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Evidence on the efficacy of school-based incentives for healthy living

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ABSTRACT

We analyze the effects of a school-based program that offers children an opportunity to win prizes if they walk or bike to school during prize periods. We use daily child-level data and individual fixed effects models to measure the effect of the prizes, with variation in the timing of prize periods across different schools allowing us to estimate models with calendar-date fixed effects to control for day-specific attributes, such as weather and proximity to holidays. On average, we find that being in a prize period increases the riding behavior of participating children by sixteen percent, a large impact given that the prize value is just six cents per student. We also find that winning a prize lottery has a positive impact on ridership over subsequent weeks; consider heterogeneity across prize type, gender, age, and calendar month; and explore differential effects on the intensive versus extensive margins.

1. Introduction

The World Health Organization reports that increasingly sedentary lifestyles are "one of the more serious yet insufficiently addressed public health problems of our time," as they lead to elevated risks of obesity, cardiovascular diseases, diabetes, colon cancer, high blood pressure, osteoporosis, lipid disorders, depression, and anxiety.[1] As these health concerns have gained prominence in policy discussions, researchers have recently begun to study how health-related behaviors might be improved by altering incentives. In particular, researchers have explored the role of incentives in the formation of exercise habits (Charness & Gneezy, 2009), weight loss (Cawley & Price, 2011; Volpp et al., 2008), and smoking cessation (Volpp et al., 2009). However, very little research in this area has focused on children's health-related behaviors despite the fact that obesity rates have tripled among American youth over the last thirty years. This paper aims to fill this important gap in the literature by considering how an opportunity to win prizes at school affects children's exercise habits.[2]

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[1] http://www.who.int/mediacentre/news/releases/release23/en/index.html.

[2] Although a large literature considers the interplay between schooling and health, most of these papers focus on the effects of completed education rather than targeted interventions. For example, see Albouy and Lequien (2009), Altindag, Cannonier, and Mocan (2011), Groot and van den Brink (2007), Jurges, Reinhold, and Salm (2011), Kenkel, Lillard, and Mathios (2006), Lleras-Muney (2005), McCrary and Royer (2011), Silles (2009, Tenn, Herman, and Wendling (2010)). Besides Just and Price (2011), which is discussed in more detail below, the only other papers

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Specifically, we analyze the effects of a school-based incentive program that was implemented with the intention of promoting physical activity through healthy modes of transportation.[3] At participating schools, principals specified "prize periods" which usually lasted one week. Children who rode their bicycle to school each day of a prize period were entered into a lottery to win a ten-dollar cash prize or a ten-dollar voucher to a local bicycle store. We estimate the effects of the program with daily child-level data on which kids rode or walked to school from seven schools in and around Boulder, Colorado, spanning the 2006–2007 through 2009–2010 school years. Because we have longitudinal data and variation in the timing of prize periods across different schools, we are able to address two types of selection that might otherwise bias the estimates. In particular, our preferred models exploit within-child variation over time by including individual fixed effects in order to address the possibility that the program affects the composition of children at the schools under consideration. Further, our preferred models exploit variation in the timing of prize weeks across schools by including exact-date fixed effects in order to address the possibility that school principals chose prize weeks on the basis of weather forecasts or other day-specific attributes common to the schools.

Our study is motivated by two particularly salient statistics that suggest that the elementary-school years are especially deserving of research. First, the obesity rate has risen more dramatically for elementary-school-aged children than it has risen for either older or younger children.[4] Second, the obesity-age profile is sharply positive during the elementary school years and flat at older ages. In 2007–2008, for example, the obesity rate was 10.4 percent for children aged two to five, 19.6 percent for children aged six to eleven, and 18.1 percent for those aged twelve to nineteen. The pattern of slightly falling obesity rates from elementary-school-ages to middle- and high-school ages has been quite stable since the late-1970s. In contrast, the gap in obesity rates between pre-school-aged children and elementary-school-aged children has changed dramatically over time. While the gap was virtually non-existent in the 1960s, it has grown steadily over the past several decades. Today the obesity rate for elementary-school-aged children is nearly twice the rate for pre-school-aged children.

