1	Statistical quantification of COVID-19 lockdown effect on air quality
2	from ground-based measurements in Ontario, Canada
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6	Hind A. Al-Abadleh, ^ξ * Martin Lysy, [‡] * Lucas Neil, [§] Priyesh Patel, ^ξ
7	Wisam Mohammed, ^{ξ} and Yara Khalaf ^{ξ}
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12	ξ Department of Chemistry and Biochemistry, Wilfrid Laurier University, Waterloo, Ontario N2L
13	3C5, Canada. [‡] Department of Statistics and Actuarial Science, University of Waterloo, Waterloo,
14	Ontario N2L 3G1, Canada. § Hemmera Envirochem Inc., Oakville, Ontario L6J 7W5, Canada.

15 ABSTRACT

Preliminary analysis of satellite measurements from around the world showed drops in 16 17 nitrogen dioxide (NO₂) with lockdowns due to the COVID-19 pandemic. A number of studies have found these drops to be correlated with local decreases in transportation and/or industry. None of 18 19 these studies, however, has rigorously quantified the statistical significance of these drops relative 20 to natural meteorological variability and other factors that influence pollutant levels during similar 21 time periods in previous years. Here, we develop a novel statistical testing framework that accounts 22 for seasonal variability, transboundary influences, and new factors such as COVID-19 restrictions in explaining trends in several pollutant levels at 16 ground-based measurement sites in Southern 23 24 Ontario, Canada. We find statistically significant and temporary drops in NO₂ (11 out 16 sites) and 25 CO (all 4 sites) in April-June 2020, with pollutant levels 20% lower than in the previous three years. 26 Much fewer sites (2-3 out of 16) experienced statistically significant drops in O_3 and PM2.5. The 27 statistical testing framework developed here is the first of its kind applied to air quality data, and highlights the need for rigorous assessment of statistical significance, should analyses of pollutant 28 29 level changes post COVID-19 lockdowns be used to inform policy decisions in Ontario, Canada.

30 INTRODUCTION

The province of Ontario in Canada declared a state of emergency on March 17, 2020 in an 31 32 effort to limit the spread of COVID-19, which caused the first related death in mid-March 2020. As a result, lockdown restrictions affected the majority of workplaces, which shifted to working from 33 34 home, including schools and universities, and the closure of recreational and shopping facilities that gather large numbers of people. Table S1 lists the timeline of restrictions in Ontario, the state of 35 36 Michigan in the U.S., which borders the southwestern part of the province, and Ohio, which can 37 influence pollution levels in Ontario via transboundary movement of pollutants. The imposition of the lockdown measures drastically reduced traffic, aviation and industrial activity in the province as 38 reported from satellite analysis.¹ Satellite data for nitrogen dioxide (NO₂) column using the 39 Tropospheric Monitoring Instrument (TROPOMI) operated by NASA and European Space Agency 40 were analyzed for the Greater Toronto area, home to Ontario's capital and Canada's most populous 41 urban region.¹ The analysis showed drastic reduction in NO₂ levels by roughly 40% relative to pre-42 lockdown. This reduction is similar in magnitude to those reported in cities in China, Europe and 43 the United States during their respective lockdowns and/or states of emergency.² Comparisons of 44 45 data in 2020 were made to the same period in 2019 to quantify the drop in NO₂ levels since weather and seasonal changes also affect the levels of these pollutants.³ Griffin et al.¹ estimated a 20% 46 reduction in satellite-measured NO₂ attributed to meteorology in Toronto. Analysis of satellite and 47 ground-based (i.e., surface) measurements of pollutant levels pre- and post-COVID-19 closures was 48 also reported for different cities from around the globe (see updated list of papers in reference ⁴). In 49 the Supporting Information, we highlight a few examples from Bejing, Wuhan, and Northern 50 China^{5,6}, the City of Pittsburgh, Pennsylvania in the U.S.⁷, and over 10,000 air quality stations in 34 51 countries.⁸ However, none of these studies has undertaken a rigorous quantification of the statistical 52

significance associated with these findings, in that such quantification is either absent or heavily reliant upon modeling assumptions which cannot be verified.⁸ This raises serious concerns over causality conclusions about the potential lockdown effect, and highlights the considerable challenge in disentangling the contribution of short-term seasonal effects and natural variability in atmospheric chemistry from the observed reduction in pollutant levels when comparing pre- and post- lockdown data.⁹

