatively weak methodological foundations. Their review included six RCTs. More recently, Petrunoff et al. (2016) conducted a review specifically of workplace-based RCTs and controlled longitudinal studies. Their review found that ten out of twelve studies reported positive results, though many were at risk of significant bias. The review by Arnott et al. (2014) of ten RCTs did not find overall evidence of successful interventions.

Some studies showed successful results of interventions. For example, Garvill et al. (2003) conducted an RCT using psychological interventions in which they provided information during the trip planning phase and found a reduction in car use amongst frequent drivers. Bamberg (2006) examined whether residential relocation was an opportune time to intervene and reduce car use, and found that a combination of information provision and a day of free public transit was enough to elicit a reduction in car trip frequency. Similarly, Jakobsson et al. (2002) used a combination of financial disincentives for driving alongside an informational campaign and found a reduction in distance and frequency of car trips, though once the financial incentive was removed, effects were unlikely to be sustained.

Many more studies using an RCT framework found no significant impact of the measured interventions. Fujii & Kitamura (2003) used monetary interventions in their RCT by providing a one-month free bus pass to university students and found no reduction in car use, while Eriksson et al. (2008) had participants fill out a prospective car diary for future trips, and found the intervention group had no significant reduction compared to the control. An RCT by Tertoolen et al. (1998) leveraged psychological interventions including information, feedback and commitment, and found no significant effect after controlling for subject characteristics. A large study of employee commuters at London Heathrow Airport, which used a series of RCT experiments to explore the impact of nudges promoting car sharing and transit, exhibited similarly little significant effects among treatment groups (UK Department for Transport, 2017).

Among such experiments in the transportation and public health literature, relatively few had statistically robust methodologies and those that did were often limited by small sample sizes. Of the studies mentioned above, many used double-digit sample sizes, with some reaching several hundred participants such as Tertoolen et al. Most crucially, too many experiments rely on self-reported results as opposed to ground-truth passive data collection, and do not measure sustained behavior change for an extended period after the end of the intervention.

2.5. Behavioral Science in TDM

Behavioral science centers around the recognition of human irrationality, and the shortcomings associated with applying a rational utility-based framework to predict behavior. People do not always behave in ways that strictly maximize their utility (e.g. satisfaction, wellbeing, etc.), but rather use predictable heuristics to simplify choices and reduce cognitive burdens. Frameworks such as Ajzen's Theory of Planned Behavior, which describes the underpinning of behavior on intentions formed by attitudes, social norms and perceived control, has long been used to explain behavior (Ajzen, 1991). Adaptations of the framework place an emphasis on the role of habit as strong predictor of future behavior, as it mediates the impact of intentions (Gärling et al., 2001; Hoang-Tung et al., 2017).

More recently, Metcalfe & Dolan (2012) have more formally brought together the fields of behavioral science and transportation. The authors collected evidence from years of field experiments to argue that market failures in transportation can be addressed through a better understanding of the transaction costs and informational barriers associated with travel decisions.

Ariely (2010) described the difficulty of incentivizing behavior through monetary rewards in comparison to appealing to social or moral norms. He provides examples to argue that once a decision is interpreted in terms of market norms (e.g. monetary benefit or cost of a choice), an appeal to basic values or ethics is rendered less effective, and irrevocably so even after market incentives are removed. "Money, as it turns out, is very often the most expensive way to motivate people. Social norms are not only cheaper, but often more effective as well." (Ariely, 2010) This finding applies to TDM studies such as this study, where an appeal to social norms (e.g. describing the environmental benefits of transit) is tested against a monetary incentive (rewards in exchange for reducing parking).

In the transportation literature, clustering of population segments based on their affinity for differing incentives can be helpful in designing TDM programs to reach their target population. For example, Anable (2005) identified six clusters of travelers (e.g. malcontented motorists, aspiring environmentalists, etc.) and argued that TDM strategies must be designed with these distinct psychographic groups in mind. A moral appeal may be effective for the environmentalist, just as aggressive pricing may work for the 'die hard drivers'. The sampling frame of this study can be expected to include many of the latter cluster, given

the focus on everyday drivers who have not shifted their travel patterns after the introduction of MIT's new commuter benefits program.

Finally, it is important to recognize the importance of psychology not only in designing TDM measures but in evaluating them as well. Specifically, a number of biases can impact the validity of self-reported behavior and attitude change measurements. For example, the social desirability bias leads to survey respondents selecting answers that they believe will please the surveyors (Fisher, 1993), while the self-serving bias can result in respondents selecting answers that help enhance their own self-image (Heider, 1958). Biases such as these must be taken into account in any survey-based research, and highlight the importance of complementing surveys with alternate means of measuring behavior change.

3. Methods

This paper presents an experiment entitled "Sustainable Commuting @ MIT." Framed as a campaign encouraging low-carbon travel, the experiment was designed as an RCT whose target population was MIT's most frequent on-campus employee parkers. The methods were shaped by findings of the 2016 biennial MIT Transportation Survey, which found that a sizable portion of the commuting population either did not know about certain aspects of the *AccessMIT* program or did not understand the benefits. The campaign was therefore designed to educate and encourage drivers to 'switch up' their commute, in line with the prior marketing materials developed as part of *AccessMIT*.

3.1. Developing the Research Sample Pool

Figure 1 illustrates how the sample pool was established. Of the Institute's 10,500 full-time employees, approximately half of them (5,400) hold a parking permit. Noting that MIT's parking facilities are a combination of gated facilities (in which drivers must tap their ID card to enter and exit the lot) and non-gated open lots, only parkers assigned to gated lots (4,100) were considered for participation due to traceability. Of this subset, some parkers held occasional permits and only parked on campus sporadically throughout the year, and as such were not considered a target audience of a campaign to reduce parking. Only permit holders that parked an average of at least one day per week during the academic year were considered, resulting in a final sample size of 2,023 employees.

An opt-out framework was approved such that all eligible parkers were automatically enrolled in the research. Using a *MailChimp* account, the researchers disseminated messages using staff email addresses. On April 4, 2017, an introductory message was sent to all prospective participants informing them of an upcoming initiative to promote MIT's commuting benefits while disclosing the upcoming research project at a high level, and provided an explicit opportunity for employees to opt out of monitoring and communication. After a week, 56 individuals opted out of the research (3%), resulting in a finalized starting sample of 1,967 staff.

