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Barcodes, Virtual Money, and Golden Wheels: The influence of Davis, CA schools' bicycling encouragement programs

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Abstract

Efforts to encourage bicycling to school can achieve numerous societal benefits, including improved childhood health, reduced traffic congestion, and even long-term effects such as increased bicycling skill and attitudes. Most of the literature on children bicycling to school focuses on the influence of infrastructure interventions, yet relatively few studies have robustly evaluated the influence of encouragement efforts. This study seeks to examine the effects of three encouragement efforts undertaken at primary and secondary schools in Davis, California: the Active4.me scanning program, the Monkey Money incentive system, and the national Bike-to-School Day celebration. I use a binomial regression to statistically analyze bicycle rack count data and Safe Routes to School classroom tallies collected by city employees and local volunteers. After accounting for the schools' physical environment and characteristics, as well as the influence of weather and the natural environment, I find that all three of the encouragement efforts increase levels of bicycling to school. I conclude by suggesting that these encouragement programs have the potential for lasting influence by providing children with the skills and confidence to bicycle later in life. I also note the value of further state support for the parent volunteers who operate these encouragement programs, in order to allow the spread of similar encouragement programs across a variety of cities, including disadvantaged communities.

Keywords:
bicycling; school travel; encouragement

1 Introduction

Efforts to increase bicycling are often categorized according to the "5 E's": engineering, education, encouragement, enforcement, and evaluation (League of American Bicyclists, 2016). While the first four E's play clear and direct roles in increasing bicycling, planners and policymakers may be inclined to implement hurried, incomplete evaluations or omit this step altogether, despite its important role in estimating the influence of the first four E's and thereby justifying their worth.

The city of Davis, California has bucked this tendency by routinely collecting data on children bicycling to school from 2006 to the present. Davis has long been known for its bicycling since the town embraced the two-wheeled mode in the late 1960s, but bicycling levels have plateaued since the 1990s (Buehler & Handy, 2008). Bicycling remains a commonly-used mode, with approximately 25% of children bicycling to school (Fitch, Thigpen, & Handy, 2016), 50% of UC Davis students bicycling to college (Gudz, Heckathorn, & Thigpen, 2016), and 28% of adults bicycling to work (Gudz et al., 2016), but the city aspires to return to its previous levels of bicycling in the 1970s and 1980s, when, for example, about 75% of UC Davis students rode a bicycle to campus (Buehler & Handy, 2008). In recent years, the city and a group of parent and community volunteers have undertaken comprehensive encouragement efforts to increase bicycling to school.

This paper uses a decade of bicycle rack count data and supplementary Safe Routes to School classroom tallies to evaluate the efficacy of these encouragement efforts. Through the use of a multilevel binomial logistic regression model, I find that the bicycle encouragement programs yield increases in the bicycle mode share to school of between ten and fifteen percent over existing rates of bicycling.

2 Conceptual Model and Literature Review

I use an ecological model as a theoretical framework to consider the broad categories of potential influences on children's school travel (Sallis, Owen, & Fisher, 2008). In the ecological model, the individual serves as the focal point, with broader influences, such as interpersonal, school, physical, natural, and policy environmental characteristics, conceptualized as concentric rings around the individual (see Figure 1). I use an ecological model to avoid the tendency in the field of travel behavior research toward over-reliance on only one level, when human behavior instead is known to be multi-faceted (Sallis et al., 2008).In Figure 1, I have used italicized text for elements that are accounted for in this study, while plain text is used for elements that have not been included. The list of elements are loosely based on the factors identified in the literature review of Stewart et al. (2012), and are not intended to be exhaustive.

