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The effects of the Australian bushfires on physical activity in children

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ABSTRACT

Objectives: To determine the impact of bushfires on children's physical activity.
Design: Natural experiment comparing device-measured physical activity and air quality index data for schools exposed and not exposed to the Australian bushfires.
Methods: Participants were drawn from 22 schools participating in a cluster randomised controlled trial of a school-based physical activity intervention that coincided with the 2019 Australian bushfires. Students in Years 3 and 4 (8–10 years old) provided data. We used propensity score matching to match 245 exposed and 344 control participants.
Main outcome measures: Minutes of moderate and vigorous physical activity.
Results: The bushfires had minimal effect on children's average weekly physical activity. Analysis of acute effects showed children maintained their levels of physical activity up to an estimated turning point of air quality index of 737.08 (95% CI = 638.63, 835.53), beyond which daily physical activity levels dropped sharply. Similar results were found for girls and boys and for children from low-to-average and higher socio-economic backgrounds.
Conclusions: Children's physical activity was not strongly influenced by the presence of smoke and targeted public health advice during the bushfires might not have had the intended effect of reducing children's outdoor physical activity. Only when air quality deteriorated to approximately 3.5 times the Air Quality index threshold (>200) deemed 'hazardous' by the Australian Department of Health did children's physical activity decline. Public health agencies should re-evaluate the effectiveness of health messages during bushfires and develop strategies to mitigate risks to children's health.

1. Introduction

Climate change has increased the frequency of extreme environmental events, such as bushfires (Nolan et al., 2020). Alongside the environmental and economic costs, these events negatively influence human health (Yu et al., 2020). For example, bushfires lead to increased hospital admissions due to respiratory complaints (Alves, 2020; Morgan et al., 2010). As these extreme climate-related events become more common in countries that have historically enjoyed good air quality (e.g., Australia, USA, Canada), their negative impacts are likely to grow (Clark et al., 2020).

In addition to directly undermining respiratory health, bushfires may decrease opportunities for participation in health-enhancing behaviour, such as outdoor physical activity. Physical inactivity is a global

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pandemic (Kohl et al., 2012). Events like bushfires could exacerbate this problem because people may stay indoors and avoid outdoor physical activity for fear of health damage due to increased smoke inhalation (Qin et al., 2019).

Little is known, however, about the effect of bushfires (and accompanying public health messages to stay indoors and avoid outdoor physical activity (Wen et al., 2009) on actual physical activity behaviour. During the 2003 California bushfires, children with asthma self-reported decreases in physical activity (Künzli et al., 2006). In the 2018 California bushfires, adults reduced daily step counts as air quality deteriorated (Rosenthal et al., 2019). In other studies, adults have reported avoiding outdoor exercise during bushfires (Kolbe and Gilchrist, 2009). Most evidence, however, relies on self-reported physical activity and, perhaps more importantly, lacks relevant comparison data during non-bushfire affected periods (Fish et al., 2017).

The bushfires starting in 2019 in New South Wales (NSW), Australia, provided a context for a natural experiment. Using data from an ongoing, multi-cohort physical activity study, we aimed to determine: (1) the impact of the bushfires on children's physical activity during this period; (2) if bushfire effects were equivalent for subpopulations of children, including low versus high socio-economic status (SES) and girls vs boys; and, (3) if bushfire effects varied across settings (i.e., home vs school). We also sought to determine if day-to-day changes in air quality during this period explained daily variations in children's physical activity. We hypothesised that children's physical activity would be negatively affected during the bushfires.

2. Method

2.1. Study population

Data were drawn from a cluster randomised controlled trial of a school-based physical activity intervention. Details of the trial can be accessed elsewhere (Lonsdale et al., 2016). Briefly, schools which expressed interest in participating were stratified based on their socio-economic status and geographic location (i.e., urban vs rural). We then paired these schools based on their strata, and recruited schools to get a balance across the strata, oversampling in strata that are more common in NSW. We did this to ensure a broadly representative sample of NSW schools and to minimise between-arm differences for the trial. The trial recruited 22 primary schools (half received the intervention) in three cohorts from government-funded schools in NSW, Australia. Students in Years 3 and 4 (8–10 years old) provided data at three time-points: baseline, post-intervention (12 months post-baseline), and maintenance (24 months post-baseline). For the purposes of this study, we used post-intervention and maintenance data, which we refer to as Time 1 and Time 2, respectively. For each cohort, data collected at Time 1 and Time 2 were collected at the same time of the year (same season).

2.2. Study design

Cohorts 1 and 2 completed Time 2 data collection prior to the bushfires that began in October 2019. For Cohort 3, Time 2 data collection coincided with the bushfires (October–December 2019). In the present study, we examined if exposure to the bushfires altered the physical activity trajectory of students in Cohort 3, compared to similar students who were not exposed in Cohorts 1 and 2. In a secondary analysis, we investigated the extent to which changes in daily air quality acutely impacted Cohort 3 students' day-to-day physical activity during the bushfire period.