3.2. Treatment Groups

With the experimental population established, the population was randomly divided into four arms: one control arm and three experimental treatment arms ('E1 Information', 'E2 Rewards' and 'E3 Both'). Randomization was carried out using the last two digits of the employee ID number and resulted in arms of

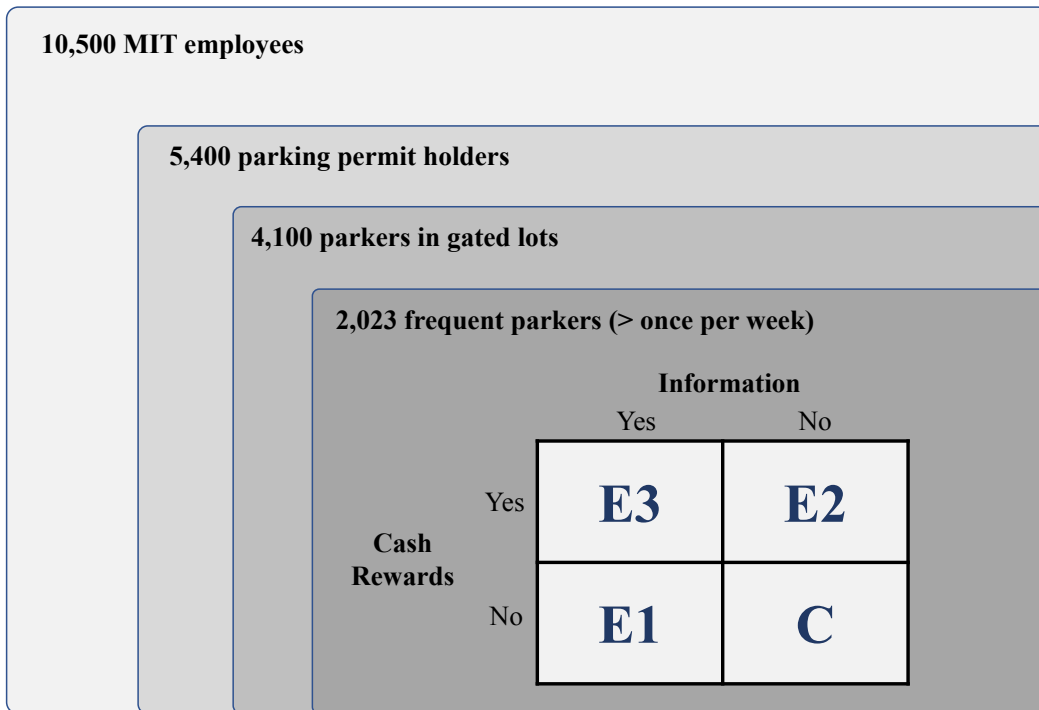


Figure 1: Composition of experimental population and treatment groups.

approximately five hundred each. Descriptive statistics of the 1,967 participants are presented in Table 1, and show that restricting the sampling frame to frequent drivers results in a higher proportion of professors and older employees compared to the general composition of staff at MIT. While employee income data was not made available to researchers, staff classifications were used as a proxy; with an overrepresentation of faculty, the average income of participants is likely higher than the Institute average. Comparing to American labor force statistics, the median age of MIT employees (45) and of experiment participants (51) is significantly higher than the nationwide median of 42 (U.S. Bureau of Labor Statistics, 2017). On race and ethnicity, the MIT workforce is relatively similar to Greater Boston statistics, albeit with a slightly higher representation among Asian employees (12% vs. 9.5% in Greater Boston) and a lower representation among Hispanic employees (6% vs. 9.5% in Greater Boston) (Donohue Institute, 2018). The average one-way commute length of 42 minutes is longer than the Greater Boston average of 31 minutes (Rocheleau, 2016).

For each of the six weeks from April 10 through May 19, 2017, emails were sent out to all participants of the three treatment groups. The complete experimental timeline is shown in Figure 2.

3.2.1. Informational Campaign (E1 & E3)

The one thousand participants in treatments E1 and E3 received six weeks of emails with information about *AccessMIT* benefits available to them. The six digests are summarized in Table 2, with example

Table 1: Descriptive statistics of population sample

	Control	E1 Information	E2 Rewards	E3 Both	All MIT Employees
N	494	481	489	503	10,471
Mean age (st. dev.)	50 (12)	50 (12)	51 (12)	52 (12)	45 (14)
Female	41%	49%	46%	47%	44%
Non-white	35%	30%	31%	30%	38%
Staff type: Faculty	20%	19%	19%	22%	10%
Staff type: Support & Service	20%	22%	23%	22%	22%
Mean years work- ing at MIT	13	14	14	14	10
Median driving distance to campus (mi)	11	10	11	10	6

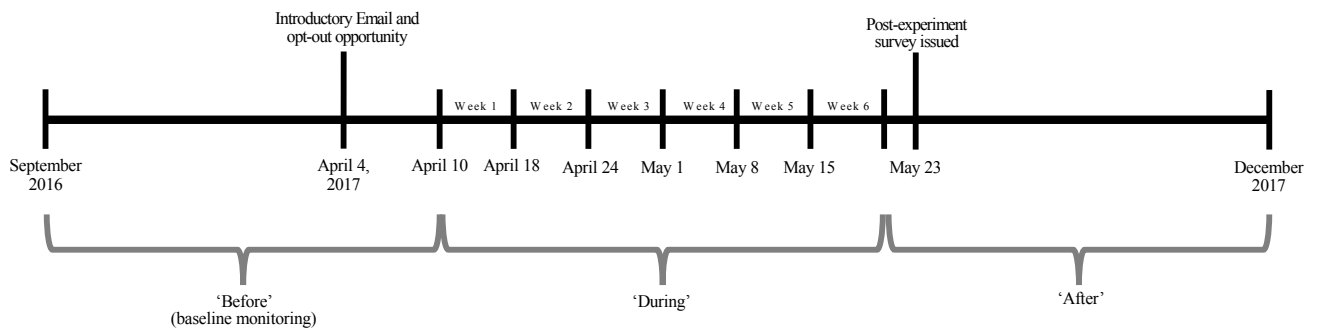


Figure 2: Experiment timeline

screenshots shown in Figure 3. The digests were designed to concisely summarize all of the commuting benefits relevant to frequent drivers, and address common misconceptions through conversations with the Parking & Transportation Office staff and a review of the 2016 Transportation Survey responses. The tone of each message aimed to suggest that even an intermittent switch to non-driving modes is beneficial, and appealed to both collective action, on environmental sustainability and local congestion, as well as individual cost savings. The content was ordered to begin and end the campaign with general trends about commuting at MIT, with specific information provided in the middle of the initiative.