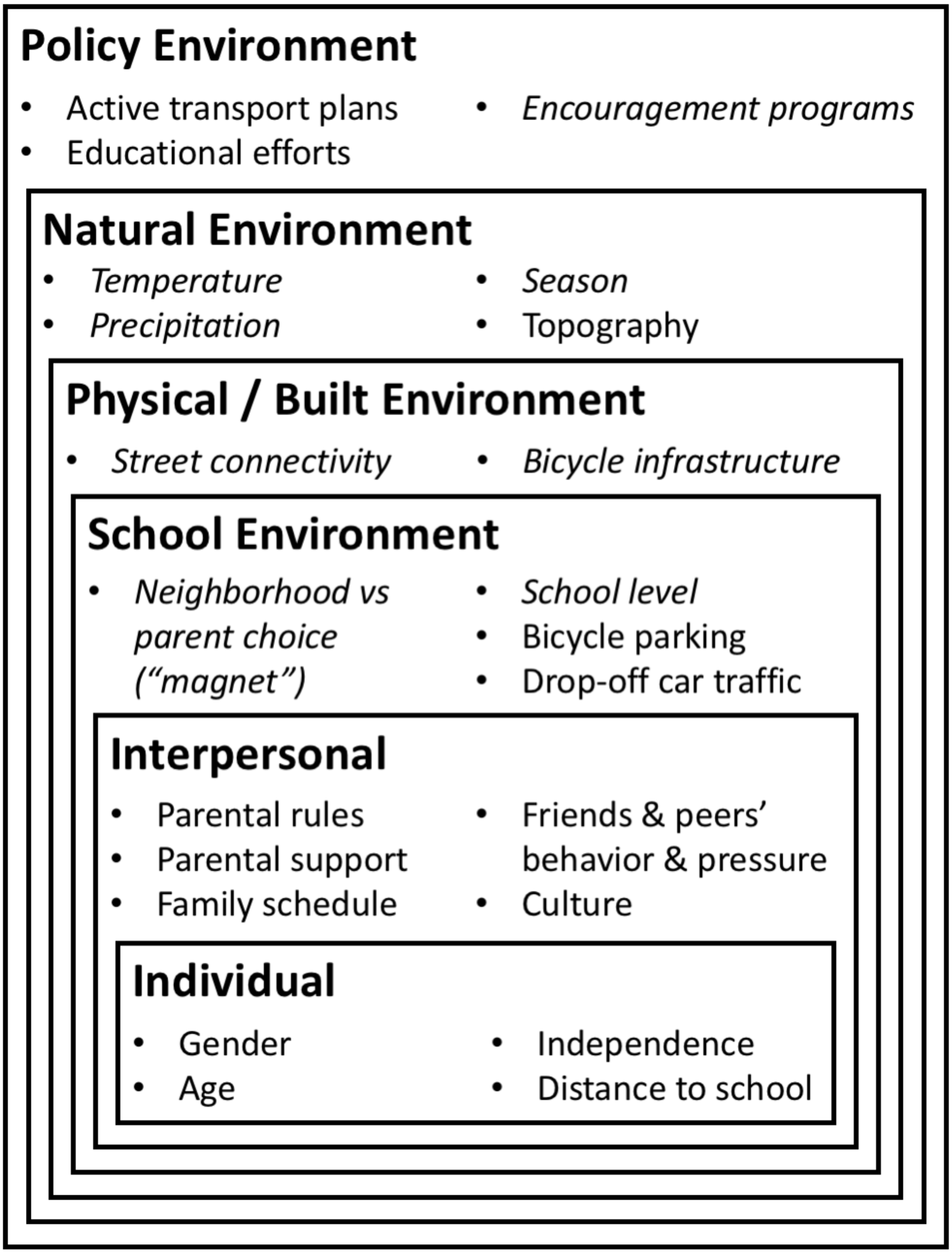

Figure 1. Socioecological Model for Bicycling to School

Studies within the field of active travel research have also been prone to emphasize the influence of the physical/built environment layer of the ecological model (Oosterhuis, 2014) while neglecting the influence of other levels, such as encouragement efforts in the policy level. Encouragement programs for active travel to school can range from celebrations (e.g. Bike to Work and Bike to School Days) to work or school bicycle commute challenges. In some instances, encouragement can overlap with education efforts, such as wayfinding signs and bicycle-specific maps which simultaneously celebrate and normalize bicycling while educating citizens about how they can travel by bicycle. In a review of both quantitative and qualitative research on active school travel, Stewart et al. (2012) identified eight common factors that serve as a hindrance or a catalyst for active school travel. Of those factors, the role of the built environment was the most frequently analyzed and encouragement the least. Furthermore, when transportation scholars analyzed the influence of school policies (i.e. encouragement efforts), they tended to focus on barriers rather than facilitators.

Nevertheless, a few notable studies have analyzed the influence of encouragement on active school travel. Using a similar approach to this study, McDonald et al. (2013) examined Safe Routes to School (SRTS) programs in Eugene, OR. The researchers compared the influence of bicycling and walking infrastructure (such as sidewalk and crosswalk construction), education efforts to increase walking and bicycling skills and awareness, and encouragement interventions (such as BTSD and a "Boltage" scanner incentive program, like the Active4.me program examined in this study). McDonald et al. (2013) found that the encouragement efforts increased levels of bicycling by four to five percent. In a similar paper looking at Texas elementary schools, Hoelscher et al. (2016) found that schools with non-infrastructure SRTS programs had higher active school travel than comparison schools.

Though these two studies have strong internal validity, with appropriate controls and sophisticated statistical models, further studies are needed to continue to establish the external validity of the relationships these authors have identified. Returning to the ecological model, this study's key explanatory variables are at the policy level: the programs to encourage bicycling to school. Variables from the natural, physical/built, and school environment levels are included as covariates. Due to the aggregate nature of the data, I am unable to include characteristics from individual or interpersonal levels of the ecological model.

3 Encouragement Efforts in Davis, CA

Consistent with the city's transportation objectives and plans, Davis primary schools began three efforts in the early 2010s to encourage bicycling to school: the Active4.me scanning program, a "Monkey Money" incentive system, and the national Bike-to-School Day (see Table 1).

3.1 Active4.me and Monkey Money

In 2010, local Davis parent Tim Starback developed a website called "Save a Gallon" to help primary school students track their non-automobile school travel (Ternus-Bellamy, 2011). Students or parents would log on to the website and enter their school travel mode for the day. Despite initial enthusiasm for the website, the second year's participation flagged, in part due to the need for daily manual entry (Ternus-Bellamy, 2011). Starback and his collaborator, Phil Cox, therefore created a more convenient scanning system in which participating students were issued unique bar codes on plastic cards that were scanned by a parent volunteer when the student arrived at school. The Save a Gallon program was thereafter rebranded as "Active4.me", and the program took off in Davis and saw widespread adoption around the US (Tim Starback, personal communication).

In the 2011-12 school year, Starback added another element to the Active4.me program, creatively called "Monkey Money". Starback was inspired to create the Monkey Money program by education research demonstrating the effectiveness of paying schoolchildren to adopt good study habits (Fryer, 2010). Children participating in Active4.me were awarded small increments, typically $0.10, of virtual Monkey Money cash for each day they traveled to school by a non-automobile mode. On particular days, the participating children could then spend their accrued virtual cash at a Monkey Money party on baked goods, toys, and other incentives donated by parents. Anecdotally, this proved to be a popular incentive among the participating children.

A common refrain from interviews with key participants in the Davis encouragement efforts was that the work of parent volunteers, or "champions", is vital (Tim Starback, Christal Waters, personal communication). The logistical challenges of Active4.me and Monkey Money can be daunting for a parent, both to initiate a program at a school and to maintain it. At any particular school, one parent typically volunteers to serve as the Active4.me champion and serve as the main scanning volunteer every morning. In most cases the parent champion will also organize a core group of other parent volunteers to assist with scanning. The parent champion can then also choose to add the Monkey Money incentives to their Active4.me program, which requires additional organization of volunteers and donations to run and to fuel the Monkey Money party. At one point, Starback considered automating the scanning process through the installation of radio-frequency identification (RFID) towers at the schools, but ultimately decided that the benefit of the human interaction between schoolchildren and the parent volunteers vastly outweighed the cost of the extra work that comes with manual scanning (Tim Starback, personal communication).