Cohort 3 consisted of six schools, of which five showed substantial decreases in air quality compared with the same period in the previous year. These five schools had bushfires nearby during data collection but were not directly impacted by evacuations or damage to property or lives. The sixth school did not have a nearby bushfire during data collection in 2019 and was excluded from the analysis. Cohort 1 and 2 schools served as controls. To minimise differences in the groups, we used propensity score matching to identify students in control schools who closely matched those in intervention schools.

2.3. Outcomes

2.3.1. Exposures

We obtained air quality data from the NSW Department of Planning, Industry, & Environment website (https://www.dpie.nsw.gov.au/air-quality), which provides historical records of air quality from monitoring sites in NSW. We identified the air quality monitoring site closest to each of the schools for the dates each student wore an accelerometer. We used the air quality index (AQI) which is calculated from five measures of air quality: Ozone, nitrogen dioxide, carbon monoxide, sulfur dioxide, particulate matter (<2.5 μm and <10 μm), and visibility. For each measure, the Australian Government provides reference standards (National Environment Protection (Ambient Air Quality)). To account for differences in measurement methods, an index for each measure is calculated as $AQI_{pollutant} = \frac{pollutant\ \ reading}{pollutant\ \ standard} \times 100$.

The AQI for a given day at a given monitoring site is the measure which is highest relative to the reference standard. Government guidelines provide advice for adjusting activities according to AQI categories that range from AQI = 0–33 (very good) to AQI > 200 (hazardous). During the bushfires, schools in affected areas received additional targeted activity recommendations from the NSW Department of Education. Advice for school principals included avoiding all outdoor physical activity (see Supplementary File 1). A media campaign also aimed to increase the reach of public health messages in response to the bushfire emergency (see examples in Supplementary File 2).

A school was considered to be exposed if it was in an area affected by the bushfires, received targeted advice from the Department of Education for children to avoid all outdoor physical activities, and had a poor AQI (i.e., AQI > 100; the threshold at which sensitive groups—including children are advised to 'reduce strenuous outdoor activities') on 3 or more days of the week in which physical activity was assessed. Children were considered exposed if they attended one of the schools classified as exposed according to these criteria.

2.3.2. Outcomes

Our primary outcome was students' moderate-to-vigorous physical activity (MVPA). We measured physical activity using GENEActiv accelerometers (Activinsights, Cambridge, UK) on the non-dominant wrist for eight consecutive days. Accelerometers collected data at 87.5 Hz, and data were processed using the GGIR package in R (van Hees, 2019; Migueles et al., 2019). The package performs auto-calibration on raw data using local gravity as the reference, and detects both abnormally high acceleration and non-wear periods. The average magnitude of dynamic acceleration is then calculated using the Euclidean norm minus one with negative values set to zero method. We applied validated cut-points to the data (Hildebrand et al., 2014) to estimate time spent in different physical activity intensities including moderate physical activity (MPA) and vigorous physical activity (VPA). To test if bushfires impacted MVPA in different settings, we separately examined physical activity during and outside of school hours (i.e., before/after school and weekends), using school bell times. Minimum wear time for data to be included in the analysis was 10 h each day for at least four days, including one weekend day (Rich et al., 2013).

2.3.3. Covariates

Students self-reported their sex, date of birth, and birth country. We estimated students' SES using student-reported perceived wealth status (Roberts et al., 2009) and perceived number of books in their home (International Association for the Evaluation of Educational Achievement, 2015). We used a stadiometer (26SM, Medtone Education Supplies, Melbourne, Australia) and a digital scale (UC-321, A&D Company

LTD, Tokyo, Japan) to measure students' height and weight. We then calculated body mass index as kg/m^2. We assessed cardiorespiratory fitness using the 20 m multistage fitness test (Welk and Meredith, 2008).

2.4. Statistical analysis

We used R (R Core Team, 2013) software for all our computations. To represent uncertainty around the estimates, we used 95% confidence intervals. An example of R code used to conduct the analyses in this study can be found in Supplementary File 3.

2.4.1. Propensity score matching - primary analysis

Based on a potential outcomes model approach to causal inference, we used propensity score matching to provide 'all-else-being-equal' comparisons between the exposed and non-exposed groups (Stuart, 2010). This matching approach aims to find strategic sub-samples of individuals in the exposed and non-exposed groups that either match participants in groups exactly on a few critical confounding variables, match approximately on many confounding variables (i.e., propensity score match), or some combination of the two (Stuart, 2010). Because of the context of the research, we matched participants exactly on intervention group (treatment or control). We then propensity score matched participants on: age, sex, device-measured physical activity and cardiorespiratory fitness (20-m shuttle run) at Time 1, whether or not the student was born in Australia, self-reported family wealth (Roberts et al., 2009), number of books in the house (International Association for the Evaluation of Educational Achievement, 2015), and, for all variables, each two-way interaction and quadratic effect. We used 1 to 2 (exposed to non-exposed) matching, without replacement, with a caliper set to 0.20. The 1:2 ratio is a limit such that up to two non-exposed students were matched with each exposed student, but if two matches were not found, only one was selected. We used logistic regression as the propensity score matching algorithm using the MatchIt R package. Matching was done using nearest-neighbour matching.