3.2.2. Monetary rewards (E2 & E3)

Treatments E2 and E3 involved offering incentives in the form of *TechCASH*, an MIT currency loaded onto employee ID cards and redeemable at on-campus dining locations, bookstores and various campus services. Participants were informed of their average weekly parking frequency during the academic year so far (September, 2016 through March, 2017 excluding holiday weeks), and were offered weekly *TechCASH* reward deposits proportional to how much they reduced their parking frequency compared to their baseline. A rewards structure benchmarked to prior personal behavior was used to avoid simply reward-

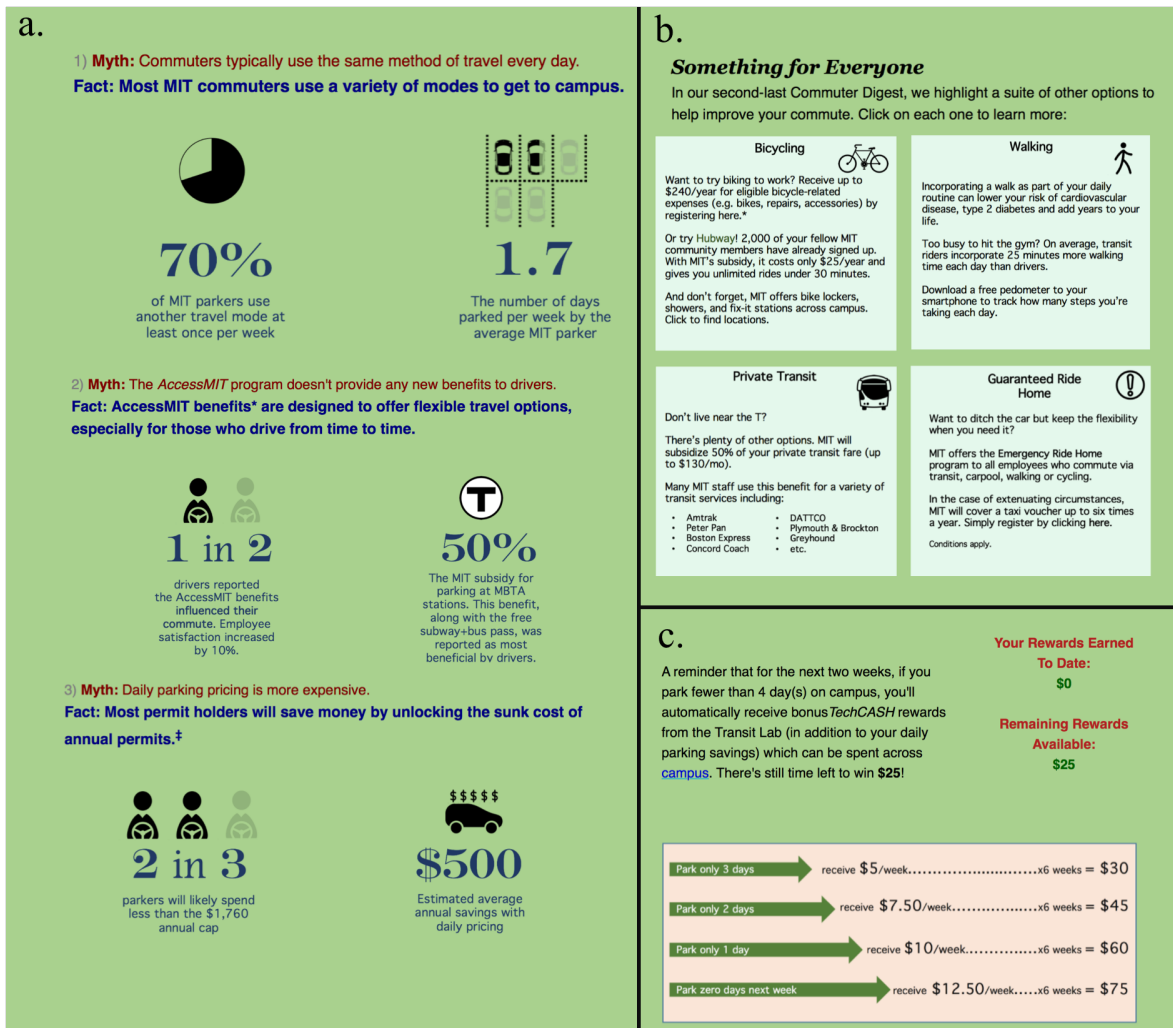


Figure 3: Samples of digest content (a-b) and rewards notification (c).

Table 2: Summary of Commuter Digest Email Campaign

	Subject Line	Description
Week 1	MIT Commuting Myths & Facts	Info-graphics of three misperceptions of MIT commuters and the benefits available to them
Week 2	Your Parking Benefits	FAQ on how the switch from annual to daily parking pricing can benefit all commuters
Week 3	A New Way to Car-pool at MIT	A three-step guide to using MIT's <i>AccessMy-Commute</i> carpool trip planner
Week 4	Riding the Rails to MIT	Q&A about Commuter Rail benefits
Week 5	Something for Everyone's Commute	Information on bicycling, private transit, Emergency Ride Home program and walking
Week 6	How MIT's Doing So Far	Statistics on interim program results

ing infrequent parkers, and is analogous to a study by Jakobsson et al. (2002) which rewarded households based on a reduction in driving distance. Rewards were disbursed weekly as follows: if a driver reduced their parking by one day (e.g., they used to park four days a week but only parked three days last week), they received \$5. For each additional day of reduction, they would receive an additional \$2.50.

Using this reward structure, participants who reduced their parking by one day or more each week could receive between \$5 and \$15 weekly, for a total of up to \$90 over six weeks. For example, a former four-day-a-week parker who parked only one day each week of the campaign would receive \$10 weekly. The subject line for E2 messages was “Your Commuting Rewards (*Date*)”, while E3 messages combined the subject lines from Table 2 with a reminder of weekly rewards (e.g. “Your Commuting Rewards (May 1-5) + MIT Commuting Myths & Facts”).

3.3. Implementation

Given the experimental framework, a number of design decisions were made that influenced user interaction and response. On communications, the medium of email was chosen (over text messages, websites, mobile apps, in-person communication, etc.) due to its universality among MIT employees and the ability for researchers to monitor via *MailChimp* whether each respondent opened and/or clicked on the email. The from-address was set as “MIT Transit Lab <sustainable_commuting@mit.edu>”, and messages were personalized with a first-name greeting and message content that was only applicable to that person (e.g. rewards recipients were only shown their past and potential future earnings).

Messages were scheduled such that E1 participants received their Commuter Digest each Monday morning at 10:30 am, while messages for the other two treatment groups were sent the preceding Sunday afternoon at 5:00 pm. This was done to ensure that participants eligible for monetary rewards were given sufficient time the day before to consider an alternate commuting method for Monday morning. While the different schedules added another potentially confounding variable, open rates across each group were not found to significantly vary. It is acknowledged that participants across treatment groups may have discussed the experiment with each other and those in the control, potentially confounding group delineations; it was found

in the post-experiment survey that 35% of control group participants were aware that some colleagues were eligible to receive rewards.

On incentive design, the *TechCASH* currency was chosen for its logistical ease and recognizability among MIT employees, and a deterministic payout was favored over lottery rewards due to the increased salience of having a non-zero rewards payout to many participants. The monetary value of rewards was designed as a linear ramp with a positive intercept such that a reduction in parking of even just one day per week would be enough to receive \$5 a week bonus, encouraging participants to overcome this hurdle.

The initial design of the experiment framed the rewards as a monetary loss rather than gain (i.e. every participant would be given \$90, then clawed back if parking was not reduced), in an attempt to leverage the behavioral economics finding that avoiding losses is a more powerful motivator than seeking gains (Kahneman & Tversky, 1992). However, this proved difficult to implement both logistically and politically, leading to a hybrid model where participants were reminded weekly of their maximum potential earnings, but the money was won, not lost.