Only two other studies consider the effects of incentives on children's health-related behavior. Carpenter and Stehr (2012) demonstrate that youth bicycle helmet laws reduced fatalities and increased helmet use but reduced youth bicycling. Just and Price (2011) analyze the impact of school-based incentives for healthy eating. Their experiment, which provided rewards to children for eating fruits or vegetables during five treatment days over a span of two to three weeks at fifteen schools, finds dramatic results – a reward valued at approximately 25 cents per child increases the fraction of children eating fruits or vegetables by 27 percentage points (80 percent). Our study complements Just and Price (2011) in several ways. Most obviously, they explore one of the two recommended behavioral changes that have the potential to reduce obesity (diet), while we explore the other (exercise). Further, both studies consider the efficacy of non-cash prizes relative to cash prizes.[5] In addition, while they consider a school-based incentive over a relatively short time horizon, we consider an incentive program that spans several school years. A challenge that both studies face is a lack of data on health outcomes, such as body mass index, which would be useful in order to measure the extent to which the observed behavioral improvements lead to improved health.

We find that the incentive provided during prize periods increases the probability that a participating child rides her bicycle to school by 3.9 percentage points, or 16.4 percent. Given that prize value was small (ten dollars) and that the lottery aspect of the reward mechanism meant that only one child was given such a prize (implying a prize value of six cents per participating student), these results highlight a low-cost approach to promoting exercise among children. That said, it is important to note that this effect may be driven in part by reminders, peer pressure, and other aspects of the program in addition to the opportunity to win a prize. In addition, our data do not allow us to test whether there are any offsetting impacts, or positive spillovers, on other types of exercise.

Our results also suggest that cash prizes have greater effects than vouchers of equal value. Further, conditional on eligibility, we find that winning a prize lottery has a persistent effect, motivating children to ride more often in subsequent weeks. We also explore heterogeneity across age, gender, and the time of year and consider the extent to which there are differential effects on the intensive margin versus the extensive margin.

The remainder of the paper is organized as follows. Section 2 describes the program and data in greater detail. Section 3 reports the results of our empirical analysis. Lastly, Section 4 provides concluding remarks.

2. Program design and data description

The intervention we consider was aimed at increasing physical activity among children by promoting non-motorized transport to and from school. The incentive

that consider the contemporaneous relationship between schooling and health are Kaestner and Grossman (2009), who consider the relationship between weight and student achievement, Rees and Sabia (2010) and Dills, Morgan, and Rotthoff (2011), who consider the effect of exercise on academic performance, and Hansen and Lang (2011) who find a positive relationship between being in school and the probability of suicide.

[3] The program under consideration is currently known as Boltage but was founded under the name Freiker – FRE-quent b-IKER.

[4] From 1963–1965 to 2007–2008, obesity rates rose from 5.0 percent to 10.4 percent for children aged two to five, from 4.2 to 19.6 percent for children aged six to eleven, and from 6.6 to 18.1 percent for those aged twelve to nineteen. These and other statistics mentioned in this paragraph are discussed from Ogden, Carroll, Curtin, Lamb, and Flegal (2010) whose analysis uses data from the National Health and Nutrition Examination Survey (NHANES).

[5] Just and Price (2011) also explore how the timing of the reward (immediately versus one month later) affects behavior.

structure provided by the program was as follows: in order to encourage children to exercise, those who rode or walked to school every day during a pre-announced "prize period" had their names entered into a drawing to win a prize. The prize, given to a single child at the end of each prize period, was ten dollars in cash during the first two years of the program, but was replaced by a ten-dollar voucher to neighborhood bicycle stores in subsequent years. In order to encourage a broader base of winners, after a child won a drawing, she was ineligible for future drawings if any children who fulfilled the requirements had not yet won a drawing. Prize periods were chosen throughout the year at the discretion of each school's principal.[6] More than 81 percent of prize periods spanned exactly five days, although shortened school weeks, severe weather, and principal discretion led to some prize periods which lasted six days (0.9 percent), four days (14.0 percent), three days (1.8 percent), and two days (1.2 percent).