Indicator pollutants of air quality in Ontario are monitored by a network of 39 stations across 59 the province maintained by the Ministry of the Environment, Conservation and Parks (MECP).¹⁰ 60 These pollutants include nitrogen oxides (NO_x), CO, O₃ and PM2.5. Sources of NO_x are closely 61 associated with combustion. In 2016, 69% of NOx originated from road vehicles and other 62 transportation in Ontario.¹⁰ Seasonal variations of NO₂ levels are observed with maximum levels 63 occurring in the winter and minimum levels observed in the summer. The seasonal NO₂ signature 64 65 can be attributed to seasonal fluctuations in the boundary layer height. In general, wind speeds 66 increase in spring and summer as the height of the boundary layers increases, which enhances dispersion and lowers concentrations.¹¹ Also, NO₂ is a photoactive molecule that dissociates to NO 67 68 and O and hence, contributes to ground-level O₃ formation. Another by-product of incomplete 69 combustion of fossil fuels is CO. Similar to NO_x, the transportation sector accounts for 71% of all CO emissions in Ontario¹⁰, and as much as 95% of all CO emissions in metropolitan areas in the 70 71 US.¹² Seasonal variations of CO levels mimic those of NO₂, with maximum levels occurring during late winter and minimum levels observed during late summer.¹² This seasonal trend is the result of 72 73 inversion conditions being more frequent during winter months than summer months. The major source of ground-level O₃ is secondary processes from the photochemical reaction of NO_x and 74 volatile organic compounds (VOCs). Transportation and general solvent use account for 43% of 75

VOCs emissions in Ontario.¹⁰ As a result of its formation chemistry, concentrations of ground level 76 77 O₃ are highly variable on an hourly, daily, seasonally, and yearly basis. The scavenging effect of 78 NO reduces local O₃ levels in urban centres in Ontario, especially during summer months. Over the 79 10-year period from 2007 to 2016, progressive reduction in NO_x emissions in Ontario and the US resulted in a decrease in the summer means of local O₃. Still, ground level O₃ in the summer 80 continues to exceed the Ontario Ambient Air Quality Criteria (AAQC) of 80 ppb (1-hr), particularly 81 in Southern and Eastern Ontario. As for PM2.5, residential sources account for 56% of all sources 82 83 by sector from fuel wood combustion in fireplaces and wood stoves, followed by industrial (21%) and transportation sectors (12%).¹⁰ Together, O₃ and PM2.5 drive smog episodes in May-September 84 85 in Ontario, which are affected by local and regional weather patterns and long-range transboundary 86 influences from industrial and urbanized US states.

The objective of this investigation is to rigorously quantify the statistical significance of 87 88 changes to air quality indicators from ground-based measurements in Southern Ontario as a result 89 of the COVID-19 restrictions. To this end, we develop a novel statistical testing framework, which accounts for seasonal variability, transboundary influences, and new factors such as COVID-19 90 91 restrictions in explaining trends in the levels of NO₂, CO, O₃ and PM2.5. Importantly, our 92 quantification of statistical significance makes minimal modeling assumptions about the data. We 93 expand on the relevance of this framework to the analysis of a one-time event such as the lockdown 94 in the Methods section and Supporting Information, and on implications for policy-making in the 95 Discussion.

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97 METHODS

98 Data acquisition

For the selected sites in this paper, ground-based hourly data of pollutant concentrations 99 were downloaded from the MECP website (http://www.airqualityontario.com). More details on 100 101 data quality are available in the Supporting Information. Hourly and daily meteorological data 102 collected by the Meteorological Service of Canada network of stations were obtained from the 103 National Climate Archives website 104 (https://climate.weather.gc.ca/historical data/search historic data e.html). Solar irradiance monitoring data were obtained by contacting the surface weather observation network maintained 105 106 by Environment and Climate Change Canada (ECCC).

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108 Statistical information.

109 Our novel statistical protocol hinges on the assessment of statistical significance via the following randomization test.^{13,14} Suppose that N_{post} daily pollutant concentrations are recorded 110 post-lockdown and N_{pre} daily pollutant concentrations are recorded pre-lockdown under similar 111 conditions. Specifically, in our analysis, N_{post} corresponds to the weekdays of a given month – say 112 113 April 2020 – whereas N_{pre} corresponds to the weekdays of the same month in the three reference years April 2017-2019. By comparing the same month across years, we account for natural variation 114 in seasonal meteorology. We eliminate weekends from our analysis since COVID-19 restrictions 115 116 affect traffic activity on weekdays and weekends quite differently.

117 Suppose that each of the N_{pre} and N_{post} daily pollutant concentrations come from an 118 independent and identically distributed (iid) sample. Under the null hypothesis H_0 that there is no 119 pre/post-lockdown difference, every permutation of the $N_{pre} + N_{post}$ observations into groups of 120 size N_{pre} and N_{post} is equally likely. Moreover, a random permutation should produce a difference 121 in medians Δ_{rand} which is not too far from Δ_{obs} , the difference in medians recorded from the actual 122 data. Thus, the p-value against H_0 is the probability of Δ_{rand} being greater than Δ_{obs} with all random 123 permutations being equally likely. This probability can be estimated to arbitrarily high precision by 124 Monte Carlo simulation, i.e., by reporting the fraction of times Δ_{rand} exceeds Δ_{obs} on a large number 125 *M* of random permutations (all of our p-values are calculated with M = 10000, thus having a Monte 126 Carlo standard error of no more than 0.005).