Table 1. Timeline of Davis Schools' Bicycle Encouragement Efforts and Rack Counts

	School Year										
	2005-06	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16
Birch Lane	X	X	X	X	X	X	ALL	ALL	ALL	ALL	ALL
Cesar Chavez	X	X	X	X	X	X	B	A & B	A & B	A & B	A & B
Davis Senior (HS)			X	X	X	X	X	X	X	X	B
Emerson (JH)			X	X	X	X	B	B	X	X	B
Harper (JH)			X	X	X	X	B	B	B	B	B
Holmes (JH)			X	X	X	X	B	B	B	B	B
King (HS)					X	X	X				
Korematsu		X	X	X	X	X	B	ALL	ALL	ALL	ALL
Montgomery	X	X	X	X	X	X	A & B	A & B	A & B	A & B	A & B
North Davis	X	X	X	X	X	X	A & B	A & B	A & B	A & B	A & B
Patwin	X	X	X	X	X	X	B	B	A & B	A & B	A & B
Pioneer	X	X	X	X	X	X	B	B	X	ALL	A & B
St. James			X	X	X	X	X				
Valley Oak	X	X	X			X					
Waldorf School			X	X	X	X	X				
Willett	X	X	X	X	X	X	A & B	A & B	A & B	ALL	ALL
Minimum	0	0	0	0	0	1	0	0	0	0	0
Median	1	2	2	1.5	2	2	6	7	8.5	9	7.5
Maximum	2	2	2	2	3	2	6	10	12	24	32

Note: "X" indicates that one or more bicycle rack counts were taken during that school year, while none of the 3 encouragement efforts analyzed in this paper were implemented.
"A" indicates that Active4.me was implemented during that school year and there was at least one bicycle count.
"B" indicates that Bike-to-School Day (BTSD) was celebrated during that school year and there was at least one bicycle count.
"ALL" indicates that BTSD, Active4.me, and Monkey Money were all implemented in the same school year and there was at least one bicycle count.
"HS" indicates that the school is a high school.
"JH" indicates that the school is a junior high school.
The count statistics refer to the minimum, median, and maximum number of counts conducted by each school in a given year.

3.2 Bike-to-School Day

The first national Bike-to-School Day (BTSD), a celebration to promote safe bicycling to school, was held on May 9th, 2012. The event has been held each subsequent May as part of the broader aims of National Bike Month (National Center for Safe Routes to School, 2016). Davis schools participated since the outset, with promotions and prizes such as a "Golden Wheel" trophy and a party for the school with the highest proportion of children bicycling to school on BTSD. Rewards, including bicycle and helmet decorations, have also been provided by the city's "Street Smarts" Safe Routes to School program. In addition, schools participating in the Monkey Money program awarded extra virtual cash rewards for bicycling to school on BTSD.

4 Methodology

4.1 Data Collection

Since the 2005-06 school year, the City of Davis has collected bicycle rack counts at 16 of the city's primary and secondary schools, including both private and public elementary (~6-12 year old children), junior high (~13-14 year old children), and high schools (~15-18 year old children), for ongoing monitoring and evaluation purposes (see Table 2 for an overview of the schools' characteristics). City transportation staff initially conducted counts every fall and spring. After the introduction of Active4.me, city staff and volunteers began collecting more frequent data for comparison with the number of children participating in the Active4.me program. The bicycle rack counts served as the dependent variable in this analysis, since they represent a closer estimate of the entire population of children who bicycle at each school, while only a subset of children participated in Active4.me.

I supplemented the bicycle rack count data with classroom travel tallies collected by the primary schools' Safe Routes to School (SRTS) programs (see the National Center for Safe Routes to School's copy of the tally sheet (National Center for Safe Routes to School, 2010)). The SRTS classroom tally and the bicycle rack count data trade off strengths and weaknesses. The bicycle rack count data provided an accurate picture of *overall* school bicycle mode share, with a small amount of measurement error (e.g. the data collector failing to see a bicycle rack hidden behind a building or counting parked bicycles that have been abandoned). The SRTS data only included information from participating classrooms, but had potentially smaller sources of measurement error (e.g. a student forgetting or mis-representing the mode they took to school) and bias (e.g. if only teachers who actively support bicycling to school participate in the classroom tallies). The SRTS classroom tallies occurred on days selected by the National Center for Safe Routes to School, and all classrooms within a primary school were invited to participate.

In Davis primary schools, an overwhelming majority of classrooms participated in the classroom tallies, suggesting that that there was little to no selection bias between the classrooms that conducted tallies and those that did not. I therefore viewed the participating classrooms as representative of the entire school. Accordingly, for SRTS classroom tallies, I coded the total number of children in participating classrooms as the school's "enrollment" and the total number of children bicycling to school in participating classrooms as the "number of bicycles in the bicycle racks". Though this may seem incompatible with the bicycle rack count entries collected by City of Davis staff and volunteers, since it did not represent the entire school population, it yielded a similar substantive and statistical interpretation: analyzing the number of children who bicycled to school while accounting for the number of children who could have bicycled to school. Over the study period, 705 bicycle rack counts or SRTS classroom tallies were conducted on 207 days. Multiplying school enrollment by the number of observations, this study has an effective sample size of 378,875 observations.

