Ambient Air Conditions and Variation in Urban Trail Use

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ABSTRACT *This study examines the effect of air quality and administrative policies on use of urban trails in Indianapolis, IN. Attention is focused on two policy variables: (1) issuance of air pollution advisories and (2) the adoption of Daylight Savings Time. Results suggest that while trail use varies with air quality, current public advisories regarding air pollution may be of limited effectiveness in reducing trail users' exposures to hazardous pollutants. In contrast, the adoption of Daylight Savings Time was associated with a statistically significant increase in traffic levels.*

KEYWORDS *Air quality, Pollution advisories, Urban trails*

INTRODUCTION

Population health has been one of many reasons put forth to support the construction of pedestrian and cycling infrastructure, including multi-use urban trails like those that have been built in Indianapolis, Indiana and most other major metropolitan areas in the USA. Among the 50 states, Indiana suffers from relatively low levels of physical activity and a high prevalence of population obesity.¹ The EPA has also designated Indianapolis' county as a non-attainment area for air quality.² Particulate matter and ground-level ozone are the most commonly exceeded criteria pollutants, both of which have been linked to adverse health effects among physically active people.^{3–5}

Urban trails have been studied from a variety of perspectives, often in disciplinary isolation.⁶ Public health researchers often focus on the effect of such facilities on individuals' physical activity levels and the concomitant effect on obesity prevalence.⁷ Another branch of the literature focuses on the effect of urban design on patterns of transportation, linking trails to population health via their impact on environmental risks.⁸ The lack of integration between these different clusters of research has limited understanding of the effects of environmental conditions and risk on physical activity and the ability of policy makers to design and identify optimal strategies to promote population health.

In this analysis, we consider the effect of environmental factors on use of Indianapolis' urban trails. Specifically, we address two sets of hypotheses. First, we evaluate the extent to which air quality (measured in terms of ground-level ozone and fine particulate matter) and weather affect counts of traffic on trails. Second, we

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evaluate the marginal impact of two related policy variables, public air quality alerts (e.g., Knozone announcements), and the adoption of Daylight Savings Time (DST), on trail traffic. While not based on a full ecologic model,⁶ this analysis begins to integrate two separate literatures on urban trails.

METHODS

Setting. This analysis focuses on five multi-use trails in Indianapolis, IN from May 1, 2004 to August 31, 2006. Thirty observation points, selected at roughly 1-mile intervals across the 33 miles covered by these trails, provide a representative sample of daily traffic throughout the trail system (see Lindsey et al.⁹ for further details). The observation period is sufficiently long to permit analyses of multiple air pollution advisories and to capture a natural experiment in which the state switched from year-round standard time to DST.

Outcome variable. Indianapolis limits use of urban trails to pedestrians and non-motorized vehicles. Daily trail traffic counts, our measure of trail use, reflect pedestrian and cyclist flows on trails, not separate trips to trails by users or numbers of different individuals in the region who use trails. Trail traffic was monitored 24 h a day, 7 days a week at each of the 30 observation points along the trail system. Trailmaster© infrared monitors recorded the time when an infrared beam was broken by a passing trail user. Two modifications were required for analysis. First, because the infrared monitors may undercount traffic when multiple users pass monitoring points simultaneously, hourly trail counts were adjusted using correction algorithms based on comparisons of direct field observations and monitor counts.¹⁰ Daily TRAFFIC was created from corrected hourly counts aggregated to daily amounts. Second, because TRAFFIC values were highly skewed, a natural logarithmic transformation was used to ensure the distributional assumptions required by the statistical analysis were met.

Independent variables. Independent variables were selected to capture the effects of weather and pollution on daily traffic counts. Two policy variables, public announcements of poor air quality and a DST indicator variable, were also included in the analysis. Variations associated with characteristics of specific trail segments and/or their users were captured using indicator variables for each observation point.