After matching, we ran primary and secondary outcome models using multilevel models via the lme4 R package. We did this because students were nested within schools. We used a doubly robust approach to models in which the following variables used in the matching procedure were also included as covariates in the model: intervention status, Time 1 device-measured physical activity (for the outcome being tested), Time 1 shuttle run result, and a set of demographics (age, sex, country of birth, wealth status and number of books available at home). In a sensitivity analysis (Supplementary File 5), we further adjusted the model for temperature. For this primary analysis, each student's mins/day of activity was averaged (weighted for weekday/vs weekend) over the Time 2 valid days; and that average was used as his or her outcome.

We also used a Difference-in-differences approach and the results were similar and did not change the interpretation of the findings (results shown in Supplementary File 6).

Missing data (day-level), due to attrition, was approximately 18%. We created 20 imputed data sets to fill any missing data values (Catellier et al., 2005). For example, on days in which students did not contain any accelerometry, we used multiple imputation to estimate their score based on all available data. This procedure has been shown to reduce bias and increase precision for physical activity data, even when data are not missing completely at random (Catellier et al., 2005). To generate the 20 imputed data sets, we used the Amelia II R package. We used these imputations for both matching and analysis, with results for analysis integrated using Rubin's rules.

2.4.2. Fixed effects models – secondary analysis

Propensity score matching aims to replicate a randomised controlled trial by ensuring that treatment groups are balanced on key factors at baseline. However, the success of propensity score matching is dependent on conditioning on all relevant pre-treatment covariates, which may not always be possible. An alternative is to use a participant fixed-effects model that treats individuals as their own control (Allison, 2009). Here, all between-person time-invariant variation is conditioned out of the model and, thus, the focus is purely on within-person variation (Allison, 2009). In this analysis we used data from participants exposed to hazardous smoke levels at some point over the 8 days that physical activity was recorded (i.e., the exposed group in the primary analysis). A fixed-effect model regressed physical activity on both linear and quadratic terms for air quality. The quadratic term was needed because we only expected air quality to influence physical activity when hazardous (AQI > 200); that is on days in which smoke from the bushfires was most prevalent. We calculated a turning point for the quadratic effect using the formula: $-\frac{\beta linear}{\beta quadratic}$. We calculated all fixed-effects models in the plm R package. We did not use multiple imputations as these models already use all available data. We run fixed-effects models for the full sample, and we also run separated models for boys and girls, and low-to-average and higher socioeconomic backgrounds.

3. Results

3.1. Air quality index levels

Table 1 shows the daily AQI average for each group at each of the timepoints of assessment.

3.2. Propensity score matching - primary analysis

Table 2 summarizes the characteristics of the sample before and after propensity score matching. After matching, we had a sample of 245 exposed and 344 control participants from 5 schools that was balanced across the matching variables (mean absolute between-group difference of $d = 0.05$) (Supplementary file 4).

Multilevel regressions showed the bushfires had minimal effect on average Time 2 weekly MVPA [Beta coefficient, β = 5.69 min/day (95% Confidence Interval, 95% CI = −1.09, 12.47)]; MPA [β = 4.19 min/day (95% CI = −1.20, 9.60)]; or VPA [β = −0.05 min/day (95% CI = −1.92, 1.80)] (Table 3). Results for specific settings (i.e., physical activity during and outside of school hours) were similar (Table 3). Furthermore, none of the moderators tested yielded significant results (Table 3).

The sensitivity analysis indicated that further adjusting for temperature did not substantially change the results—i.e., the results from this sensitivity analysis reinforced the null effects of exposure to the bushfires on physical activity in the study sample (Supplementary File 5).

3.3. Within-subject fixed-effects – secondary analysis

Table 4 shows the characteristics of the subsample included in this analysis of acute effects of smoke on daily physical activity (i.e., data from 352 children in Cohort 3 from 5 schools in areas affected by bushfire smoke in October - December 2019). A fixed-effects model showed that children maintained their daily levels of physical activity up until an estimated turning point of AQI = 737.08 (95% CI = 638.63,

Table 1
Daily AQI average across groups and study timepoints of assessment.

	Timepoint 1		Timepoint 2	
AQI	Exposed	Non-exposed	Exposed	Non-exposed
Day 1	92.60 (107.94)	42.50 (19.58)	569.00 (1131.46)	32.75 (3.73)
Day 2	43.8 (9.98)	41.87 (26.16)	101.80 (51.17)	36.50 (6.24)
Day 3	58.00 (33.37)	58.87 (43.55)	455.60 (697.56)	43.25 (11.78)
Day 4	82.00 (81.55)	53.50 (26.50)	134.00 (84.30)	41.37 (15.05)
Day 5	60.80 (21.00)	34.62 (15.93)	63.00 (16.95)	48.50 (20.68)
Day 6	45.80 (17.10)	46.50 (24.32)	106.80 (83.60)	38.87 (5.88)
Day 7	38.20 (12.67)	49.00 (21.58)	164.00 (93.86)	32.87 (4.42)
Day 8	47.80 (25.62)	35.62 (12.62)	358.40 (211.22)	38.37 (13.22)

Values are mean (SD); AQI, Air Quality Index.