4. Results

4.1. Analysis Metrics and Criteria

Evaluation of experimental results took place using a combination of passively-collected data and a post-campaign survey capturing stated attitudes and reported behavior. Primary behavioral variables included the number of days parked each week before, during, and after the initiative, as well as the use of the local transit pass integrated in employee ID cards. The ‘before’ period was from September, 2016 to April, 2017; the ‘during’ period was the six weeks between April 10 and May 19, 2017; and the ‘after’ period was from late May to December, 2017. Beyond parking and transit usage, subsidy claims for parking at MBTA transit stations and private transit services were also analyzed. Engagement variables including email open rates and unsubscriptions were monitored, facilitating segmentation by user participation levels. An exit survey asked participants about their awareness and perceptions of the various benefits and interventions offered, and questions on recalled behavior change helped corroborate any changes revealed through the data. Independent variables included employee attributes such as date of hire and staff type, along with geographic data on employee place of residence and transit accessibility aggregated at the census block group level. Summary statistics and a set of difference-in-differences regression models are presented to explore trends among each treatment arm, as well as the ‘top performers’ in each group as defined by the highest reduction in parking and/or increase in transit use.

4.2. Campaign Engagement

During the six-week campaign, a majority of message recipients were engaged in the communications as gauged by email open rates, click rates and unsubscriptions. Approximately two-thirds of recipients opened multiple email messages and remained subscribed, with open rates typically between 40-60%. This meant that approximately half of our target population may have received the information sent each week. E2 tended to have the most active participation on any given week, with users opening the message to see whether they won *TechCASH* rewards that week. However, E2 also reported a slightly higher frequency of mid-campaign unsubscriptions, suggesting that the treatment was the most polarizing: either users appreciated the rewards and opened their emails, or were bothered by notifications of zero winnings each week and chose to opt out.

Table 3: Change in Parking and Transit Usage

	Control		E1 Information			E2 Rewards			E3 Both			
	Mean	SD	% ^a	Mean	SD	% ^a	Mean	SD	% ^a	Mean	SD	% ^a
Parking Days Per Week												
Before campaign	2.96	1.27		3.04	1.23		3.00	1.23		2.88	1.27	
During campaign	2.96	1.43	51%	2.98	1.41	54%	3.04	1.43	47%	2.82	1.47	52%
After campaign	2.52	1.30	77%	2.46	1.28	81%	2.48	1.28	77%	2.38	1.27	78%
Transit Days Per Week												
Before campaign	0.31	0.63		0.32	0.67		0.37	0.74		0.39	0.76	
During campaign	0.32	0.71	25%	0.35	0.77	28%	0.43	0.90	30%	0.47	0.99	27%
After campaign	0.32	0.66	34%	0.34	0.68	35%	0.41	0.79	37%	0.43	0.83	34%
Difference-in-differences^b												
Parking (before-to-during)				-0.07			+0.04			-0.07		
Parking (before-to-after)				-0.14			-0.08			-0.06		
Transit (before-to-during)				+0.02			+0.05			+0.07		
Transit (before-to-after)				+0.01			+0.03			+0.03		

^aPercent of drivers who reduced their parking or increased their transit use, respectively, compared to before the campaign.

^bMean change benchmarked against control: e.g. $(E1_{During} - E1_{Before}) - (Control_{During} - Control_{Before})$.

4.3. Change in Travel Behavior

Changes in travel patterns during and after the experiment largely tracked seasonal trends, with both parking and transit usage decreasing as the weather warmed and the MIT spring academic term ended. As shown in Table 3, all four arms had a similar mean and standard deviation of parking frequency throughout the academic year prior to the campaign. A slight majority of participants were found to have reduced their parking during the campaign in all treatment arms except E2, with the information treatment exhibiting the largest proportion (54%). Following the experiment, over the ensuing seven months, treatments E1 and E3 showed a slightly higher proportion of parkers who reduced their frequency than the control. Such reductions in parking may have been a result of mode shift or telecommuting, as noted in survey results. On transit, use of employee MBTA passes (measured in days where at least one transit trip was made) tended to be significantly lower, consistent with the auto-oriented tendency of the selected population. All treatments exhibited slightly increased transit usage relative to the control, as shown by the differences-in-differences.

Figure 4 illustrates the changes in parking frequency across arms. The upper plot shows all participants, while the lower plot shows only ‘active’ participants, defined as those who opened at least two emails during the campaign and did not unsubscribe (this distinction is used to focus on participants who were most likely impacted by the nudges). Among all participants, treatments E1 and E3 exhibited the largest decrease during the experiment (-0.07 days per week), while among active participants, treatment E3 had the same magnitude of decrease in parking. Post-experiment, treatment E2 had the largest sustained decrease (-0.56 for both groups). Comparing difference-in-differences using an unpaired two-sample t-test (null hypothesis: zero difference-in-differences) yielded no significant differences at $p < 0.05$ except for treatment E1, which exhibited significance from before to after the experiment.

Figure 5 similarly illustrates the changes in transit use across arms, and indicates a slight increase in aver-

age ridership during the six-week experiment across all three treatment groups.

A linear regression was conducted as per Equation 1 using the average weekly parking frequency of person i in period t as the dependent variable regressed against the treatment type, time period and a vector of covariates \mathbf{X}'_i , with scalar coefficients β_{0-3} , and vector γ , respectively. Covariates included dummy variables for whether the person was a faculty member, a support staff, a recent hire (under 10 years), as well as whether their commute by transit is at least 20 minutes longer than by driving at peak hour (using Google Maps Directions API). A continuous variable of prior parking frequency was also included in select models.

$$\text{park}_{it} = \beta_0 + \beta_1 \text{Treatment}_i + \beta_2 \text{Period}_t + \beta_3 (\text{Treatment} * \text{Period})_{it} + \mathbf{X}'_i \gamma + \varepsilon_{it} \quad (1)$$

Table 4 indicates no significant treatment effect population-wide nor just among active participants. Interaction terms of demographic and spatial covariates with treatment groups were insignificant as well. Faculty tended to reduce their parking more than other types of staff, as did employees over 60; many employees in this category have more flexible working hours and tend to reduce them at the end of the academic term. Figure 6 shows the distribution of changes in parking across each arm. We observe a larger left tail for E3 than the control, with 17% of combination participants reducing at least one day a week (versus only 14% in the control), 8% reducing at least two days (versus 5%) and 4% reducing at least three days (versus 2%). On the right tail, the control group exhibited the largest increases in parking during the campaign, confirming that changes were not symmetric across both tails. Put differently, 39% of the top changers were among the E3 group, meaning that while E3 did not exhibit an across-the-board shift, it contained the highest proportion of ‘top performers’.

Further investigation of the left tail indicates some common characteristics of the 87 ‘top performing’ participants in E3, as defined by a parking reduction of at least one day a week. While the group had a composition of employment types (e.g. faculty, support staff, other academics, etc.) similar to Institute proportions, it tended to be comprised of more recent hires, with 26% being hired in the last five years (versus only 19% across the group as a whole); age and gender, however, did not significantly vary. Using geospatial data aggregated at the census block group level, it was observed that the top performers tended to live in areas where transit travel times are more similar to driving times, with an 18% smaller time penalty compared to the general population.