Weather. Daily weather data were obtained from NOAA's National Climate Data Center¹¹ and the Indiana State Climate Office.¹² Daily weather conditions were captured by eight variables. AVGINDEX is the average temperature index (adjusted for wind chill or humidity as appropriate) for the day. Index values were chosen because we believe they are better indicators of the comfort levels experienced by people outdoors than unadjusted temperatures. ABSDIFFINDEX is the absolute difference between the index value and unadjusted temperature. We hypothesized that extreme weather, whether characterized by negative wind chills or positive heat index values, would discourage use. TRENDINDEX is the difference between the daily index value and the average of the index values over the previous 7 days. The value is unadjusted for days falling between the first day of spring and the last day of summer, but the sign is reversed for days falling between the first day of fall and the last day of winter. We hypothesized that people would be less likely to use the trails on days in summer (winter) that were hotter (colder) than what was experienced in the immediate past.

The measurement of precipitation was complicated by the fact that the National Weather Service reports unmeasured traces as well as measured amounts of precipitation. We were left with two choices: assign an arbitrary value to the trace measure and include precipitation as a scalar measure or represent the precipitation variables using categories. We chose the latter option for our final specification, although overall model fit and the direction and significance of the precipitation variables were robust to both representations. Thus, precipitation was captured by four variables: TRACESNOW, SNOW, TRACERAIN, and RAIN. SNOW and RAIN take on a value of one on days when the National Weather Service reported measurable amounts of snow or rain fell, respectively. Trace indicates that a non-measurable amount of snow or rain was recorded. The reference categories are no snow and no rain, respectively. We hypothesized that people would be discouraged from using trails by precipitation, with the effect smaller for traces of precipitation than for larger, measurable amounts of precipitation.

SUNSHINE is the actual number of hours of sunshine experienced during the day in question. Although NOAA reports sunshine as a proportion of the number of hours of daylight, we transformed the data to obtain actual hours because it better quantifies the window of opportunity to use the trail during periods of sunshine. If we had used the proportion as our sunshine measure, the 8 h of sunshine experienced on a clear day in winter would be treated the same as the 16 h experienced on a similarly clear day in summer. We hypothesized that people would be more likely to use the trails the greater the amount of sunshine.

Pollution. Daily records of air quality were obtained from the EPA's Air Quality System Technology Transfer Network.¹³ Air quality was captured by two variables, O₃ and PM_{2.5}, representing the highest daily reported amounts of ground-level ozone and fine particulate matter, respectively. The measurement of ground-level ozone was complicated by the fact that the EPA only monitors ozone during periods of the year when it is likely to reach unacceptable levels (in 16 states, including Indiana, "ozone season" runs from May 1 to October 31).¹³ If we were to delete all observations with missing values, it would create significant selection bias that could affect our estimates. Instead, we include a missing variable indicator, NOO3MEAS, which takes on a value of 1 when no ozone measurement is available and a value of 0 when an ozone measurement is available. This indicator variable identified those periods of the year when the EPA does not monitor. Statistically, it serves the same function as a missing variable indicator,¹⁴ a modified zero-order regression technique for handling missing independent variable values while retaining the observations with such missing values for analysis.

We also considered using a summary measure of air pollution, the air quality index (AQI), in lieu of O₃ and PM_{2.5}. We found that the association between trail use and the AQI depended on the main pollutant that drove the AQI value. As a consequence, we chose to use measures of the two main pollutants observed during the study period. Over the 853-day period of observation, ground-level ozone and fine particulate matter were the main pollutants on which the AQI was based 98.8% of the time.

State Fair. One trail segment is immediately adjacent to the State Fair Grounds. Counts at this observation point are unusually high during the days when the State Fair is held, in part because people pass the counter walking to and from nearby parking. To control for this aberrant effect, we included a dummy variable,

STATEFAIR5, which takes on a value of one for this segment of the trail on days when the State Fair is held.

Policy Variables. The effects of two policies on trail use were included in the analysis. First, we take advantage of a natural experiment in which Indiana adopted DST in the last year of our study. DST takes on a value of one on days when DST was in effect. We hypothesize that traffic will be higher on days when there are more hours of daylight in the evening due to DST.