After consolidating the bicycle rack count data into a single database, I assembled other relevant details regarding the school's physical environment and characteristics as well as information regarding season, temperature, and precipitation on the rack count collection dates (see Table 3 for a full description of the variables collected). I determined the school enrollment through a California Department of Education data portal, and in the presence of missing data, I supplemented with enrollment data from ElementarySchools.org and the National Center for Education Statistics (ElementarySchools.org, 2016; National Center for Education Statistics, 2016). For the physical environment level, the City of Davis provided information about the timing and location of rapid rectangular flashing beacons as well as school status – as a neighborhood school or "magnet" school. Magnet schools offer special programs, such as second-language immersion, Montesorri education, and Gifted and Talented Education (GATE) programs, and attract students from beyond the school's normal catchment area. I gathered Walk Score and Bike Score data, which seek to provide a metric for the ease of walking and bicycling from a given destination to nearby amenities, for each school from their respective websites (Walk Score, 2016). For weather data, I relied on Weather Underground's historical record of precipitation and temperature at UC Davis's airport.

I gathered data on the independent variables of interest (the timing and presence of the Active4.me and Monkey Money encouragement efforts) by examining the aggregate, anonymized Active4.me data. Note that the *counts* from Active4.me were not used in this study. Instead, the *presence* of an active Active4.me program at a school was indicated through dummy variables in the statistical model. I determined whether a count observation was on a BTSD through online resources published by the National Center for Safe Routes to School (National Center for Safe Routes to School, 2016).

Table 2. School Characteristics

Schools	Average Enrollment	Walk Score[1]	Bike Score[1]	Magnet School Status[2]	School Level
Birch Lane	602	31	86	Montessori	Elementary
Cesar Chavez	609	49	93	Spanish Immersion	Elementary
Korematsu	436	34	84	GATE	Elementary
Montgomery	448	37	87	Spanish Immersion	Elementary
North Davis	541	44	91	GATE	Elementary
Patwin	431	51	89	-	Elementary
Pioneer	544	28	84	GATE	Elementary
St. James	299	59	90	-	Elementary
Valley Oak	519	66	99	-	Elementary
Waldorf School	175	20	83	-	Elementary
Willett	519	47	91	GATE	Elementary
Emerson	476	39	87	-	Junior High
Harper	693	12	76	-	Junior High
Holmes	727	49	93	-	Junior High
Davis Senior	1,709	47	92	-	High School
King	58	84	100	-	High School

Note: [1] Walk Score and Bike Score are scores on a scale from 0 to 100, developed by WalkScore.com with the intent to measure the walk and bicycle accessibility of a given street address to nearby destinations (Walk Score, 2016).

[2] Schools offering special programs are considered "magnet" schools, as they attract students from outside of the school's normal catchment. A "–" indicates that no special programs are offered at that school (i.e. it is a neighborhood school). GATE stands for "Gifted and Talented Education".

Table 3. Variable Descriptions and Sources

Level of Ecological Model	Variable	Description	Source
Dependent Variable	**Bicycles**	Number of children's bicycles parked in the bicycle racks at a school	City of Davis Excel spreadsheets
Number of Trials	**Enrollment**	Number of children attending a school	(California Department of Education, 2016; ElementarySchools.org, 2016; National Center for Education Statistics, 2016)
Time Characteristics	**Day of the week**	Days of the school week, derived from the observation date (dummy coded with Monday as the reference category)	-
School Environment	**School type**	Whether a school was a "magnet" school for Spanish Immersion, Gifted And Talented Education, or Montessori (dummy coded with neighborhood school as the reference category)	City of Davis, personal communication
	School level	School's grade level (dummy coded with elementary school as the reference category)	(California Department of Education, 2016)
Physical / Built Environment	**Rapid rectangular flashing beacon (RRFB)**	Presence of a RRFB within half a mile of a school (dummy coded)	City of Davis, personal communication
	Walk score	Score representing how accessible a school is by walking	(Walk Score, 2016)
	Bike score	Score representing how accessible a school is by riding a bicycle	(Walk Score, 2016)
Natural Environment	**Season**	One of the four seasons, derived from historic equinox and solstice data (dummy coded with winter as the reference category)	-
	Temperature (maximum)	Maximum daily temperature, from historic weather data	(Weather Underground, 2016)
	Precipitation	Presence of rain (dummy coded)	(Weather Underground, 2016)
Policy Environment:	**Active4.me program**	Level of activity of an Active4.me scanning program (dummy coded with absence as the reference category)	(Starback, 2016)

Encouragement Efforts	**Monkey Money program**	Presence of a Monkey Money incentive program (dummy coded)	(Starback, 2016)
	Monkey Money party	Presence of a Monkey Money party within the next three weeks (dummy coded)	(Starback, 2016)
	Bike to School Day	Whether the observation is on BTSD (dummy coded)	(National Center for Safe Routes to School, 2016)

Due to the staggered introduction of these three programs, I was able to employ a quasi-experimental design, using schools without the encouragement programs as controls against which to compare the schools adopting one or more of these three encouragement “interventions”. The use of a quasi-experimental design represents an important contribution to the literature, as intervention studies (i.e. research that evaluates strategies intended to change behavior) are difficult to organize and execute due to their intensive time and resource requirements, and are therefore rarely implemented (Handy, van Wee, & Kroesen, 2014).

Most of the variables were coded as dummy variables. The exceptions to this pattern were the bicycle count day’s temperature and the Walk Score and Bike Score variables. For each of these variables, I rescaled their value from their original scale (e.g. Fahrenheit, days) by subtracting each value from the overall mean value in the sample and dividing by two standard deviations. I adopted this approach in order to improve later statistical modeling (McElreath, 2015) and to allow for more direct comparison with the dummy variables (Gelman, 2008).

4.2 Statistical Modeling

Based on the schools’ enrollment, I modeled the number of children bicycling to any given school as an aggregate binomial process (see Table 4 for the full model formula). I viewed each child’s decision to bicycle to school as a Bernoulli trial (i.e. a “coin flip”: a random trial with two possible outcomes: “bicycle” or “not bicycle”), and the sum of the children’s decisions at each school led to a binomial likelihood with the number of bicycles in bicycle racks as the outcome and the total enrollment as the number of trials. I used the R statistical programming language and the *rstan* and *rethinking* packages to estimate the statistical models (McElreath, 2016; R Core Team, 2016; Stan Development Team, 2014).