Additionally, the top parking reducers also had a slightly lower baseline parking frequency (3.0 vs 3.2), suggesting that the treatment was more effective on occasional parkers than five-day-a-week drivers.

4.4. Exit Survey Results

An exit survey was conducted following the conclusion of the six week campaign. Personalized links to a web-based Qualtrics survey were distributed via email such that responses could be traced back to user behavior. After being open for two weeks, 37% of experiment participants completed the survey.

Table 5 summarizes key survey results. Treatments E2 and E3 tended to have more frequent user engagement, with participants most often reporting to have “always read” the messages. While the survey response rate is biased towards those who were previously engaged in the email campaign (i.e. 86% of survey respondents were active participants compared to only 66% across the general sample), the relative differences between treatments are nonetheless appreciable. On employee benefits, respondents were asked about their awareness and use of (a) their free MBTA local transit pass, (b) the 60% commuter rail subsidy,

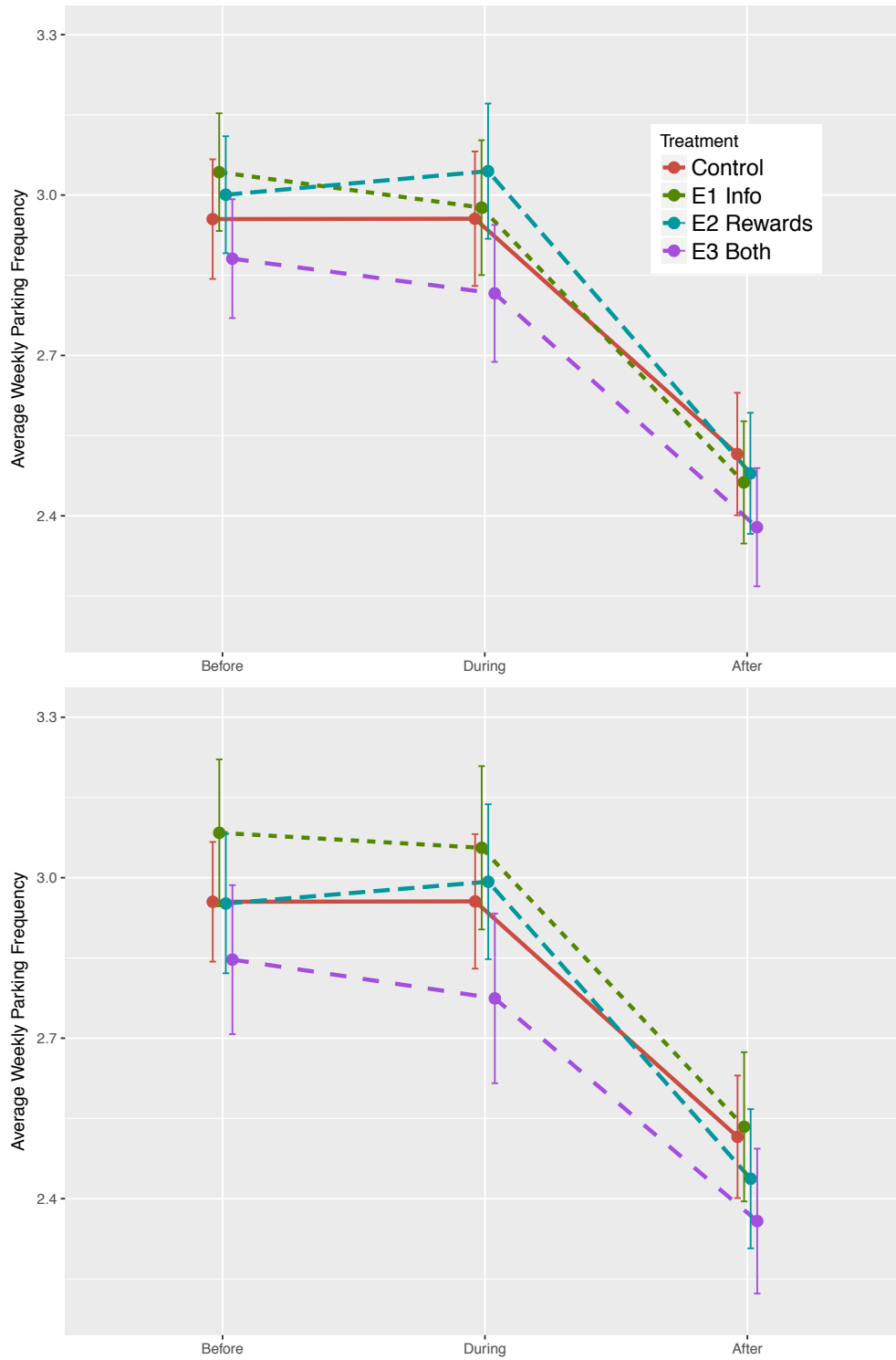


Figure 4: Plot of changes in mean parking frequency for all (top) and active (bottom) participants. The downward trend among all groups can be attributed to seasonal variation as the 'after' period includes summer vacation.