127 The randomization test described above is nonparametric, making no modeling assumptions 128 other than the lockdown data and the reference year data both originating from iid samples. 129 Moreover, the resulting p-value calculation is exact, in contrast to most statistical tests for which the 130 p-value is only valid asymptotically for large pre- and post-lockdown samples.

To the best of our knowledge, this is the first application of such a randomization test to air quality data. It is also worth noting that randomization tests such as ours do not necessarily rely on assumptions about iid sampling or other elements of a statistical model, which can be especially advantageous for the analysis of one-time events such as COVID-19. Additional explanation for both points is provided in the Supporting Information.

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137 Data availability. The data that support the findings of this study are available from the138 corresponding authors upon reasonable request.

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Computer code. A self-contained library written in the R programming language documenting all
 p-value and boxplot calculations are available from the corresponding authors upon request.

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143 **RESULTS**

Assessing variation in temperature and solar irradiance in 2017-2020. The overlap of seasonal 144 variations in the concentrations of NO₂, CO, O₃ and PM2.5 with measures enforced by the Ontario 145 government to limit the spread of COVID-19 complicated the assessment of reductions associated 146 with reduced traffic, aviation, and industry emissions. Figure 1 shows the locations of the air quality 147 148 stations, meteorology and solar irradiance stations that collect hourly data on pollutant levels, temperature and radiative forcing, respectively. To assess meteorological changes in 2020 relative 149 to reference years, 2017-2019, Figure S1 shows box plots of daily mean temperature for three 150 151 locations selected based on their type (rural versus urban) from January until June. Below each box 152 in the plot is the p-value value calculated from the randomization test described in the Methods 153 section. The set of p-values on the right test whether there is a statistically significant difference 154 between the median monthly temperature in 2020 compared to 2017-2019.

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Figure 1: Map of Southern Ontario showing locations of air quality stations maintained by MECP,national meteorological and irradiance stations maintained by ECCC.

For March 2020, the p-value is less than 0.05 for all sites, suggesting that a potential lockdown effect 160 161 on air pollutants might be masked by unusually high temperatures relative to the reference years. 162 On the other hand, p > 0.05 for April, May, and some sites in June 2020. These data suggest that 163 temperature was not significantly different in 2020 compared to reference years, and therefore does 164 not confound pollutant concentration months when the lockdown is both in full and waning force. The other set of p-values below the boxes to the left side tests the difference between medians in the 165 reference years (a generalization of the randomization test above to more than two samples is 166 167 provided in the Supporting Information). The p-values for February, March, and June are all greater 168 than 0.05, indicating that 2017-2019 median temperatures were not statistically different during 169 those months. In contrast, the corresponding p-values for January, April, and May 2017-2019 are 170 well below 0.05. Since the months within these reference years did not experience the lockdown 171 effect, the low p-value indicates that there is considerable natural variation in seasonal meteorology 172 during these months, making it difficult to detect the specific impact of COVID-19 in 2020.

As shown in Figure 1, the two stations in Southern Ontario for measuring solar irradiance are in Ottawa and Delhi. Figure S2 shows the daily solar global horizontal irradiance (GHI) at these locations from January till June between 2017-2020. GHI values were obtained from the measured radiation field. In this case, the p-values are all generally greater than 0.05, indicating that there is little difference in solar irradiance between these years.

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Assessing variation in pollutant levels. Figure 1 shows the locations of selected air quality stations in Southern Ontario that collect hourly data on pollutant levels analyzed here. Each air quality station measured hourly levels of NO₂, O₃ and PM2.5. Only four out of the sixteen stations reported CO measurements: Hamilton Downtown, Ottawa Downtown, Toronto West, and Windsor

Downtown. The MECP's rationale behind choosing these sites for CO measurements is that 183 Hamilton and Windsor are in the top five of the most polluted cities in Ontario. Toronto West station 184 is near the busiest highway in North America, Hwy 401.¹⁵ Ottawa was likely chosen because it is 185 186 the nation's capital city and is technically located in Eastern Ontario, further away from the US 187 border with little industrial activity. The next few sections describe the variation in pollutant levels at different resolutions: hourly, daily, weekly and monthly in order to show how data resolution 188 affects the type of conclusions that can be made. As detailed above, the statistical approach we 189 190 developed here aims at quantifying the significance in the difference between median pollutant 191 levels of weekdays (no weekends) per month in 2020 and the previous three years, 2017-2019, used as reference. 192

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Variation in NO₂ levels. Figure S3 shows the diurnal average levels of NO₂ in April over 2017-194 195 2019 and 2020 for Grand bend (rural), Kitchener (urban), and Toronto West (urban). These data are 196 superimposed with solar irradiance and average hourly temperature for each location. April was chosen because it followed two weeks of COVID-19 lockdown measures in Ontario. As a 197 198 photoactive molecule, the data show a reduction in the NO₂ levels with increasing solar irradiance, 199 which peaks around 12:00-13:00. Overall, the concentrations of NO₂ in Grand Bend range from 1.5 200 -3 ppb, Kitchener from 2.5 -11 ppb, and from 5 -22 ppb for Toronto West, which peak around 201 06:00 during the morning rush hour. While the average data in Figure S3 show lower diurnal NO₂ levels in 2020 compared with the average data in 2017 - 2019, standard deviation calculations (± 1 202 203 σ) revealed extensive overlap between the two cases (see shaded areas). Based on this data, we 204 could not conclude that the reduction observed in April 2020 is statistically significant relative to 205 2017-2019.