Individual schools may exhibit distinct patterns of school travel, due to factors not included in the statistical model. I accounted for the strong possibility of correlated observations within a school by employing a Bayesian multilevel binomial logistic regression model. This model specification estimated a random intercept for each school, which helps prevent model overfitting (i.e. where a model loses generalizability by learning “too much” from the data in the sample) by pooling the information across schools (McElreath, 2015). By design, the multilevel model also accounted for the imbalance in sampling present in this study (McElreath, 2015), which otherwise could have biased parameter estimation. Each school’s intercept can be interpreted as capturing aspects of the school that aren’t included explicitly in the model as covariates, such as the physical environment or unique school policies.

I estimated three statistical models to facilitate model comparison. The first model is an intercept-only model, which estimates the average bicycling rate across schools as well as a unique intercept for each school. This model indicates how different each school is from another, in the absence of other predictors, and serves as a useful base for comparison with later models.

In the second model, I added covariates to the intercept-only model in an effort to determine the relative influence of various independent variables, including physical characteristics, such as weather and day of the week, as well as features of the built environment, such as the installation of rectangular rapid flashing beacons (RRFBs). In the final model, I added the three independent variables of interest – the presence of an Active4.me program at a school, the addition of Monkey Money incentives and parties, and the celebration of BTSD – to the covariate model to account for their independent contribution to Davis children's probability of bicycling to school, and also estimated random slopes for BTSD by school.

I used weakly informative, regularizing priors in order to avoid overfitting (McElreath, 2015), and I compared the models out-of-sample predictive ability using the widely applicable information criteria (WAIC) and Akaike weight (Watanabe, 2010). I made inferences about the variables' influence using the parameter posterior distributions rather than employing null hypothesis testing to generate p-values, which are notoriously difficult to interpret properly (Nuzzo, 2014).

Table 4. Full Model Formula

Model			Model Elements
$Bicycles_{ij}$	$\sim Binomial(Enrollment, p_{ij})$		Binomial likelihood
$logit(p_{ij})$	$= a + a_j +$		Fixed and varying intercepts
	$+ \beta_{cov}[covariates_i]$		Fixed slopes
	$+ \beta_{a4m}[Active4me_i]$		
	$+ \beta_{mm}[Monkey\ Money_i]$		
	$+ (\beta_{btsd} + \beta_{btsdj})[BTSD_{ij}]$		
α	$\sim Normal(0,10)$		Prior for fixed intercept
$(\beta_{cov}, \beta_{a4m}, \beta_{mm}, \beta_{btsd})$	$\sim Normal(0,10)$		Priors for fixed slopes
$\begin{pmatrix} \alpha_j \\ \beta_{btsdj} \end{pmatrix}$	$\sim MVNormal\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, SRS\right)$	$j = 1 \dots 16$	Prior for the distribution of varying intercepts and slopes
$(\sigma_j, \sigma_{btsdj})$	$\sim HalfCauchy(0,1)$		Prior for standard deviations
R_j	$\sim LKJCorr(2)$		Prior for correlation matrix

Note: The subscript "i" refers to the ith observation and "j" to the jth school.

4.3 Limitations

Though this study benefited from the collection of data over the course of a decade, the implementation of encouragement efforts such as Active4.me and Monkey Money might have suffered from selection effects, whereby these programs might have been directed toward schools with particular characteristics, rather than being randomly assigned. These characteristics could have included differences in the outcome variable (i.e. schools that have very little bicycling are more likely to be targeted) or aspects of the school, such as the enthusiasm of a particular parent, interest of a school official or teacher, or a conducive physical environment and infrastructure for bicycling. In this case, the main criteria for introduction of Active4.me was the presence of a willing parent to champion the program.

As these encouragement programs were part of a city-wide effort, it was impractical to reduce the threat of selection bias through random assignment. However, the quasi-experimental design accounted for the possibility of bias through the influence of unobserved variables by using control and intervention cases and collecting longitudinal data. The multilevel regression models also controlled for differences in the schools' physical environment and variation in the natural environment across observations.

The nature of the bicycle rack count data, collected in aggregate at the school level, limited my ability to analyze variables shown in the literature to strongly influence bicycling to school. I therefore was unable to account for individual characteristics that might influence the decision to bicycle to school, such as age, gender, and parental support and rules. Accounting for the effect of infrastructure changes was also more challenging with school-level observations, as I could not estimate or determine what proportion of children, or indeed, which specific children, would be affected by any changes.

5 Results

The models' parameters' posterior densities were approximately Gaussian-distributed, allowing me to summarize the parameters by their mean and standard deviation values (Table 5). I briefly describe the model results and interpret the model parameters through a counterfactual scenario in the following section, before examining their implications in the subsequent discussion section.

5.1 Intercept Model

The first model, including only an overall intercept and varying intercepts for each of the 16 schools in the sample, estimated that there is substantial variation (standard deviation of 0.78 for the varying intercepts) between schools in bicycling levels. It also found that, on average, 20 percent of Davis children bicycled to school.

5.2 Covariates Model

The installation of rectangular rapid flashing beacons within a half mile of a school was associated with small decreases in bicycling, conditional on the influence of the other variables in the model. The model's estimate for the influence of Walk Score was strongly negative yet uncertain. Schools with high Bike Scores were more likely to have high bicycling rates, but the effect was also uncertain.

Though all three magnet programs had highly uncertain parameter estimates, the GATE and Montessori schools had substantially higher probabilities of bicycling to school, while the influence of being a Spanish Immersion school was more equivalent to that of a neighborhood school. Junior high students are substantially more likely to bicycle to school than elementary school children, while the model estimates for high school students was small, positive, and had a wide 89% credible interval spanning zero.