The data used in this study were collected as a part of the program's implementation. Information on gender and age was collected from the online registration form for the program. Our data on active commuting behavior was collected by radio-frequency identification (RFID) tags. These were affixed to each child's bicycle helmet, so that her arrival to school could be recorded by RFID readers installed close to the school's bicycle racks. Once such a tag was is in place, participating students needed only pass under a RFID reader in order to register as having actively commuted in a given morning.[7] While the program was conceived around the idea of promoting activity through increased bicycle use, other forms of active commuting (e.g., foot-powered scooters, pogo sticks, skateboards) were also allowed, including walking. "Walkers" were also given RFID tags and were not distinguished from "riders" in the data. In the text, we generally use "bikers" and "riding" since biking was the dominant active commuting method.[8]

Our data shows which days each student did and did not actively commute to school for the duration of the program. Since it is crucial to our ability to obtain a valid counterfactual for the riding behavior observed during prize periods, it is important to note that children had an incentive to report whether they actively commuted to school during non-prize periods as well. In particular, the program also included end-of-year rewards based on cumulative activity throughout the year – as students accumulated more non-motorized trips to school, they became eligible for increasingly valuable prizes at an end-of-year drawing, with top prizes including iPods® and digital cameras.[9] As such, our estimates should be interpreted as the effect of the ten-dollar incentive *over and above* the effects of the end-of-year incentives. We also note that administrators reminded students that cheating in the active-commuting initiative was equivalent to cheating on a test and, at some schools, students were required to sign an honor code claiming that they would not cheat.[10]

Our sample includes all children with at least one recorded active commute at seven participating schools within a 15-mile radius of Boulder, Colorado.[11] All of the schools include the children in Kindergarten through sixth grade, although two schools also include children in grades seven and eight. Overall, the data spans the four school years running from the fall of 2006 to the spring of 2010 but, because the program was not implemented at every school in every year, the duration of the time series varies from school to school. In particular, the sample includes four years of data for three schools; three years of data for one school; two years of data for one school; and one year of data for two schools. These eight schools provide 1589 child observations, 3113 child-by-school-year observations, and 536,613 child-by-exact-day observations.

It is important to note that not all students at these schools participated in this voluntary program. The National Center for Education Statistics Common Core of Data records that 10,207 children were enrolled at these schools during the sampling period, implying a participation rate of approximately 30 percent. Thus, in order to obtain estimates of the effect of prize periods on *all* students rather than participating students, one simply needs to multiply the estimates presented in the subsequent sections by 0.3.

Summary statistics for the sample of participants are shown in Table 1. 57 percent of the children in the sample are male and the average age is approximately nine. Because the program was introduced to different schools at different times, some schools contribute more observations than others and a relatively large share of the data comes from later years. Approximately half of the observations correspond to prize periods, suggesting that principals were quite active in implementing the program. However, just 20 percent of observations correspond to prize periods with cash rewards, because a majority of the data comes from later years when vouchers were used instead of cash. On average, across prize periods and non-prize periods, children in the sample chose to ride to school almost a quarter of the time. The next section explores the extent to which prize periods had an effect on the decision to ride.

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[6] We discuss the potential for this discretion to introduce bias – and the steps we take to address this concern – below.

[7] A video of RFID in action is available at http://www.streetfilms.org/boulder-goes-bike-platinum/. In addition, parents could log into a password-protected website and manually enter their child as having actively commuted to school if her child forgot to pass under the reader.

[8] RFID tags cost $1.15 each, the reader costs $6890, and annual maintenance costs $950.

[9] One school which we include in the analysis focused *solely* on end-of-year awards. As such, it serves solely to help identify day-of-year fixed effects.

[10] In the end, administrators report that they have not found cheating to be a problem.

[11] More data was made available but inconsistencies in the application of treatment made the value of their inclusion questionable. For example, in one school, prizes were promised by the principal but not awarded to eligible children.

Table 1
Summary statistics.

Ride (1 if yes)	0.23
Prize (1 if yes)	0.50
Cash prize (1 if yes)	0.20
Male (1 if yes)	0.57
Age	9.32
School 1 (1 if yes)	0.27
School 2	0.23
School 3	0.08
School 4	0.16
School 5	0.05
School 6	0.13
School 7	0.08
2006/2007 (1 if yes)	0.06
2007/2008	0.15
2008/2009	0.37
2009/2010	0.42
Child observations	1589
Child by school year observations	3113
Child by exact day observations	536,613

Notes: Sample means for the listed indicator variables are constructed using child-by-exact day observations. "Ride" is equal to one on days when a child uses any method of active commuting to get to school.