206 We then calculated the daily NO₂ levels for each station from January until June in 2020 for 207 comparison with the daily average of each month from 2017-2019. Figure S4-S6A show selected 208 data for the same locations in Figure S3. The values of the standard deviation were removed for 209 clarity. The trends in the daily NO₂ concentrations over a five-month period shows a great degree of overlap between the 2020 and average 2017 - 2019 data. Also, these data show the seasonal 210 reduction in NO₂ in the spring months compared to winter. The start of the COVID-19 lockdown in 211 March 2020 is marked in these Figures. There is no clear evidence that additional reductions in 212 213 daily NO₂ levels were observed in the daily values in 2020 compared with the average daily values 214 in reference years in any of the stations we analyzed. We then looked at median values of NO₂ 215 levels for weekdays only (no weekends) for all weeks from January until the end of June, per year 216 in 2017-2020. Figures S4-S6B show selected data from this type of analysis for the same stations 217 in Figure S3. The median of weekdays analysis did not reveal clear reduction in NO₂ levels in the 218 weeks after the COVID-19 lockdown either.

219 Following the hourly, daily and weekly analyses described above, the weekdays distribution 220 in NO₂ levels in a given month in 2020 and in reference years was graphically analyzed using box 221 and whisker plots. Figure S7 shows representative plots for the three air quality stations shown in 222 Figure S3. The p-values for March 2020 are all statistically insignificant, perhaps linked to unusually 223 high temperatures during this month. On the other hand, many stations recorded drops in NO₂ 224 concentrations below the 0.05 significance level in April-June. Of particular note is Toronto West 225 in April 2020, for which a significant drop was reported despite the statistically significant 226 differences between the reference years. In other words, the difference between April 2020 and the 227 reference years is large, even compared to the considerable seasonal variability of pollutant levels which naturally occurs during the month of April. As presented in the following sections, the 228

weekdays median values for NO₂ were used to calculate the percentage difference in 2020 relative
to the reference years, 2017-2019, and also to calculate the p-values used to quantify the statistical
significance of the percent difference.

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Variation in CO levels. Figure S8 shows box and whisker plots for the weekday distribution in CO levels in four air quality stations, Hamilton Downtown, Ottawa Downtown, Toronto West and Windsor Downtown. These are all urban stations, each of them having a significantly lower median CO value in April 2020 than in the reference years. There is also some evidence that the lockdown is easing, with many p-values above 0.05 in May-June 2020. Similar to NO₂, the weekdays median values for CO were used to calculate the percentage difference in 2020 relative to the reference years, 2017-2019.

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241 Variation in O₃ and PM2.5 levels. Figure S9 shows box and whisker plots for the weekday 242 distribution in the concentrations of O₃ and PM2.5 over 2017-2019 and 2020 for the sites that 243 experienced statistically significant drops in each pollutant per Table 1. For O_3 , the sites shown in 244 the figure are Sarnia and Windsor West, with Toronto West added for comparison given its 245 proximity to Hwy 401. For PM2.5, the sites shown in the figure are Hamilton West, Ottawa 246 Downtown and Windsor Downtown. The raw data show the seasonal changes in O₃ levels for these 247 selected sites that increase in spring and summer months. The apparent trend in PM2.5 levels is a 248 narrower distribution of data points in May and June compared to earlier months for all years, and 249 in 2020 in general, compared to reference years, 2017-2019. Similar to NO₂ and CO, the weekday 250 median values for O₃ and PM2.5 were used to calculate the percentage difference in 2020 relative to the reference years, 2017-2019. 251

Table 1: Summary of the percentage *decrease* in pollutant levels in 2020 relative to the same period
 in 2017-2019. The statistically significant values are highlighted in p-values below 0.05 listed in
 parentheses.