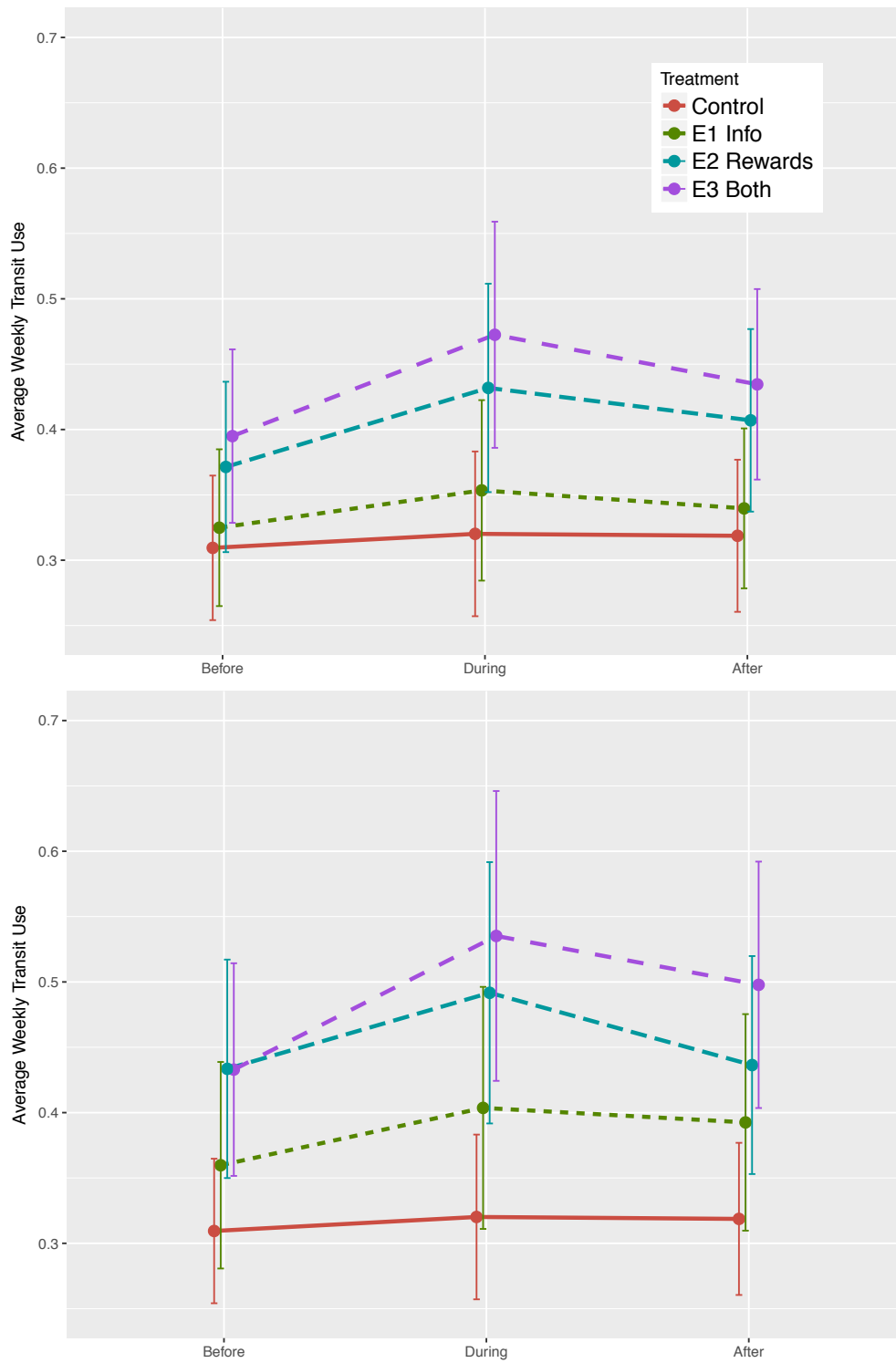


Figure 5: Plot of changes in mean transit use (days per week with at least one transit trip) for all (top) and active (bottom) participants. Transit riders are found to exhibit less seasonal variation than parkers.

Table 4: Regression Analysis of Parking and Transit Use (N=1967)

	Parking ^a	Parking with covariates ^a	Parking with covariates, <i>active</i> participants only ^a	Transit use ^b	Transit use with covariates ^b	Transit use with covariates, <i>active</i> participants only ^b
(Intercept)	2.955***	3.069***	3.057***	0.309***	0.835***	0.867***
During treatment	0.001	0.001	0.001	0.011	0.011	0.011
After treatment	-0.439***	-0.439***	-0.439***	0.009	0.009	0.009
E1 Information	0.088	0.070	0.099	0.015	0.024	0.071
E2 Rewards	0.046	0.033	-0.013	0.062	0.067	0.119*
E3 Both	-0.074	-0.106	-0.136	0.086	0.079	0.109*
During * E1	-0.067	-0.067	-0.029	0.015	0.015	0.029
During * E2	0.043	0.043	0.040	0.050	0.050	0.047
During * E3	-0.066	-0.066	-0.073	0.066	0.067	0.092
After * E1	-0.141	-0.141	-0.110	0.006	0.006	0.024
After * E2	-0.082	-0.082	-0.075	0.026	0.026	-0.006
After * E3	-0.063	-0.063	-0.050	0.030	0.030	0.056
Is faculty		-0.175***	-0.192***		-0.050*	-0.084**
Is support staff		0.066	0.048		0.075*	0.035
Recent hire (< 10 years)		-0.382***	-0.384***		0.054*	0.088***
Transit > 20 min longer than driving		0.264***	0.272***		-0.193***	-0.175***
Age over 60		-0.197***	-0.140**		-0.047*	-0.022
Past year average weekly parking frequency					-0.144***	-0.163***
R ²	0.03	0.06	0.06	<0.01	0.09	0.10
Adj R ²	0.03	0.06	0.06	<0.01	0.08	0.10

Note: '***': p < 0.001; '**': p < 0.01; '*': p < 0.05; '.' : p < 0.10

For the time period dummy, "Before" is the reference case; for treatment groups, "Control" is the reference case; for staff type, all non-faculty and non-support staff (incl. research, administrative, and service staff) are the reference case.

^aDependent variable: change in weekly parking frequency (negative change indicates reduction in parking)

^bDependent variable: change in days per week using transit (positive change indicates increase in transit use)

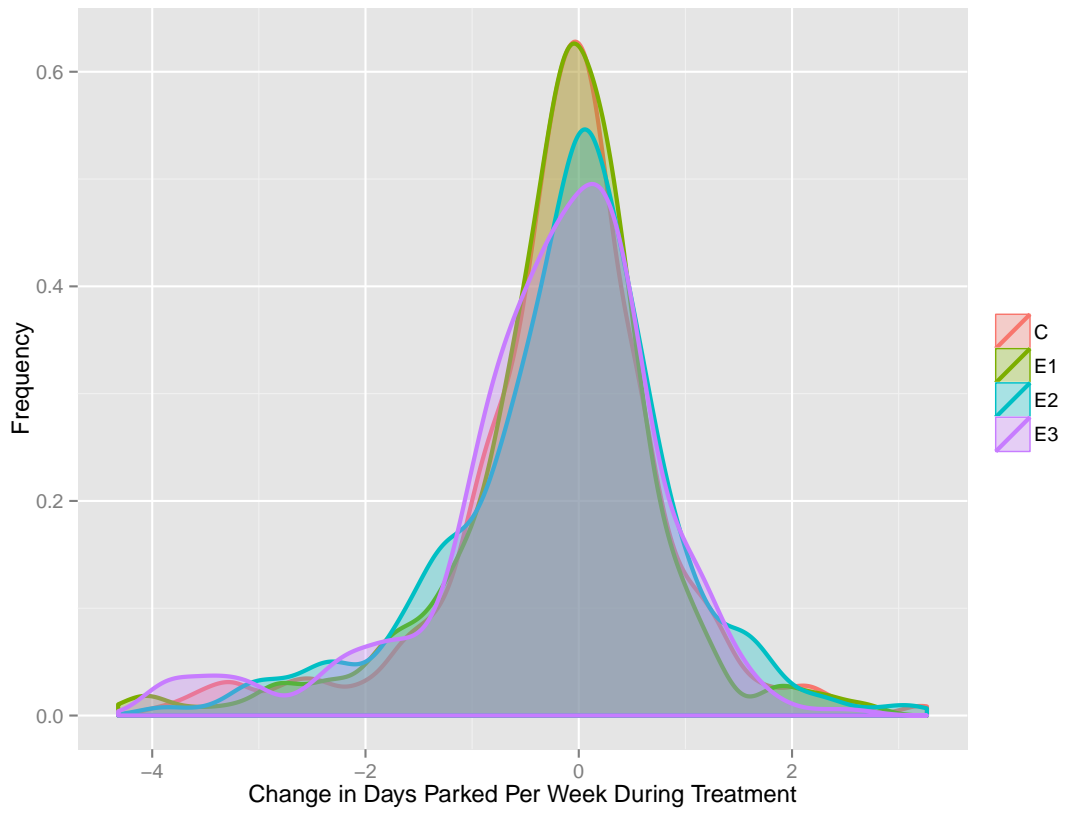


Figure 6: Distribution of change in parking frequency by treatment arm

(c) the 50% subsidy on parking at MBTA stations, (d) the 50% private transit subsidy, and (e) the *Access-MyCommute* dashboard and trip planner. Save for the private transit subsidy, the three treatment arms indicated higher use of all the benefits than the control. The free MBTA pass was the most commonly used benefit, with 25% and 23% of E2 and E3 respondents, respectively, reporting ‘frequent’ use compared to only 16% in the control.