Second, we consider the effect of public air pollution advisories on trail traffic. Air pollution advisories are made by the Department of Public Works, City of Indianapolis when air quality is expected to exceed safe levels. These advisories emphasize actions that individuals can take to reduce generation of pollutants, including refueling vehicles during evening hours rather than during the daytime and postponing mowing lawns and other activities involving use of gasoline-powered engines. The city issued 14 air pollution advisories during the study period.

If we were to simply include an indicator variable for days when announcements were made, the variable would capture not only the effect of the announcement itself, but also some of the effect of high pollution levels that typify such days. The effect attributed to the pollution variables would be correspondingly reduced. To isolate the effect of the public announcement over and above the effect of poor air quality, we instead estimated the probability of a public announcement being made as a function of the levels of ozone and particulate matter experienced on a given day using logistic regression. We also included a count of the number of announcements made to that point in the calendar year to capture the reluctance of city officials to issue a large number of alerts that might cause the public to become desensitized to air alerts. By including the residuals generated by this logistic regression, DIFFKNOZONE, in the analysis of trail traffic, we are able to identify the effect of air pollution advisories while fully controlling for levels of pollution.

Definitions, units of measurement, and summary statistics for all variables are provided in Table 1. While our dataset includes 853 days for a total potential of 25,590 daily traffic counts across the 30 locations, the total number of observations used in our analyses is 22,007. Lost observations were due variously to counter malfunctions, loss of power, insect infestation, vandalism, and human error in operation of data collectors.

Specification. The study design generated a panel of data structured over 30 trail points and 853 days. There are several ways to handle such panel data, including random effects models, fixed effects models, and generalized estimating equation (GEE).¹⁵ The choice between these methods is typically driven by assumptions about the error distribution. The fixed effects model (also called the least squares dummy variable model) corrects for heterogeneity across trail segments by treating between-segment differences as parameters to be estimated. Because our panel is very “long,” the fixed effects model is ideally suited for assessing the impact of temporal variables on traffic levels without the need to impose restrictive assumptions about the underlying data distribution required by either the random effects or GEE approaches.

We also conducted a secondary analysis in which select temporal variables were allowed to interact with trail segment indicators. These interaction effects reveal if the responses of trail traffic to policy actions depend on location. The relatively small number of trail segments does not support a more sophisticated analysis to

TABLE 1 Summary statistics of model variables

Variable	Definition	Mean (standard deviation) [minimum, maximum]
TRAFFIC	Daily count, adjusted using correction algorithm	377.8 (569.3) [0, 6155]
AVGINDEX	Average daily temperature index, °F	55.8 (22.0) [−8.61, 93.6]
ABSDIFFINDEX	Absolute value of humidity index/wind chill adjustment, °F	3.23 (3.31) [0, 18.0]
TRENDINDEX	Difference of temperature from previous week's average, °F	−0.67 (9.69) [−37.82, 39.87]
TRACESNOW	Dummy variable for trace of snow (reference: no snow)	0.06 (0.24) [0, 1]
SNOW	Dummy variable for measurable snowfall (reference: no snow)	0.05 (0.22) [0, 1]
TRACERAIN	Dummy variable for trace of rain (reference: no rain)	0.15 (0.36) [0, 1]
RAIN	Dummy variable for measurable rain (reference: no rain)	0.36 (0.48) [0, 1]
SUNSHINE	Hours of actual sunshine, hours	7.38 (4.79) [0, 15.0]
STATEFAIR5	Dummy variable for State Fair at nearest trail segment	0.001 (0.04) [0, 1]
O3	Highest level of ground level ozone, ppm	0.03 (0.03) [0, 0.1]
NOO3MEAS	Dummy variable for no ozone measurement taken	0.43 (0.49) [0, 1]
PM2.5	Level of particulate matter, µg/m ³	15.37 (8.52) [2.5, 57.1]
DST	Dummy variable for Daylight Savings Time	0.18 (0.38) [0, 1]
KNOZONE	Air quality alert variable (reference: no alert)	0.02 (0.13) [0, 1]

identify the specific features of the trails (or their associated users) that might explain location-specific effects.