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AO station	Pollutant											
name ^a	NO ₂ (ppb)			CO (ppm)			O ₃ (ppb)			PM2.5 (µg m ⁻³)		
R = Rural	COVID-19 related decrease (%) ^b											
U = Urban	Apr	May	Jun	Apr	May	Jun	Apr	May	Jun	Apr	May	Jun
Grand Bend (R)	39 (0.01)	n.o.	n.o.	No measurements			n.o. (0)	0.1	n.o.	n.o.	2	n.o.
Guelph (U)	22 (0.05)	22	n.o.	No measurements			n.o.	2	n.o. (0.05)	n.o.	27	n.o. (0.02)
Hamilton Downtown (U)	27	15	38 (0.05)	20 (0.01)	4	10	n.o.	n.o.	n.o. (0.02)	6	15	n.o.
Hamilton Mountain (U)	27	5	28	No measurements			n.o.	3	n.o. (0.04)	19	27	n.o.
Hamilton West (U)	22	21	17	No measurements			n.o.	n.o.	n.o. (0.02)	11	32 (0.03)	n.o.
Kitchener (U)	24	29 (0.03)	39 (0)	No measurements			2	2	n.o.	10	25	n.o.
London (U)	29 (0.01)	20 (0.02)	18 (0.02	No measurements			n.o.	4	n.o.	32	15	n.o.
Ottawa Downtown (U)	16	15	17	18 (0)	14 (0.01)	6	n.o.	n.o.	n.o. (0.02)	n.o.	24 (0.04)	n.o.
Parry Sound (U)	7	14	n.o.	No measurements			n.o.	n.o.	n.o.	15	n.o.	n.o.
Sarnia (U)	42 (0.02)	30	13	No measurements			14 (0)	18 (0)	1	n.o.	2	n.o.
Toronto Downtown (U)	n.o.	n.o. (0.01)	n.o.	No measurements			5	21	n.o.	n.o.	12	n.o. (0.01)
Toronto East (U)	30 (0.01)	22	21	No measurements			n.o. (0.02)	2	n.o. (0.01)	9	18	n.o.
Toronto North (U)	30 (0.03)	7	2	No measurements			n.o. (0.01)	1	n.o. (0.03)	0.4	29	n.o.
Toronto West (U)	27 (0)	21 (0.01)	13	18 (0)	10	2	n.o. (0.01)	n.o.	n.o. (0.03)	n.o.	21	1
Windsor Downtown (U)	17	40 (0)	19 (0.03)	11 (0.03)	17 (0.01)	11	4	n.o.	n.o.	n.o.	26 (0.04)	0
Windsor West (U)	7	40	11	No measurements			12	8	n.o.	n.0.	n.o.	n.o.

256 Notes: ^{*a*} See Table S2 for station type and Figure S1 for location. ^{*b*} % decrease in 2020 in a given 257 month = (median in 2020 – median in 2017-2019)*100% / (median in 2017-2019). See Figures

257 month = (median in 2020 – median in 2017-2019)*100% / (median in 2017-2019). See Figures 258 1,2, 4a-c for examples. 'n.o.' = no decrease observed, on the other hand, an increase was observed 259 in pollutant level in 2020 relative to 2017-2019.

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Assessing the variability of pollutant levels within the reference years 2017-2019. Table S2 lists the p-values calculated for the concentration distribution of each pollutant within the three year period 2017-2019. The main assumption is that seasonal factors are the major contributors to the

concentration distribution in each year, which are similar over a three year period. The statistical 265 266 significance test used here resulted in p < 0.05 for a number of sites in a given month. Tables S3-S18 list the median values for each pollutant in April – June over 2017-2019. Median values for 267 268 2020 are also listed. The median values provide an accurate indication of the similarity between 269 years reflected in the calculations of the p-values. For example, the p-value for May in 2017-2019 for NO₂ levels at Grand Bend station is 0. The median values for NO₂ listed in Table S3 are 2.8, 270 4.0, and 1.6 for 2017, 2018 and 2019, respectively. Hence, the p-value of 0 indicates that there is 271 272 considerable natural variation in NO₂ concentration levels from year to year between 2017-2019. 273 Other examples of statistically significant differences over the reference years are highlighted in 274 Table S2 with underlined p-values. When the p-value for 2020 is less than 0.05, this indicates that 275 there is a significant difference between 2020 and the past three years that could be attributed to new 276 factors such as the COVID-19 lockdown restrictions. In the case when p-values for the reference 277 years are also less than 0.05, this indicates that 2020 stands out despite considerable variability 278 among the reference years. This suggests the presence of new unique factors in 2020 that are 279 separate from those causing the difference in pollutant levels among the reference years. This result 280 is different from the scenario where p-values are less than 0.05 for the reference years, but greater 281 than 0.05 for 2020. This result would suggest that seasonal meteorology can account for large 282 differences between years, compared to which the lockdown effect is insignificant.