Table 2
Baseline descriptive characteristics of the study sample.

	Before propensity score matching			After propensity score matching		
	Control	Exposed	SMD	Control	Exposed	SMD
n	588	404		344	245	
Received intervention (%)	275 (49.5)	151 (39.6)	0.20	150 (43.1)	109 (43.4)	0.01
BMI (mean (SD))	18.99 (3.69)	19.03 (3.79)	0.01	19.08 (3.76)	19.10 (3.88)	0.00
Shuttles on 20-m multi-stage fitness test (mean (SD))	27.17 (16.05)	26.78 (15.40)	0.03	26.45 (15.69)	26.37 (15.82)	0.01
Age (mean (SD))	9.72 (0.68)	10.03 (0.72)	0.44	9.86 (0.67)	9.92 (0.71)	0.09
Gender = Female (%)	276 (49.8)	195 (51.2)	0.03	191 (54.9)	129 (51.4)	0.07
Wealth (%)			0.28			0.05
Very Wealthy	61 (11.3)	28 (7.4)		30 (8.6)	24 (9.6)	
Quite Wealthy	167 (31.0)	120 (31.7)		108 (31.0)	74 (29.5)	
Average	263 (48.9)	218 (57.5)		186 (53.4)	135 (53.8)	
Not Very Wealthy	42 (7.8)	12 (3.2)		18 (5.2)	14 (5.6)	
Not at all Wealthy	5 (0.9)	1 (0.3)		6 (1.7)	4 (1.6)	
Number of books at home (%)			0.19			0.13
None or very few (0–10 Books)	45 (8.4)	35 (9.2)		32 (9.2)	21 (8.4)	
Enough to fill one shelf (11–25 Books)	120 (22.3)	99 (26.1)		77 (22.1)	65 (25.9)	
Enough to fill one bookcases (26–100 books)	185 (34.4)	99 (26.1)		114 (32.8)	70 (27.9)	
Enough to fill two bookcases (101–200 Books)	100 (18.6)	72 (18.9)		64 (18.4)	46 (18.3)	
Enough to fill 3 or more bookcases (>200 Books)	88 (16.4)	75 (19.7)		61 (17.5)	49 (19.5)	
Number born overseas (%)	69 (12.8)	93 (24.5)	0.30	52 (14.9)	55 (21.9)	0.18
After school physical activity						
Vigorous (mean (SD))	5.06 (4.38)	4.31 (3.76)	0.18	4.92 (3.90)	4.96 (3.88)	0.01
Moderate (mean (SD))	25.87 (11.98)	27.17 (13.48)	0.10	26.33 (11.75)	27.12 (12.68)	0.07
Light (mean (SD))	81.11 (22.51)	91.15 (26.45)	0.41	82.80 (22.81)	86.61 (25.65)	0.16
Before school physical activity						
Vigorous (mean (SD))	2.79 (3.74)	1.68 (3.31)	0.32	3.04 (3.71)	2.78 (3.96)	0.07
Moderate (mean (SD))	15.35 (12.65)	12.03 (10.03)	0.29	16.06 (11.85)	15.46 (11.90)	0.05
Light (mean (SD))	49.93 (28.83)	44.93 (27.91)	0.18	49.60 (25.64)	48.00 (28.07)	0.06
During school physical activity						
Vigorous (mean (SD))	8.48 (5.93)	5.50 (3.70)	0.60	6.52 (4.06)	6.18 (4.23)	0.08
Moderate (mean (SD))	30.55 (15.94)	30.51 (13.85)	0.00	28.84 (14.42)	29.17 (14.18)	0.02
Light (mean (SD))	81.76 (34.29)	90.04 (28.70)	0.26	79.99 (33.95)	82.29 (30.25)	0.07
Weekend physical activity						
Vigorous (mean (SD))	10.86 (9.82)	8.11 (7.76)	0.31	10.31 (8.87)	10.23 (8.36)	0.01
Moderate (mean (SD))	61.61 (32.51)	56.16 (29.08)	0.18	59.92 (30.57)	60.20 (30.14)	0.01
Light (mean (SD))	190.02 (57.70)	199.15 (59.37)	0.16	187.24 (60.98)	192.98 (61.80)	0.09
Individual sport day occurred during data collection = Yes (%)	300 (55.8)	250 (65.8)	0.21	203 (58.3)	155 (61.8)	0.07
Team sport day occurred during data collection = Yes (%)	381 (70.8)	249 (65.5)	0.11	230 (66.1)	163 (64.9)	0.02
Days of Active Travel			0.17			0.13
0	190 (35.3)	136 (35.8)		123 (35.3)	91 (36.3)	
1	37 (6.9)	22 (5.8)		26 (7.5)	16 (6.4)	
2	49 (9.1)	28 (7.4)		32 (9.2)	19 (7.6)	
3	52 (9.7)	28 (7.4)		32 (9.2)	22 (8.8)	
4	34 (6.3)	18 (4.7)		25 (7.2)	13 (5.2)	
5	176 (32.7)	148 (38.9)		110 (31.6)	90 (35.9)	

Note: SMD = Standardised Mean Difference.