3. Empirical analysis

3.1. Overall effects of the program

To begin, we focus only on within-child variation over time to estimate the effects of being in a prize period on the probability of riding on a particular day.[12] In particular, we estimate the linear-probability model,

$$Ride_{id} = \beta Prize_{id} + \alpha_{iy} + u_{id}, \quad (1)$$

where $Ride_{id}$ is an indicator variable equal to one if child i actively commutes to school on calendar day d; $Prize_{id}$ is an indicator variable equal to one if there is a prize period ongoing on date d at child i's school; α_{iy} are child-by-academic-year fixed effects; and u_{id} is a random error term. The set of child-by-academic-year fixed effects control for all of a child's characteristics in a given year, including the characteristics of her school, that might be related to both their probability of riding and the specification of prize periods. This accounts for several sources of potential bias. For example, with these fixed effects in the model, the estimates would continue to be unbiased even if schools where riding to school was very popular had more prize periods. Implicitly, this model uses each child's probability of riding during non-prize periods as the counterfactual for her probability of riding during prize periods. The identifying assumption, which will be relaxed in subsequent specifications, is that principals do not systematically choose to have prize periods at times of the year when children are systematically more/less likely to ride to school. We have estimated the standard errors separately clustering on the individual, school-by-year, and school – we report the most conservative estimates which cluster at the school level.

The estimated effect of prize periods based on Eq. (1) is reported in Column 1 of Table 2. This estimate suggests that participating students are 2.0 percentage points more likely to ride during prize periods than non-prize periods, although the estimate is not statistically significant at conventional levels. In Column 2, we include day-of-the-week fixed effects. This controls for any direct effects of particular days on ridership, but also accounts for potentially non-random prize-period lengths (i.e., those not falling on the usual Monday–Friday pattern) that would otherwise influence the estimated treatment effect. These controls do not change the estimated effect of prize periods.[13]

It is important to note that any systematic relationship between weather patterns and the specification of prize periods may bias the estimated effects presented in columns 1 and 2. The direction of this potential bias is unclear, however. Although students are likely to ride less when weather is bad, principals may respond by increasing or decreasing the incentive to ride during these times. We address this potential issue in Column 3 by including year-by-month fixed effects and in Column 4 by including year-by-week fixed effects. These estimates suggest that the prize periods significantly increase the probability a child actively commutes by 4.2–4.8 percentage points, or 17.6–20.4 percent. That these estimated effects are larger than the estimated effects in Columns 1 and 2 suggests that prize periods tend to be more frequent during months (weeks) of the year when riding behavior tends to be low.

Our preferred model takes the controls for time of year as far as the data allows by including exact-date fixed effects in the empirical model:

$$Ride_{id} = \beta Prize_{id} + \alpha_{iy} + \gamma_d + u_{id}. \quad (2)$$

In this model, the estimates exploit variation in the timing of prize periods across different schools. As such, the estimates use the *change* in riding behavior from day g to day h at schools where days g and h were treated similarly (i.e., both occurred during prize periods or neither occurred during prize periods) as a counterfactual for the *change* observed at schools in which one occurs during a prize period and the other does not. The estimate based on this model is shown in Column 5. This estimate implies that prize periods increase ridership among participating students by 3.9 percentage points, or 16.4 percent.[14]

[12] Although it may seem appealing to instead estimate the effect of a student being in a prize period on a given day *and still being eligible to win the weekly prize because he rode all previous days of the prize period*, we do not take this approach out of concern that *continued* eligibility is less likely to be exogenous than is being in a prize week. For example, a child who catches a cold will have a reduced likelihood of riding to school for several days but will become ineligible for the weekly contest after the first day he does not ride. In general, this approach would be susceptible to all such unobservable determinants of ridership that are serially correlated over time.

[13] The estimates on each day of the week (not shown) reveal that there tends to be relatively high ridership on Wednesdays and low ridership on Mondays and Fridays.

[14] Although the estimate only changes slightly across the specification that controls for year-by-week fixed effects and the specification that controls for exact-date fixed effects, we note that such a change is not unreasonable given that prize-periods did not always span the five days of a week.

Table 2
Estimated effect of being in a prize period on the probability of riding to school.