RESULTS

Estimates from the fixed effects model are reported in Table 2. Interaction effects are reported in Table 3. The model explains variations in trail traffic fairly well, with an adjusted R^2 of 0.85. All coefficients, except for DIFFKNOZONE, the pollution advisory variable, are statistically significant at a 5% level. Because the dependent variable is expressed as a natural logarithm, coefficients may be interpreted as the proportional change in the dependent variable associated with a change in the independent variable. To facilitate comparison of the effects of different independent variables, we also include elasticity measures for each variable. The elasticity measures may be interpreted as the percentage change in the dependent variable associated with a percentage change in the independent variable, calculated at the mid-range for each variable. As a unit free measure of effect, direct comparisons of the effects of different independent variables can be made even if they are measured on different scales. Selected results are discussed below.

Weather. Increased hours of sunshine are associated with significantly higher levels of trail traffic. Although rainfall, particularly heavier rainfall, is associated with significantly lower levels of trail traffic, snowfall, in contrast, is associated with significantly higher levels of trail traffic.

TABLE 2 Results of the fixed effects model

Variable ^{a,b}	Coefficient (<i>p</i> value)	Elasticity ^c
AVGINDEX	0.025 (0.000)	1.063
ABSDIFFINDEX	−0.036 (0.000)	−0.324
TRENDINDEX	−0.002 (0.000)	−0.002
TRACESNOW	0.054 (0.002)	0.003
SNOW	0.070 (0.000)	0.004
TRACERAIN	−0.102 (0.000)	−0.005
RAIN	−0.363 (0.000)	−0.018
SUNSHINE	0.051 (0.000)	0.382
STATEFAIR5	1.385 (0.000)	0.693
O3	−2.515 (0.000)	−0.126
NOO3MEAS	−0.197 (0.000)	−0.099
PM2.5	−0.006 (0.000)	−0.179
DST	0.025 (0.017)	0.013
DIFFKNOZONE	−0.157 (0.104)	−0.079
CONSTANT	4.040 (0.000)	n/a

^aDependent variable: $\ln(\text{TRAFFIC})$

^bTrail site indicator variables included in analysis but not reported

^cElasticity shows the percentage change in trail count in response to a one percentage change in the independent variable, evaluated at the midrange value of the independent variable

Air quality. Both high levels of ozone and fine particulate matter are associated with significantly lower levels of trail traffic. Because ozone and fine particulate matter are measured in different units, comparisons of effect size are difficult to determine from coefficients alone. As noted previously, to overcome this problem, we express effects using unit-free elasticities. This calculation reveals that traffic levels are more sensitive to the same percentage increase in fine particulate matter (elasticity of −0.18) than ground-level ozone (elasticity of −0.13).

Policy variables. Across all 30 trail segments, the adoption of DST is associated with a 2.5% increase in trail traffic ($p < 0.05$). The coefficient on the corrected air pollution advisory variable, although negative, is not statistically significant ($p > 0.10$).

Site-specific interactions. Interaction effects are reported in Table 3. *F* tests reveal there are significant differences in the relationship between traffic levels across trail locations for the adoption of DST and measured changes in air quality but not for air pollution advisories. Significant differences across trail segments in the air quality effects are limited to three segments, with traffic levels much more responsive to ground-level ozone than in the reference trail segment (the one with the median traffic level). Significant differences across trail segments with respect to the adoption of DST are much more widespread, with the observed differential change in traffic ranging from a one-third decline to a one-quarter increase.