The model coefficients indicated that children were most likely to bicycle to school on Tuesdays and Wednesdays and least likely to bicycle on Thursdays and Mondays. Compared to winter, the model estimated that children were more likely to bicycle to school in the fall, spring, and summer, in ascending order of increasing probability. As maximum temperatures increased, children were more likely to bicycle to school. Rain appeared to be a strong deterrent to bicycling.

Even after accounting for school characteristics, physical characteristics, and aspects of the built environment, substantial variation remained between schools. However, inclusion of covariates slightly reduced the standard deviation of random intercepts, and in some cases, reduced previously large random intercepts almost to zero.

5.3 Full Model

I tested a number of different ways to summarize and conceptualize the influence of Active4.me program, including the mere presence of a parent volunteer on the bicycle rack count day, the number of scans during the week of the count, and the number of preceding weeks in which a parent volunteer scanner was present. The variable with the best explanatory power was the number of scans during the week of the count.

Schools with strong Active4.me programs, with parent volunteers present all five days of the week of the count, increased the probability that children would bicycle to school. In contrast, less robust Active4.me programs in which parent volunteers were only present one to four days during the count week, moderately decreased the probability of children bicycling to school, compared to the baseline of no Active4.me program at all.

The Monkey Money program provided a small, positive, and uncertain bump in the probability of children bicycling to school. This variable can be seen as an interaction term with Active4.me, as Monkey Money can only be accrued if Active4.me is present at the school. Therefore, Monkey Money provided a small boost to the effectiveness of Active4.me. The practice of distributing higher amounts of virtual Monkey Money on BTSD increased bicycling rates, though this was likely primarily due to the influence of BTSD. The model estimated that Monkey Money parties increase rates of bicycling in the weeks leading up to the party. Furthermore, Bike-to-School Day dramatically and unsurprisingly increased the likelihood that children bicycle to school.

The covariate coefficient estimates were similar to the covariate model in all but a few notable instances. The parameter estimates for Wednesdays and for spring decreased, thanks to the introduction of the BTSD variable in the full model. The coefficient for BTSD was positive, and since the BTSD celebration is held on a Wednesday in May (i.e. spring), the Wednesday and spring coefficients decreased as a consequence.

To ease the interpretation of the coefficients related to the encouragement efforts, I created a counterfactual posterior prediction plot to estimate the number of additional children who bicycle to school as a result of Active4.me, Monkey Money, and Monkey Money Parties, relative to a baseline without these programs (Figure 2). The baseline scenario and the counterfactual scenarios all shared the same values for the covariates, creating the following context: a neighborhood (non-magnet) elementary school with an enrollment of 500 children, on a Monday in the winter, with average temperature and no rain, with average Walk and Bike Scores, and not on a Bike-to-School Day. I chose the covariate values in order to return *conservative* estimates of additional children bicycling to school, thanks to setting the season to winter and the day as Monday, which have less positive associations with probability of bicycling to school, relative to other seasons and days of the week.

For this hypothetical school and context, Active4.me on its own was predicted to cause roughly five additional children, on average, to ride a bicycle to school, and the combined effects of Monkey Money and Monkey Money Parties increased that predicted total to approximately seven extra children bicycling to school. In other words, the Active4.me and Monkey Money encouragement programs were expected to boost the proportion of children bicycling to school by roughly one percent of this hypothetical school's population and by ten to fifteen percent compared to the hypothetical school's baseline bicycling mode share.

Table 5. Model Parameter Estimates

	Variables	Intercept Model Mean	Intercept Model SD	Covariate Model Mean	Covariate Model SD	Full Model Mean	Full Model SD
	Mean intercept	-1.37	0.20	-2.41	0.34	-2.31	0.33
	S.D. of random intercepts by school	0.78	0.15	0.66	0.18	0.62	0.18
	S.D. of BTSD random slopes by school	-	-	-	-	0.56	0.14
	Birch Lane	0.30	0.20	0.05	0.73	-0.01	0.62
	Cesar Chavez	-0.33	0.20	-0.01	0.52	-0.04	0.45
	North Davis	0.33	0.20	0.06	0.39	0.05	0.34
	Montgomery	-0.51	0.20	0.03	0.50	0.11	0.45
	Willett	0.46	0.20	0.22	0.37	0.30	0.33
	Pioneer	-0.46	0.20	-0.57	0.38	-0.57	0.33
	Korematsu	0.17	0.20	0.27	0.41	0.26	0.36
Random intercepts	***Patwin***	0.12	0.20	1.16	0.37	1.00	0.37
	Emerson	1.03	0.20	0.02	0.42	-0.03	0.38
	Holmes	1.22	0.20	-0.12	0.51	-0.09	0.47
	Harper	0.80	0.20	0.01	0.52	0.09	0.48
	Valley Oak	-0.36	0.20	0.00	0.47	0.03	0.45
	St. James	-1.59	0.22	-0.78	0.47	-0.67	0.48
	Waldorf School	-1.02	0.22	-0.37	0.51	-0.38	0.48
	Davis Senior	0.20	0.20	0.25	0.57	0.19	0.53
	King	-0.26	0.25	-0.28	0.55	-0.29	0.51
	Rectangular Rapid Flashing Beacon	-	-	0.07	0.01	0.05	0.01
	Walk Score	-	-	-0.48	0.70	-0.49	0.65
	Bike Score	-	-	0.69	0.79	0.73	0.70
	Neighborhood School	-	-	-	-	-	-
	Spanish Immersion	-	-	0.28	0.59	0.15	0.55
	GATE	-	-	0.92	0.50	0.83	0.46
	Montessori	-	-	1.07	0.84	1.07	0.74
	Elementary School	-	-	-	-	-	-
	Junior High School	-	-	1.93	0.57	1.94	0.54
	High School	-	-	0.56	0.63	0.64	0.61
	Monday	-	-	-	-	-	-
	Tuesday	-	-	0.21	0.02	0.19	0.02
	Wednesday	-	-	0.38	0.02	0.11	0.02
	Thursday	-	-	0.03	0.01	-0.02	0.02
	Friday	-	-	0.09	0.02	0.04	0.02
	Winter	-	-	-	-	-	-
	Fall	-	-	0.14	0.01	0.13	0.01
	Spring	-	-	0.17	0.01	0.04	0.01
	Summer	-	-	0.27	0.02	0.21	0.02
	Temperature (F)	-	-	0.14	0.01	0.17	0.01
	Presence of Rain	-	-	-0.26	0.01	-0.28	0.01
	Active4.me: not present	-	-	-	-	-	-
	Active4.me: 1-4 days a week	-	-	-	-	-0.06	0.02
	Active4.me: 5 days a week	-	-	-	-	0.10	0.01
	Monkey Money	-	-	-	-	0.01	0.02
	Monkey Money x Bike-to-School Day	-	-	-	-	0.08	0.05
	Monkey Money Party	-	-	-	-	0.04	0.02
	Bike-to-School Day	-	-	-	-	0.58	0.17
	WAIC	413009.9		409002.0		406619.3	
	Akaike weight	0		0		1	
	Number of observations	705		705		705	