	(1)	(2)	(3)	(4)	(5)
Prize	0.020	0.020	0.048***	0.042**	0.039**
	(0.013)	(0.013)	(0.012)	(0.016)	(0.015)
Observations	536,613	536,613	536,613	536,613	536,613
Child-by-year observations	3113	3113	3113	3113	3113
Child observations	1589	1589	1589	1589	1589
Pr(ride) during non-prize weeks	.24	.24	.24	.24	.24
Impact (%)	8.3	8.3	20.4	17.6	16.4
Child-by-year FE	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	No	Yes	Yes	Yes	n/a
Year-by-month FE	No	No	Yes	n/a	n/a
Year-by-week FE	No	No	No	Yes	n/a
Exact-date FE	No	No	No	No	Yes

Notes: All estimates are based on linear probability models. Standard error estimates, clustered on the school, are shown in parentheses. Percent impacts are calculated as one hundred times the estimated treatment effect divided by the probability that students ride during non-prize periods.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

3.2. Effects of cash prizes versus voucher prizes

As described above, prize winners were given cash during the first two years of the program while they were given certificates worth ten dollars at nearby bicycle stores in subsequent years. Thus, the estimated effects discussed in the previous section represent a weighted average of the effects of the different reward schemes. In order to explore the extent to which the cash prizes used in the first two years of the program had different effects from the vouchers used in subsequent years, we add to the empirical models discussed above an interaction between an indicator for being in a prize week and an indicator for years in which cash prizes were awarded. As such, our preferred model is

$$Ride_{id} = \beta Prize_{id} + \delta Prize_{id} \times Cash_y + \alpha_{iy} + \gamma_d + e_{id}, \qquad (3)$$

where β is the effect of prize periods in which the prize is a voucher and δ is the *additional* effect of prize periods in which there is a cash prize the effect of *over and above* the effect of prize periods in which the prize is a voucher.

Panel A of Table 3 presents the results of this exercise. Although it is not statistically significant, our preferred estimate in Column 5, which includes child-by-year and exact-date fixed effects, suggests that cash prizes induce levels of active commuting approximately four-and-a-half-times higher than voucher prizes. The point estimates imply that the opportunity to win a voucher increases the probability a participating child rides by 3.2 percentage points (13.6 percent) while the opportunity to win cash induces a 14.4 percentage-point increase (61 percent). Though our estimates are by no means definitive, as the standard error estimates are fairly large, these results are consistent with Just and Price (2011) who also find children to be most responsive to cash in addition the general expectation that individuals should prefer unrestricted rewards to those that impose restrictions on use (Waldfogel, 1993). Further, to impose restrictions that relate closely to the activity being incentivized – recall, the vouchers were only redeemable at area bicycle stores – may be even more costly. For example, whether vouchers that could be used to purchase toys or candy would yield the same drop off in incentive power remains an open question.

Because cash prizes were awarded in the first two years of the program and vouchers in the second two, the reduced incentive of vouchers found in Panel A might actually reflect a more-general dampening effect of the program over time. In order to rule out this explanation, we estimate

$$Ride_{id} = \beta Prize_{id} + \delta Prize_{id} \times Cash_y + \eta Prize_{id} \times YearsOfProgram_{id} + \alpha_{iy} + \gamma_d + e_{id}, \qquad (4)$$

where the variable *YearsOfProgram* is the number of years since the program was implemented at an individual's school. This equation separately estimates the additional effectiveness of cash (δ) and the extent to which the program becomes more or less effective over time (η). The results of this analysis, shown in Panel B, indicate that additional effect of cash is not due to changes in the effect of the program over time. Further, they suggest that the efficacy of the program does not diminish in subsequent years after introduction.

3.3. Heterogeneity across gender and age

Obesity rates vary with gender and age, and in Table 4 we look at whether the program had heterogeneous effects on riding by gender and age. First, columns 1 and 2 estimate the effects separately for participating males and females using our preferred model. These estimates are nearly identical. Both male and female children ride 24 percent of the time on non-prize-period days, the opportunity to win a prize increases male ridership 4.0 percentage points and increases female ridership 3.7 percentage points. These estimates correspond to effects of 16.9 percent and 15.6 percent, respectively.

In columns 3–7 we report the estimated effects for subsamples stratified by age in two-year increments. Across these columns, prizes appear to have similar effects across ages five through ten, increasing ridership from 4.1 to 4.5 percentage points. However, the program appears to lose

Table 3
Do cash prizes have bigger impacts than vouchers?