The vast majority of participants already knew about the free MBTA pass, so the aforementioned increase in usage cannot be attributed simply to awareness. Participants were less aware of other program elements, notably the online trip planner and private transit subsidy, with a third of informational digest recipients reporting that they learned about the online dashboard during the campaign.

In general, survey results tended to markedly overstate behavior changes compared to passive travel data. Participants were asked what travel modes they use when not driving, and while 47% of the control group responded that they always drive alone to campus, only a third of E2 and E3 participants responded similarly. The largest reported mode shift during the experiment was toward public transit, by twelve percentage points, followed by working from home by six points. This suggests that if experimental results were measured solely using stated behavior, the finding would be a resounding success in shifting single-mode drivers toward occasional transit use. The revealed behavior, however, dampens these results.

In order to gauge the effectiveness of each campaign element, participants who reduced their parking were asked to rate how strongly each element influenced their decision. For rewards recipients, *TechCASH* was unsurprisingly the largest motivator, while one’s desire to reduce their carbon footprint was the largest motivator for the information group. Peer influence was consistently rated as least influential, although this tends to be more of an implicit motivator than consciously recognized (Feygin & Pozdnoukhov, 2017).

Informational digest recipients were asked to indicate which message(s) they found interesting or helpful. The message with subject line “Your Parking Benefits” was overwhelmingly rated as most helpful, and was the only digest to be indicated as so by the majority of participants. It outlined the rationale behind the switch from annual to daily parking pricing, and explained why it benefits all commuters (in that occasional parkers can save money while frequent parkers are protected by an annual cap on billing). The helpfulness of this message potentially indicates a prior lack of understanding about daily pricing and presents an opportunity for the Institute to ensure it is properly communicated.

Finally, participants were asked if they anticipated parking enough times during the 2016-2017 academic year to reach the annual cap of \$1760 in daily parking fees. Substantially fewer treatment recipients anticipated parking enough times to do so (37-41% compared to 49% in the control group). To test whether this was simply due to response bias resulting from low-frequency parkers, we estimated the true likelihood of each parker reaching this annual cap by extrapolating parking trends to date. Interestingly, all three treatment groups tended to *underestimate* their parking frequency and associated likelihood of reaching the cap. For example, 49% of control group participants anticipated reaching the cap while 52% were estimated to actually do so (an underestimation by three percentage points); in contrast, only 37% of E2 participants anticipated reaching the cap while 49% of them were estimated to actually do so (an underestimation of twelve percentage points). This may again suggest campaign participants painted a rosier picture of their behavior change than was actually exhibited, or may be in part due to social desirability bias, in which treatment group survey respondents select answers that they believe the surveyors wish to observe, or self-serving bias, in which respondents select answers that help enhance their own self-image. In this case, either bias would lead participants to overstate their reduction in parking. It should further be noted that the 37% of participants who completed the exit survey are likely biased towards those who felt

strongly about the TDM program (positively or negatively) and those who wished to signal they care.

In answering the two research questions introduced at the outset of the paper, we can extract insights from the experimental outcomes. First, we ask how behavioral incentives involving targeted information and monetary rewards can be used independently or in tandem to encourage alternatives to drive-alone commuting. The results indicate, consistent with prior literature, that achieving a widespread behavior shift using these interventions is difficult. Information provision is crucial to raise awareness, but complementing the messaging with monetary incentives proved highly effective in increasing email open rates. That said, a pitfall of the monetary rewards is that participation may become skewed towards those whose sole objective is to win money and ignore the ‘content’ of the campaign. The evidence for this is that significantly more E3 participants exited the campaign still unaware of the *AccessMIT* benefits compared to E1 (most notably, 28% of E3 participants still claimed not to know about the MBTA station parking subsidy after the campaign, while only 15% of E1 participants claimed as such). Of course, the other factor is that information-only campaigns may ‘preach to the choir’ as only TDM-receptive commuters make the effort to read and engage with the content. Finally, in answering this question we learn that encouragement of alternative modes can result in a subjective change in perceptions that does not translate into behavior change, as discussed above. Given that those who received monetary rewards were most likely to overstate their behavior change, an important takeaway of this study is the need to square ground truth travel patterns with survey results which are so often relied upon to gauge experiment success.

The second research question asks about the extent to which temporary incentives can retain their effectiveness beyond the duration of the program. Because statistically significant behavior changes were not observed during or after the campaign, the answer is null. Nonetheless, the heightened awareness of the commuter benefits and the community discussions sparked by the campaign can reasonably be expected to continue but we do not have another survey six months after the end of the experiment to evidence this.

5. Discussion

Using controlled randomization, an opt-out framework and three treatment arms allowed the distinction of the relative effects of information provision and small monetary incentives. Unlike many past experiments that rely on volunteer participants (e.g. Garvill et al. 2003; Bamberg 2006; Hunter et al. 2016, etc.), this study was bolstered by a truly randomized sample whose 3% opt-out rate meant that self-selection effects were minimized to an extent rarely seen in comparable studies. The opt-out nature of this experiment was instrumental in ensuring exposure among those with strong preferences for driving, who would likely not opt in to a campaign branded to promote non-car travel. As found in the behavioral science literature, the hurdle of opting out is enough to ensure that most individuals who may be borderline-receptive to our campaign would remain engaged, even through it meant that the results were not as significant as if we had only nudged those who actively signed up.