Table 3
Estimated effects of exposure to the bushfires on physical activity outcomes.

Daily average	Beta coefficient (95%CI)
MVPA (min/day)	5.69 (−1.09, 12.47)
Moderation effect, sex (ref. is girls)	−5.74 (−18.33, 6.85)
Moderation effect, SES (ref. is high)	2.62 (−11.74, 16.98)
MPA (min/day)	4.19 (−1.20, 9.60)
Moderation effect, sex (ref. is girls)	−4.39 (−13.54, 4.75)
Moderation effect, SES (ref. is high)	2.10 (−8.83, 13.04)
VPA (min/day)	−0.05 (−1.92, 1.80)
Moderation effect, sex (ref. is girls)	−1.34 (−5.28, 2.58)
Moderation effect, SES (ref. is high)	0.45 (−3.25, 4.16)
Outside of school	
MVPA (min/day)	4.10 (−4.28, 12.50)
MPA (min/day)	3.22 (−3.30, 9.75)
VPA (min/day)	0.82 (−1.26, 2.92)
During school	
MVPA (min/day)	1.21 (−3.79, 6.22)
MPA (min/day)	1.57 (−2.38, 5.54)
VPA (min/day)	−0.36 (−1.62, 0.89)

MVPA, Moderate-to-vigorous physical activity; MPA, Moderate physical activity; VPA, Vigorous physical activity; SES. socio-economic status. Coefficients represent effects of the bushfires on physical activity outcomes.

835.53), after which daily MVPA levels dropped sharply (Fig. 1). When AQI was at its worst (AQI = 2593), children had approximately 60 min less daily MVPA than on days when AQI was at its best (AQI = 36). Similar results were found for girls and boys (Fig. 2) and for children from low-to-average and higher SES backgrounds (Fig. 3).

Table 5 reports the estimated effects of air quality on individual-level physical activity of different intensities (i.e., MPA and VPA) using individual fixed-effect regressions. We found a significant quadratic effect of AQI on MPA, with a turning point of AQI = 761.26 (95% CI = 676.40, 846.12), after which levels of MPA dropped. For VPA, the relationship was negative and linear. We observed that an increase in AQI of 1 SD was associated with a small reduction in VPA of 0.35 min per day (95%

Table 4
Baseline descriptive characteristics of exposed children during the bushfires.

n	352
Received intervention (%)	39.6
BMI, kg/m^2 (mean (SD))	19.84 (4.18)
Shuttles on 20-m multi-stage fitness test, laps (mean (SD))	30.79 (17.62)
Age, years (mean (SD))	11.01 (0.73)
Gender = Female (%)	48.01
Wealth (%)	
Very Wealthy	6
Quite Wealthy	26
Average	63
Not Very Wealthy	2.7
Not at all Wealthy	0.3
Number born overseas (%)	78.7
After school physical activity (average min/day)	
Vigorous (mean (SD))	3.00 (7.94)
Moderate (mean (SD))	23.04 (23.74)
Light (mean (SD))	85.47 (34.97)
Before school physical activity (average min/day)	
Vigorous (mean (SD))	1.64 (7.90)
Moderate (mean (SD))	13.21 (20.15)
Light (mean (SD))	46.65 (30.78)
During school physical activity (average min/day)	
Vigorous (mean (SD))	5.22 (6.23)
Moderate (mean (SD))	30.26 (19.83)
Light (mean (SD))	86.08 (33.21)
Weekend physical activity (average min/day)	
Vigorous (mean (SD))	9.85 (18.21)
Moderate (mean (SD))	66.52 (50.65)
Light (mean (SD))	218.24 (53.25)

Note: SD = Standard Deviation.

CI = −0.57, −0.12).

Table 5 also shows the estimated effects of air quality on physical activity in different settings. During school, an increase in AQI of 1 SD resulted in a reduction in MPA of 2.02 min per day (95% CI = −2.50, −1.54). VPA was also impacted during school, with every 1 SD increase in AQI associated with a small reduction in VPA by 0.62 min per day (95% CI = −0.77, −0.47). We did not observe any significant relationship between physical activity and AQI outside of school hours.

4. Discussion

Our findings suggest that children's physical activity was not strongly influenced by the presence of smoke and that targeted public health advice during the bushfires might not have had the intended effect of reducing children's outdoor physical activity. Only when air quality deteriorated to approximately 3.5 times the threshold deemed 'hazardous' by the Australian Department of Health did children's physical activity decline. We had expected an impact of bushfires on children would lead to missed opportunities for health-enhancing physical activity. Rather, by maintaining usual levels of physical activity, children are likely experiencing harmful impacts of smoke exposure during bushfires.

Our natural experiment has several strengths. We used device-measured physical activity and were able compare cohorts of children with no exposure to bushfire smoke to cohorts of children who experienced severe smoke exposure. These cohorts were relatively homogenous and by using propensity score matching we further reduced bias arising from confounders. Because smoke levels at specific schools varied daily, we were also able to analyse within-child relationships between daily air quality and daily physical activity. These types of robust analyses are typically not possible in epidemiological studies of air pollution. Australia monitors air quality using an extensive network of accredited air quality monitoring stations which minimized measurement error in the exposure measures. We were also able to obtain air quality data from monitoring stations that were nearby most schools (average distance = 5.4 km).