	(1)	(2)	(3)	(4)	(5)
Panel A: estimating the additional effect of cash prizes					
Prize	0.019	0.019	0.041**	0.036*	0.032*
	(0.014)	(0.014)	(0.012)	(0.015)	(0.014)
Prize × cash	0.003	0.003	0.044	0.051	0.112
	(0.023)	(0.023)	(0.044)	(0.073)	(0.092)
Observations	536,613	536,613	536,613	536,613	536,613
Child-by-year observations	3113	3113	3113	3113	3113
Child observations	1589	1589	1589	1589	1589
Pr(ride) during non-prize weeks	.24	.24	.24	.24	.24
Coupon impact (%)	8	7.9	17.3	15.3	13.6
Cash impact (%)	9.1	9.1	35.7	37	61
Child-by-year FE	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	No	Yes	Yes	Yes	n/a
Year-by-month FE	No	No	Yes	n/a	n/a
Year-by-week FE	No	No	No	Yes	n/a
Exact-date FE	No	No	No	No	Yes
Panel B: disentangling the effect of cash from differential effects over time					
Prize	0.065	0.065	0.058	0.035	0.042
	(0.050)	(0.050)	(0.041)	(0.045)	(0.051)
Prize × cash	−0.017	−0.017	0.035	0.052	0.107
	(0.032)	(0.032)	(0.049)	(0.079)	(0.091)
Prize × program year	−0.015	−0.015	−0.006	0.000	−0.003
	(0.014)	(0.014)	(0.012)	(0.012)	(0.014)
Observations	536,613	536,613	536,613	536,613	536,613
Child-by-year observations	3113	3113	3113	3113	3113
Child observations	1589	1589	1589	1589	1589
Pr(ride) during non-prize weeks	.24	.24	.24	.24	.24
Coupon impact (%)	27.6	27.6	24.5	14.7	17.9
Cash impact (%)	20.3	20.5	39.4	36.7	63
Child-by-year FE	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	No	Yes	Yes	Yes	n/a
Year-by-month FE	No	No	Yes	n/a	n/a
Year-by-week FE	No	No	No	Yes	n/a
Exact-date FE	No	No	No	No	Yes

Notes: All estimates are based on linear probability models. Standard error estimates, clustered on the school, are shown in parentheses. Percent impacts are calculated as one hundred times the estimated treatment effect divided by the probability that students ride during non-prize periods.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4
Heterogeneity across gender and age.

	(1) Male	(2) Female	(3) Age 5–6	(4) Age 7–8	(5) Age 9–10	(6) Age 11–12	(7) Age 13–14
Prize	0.040**	0.037*	0.045*	0.041	0.043*	0.035**	0.012
	(0.014)	(0.018)	(0.019)	(0.022)	(0.018)	(0.014)	(0.011)
Observations	308,369	228,244	53,624	153,565	163,156	122,835	38,003
Child-by-year observations	1789	1324	314	894	947	708	219
Child observations	884	705	186	662	720	501	158
Pr(ride) during non-prize weeks	.24	.24	.21	.28	.26	.23	.05
Impact (%)	16.9	15.6	21.4	15.0	16.6	15.2	22.3
Child-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exact-date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All estimates are based on linear probability models. Standard error estimates, clustered on the school, are shown in parentheses. Percent impacts are calculated as one hundred times the estimated treatment effect divided by the probability that students ride during non-prize periods.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

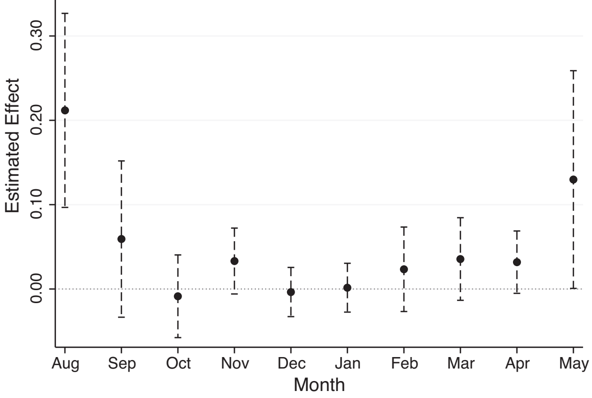

Fig. 1. Estimated effects on riding behavior across the year. *Notes:* All estimates are based on linear probability models in which an indicator variable for being in a prize period is interacted with each month of the year, in addition to child-by-school-year fixed effects and exact-date fixed effects. 95-Percent confidence intervals are shown around point estimates.

power at older ages, as the estimated treatment effect is 3.5 percentage points for eleven- and twelve-year-olds and only 1.2 percentage-points (and no longer statistically significant) for thirteen- and fourteen-year olds.