DISCUSSION AND CONCLUSIONS

Our analyses show trail traffic levels are associated with ambient air quality, suggesting a potential benefit of reducing air pollution will be an increase in physical activity. A limitation of our outcome variable, TRAFFIC, is that it does not distinguish between differences that are due to changes in the number of users of

TABLE 3 Interaction effects by trail segment

Trail segment ID ^a	DST ^b	O3 ^c	PM2.5 ^d
1	24.4	−0.05	−0.24
2	NS ^e	NS	NS
3	NS	NS	NS
4	NS	NS	NS
5	NS	NS	NS
6	NS	NS	NS
7	7.9	NS	NS
8	4.5	NS	NS
9	4.7	NS	NS
10	−3.1	NS	NS
11	4.2	NS	NS
12	5.0	NS	NS
13	−10.0	NS	NS
14	−14.9	NS	NS
15	−13.5	NS	NS
16	NS	NS	NS
17	9.7	NS	NS
18	3.5	NS	NS
19	−32.2	NS	NS
20	−10.0	NS	NS
21	−6.4	−0.33	NS
22	−22.6	−0.48	NS
23	−1.8	−0.62	NS
24	−12.2	NS	NS
25	−9.2	NS	NS
26	2.2	NS	NS
27	6.8	NS	NS
28	5.6	NS	NS
29	−2.1	NS	NS
30	0.5	NS	NS

^aReference trail segment (with median level of use) is ID=1
^bValue represents percentage change in traffic during DST period
^cValue represents segment-specific elasticity evaluated at ozone midrange value
^dValue represents segment-specific elasticity evaluated at fine particulate matter midrange value
^eNS indicates effect not statistically different from median trail segment (segment 1)

trails from those that are due to changes in the intensity of use by a given set of users. Such distributional issues have public health ramifications, especially when considering exposures to hazardous pollutants.

Our data do not allow us to determine the mechanism by which air pollution directly affects the behavior of potential trail users (i.e., beyond any indirect effects that can be attributed to pollution advisories). One possibility is that individuals are able to perceive air pollution through reduced visibility due to smog, especially smog associated with particulate matter. A second possibility is that potential trail users experience acute (i.e., immediate) health effects when exposed to ambient air pollution that make trail activities more difficult. Empirical evidence about acute respiratory responses to ambient air pollution is mixed.^{4,5,16} The lack of a clear impact on short-term lung function may reflect evidence that personal exposure and ambient concentrations are only weakly correlated, especially for ground-level

ozone.¹⁷ In contrast, empirical evidence on the effects of particulate matter on cardiac function is relatively well established.¹⁸ Thus, the acute health response hypothesis may not only explain our findings of a direct impact of ambient air pollution apart from the air quality advisories but also why the effect appears to be greater for particulate matter than ground-level ozone.

We found that public air pollution advisories issued by the Department of Public Works are not significantly associated with different levels of trail traffic in Indianapolis. Such a result is confirmatory of evidence from other experiments that have found that advisories are only marginally effective in changing behavior.^{19,20} A common explanation for the failures of advisories to influence behaviors is the “cry wolf” phenomenon whereby people become desensitized to warning messages that are frequently issued.²¹ The agency issuing the air quality advisories was aware of this possibility and reportedly considered this factor when deciding whether to issue advisories. Other potential explanations for this apparent ineffectiveness of alerts include poorly designed messages, including the failure to contextualize them, lack of agency credibility, and the costs of behavior change being greater than the perceived benefits of behavioral change.^{22,23} A fifth possibility and one that is at least partially supported by our results is that potential trail users were able to perceive and react to ambient air pollution independently of the air quality alerts. These and other hypotheses could be explored through additional research involving surveys of trail users and others about their reactions to the advisories.

Because air pollution advisories generally were issued in a consistent fashion throughout the study period, our data cannot inform policy makers about the most effective design and implementation of such advisories. Existing research suggests a person’s beliefs about the efficacy of individual actions to reduce pollution and his or her social status (or dimensions of it like education) may affect individual decisions whether to change behavior in response to air pollution advisories.^{24,25} Researchers also have confirmed the existence of complicated race and gender interactions with beliefs and attitudes about risk.²⁶

We were able to take advantage of a natural experiment that occurred during our study period, namely, the adoption of DST. The degree to which our estimates reflect the true impact of DST on trail traffic depends on the extent to which other temporal factors may have coincided with the adoption of DST. While our time frame was long enough to include several months of observations both with and without DST in effect, it was probably sufficiently short to exclude most other time-dependent factors that might substantially affect traffic levels (e.g., changes in population or transportation costs).