Our results indicate that the combination treatment was generally effective at influencing awareness, attitudes and hypothetical intentions, but did not translate into action (most evident in the fact that E3 participants reported a fifteen percentage point increase in the stated use of alternate modes, yet only had a small decrease in parking through passive data collection). We observed a stronger behavioral effect on occasional parkers than on full-time drivers, the latter of whom frequently cited a lack of viable alternatives to driving, as well as unaffordable housing near MIT or any areas well-served by transit. Many participants cited a desire to reduce their carbon footprint, albeit with a minority complaining of environmental guilt-tripping suggested by the campaign’s appeal to sustainability. The main barrier to behavioral change

Table 5: Selected Post-Experiment Survey Results (N=728)

		Control	E1 Info	E2 Rewards	E3 Combination	
Campaign Engagement	Mean Likert score (0=never saw; 5=always read)	-	3.23	4.05	3.96	
	Interaction with messages	-	3.23	4.05	3.96	
Use of benefit	Free MBTA subway & local bus pass	16/53/30	18/57/25	25/51/23	23/54/23	
	Subsidized commuter rail	% frequently use / 2/3/95	6/8/86	5/4/91	5/5/90	
	Subsidized MBTA station parking	% occasionally use / 3/2/95	4/8/89	3/7/90	3/11/85	
	Private transit subsidy	% never use 1/1/98	1/3/96	2/1/97	1/2/97	
	AccessMyCommute Dashboard & Trip Planner	2/9/90	0/26/74	1/17/82	1/23/76	
Raised awareness	Free MBTA subway & local bus pass	-	89/9/1	-	84/12/4	
	Subsidized commuter rail	% knew already / -	67/22/10	-	65/15/21	
	Subsidized MBTA station parking	% learned during campaign / % -	50/35/15	-	38/34/28	
	Private transit subsidy	don't know -	29/32/39	-	25/26/49	
	AccessMyCommute Dashboard & Trip Planner	-	34/34/32	-	33/34/34	
Alternate modes used	I always drive alone to campus	47%	43%	34%	32%	
	Public Transit	21%	24%	34%	32%	
	Carpool / passenger / shared ride	11%	10%	6%	12%	
	Bicycle	% selected (multiple allowed)	8%	5%	7%	4%
	Walk	2%	1%	2%	3%	
	Work from home	7%	12%	14%	12%	
	Other:	4%	5%	4%	6%	
Influence of campaign elements	TechCASH Rewards	Mean Likert 1.98	2.06	3.01	3.04	
	Increased awareness of benefits	Score (0=least influence; 5=most influence)	2.42	2.6	2.13	2.24
	Desire to reduce carbon footprint	2.57	2.82	2.69	2.76	
	Peer influence	1.3	1.36	1.11	1.04	
Helpfulness of commuter digests	Week 1: Commuting Myths & Facts Highlighting common misperceptions about transportation benefits	-	37%	-	27%	
	Week 2: Your Parking Benefits Outlining the perks of daily pricing	-	62%	-	67%	
	Week 3: A New Way to Carpool Introducing the carpool partner matching tool.	Helpfulness of commuter digests (% responding yes)	-	10%	-	4%
	Week 4: Riding the Rails to MIT Highlighting commuter rail and its subsidies	-	20%	-	13%	
	Week 5: Something for Everyone's Commute Introducing the Bike Benefit, private transit subsidy and Emergency Ride Home.	-	24%	-	22%	
	Week 6: How We're Doing Results of the initiative & recognition to top departments.	-	21%	-	27%	
	Larger influence	TechCASH Rewards most influential Information Campaign most influential Both equally influential	% selected "larger influence"	- - -	- - -	45% 9% 46%
Rewards	Awareness of how to spend TechCASH	% selected "yes"	-	-	79%	73%
Contagion	Awareness that others received rewards	% selected "yes"	35%	26%	-	-
Peer Influence	Whether participant discussed commuting benefits with colleagues	% selected "yes"	51%	64%	52%	55%
Carpooling	Mean Likert score (0=never; 5=always)	1.73	1.59	1.69	1.82	
	Frequency of carpooling	1.73	1.59	1.69	1.82	
	Use of dashboard to find carpoolers	Yes and we've shared a ride at least once	0%	0%	1%	2%
	Yes but I've never shared a ride	% selected	12%	12%	9%	11%
	No but I'm interested	24%	27%	27%	22%	
No and I'm not interested	64%	61%	63%	65%		
Daily Pricing	Mean Likert Score (0=no influence; 5=strong influence)	1.98	1.96	2.03	2.05	
	Extent to which daily pricing affects travel behavior	1.98	1.96	2.03	2.05	
Pricing Cap	Anticipate reaching annual cap	49%	41%	38%	37%	
	Do not anticipate reaching annual cap	22%	29%	29%	30%	
	Unsure	22%	23%	26%	27%	
	Unaware of cap	7%	7%	7%	6%	

Note: percent sums may not equal 100% due to rounding.

is the lack of attractive alternatives to drive-alone. This campaign was designed as a series of nudges to help commuters explore new modes of travel, but in some cases exploration led simply to confirmation that driving was the preferable mode.

Feedback suggested the rewards-only emails were somewhat irritating amongst those who were unable or unwilling to reduce their parking (and were thus reminded of all their foregone rewards money), while the information-only messages were well-received but often glossed over among the deluge of staff emails. Nonetheless, general perception of the campaign was positive, with complimentary comments outnumbering negative feedback by a ratio of three to one. This is unsurprising, given the focus on ‘carrots’ over ‘sticks’ in the experimental design.

At a cost of \$16,600 or approximately eight dollars per participant, the costs are relatively straightforward to quantify. Benefits are understandably more diffuse, but include such aspects as: reduced parking demand where noted; an increase in employee engagement measured by participants more frequently discussing commuting benefits with colleagues; a reduction in carbon-intensive travel and increase in healthy travel modes reported in survey results; and an expanded constituency of support for sustaining and growing MIT’s TDM initiatives. Positive feedback received from participants suggests that the program has inspired champions within the Institute that will advocate for TDM programs in the future. Since participants overstated their behavioral changes, we need to be careful not to overestimate these broader benefits.

Various limitations in the experimental design are to be acknowledged. First, the structure of providing rewards for reductions in parking, while more efficient than simply rewarding all non-drivers, suffers from the bluntness of not specifically targeting those who reduce for certain reasons. For example, because the campaign occurred as the spring academic term was ending, it coincided with a seasonal reduction in parking and resulted in higher rewards payouts than if the campaign were launched in the middle of the Boston winter. Some participants openly admitted to parking on a nearby street with free parking to avoid being tracked. Future campaigns with more restricted budgets could instead offer lottery prizes, which take advantage of how people tend to overestimate small probabilities (Kahneman & Tversky, 1979). Another limitation was that by limiting the sampling frame to frequent parkers, the experiment failed to test how the interventions might affect occasional or intermittent drivers who park less often to begin with. While frequent parkers may be seen as the segment most worth targeting, reducing the number of occasional drivers is an important step towards reducing peak demand (which may occur during inclement weather or special events). Furthermore, while emails sent to participants were individualized to show their parking history, the overall interventions were not tailored to each commuter. Future studies could feasibly incorporate a higher degree of individualized travel planning, such as notifying commuters how many potential carpool partners may reside along their route.

Finally, as a kernel of optimism for future TDM experimentation, it should be emphasized that this RCT took place shortly after MIT significantly overhauled its commuting benefits. Having achieved a baseline drive-alone mode share of only 24% (compared to 45% across the City of Cambridge), the ‘low-hanging fruit’ had long been picked and the remaining drivers likely face more arduous barriers to changing their travel mode. A similar RCT conducted in the absence of attractive commuter benefits might find different results.

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