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Assessing the variability of pollutant levels in 2020 relative to the reference years 2017-2019. As detailed in the Methods section, the calculated p-values reflect the degree of similarity in the distribution of daily pollutant levels in 2020 and the reference years: p-values < 0.05 indicate statistically significant difference between the 2020 median weekday levels and those in reference

years. The calculated percentage difference, which could indicate increase, decrease, or no change 288 289 in pollutant levels, can be attributed to new factors other than temperature and solar irradiance 290 because it was calculated for the same monthly period. These factors would include the effect of 291 COVID-19 measures on reducing traffic, aviation and industrial activities. It could also include new 292 residential sources, which increased in contribution due to 'go home and stay at home' public health 293 advisories starting in March 2020. Another important factor that has been known to influence air 294 quality in Ontario is transboundary air pollution from the United States that increases the 295 concentration of pollutants studied here. The US did not enforce COVID-19 lockdown measures 296 during the same time period as Ontario. As highlighted in Table S1, 'stay at home orders' in 297 Michigan and Ohio were implemented after Ontario and were beginning to be lifted well before 298 Ontario lifted its 'stay at home' order. This difference in lockdown enforcement was expected to 299 have a big impact on NO_x and CO levels for stations in the Windsor and Sarnia area, along the US 300 border, which are heavily impacted by transboundary transport, in so much that any impact from 301 COVID-19 lockdown measures would be difficult to disentangle from US sources impacting these 302 sites.

The weekday median values for the pollutants analyzed here were used to calculate the percentage difference in two ways to highlight two cases: In case 1, percentage difference values were calculated for each month in 2020 relative to the corresponding month in the reference years, 2017-2019 (Table 1). This type of calculation assumes that seasonal variability is similar for each



Figure 2: Percentage difference in weekday median levels of NO₂ in 2020 relative to the same
period in reference years, 2017-2019 for selected sites. The data for April – June are listed in
Table 1 for these sites. The '*' highlight the statistically significant decreases based on the pvalues.

313 314

month, and hence any statistically significant difference in pollutant levels is due to new factors such 315 316 as transboundary influences or COVID-19 restrictions. Figure 2 shows graphical representation of 317 the percentage decrease in pollutant levels for selected sites. In case 2, percentage difference values 318 were calculated relative to January in 2020 and in the reference years 2017-2019. Then, if an extra 319 decrease was observed for a given pollutant in 2020 relative to reference years, the difference in the percentages was calculated to quantify that extra decrease as reported in Table S19. This type of 320 321 calculation shows the magnitude of seasonal changes in each pollutant for 2020 and reference years 2017-2019 relative to their highest levels in January. The assumption here was that new factors that 322 323 might influence pollutant levels in 2020 beyond seasonal changes will be manifested as either increases or decreases in percentage. Figure S10 shows graphical representation of this extra 324 decrease in NO₂ concentrations for selected sites. Therefore, the calculated p-values were used to 325

quantify the statistical significance of these percentages in cases 1 and 2. For Tables 1 and S19, the data are only shown for April until June since COVID-19 lockdown measures started March 17, 2020 in Ontario. The statistically significant percentages are highlighted in shaded areas based on the p-values listed in parentheses. These p-values are the same as those listed in the monthly 2020 columns in Table S2. Calculated percentages that indicate no change or an increase in pollutant levels were assigned 'n.o.' in an effort to highlight *decreases* attributed to the impact of COVID-19 lockdown measures or other new factors.

333 Figures 2 and 3 show selected data from Table 1 for selected sites to graphically demonstrate 334 differences in NO₂ and CO changes among different sites over the months in 2020 before and after 335 the COVID-19 measures came into effect. Percentages were calculated in these figures according 336 to case 1 described above. Figures S10 and 4 show the extra decreases observed in 2020 for NO_2 337 and CO, respectively, for selected sites from percentages calculated according to case 2 described 338 above, which are also listed in Table S19. Transportation sources contribute 69% and 87% of NO₂ 339 and CO emissions in Ontario, respectively.¹⁰ The statistically significant decreases in NO₂ levels occurred in April and ranged from 22-42% depending on the location of the station (Table 1). For 340 341 example, Figure 2a shows that the rural station, Grand Bend, experienced a 39% reduction in NO₂ 342 levels in April, no change in May, and a 20% increase in June. The p-value associated with the latter 343 percentage is 0.2 (Table S2), and hence the calculated increase in NO₂ June 2020 levels is considered 344 statistically insignificant (i.e., June weekday median levels in 2020 are within the distribution of the 345 corresponding values in June 2017-2019). Urban sites that experienced a statistically significant 346 reduction in NO₂ levels in April 2020 include Guelph (22%), London (29%), Sarnia (42%), Toronto 347 East, North, and West (~30%). Other urban sites experienced a statistically significant reduction in NO₂ levels in May 2020, which include Kitchener (29%), London (20%), Windsor Downtown 348



Figure 3: Percentage difference in weekday median levels of CO in 2020 relative to the same
period in reference years, 2017-2019 for selected sites. The data for April – June are listed in
Table 1 for these sites. The '*' highlight the statistically significant decreases based on the pvalues.



April does not align with that in Figure S10a. The box plot for the NO₂ data in Grand Bend is shown in Figure S7a where there is a clear fluctuation in the median 2020 data over February – June relative to January compared to a progressive decrease in the corresponding data for 2017-2019. Given the location of this site on the Canadian shore of Lake Huron, it is very likely that these fluctuations are due to transboundary influences from Michigan, USA.