There are a number of limitations. We were not able to differentiate between outdoor and indoor physical activity. It is possible that indoor physical activity replaced outdoor physical activity in accord with public health advice. This, however, seems unlikely because when there were very large increases in AQI, we observed large decreases in physical activity. This suggests indoor physical activity did not compensate for missed outdoor opportunities. Also, in Australia, children's physical activity environments and opportunities tend to be outdoor orientated. For example, most schools' play spaces and sporting facilities are

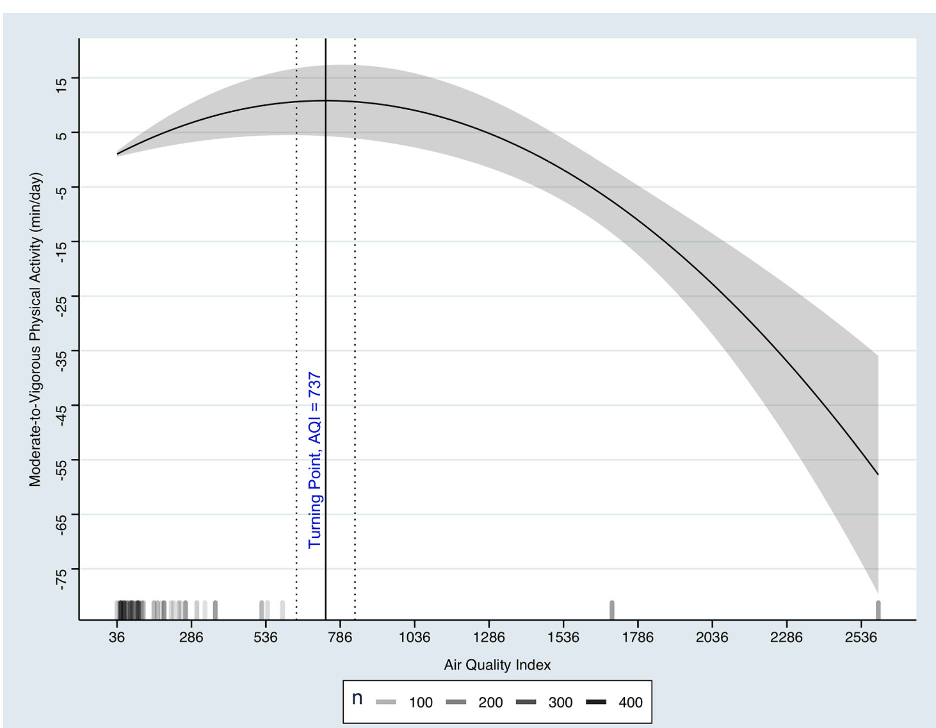

Fig. 1. Within-subject variations in daily moderate-to-vigorous physical activity and air quality.

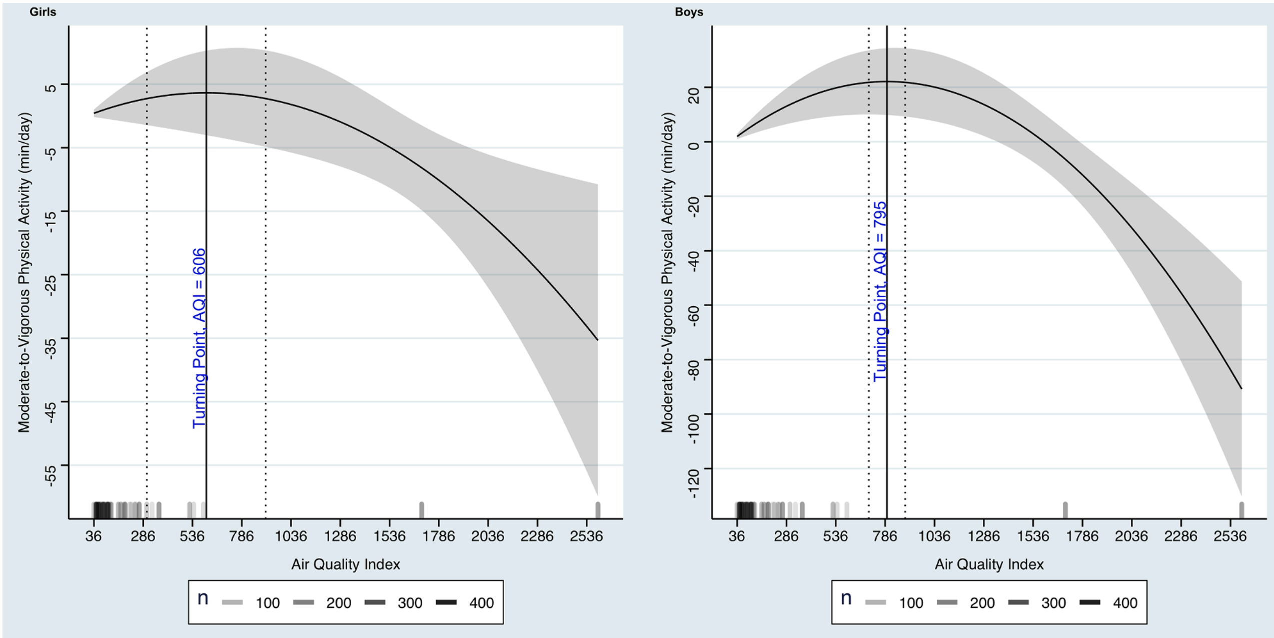

Fig. 2. Within-subject variations in daily moderate-to-vigorous physical activity and air quality, for girls and boys.