Note: All models converged with $\hat{R} < 1.01$, number of effective samples > 1000 (see (Stan Development Team, 2016) for details of these two convergence metrics), and with Markov chains showing stationarity and good mixing for all parameters.

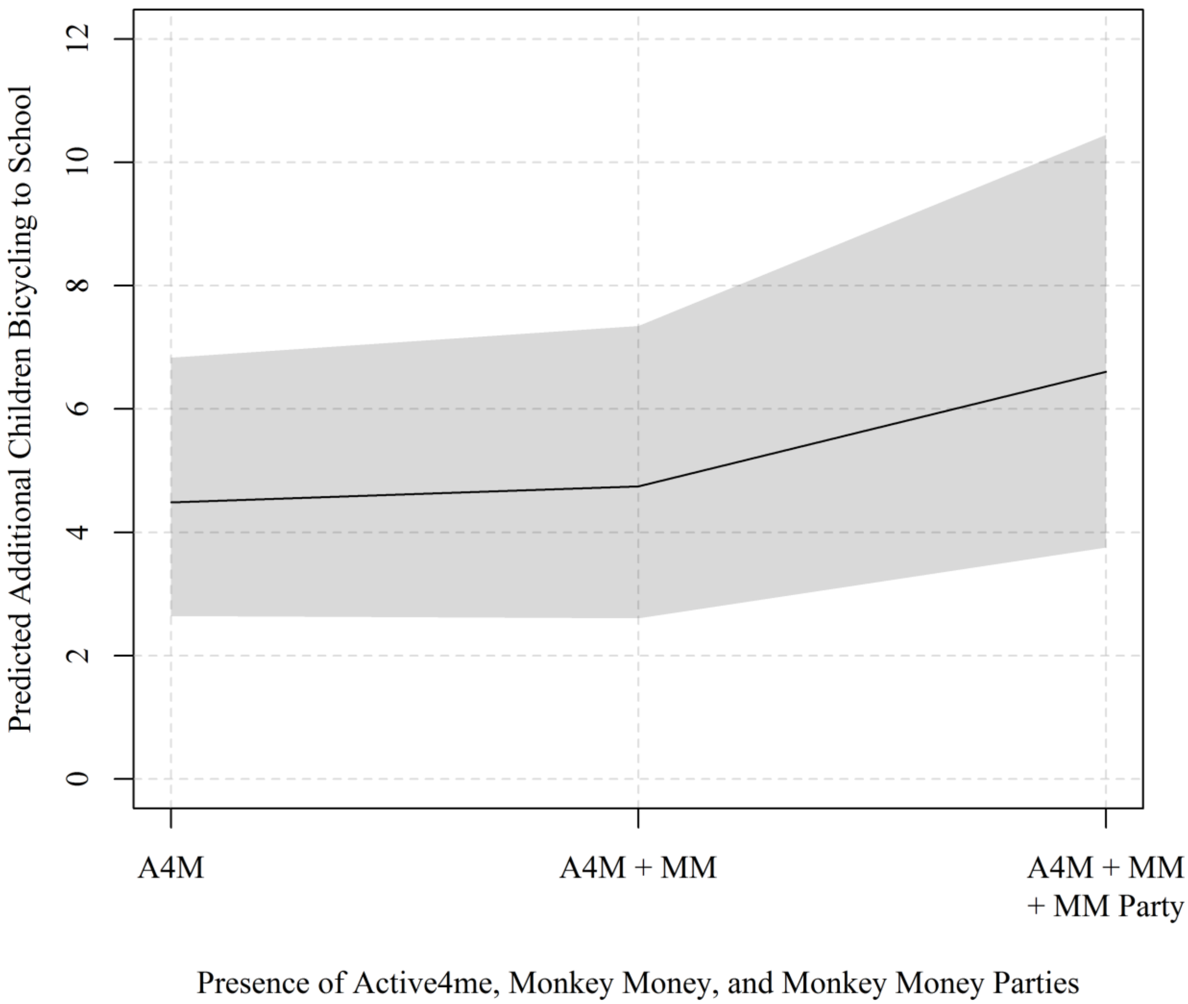

Figure 2. The Predicted Influence of Active4.me, Monkey Money, and Monkey Money Parties on the Number of Additional Children Bicycling to School

Note: The model predictions are based on the other variables in the model set to values that create the following baseline scenario: an elementary school with an enrollment of 500 children, on a Monday in the winter, with average temperature and no rain, a neighborhood school with average Walk and Bike Scores, and not on a Bike-to-School Day. The grey shading represents the 89th-percentile credible interval.