The data in Figure 3 for CO levels in different urban sites show a ca. 20% statistically 368 significant reduction in April 2020 for Hamilton Downtown, Ottawa Downtown, and Toronto West. 369 370 Windsor Downtown experienced 11% reduction in April 2020. The statistically significant 371 reduction in CO levels continued in May 2020 for Ottawa Downtown (14%) and Windsor Downtown (17%). All of these urban sites experienced a statistically insignificant reduction in CO 372 373 in June 2020, which coincided with the second phase of lifting restrictions in Ontario (see Table S1). Moreover, data in Figure 4 show that these sites experienced a statistically significant 2-16% extra 374 375 decrease in CO levels in 2020 beyond seasonal variability observed in the same months in 2017-376 2019. This trend in the data agrees with that shown in Figure 3.

The data in Figure 5 for O_3 levels in different urban sites show statistically significant reductions in March - May 2020 for Sarnia and Windsor West, both of which are border cities with Michigan, USA with extensive industrial activity. The reduction observed in March 2020 for these sites of nearly 40%, is higher than that observed for the Toronto West site at 24% (Figure 5e), which is near Hwy 401. For the latter site, the reductions observed in April and May were not statistically significant, suggesting dominance of seasonal factors or other factors that affects the chemistry of ozone production in these sites.⁹

Figure 6 a-c show the variability in PM2.5 levels for the urban sites that experienced a 3540% statistically significant reduction in May 2020, which are Hamilton West, Ottawa Downtown



Month
Figure 4: Percentage difference in weekday median levels of CO in 2020 and 2017-2019 relative
to January of the same year(s). The vertical lines highlight the statistically significant percentage
decreases based on the p-values listed in Table 1 for April – June.



Month
Figure 5: (a-c) Percentage difference in weekday median levels of O₃ in 2020 relative to the same period in reference years, 2017-2019. The data for April – June are listed in Table 1 for these
sites. (d-f) The percentage in O₃ median values in 2020 and 2017-2019 relative to January of the same year(s). The vertical lines highlight the statistically significant percentage decreases based on the p-values listed in Table 1 for Apr – June.

and Windsor Downtown. The relatively large reduction in Hamilton West site was also observed 397 when the percentage was calculated relative to January of the same year(s) (Figure 6d). This result 398 399 suggests that the Ontario lockdown on the industrial activity in Hamilton had a significant impact 400 on the levels of PM2.5, which was not observed in the other sites. The Ottawa Downtown site experienced 11% reduction in PM2.5 (Figure 6e), which likely reflects the effect of the City's 401 lockdown on transportation. The Windsor Downtown site experienced only 7% reduction in PM2.5 402 (Figure 6f), which was likely influenced by the industrial activity in Michigan, USA. Interestingly, 403 404 levels of PM2.5 were higher in June 2020 compared to previous years in all of the sites analyzed.

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Figure 6: (a-c) Percentage difference in weekday median levels of PM2.5 in 2020 relative to the
same period in reference years, 2017-2019. The data for April – June are listed in Table 1 for
these sites. (d-f) The percentage in PM2.5 median values in 2020 and 2017-2019 relative to
January of the same year(s). The vertical lines highlight the statistically significant percentage
decreases based on the p-values for Apr – June.

415 **DISCUSSION**

Sites within the City of Hamilton were expected to see little impact from decreased 416 transportation and industrial activity, as many of the city's industry were likely classified as 417 "essential services" during the lockdown that started in mid-March. As a result, only one site in the 418 419 city had a statistically significant drop in NO₂ (Hamilton Downtown – June). The statistically 420 insignificant drops in NO₂ at all other sites in Hamilton could be due to slowed production or could be due to annual variability driven by atmospheric chemistry.⁹ This result matches the observations 421 of Shi and Brasseur⁵, who found substantial variability in NO₂ levels, as well as other pollutants, in 422 423 Beijing, which had less severe lockdown measures than Wuhan.

In the Toronto region, NO₂ levels were expected to be significantly impacted by local 424 sources, such as transportation and industry given their relatively large distance from significant 425 U.S. sources of the Ohio Valley. All Toronto sites saw large drops in NO₂ levels in April 2020 426 relative to 2017-2019, except Toronto Downtown. The drop in NO₂ levels observed here are similar 427 to reported by Griffin *et al.*¹ after accounting for seasonality estimated in their analysis. The Toronto 428 429 West site also saw a drop in measured CO levels. While not all decreases in pollutant levels were 430 significant compared to previous years, the trend suggests that decreased movement of the 431 population and industry played a considerable part in the observed drops. These results corroborates the findings of Griffin *et al.*¹ who found that reductions in NO₂ in the Toronto region are not entirely 432 433 due to COVID-19 related emissions reductions. The mix of significant and insignificant decreases from previous years could be due to the fact that a number of industries within the Toronto region 434 were likely still operating during the lockdown, given their "essential services" status. These 435 findings could also be highlighting the importance of other factors such as meteorology and 436 atmospheric chemistry.⁹ 437