Our analysis also reveals that trail traffic and its association with other factors vary by trail segment. We hypothesize that such differences may be due to either trail characteristics or characteristics of users across different parts of the trails.²⁷ It is also possible that trail characteristics may affect traffic responses to weather and air quality. For example, trail segments with ample vegetation may offer more shade to offset the impact of high temperatures. Similarly, the effect of extending daylight during evening leisure hours may depend on the amount of perceived crime in the vicinity of a trail segment and the effect of better lighting on perceived risk of victimization.

The use of a fixed effects specification allowed us to identify these trail-segment-specific effects but offers no insights as to why such differences might exist. Spatial multicollinearity makes it difficult to isolate the effects of specific aspects of urban form on trail use.²⁸ Because our panel consisted of only 30 trail segments, we lacked sufficient unique variation in trail characteristics to be able to estimate a more

informative mixed model with both fixed and random effects. Similarly, while a multi-level model would allow us to distinguish segment-specific effects due to differences in trail characteristics from those due to differences in users of different parts of the trail system, our data do not include the needed information on users across the different trail segments to perform such an analysis.

While we were unable to undertake a rigorous analysis of the possible causes of trail-segment-specific effects, we informally examined the pattern of results to identify possible hypotheses for future research. The effect of DST on trail use was most positive along the trail segments that passed through an economically advantaged residential neighborhood and most negative along segments that passed through the most industrial neighborhood. We hypothesize that this effect may reflect the differences in discretionary recreational use along these trail segments. The ozone effect is concentrated almost exclusively in trail segments running through the most industrial neighborhood. While this effect may be due to users of these trail segments being more sensitive to air quality, we think it more likely that the poor air quality is concentrated in this industrial section of town and may be understated by global air quality measurements.

RELEVANCE TO POLICY, MANAGEMENT, AND PUBLIC HEALTH

Our findings have several implications for policy, management, and, potentially, public health. The results of this paper suggest that urban trail use varies not only with weather conditions like temperature but also with ambient air quality. Although some users independently adjust their outside physical activities in response to poor air quality, the need for continuing education about the deleterious effects of air pollution remains. Healthcare providers may wish to include risk modification strategies when recommending exercise regimes, especially for those individuals with respiratory-related risk factors. Because our findings suggest that current public announcements regarding air quality may be of limited effectiveness, at least from the perspective of their marginal impact on trail users' physical activity and exposures to hazardous pollutants, new strategies should be explored. The advisories issued during the period covered by this study emphasized actions individuals can take to reduce generation of pollutants but did not stress specific warnings about the potential health effects of using trails on days with poor air quality. Anecdotal evidence from conversations with trail users who continued using trails when pollution levels were unhealthful indicated they did so because they consciously decided that the benefits of physical activity, which are relatively direct and may be seen in the short term, outweighed the risks of adverse effects that are more probabilistic and longer term. The nature of these types of trade-offs is not well understood from the perspective of health sciences, and communication of them to a general population is a very difficult task. In light of these complexities, air pollution managers need to consider the multiple objectives of advisories and the conflicting priorities of citizens and consider more strategic approaches to issuance of advisories, including more refined and targeted messaging.

The strongest policy implication that can be drawn from our results pertains to the adoption of DST that resulted in a 2.5% increase in overall trail traffic, although the large variation by trail segment suggests that the impact of extending hours of evening daylight may depend on type of user or trail characteristics. Implementation of DST increased hours of daylight available for discretionary activity. Other policy interventions that have the practical impact of increasing discretionary time for

physical activity during daylight hours may have comparable effects. Examples include flextime for employees, shifts in standard work hours (e.g., beginning and ending an hour earlier each day), as well as further extensions of DST through the calendar year.

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