3.4. Heterogeneity by time of year

Incentives might have different effects at different times of the year, perhaps because of weather or spillovers from school holidays. Fig. 1 plots the estimated effect of prize periods by the month of the year. The estimation strategy continues to control for child-by-year and exact day fixed effects, but breaks the estimated effect of prize weeks out by month with a series of month indicator variables interacted with prize week status:

$$Ride_{id} = \beta_m Month_m \times Prize_{id} + \alpha_{iy} + \gamma_d + e_{id}. \quad (5)$$

In Fig. 1, we present estimated-treatment effects (and associated 95-percent confidence intervals) for each month of the year. These estimates reveal a systematic pattern, with the strongest effects occurring towards the beginning and end of the school year. Although we cannot rule out other mechanisms, this may be due to increased costs of active commuting during the winter. In support of this hypothesis, the estimated-prize-week effect is much larger in November than October while November had far less precipitation than October during the years we consider.[15]

[15] In particular, Boulder, Colorado had 3.71 in. of precipitation in October of 2006 versus 0.74 in. in November of 2006, 1.38 in. of precipitation in October of 2007 versus 0.47 in. in November of 2007, 1.18 in. of precipitation in October of 2008 versus 0.13 in. in November of 2008, and 3.26 in. of precipitation in October of 2009 versus 0.93 in. in November of 2009. These and similar statistics are available from the Earth System Research Laboratory, Physical Sciences Division: http://www.esrl.noaa.gov/psd/boulder/Boulder.mm.precip.html.

3.5. Effects on the extensive versus intensive margins

In order to consider the intensive and extensive margins of commuting behavior, we collapse the data to the child-by-week level. As such, we regress measures of weekly riding activity on whether or not a week corresponded to a prize period.[16] As outcome variables, we consider the probability that a child rode to school more than D times in a given week for $D = \{0, 1, 2, 3, 4\}$. We continue to use a linear probability model and to control for student-level characteristics in a flexible manner by including student-year and week fixed effects in the empirical model.

Column 1 of Table 5 focuses on the extensive margin, estimating the impact of a prize period on the probability that a participating child rides to school at least once in a given week. The estimates imply that prize weeks raise the probability a child rides one or more times by approximately 10 percentage points, which corresponds to a 25 percent increase over non-prize weeks where 41 percent of the children ride at least once. Given the outcome variable under consideration, this estimate can be interpreted as evidence that the incentive induces children to ride who typically would not.

Columns 2–5 of Table 5 focus on the intensive margin, sequentially estimating the effect on the probability that a child rides to school more than one, two, three, and four times in a given week. Although the estimated percentage point impacts tend to fall moving from left to right, which suggests that the incentive has relatively weak impacts at higher margins, the story is different when one considers the baseline probabilities with which children tend to ride more than D days in a given week for each D. In particular, the percent impacts *increase monotonically* in D. These estimates suggest that prize periods increase the probability that a child rides to school five days in a week by 63.7 percent. The growing percentage impact across Columns 2–5 indicates that there are disproportionate effects of prize periods on commuting behavior – the number of children riding five days is increased proportionally more than the number riding four or more days, the number of children riding four or more days is increased proportionally more than the number of children riding three or more days, and so on.

3.6. Effects of winning a prize lottery

In this subsection, we analyze the effect of winning a prize lottery on a child's subsequent activity. Because there are multiple mechanisms through which winning may affect a child's riding behavior, it is not clear *ex ante* what effects one should anticipate. As described in Section 2, once a child has won a prize she cannot be selected in future drawings, unless there are no other eligible children who have not yet won a prize. As such, winning may reduce a child's subsequent riding behavior by reducing the impact of prize periods. On the other hand, being rewarded for

[16] For this analysis, we restrict our attention to five-school-day weeks. Further, we do not use any weeks in which a prize period spanned a portion of the week.

Table 5
Estimated effects on intensive and extensive margins (analysis at weekly level).