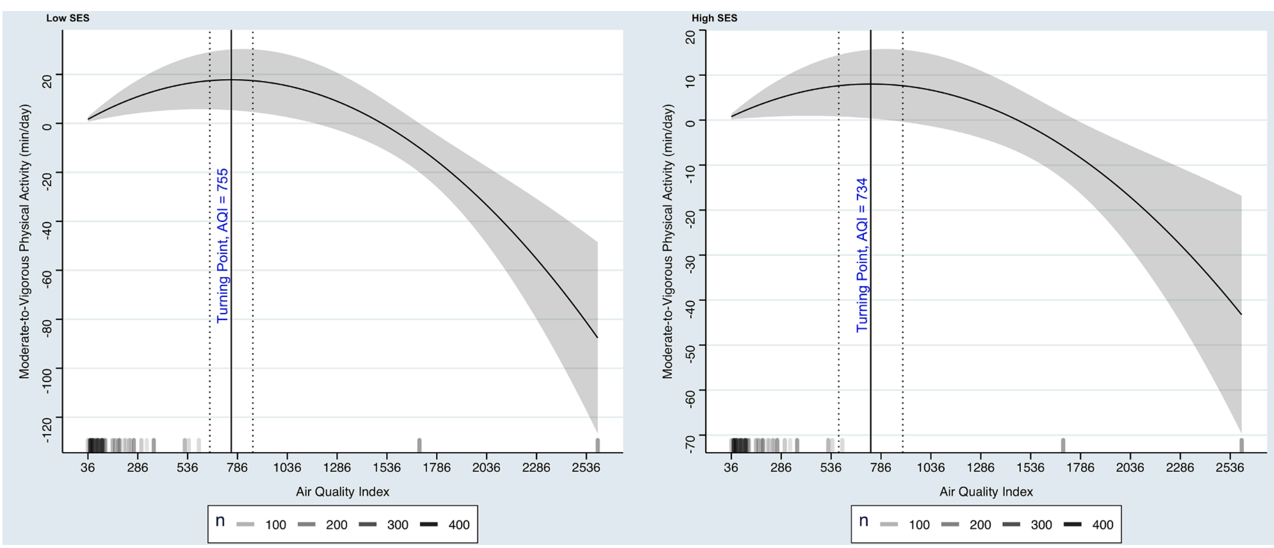

Fig. 3. Within-subject variations in daily moderate-to-vigorous physical activity and air quality, for children from low-to-average and higher socio-economic backgrounds.

outdoors and Australia's most popular sports are played outdoors (Australian Sports Commission, 2019). Another limitation relates to our assignment of daily AQI readings to individuals using data from the monitoring station nearest to their school. While this is the standard approach to studies of air pollution and health, it assumes that children also lived near their school and we acknowledge that individual exceptions could contribute to exposure misclassification. The effect of wind direction on smoke could also influence exposure accuracy. Wind could have moved smoke over monitoring stations but not over nearby schools. Smoke coverage in these areas, however, tended to be widespread and we, therefore, believe our exposure estimates are robust. Despite being valid, our measure for student-reported socioeconomic status could be outdated (i.e., the item used asks for number of books at home as a proxy for socio-economic status). Lastly, results from the turning-point analysis (i.e., Fixed-effects models) are likely to be driven by the small number of days in which AQI was extreme and results need to be interpreted with caution.

Based on limited previous evidence, we hypothesised that polluted air would reduce physical activity. Strikingly, children's physical activity levels during smoke exposure in our study remained relatively unchanged despite public health messaging and targeted recommendations from the NSW Department of Education (Supplementary File 1). These messages advised parents/carers and schools to avoid all outdoor physical activity for children and were well broadcast (Supplementary File 2), particularly as the bushfires escalated to a state of emergency. This contrasts with findings from a previous study conducted in California (Künzli et al., 2006), where children with asthma self-reported reductions in their physical activity levels. It is plausible that children with asthma will spontaneously reduce their activity when smoke is high (or their parents may be more vigilant) compared with kids without asthma (and their parents) whose behaviour seems largely unaffected by smoke until levels are extreme.

Table 5
Estimated effects of Air Quality Index on individual-level physical activity outcomes.