6 Discussion

6.1 Implications for Active School Travel

The finding that a robust Active4.me program boosts bicycling to school was consistent with previous research (McDonald et al., 2013) that demonstrates the efficacy of encouragement programs for active travel to school. The statistical model suggested that in a conservative scenario, the introduction of an Active4.me program can boost a primary school's existing bicycle mode share by ten percent, with further small gains due to the addition of a Monkey Money program.

Perhaps the most surprising finding was the strongly negative coefficient estimate for less robust Active4.me programs. It may be that introducing a system of tracking behavior has potential unforeseen adverse consequences. The decreased number of children bicycling to schools with less consistent Active4.me programs could be the result of extrinsically encouraging a behavior that was previously intrinsically motivated, consistent with findings from other fields (Gneezy, Meier, & Rey-Biel, 2011).

I was initially surprised to find that the magnet schools were estimated to have higher rates of bicycling than the lone neighborhood school, Patwin Elementary, since a greater proportion of Patwin's pupils are likely to live within feasible bicycling distance to school. However, these estimates were uncertain, and it was possible that this model result reflects the fact that Patwin schoolchildren were using a different active mode to get to school: walking. Evidence for this conjecture came from the full model with varying slopes for the effect of BTSD: Patwin had the highest random slope by far, indicating that on BTSD, the Patwin neighborhood schoolchildren could easily bicycle to school, and did so in droves.

6.2 Implications for Future Travel

American children and young adults are bicycling at historically low levels, and at levels well below those of "cycling nations" such as the Netherlands and Denmark (Pucher & Buehler, 2008). These patterns persist into adulthood, suggesting that in addition to national efforts to build bicycling facilities, bicycling experiences as a child can increase the probability of later adult bicycling. This conjecture, derived from cross-sectional, national-level patterns, is corroborated by evidence from studies using longitudinal data sets, which suggest that early travel experiences with alternative modes of transportation is associated with continuing to use alternative modes later in life (Smart & Klein, 2017) and with gaining the skills and attitudes necessary to use these modes (C. Thigpen, 2018; C. G. Thigpen & Handy, 2018). These long-term influences of childhood active travel are an important consideration, given active transportation's ability to increase the average American's level of physical activity and help address the environmental impacts of daily travel.

6.3 Policy Implications

The parent champions' hard work to run Active4.me scanning programs was voluntary. However, the statistical models suggested that the efficacy of an Active4.me program was predicated on the consistent presence of parent volunteers, each day of the week. Parent volunteers dedicated their personal time (to scan children in for Active4.me) and money (to purchase prizes for Monkey Money parties). In addition to small-scale tokens of appreciation, such as schools providing free coffee or tea for parent volunteers, it may be worth reimbursing parent volunteers with a small stipend, especially given evidence that gender, family roles, and social class disparities influence parent traffic safety volunteerism (McLaren & Parusel, 2011). The eligibility determination guidance suggests this is possible using funds from California's Active Transportation Program (ATP) or Congestion Management and Air Quality (CMAQ) Improvement Program, as long as the stipend is clearly not being used to pay volunteers for their time (Caltrans Divison of Local Assistance, 2015). As long as this condition is being met, I argue that reimbursing parent volunteers should be a welcomed attribute of a healthy Safe Routes to School program, particularly in other, less affluent cities, if finding volunteers is more challenging due to most households having dual-earning parents with less flexible schedules.

The MAP-21 federal authorization bill introduced a focus on performance and outcome-based evaluation of metropolitan planning organization's long range plans (U.S. Department of

Transportation, 2015). I suggest that in addition to evaluating existing policies, the feedback loop from policy evaluation to policy change should also include evaluation of programs not included in the initial policy's scope as a way to identify new avenues to achieve the same policy goals.

6.4 Suggestions for Future Research

Key components behind the high count frequency and long duration of the city of Davis' evaluation effort were the bicycle rack counts' ease of implementation and low cost. In contrast, classroom tallies or parent surveys require greater effort and time to implement, as also documented in Canada (Sersli, Gray, & Winters, 2016). I recommend bicycle rack counts to cities interested in evaluating school-level policies and programs over multi-year time horizons, with sufficient data to detect impacts, and in a way that requires minimal data collection burden.

Despite the non-random application of the Active4.me and Monkey Money programs at Davis schools over time, the temporal pattern nonetheless yielded a robust quasi-experimental design. I suggest that planners incorporate this approach, called a "stepped wedge design", into their programming plans from the beginning. By only having a few schools adopt a new program or policy at any given time, the other schools were able to serve as control cases in later evaluation. This approach can also reduce the time and resource burdens of program implementation and allow for lessons learned at the first schools to experience the intervention to be applied from the beginning at the remaining schools.

This study demonstrated that the encouragement efforts of Active4.me and Monkey Money can increase rates of bicycling to school. Further studies could evaluate other aspects of these programs, such as the influence of stipends to reimburse parent volunteers for their time or the impact of changing a magnet school to a neighborhood school. Researching the influence of the "human element" (i.e. the interaction between students and parent volunteers) in the Active4.me scanning program could also be worthwhile, as comparable scanning programs (e.g. the "Boltage" scanner program) relied on RFID towers rather than parent volunteers (McDonald et al., 2013).

7 Conclusion

I analyzed a decade of data collected by the city of Davis on local schools' bicycle rack occupancy to evaluate the influence of three major encouragement efforts: Bike-to-School Day, Active4.me, and Monkey Money. In addition to well-established physical, environment and school characteristics, I found that all three programs increase the probability of children bicycling to school. A robust Active4.me program increased rates of bicycling to school, as did an imminent Monkey Money party within the next few weeks. BTSD dramatically increased the number of children bicycling to school, particularly in neighborhood schools. I suggest that the parent volunteer efforts to run encouragement programs such as these could benefit from stipends and that the results of these successful encouragement efforts have positive long-term implications for children's later travel patterns as adults.

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