Outcome	(1) Rides > 0	(2) Rides > 1	(3) Rides > 2	(4) Rides > 3	(5) Rides > 4
Prize	0.104**	0.111**	0.097***	0.080**	0.062**
	(0.036)	(0.032)	(0.024)	(0.022)	(0.019)
Observations	68,725	68,725	68,725	68,725	68,725
Child-by-year observations	3113	3113	3113	3113	3113
Child observations	1589	1589	1589	1589	1589
Pr(ride) during non-prize weeks	.41	.33	.26	.19	.10
Impact (%)	25.1	33.7	38.0	43.0	63.7
Child-by-year FE	Yes	Yes	Yes	Yes	Yes
Year-by-week FE	Yes	Yes	Yes	Yes	Yes

Notes: All estimates are based on linear probability models. Standard error estimates, clustered on the school, are shown in parentheses. Percent impacts are calculated as one hundred times the estimated treatment effect divided by the probability that students ride at least *D* times during non-prize periods.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

their activity may lead children to associate more positive feelings with riding to school, inducing them to ride more often.

In order to measure the effect of winning a prize drawing, we estimate a model with a series of indicator variables that reflect whether a child won a prize in the past fifteen days in addition to a series of indicator variables that reflect whether a child was eligible to win a prize (by riding every day of a prize period) in the past fifteen days. That is, we estimate

$$Ride_{id} = \sum_{k=1}^{15} \delta_k Win_{i,d-k} + \sum_{k=1}^{15} \beta_k Eligible_{i,d-k} + \gamma_{iy} + \gamma_d + e_{id}, \quad (6)$$

where $Ride_{id}$ is an indicator variable that equals one if child i rides on exact date d, $Win_{i,d-k}$ is an indicator variable that equals one if child i won a prize drawing k days ago, and $Eligible_{i,d-k}$ is an indicator variable equal to one if child i was eligible to win a prize drawing held k days ago, while γ_{iy} and γ_d are child-by-year and exact-day fixed effects, respectively. Essentially, this model compares the activity of prize-drawing winners to the activity of children who were eligible but not selected in a prize drawing.

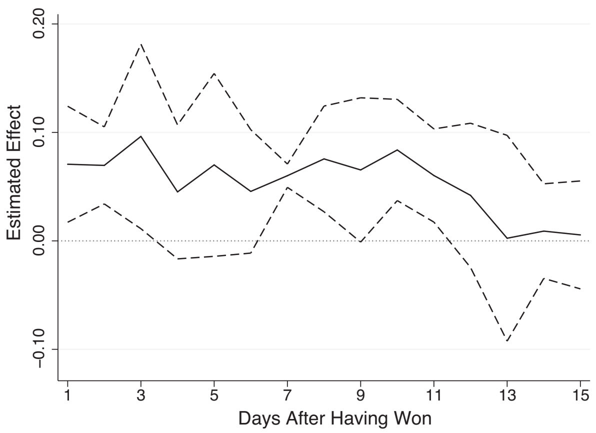

Fig. 2. Estimated effects of winning a prize drawing conditional on eligibility by time since winning. *Notes:* All estimates are based on linear probability models that include a set of indicator variables for having won a prize drawing k school days ago for $k = \{1, 2, \ldots, 15\}$, in addition to a similar set of indicator variables for having been eligible to win a prize drawing in prior days, child-by-school-year fixed effects and exact-date fixed effects. 95-Percent confidence intervals are shown around point estimates.

We present these estimates in Fig. 2, showing that being selected in a prize drawing has a positive impact on active commuting. Further, the effect appears to persist for at least two weeks. Beyond two weeks, the effect appears to fade to zero.

4. Conclusion

In this paper, we have assessed the efficacy of a school-based program for promoting physical activity among children. Using data generated as part of the Freiker/Boltage pilot program, our findings indicate that children are highly responsive to small weekly prize lotteries that reward active commuting to school. Although there is suggestive evidence that ten-dollar-cash prizes have the greatest effect, ten-dollar vouchers to a local bicycle store increase ridership by 13.6 percent among participants. Prize periods encourage ridership along the extensive margin and all intensive margins, increasing the number of children who ride once per week, twice per week, and so on. In addition, *winning* a prize lottery also motivates children to increase their activity even though, under the program rules, it substantially reduces their probability of winning future lotteries.

To our knowledge, we provide the first systematic study of the effects of economic incentives on children's exercise behavior. The results suggest that school-based initiatives can be successfully employed as a tool to increase physical activity, even with very inexpensive rewards. Future work will be necessary to explore whether children respond similarly in alternative settings and whether alternative reward mechanisms might be more effective.

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