	Linear model	Quadratic model	
		Linear term	Quadratic term
Daily average	Beta coefficient (95%CI)	Beta coefficient (95%CI)	Beta coefficient (95%CI)
MVPA (min/day)	−1.21 (−2.20, −0.23)	7.13 (3.43, 10.82)	−1.58 (−2.26, −0.90)
MPA (min/day)	−0.86 (−1.66, −0.05)	6.73 (3.70, 9.76)	−1.44 (−1.99, −0.88)
VPA (min/day)	−0.35 (−0.57, −0.12)	0.39 (−0.44, 1.24)	−0.14 (−0.29, 0.01)
Outside of school			
MVPA (min/day)	0.02 (−0.58, 0.64)	−0.61 (−1.79, 3.03)	−0.10 (−0.54, 0.32)
MPA (min/day)	−0.01 (−0.49, 0.51)	1.02 (−0.96, 3.01)	−0.18 (−0.54, 0.17)
VPA (min/day)	0.03 (−0.11, 0.17)	−0.25 (−0.83, 0.31)	0.05 (−0.04, 0.15)
During school			
MVPA (min/day)	−2.64 (−3.24, −2.04)	−0.45 (−2.81, 1.89)	−0.40 (−0.82, 0.016)
MPA (min/day)	−2.02 (−2.50, −1.54)	0.17 (−1.71, 2.06)	−0.40 (−0.74, −0.06)
VPA (min/day)	−0.62 (−0.77, −0.47)	−0.74 (−1.33, −0.15)	0.02 (−0.08, 0.12)

MVPA, Moderate-to-vigorous physical activity; MPA, Moderate physical activity; VPA, Vigorous physical activity. Coefficients are changes in outcome per 1 standard deviation increment (i.e., (AQI = 604) in Air Quality Index.

The most plausible explanation for our findings is that decisions to proceed with usual organized sport and physical activity, active travel, and children's incidental physical activity were not strongly influenced by the presence of smoke or public health advice during the bushfires. Small reductions in physical activity with deteriorating air quality during school hours suggests that principals and teachers might have imposed some limits on children's outdoor physical activity. This may have been in response to targeted health advice from the state Department of Education for bushfire affected schools. Nevertheless, overall physical activity was not reduced on most days when the air quality index exceeded hazardous. This is a worrying finding because of the short and long-term health impacts of exposure to air pollutants, including those present in bushfire smoke (Alves, 2020; The Lancet Respiratory Medicine, 2020), to which children are particularly susceptible (Friedrich, 2018). Exposure to air pollutants while children's lungs and immune systems are developing contributes to disproportionate disease morbidity among children (Daigle et al., 2003; Guarnieri and Balmes, 2014) and may increase the risk of chronic diseases later in life (Friedrich, 2018). Children's higher ventilation rates compared with adults and their relatively larger dose of pollutants per weight add to children's vulnerability. Being physically active in the presence of air pollutants introduces additional risks. Higher ventilation rates during exercise increase the total inhaled dose of pollutants and dehydrate and damage airways. These effects also combine to result in deeper penetration of pollutants including harmful fine particulates (Daigle et al., 2003; Guarnieri and Balmes, 2014; Kippelen et al., 2012). Being physically active indoors may not fully manage these risks. Residential houses and schools are generally insufficiently insulated and often not equipped with air purifiers or air conditioning to offer protection from outdoor pollutants (Yu et al., 2020). More research is needed to improve our understanding of the impacts of bushfire smoke on paediatric lung health (Alves, 2020; The Lancet Respiratory Medicine, 2020), but evidence to date suggests physical activity in the presence of smoke is likely harmful.

5. Conclusions

This natural experiment found that, despite the presence of smoke and public health advice to avoid outdoor physical activity during the catastrophic Australian bushfires, children generally maintained their typical levels of physical activity. When air quality deteriorated to more than triple the threshold deemed hazardous, physical activity levels declined. A growing body of evidence predicts many parts of the world will experience an increased frequency of extreme climate-related events, such as catastrophic bushfires. Alongside climate action to address factors that contribute to bushfires, public health agencies should evaluate the effectiveness of health messages during bushfires and develop strategies to mitigate risks to children's health.

Ethical approval

The study was approved by the Australian Catholic Universities Research Ethics Committee.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Declaration of Competing Interests

All authors have completed the ICMJE uniform disclosure form at www.icmje.org/coi_disclosure.pdf and declare: no support from any organisation for the submitted work; CL has received research grants from the National Health and Medical Research Council and from the NSW Department of Education; no financial relationships with any organisations that might have an interest in the submitted work in the previous three years; no other relationships or activities that could appear to have influenced the submitted work.

Contributorship

BdPC had the original idea. BdPC, TH, and CL contributed to the design of this study. BdPC, MN, and PP conceptualised the design of the present analysis and analysed the data. BdPC, TH, and CL wrote the first draft of the manuscript. BdPC and CL had full access to the data in the study and can take responsibility for the integrity of the data and the accuracy of the data analysis. BdPC and CL are the guarantors. All other authors made important intellectual contributions by critically revising the study protocol, manuscript drafts and the final submitted manuscript. All authors agree to being accountable for all aspects of the work related to the accuracy or integrity of any part of the work. The corresponding author (BdPC) attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.

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