Medium sized cities in Southwestern Ontario were also expected to have little impact from 438 transboundary sources for NO₂ with transportation making a larger impact on NO₂ and CO sources 439 440 than industry. While some of these cities have manufacturing facilities, they are not expected to be 441 on the scale of Toronto or Hamilton. As seen in Table 1, Kitchener and London had statistically 442 significant drops in NO_2 in all but one month, with the remaining month still showing a large drop 443 in NO₂. Guelph had a statistically significant drop in April and a large (albeit insignificant) drop in 444 May. This data suggest that the drop in NO_2 could be directly linked with decreased traffic in these cities. This is corroborated by transportation data from Kitchener that saw a 55% decrease in traffic 445 446 in early May, and a 47% decrease in late May – early June in 2020 compared to previous traffic counts within the city (Table S20). Furthermore, Ottawa experienced statistically insignificant drops 447 448 in NO₂ in all three months, as well as statistically significant drops in CO in April and May. This 449 likely reflects the effect of the City's lockdown on transportation and is reinforced by the findings 450 for PM2.5 levels in the city.

451 Sarnia, Windsor Downtown and Windsor West were expected to have a large transboundary 452 influence from both Michigan and Ohio, but also a potentially significant influence from 453 transportation. Given the wide range of dates of closures and re-openings across the two US states 454 and Ontario, it was expected that little to no difference would be seen in 2020 compared to previous 455 years. Any difference was expected to be seen in April since all three jurisdictions were closed in 456 this month. However, both Windsor sites saw significant decreases in NO₂ in May, with Windsor 457 Downtown also seeing a significant drop in NO₂ in June and a significant decrease in CO in May. 458 Only Sarnia saw a significant decrease of NO₂ in April. This may suggest that Sarnia is more 459 impacted by local transportation, including cross border traffic, as opposed to Windsor, which is impacted by local industry immediately across the border in and around Detroit. It is not clear why 460

461 the Windsor sites did not see a significant drop in April but did in May and June, which requires 462 further analysis. Again, this finding is similar to that of Griffin *et al.*¹ who found that NO₂ levels in 463 this region of the province were difficult to recreate as a result of difficulties in estimating changes 464 in US-based emissions due to reduced activity during COVID lockdowns.

The statistically significant drops in CO at sites across the province, especially in April, highlight the drop in transportation during the pandemic. The drop in CO concentrations continued into May, with half of the sites recording a statistically significant drop. As the province relaxed quarantine measures and the population re-emerged during May and June, the drops in CO were generally smaller than April, and not always statistically significant.

In conclusion, the government measures to limit the spread of COVID-19 in Southern 470 471 Ontario resulted in statistically significant reduction in pollutant levels emitted from the 472 transportation and industrial sectors in the majority of the sites analyzed. These reductions were 473 beyond the seasonal variability observed within the last three years. Other sites were influenced by 474 transboundary and/or other local influences (i.e., industry) that countered local reductions in human 475 activity. Results presented here are highly significant because (1) they highlight the need to carry 476 out rigorous statistical analysis that accurately quantifies the significance of short term events on 477 pollutant levels, (2) our analysis provides numerical evidence to the magnitude that large scale 478 lockdowns have on air quality in Southern Ontario since worsening air quality is one of the impacts 479 of climate change¹⁶, and (3) policy makers would be better informed when planning for mitigation 480 and adaptation for long-term and lasting positive effects of reducing air pollution.¹⁷ That being said, 481 meaningful change with respect to air pollution and air quality can only be solved with meaningful 482 local change in select circumstances. Our results highlight the impact that transboundary pollution and local industrial sources can have, limiting the effect that changing local transportation modes, 483

as an example, can have on local air quality. Furthermore, our results also suggest that seasonal meteorology can account for large differences between years, compared to which the lockdown effect is insignificant. This highlights the importance of considering all factors that influence air pollution and that policies critical to one jurisdiction may not have a significant impact in another jurisdiction. As the province continuously monitors and reports the effect of air quality regulations for different sites, future data collection should also focus on specific chemical compounds or classes that affect local O₃ and PM2.5 formation⁹ to disentangle local versus transboundary sources.

In light of recent research that correlates long term exposure to NO₂,¹⁸ PM2.5 and PM10 in 491 polluted cities¹⁹ with fatalities caused by COVID-19, future analysis should also focus on analyzing 492 the relationship between pollution levels, number of confirmed COVID-19 cases and deaths in the 493 494 sites analyzed here. Since airborne transmission is identified as the dominant route for the spread of COVID-19,^{20,21} research that correlates PM levels in Southern Ontario and the rates of infections 495 496 and deaths are worth investigating. It is important to account for population density, age, race, 497 socioeconomic status and establish a clear baseline from previous years on major causes of 498 respiratory diseases and fatality.

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503 AUTHOR INFORMATION
504
505 Corresponding Authors
506 * H.A.A.: Phone: (519)884-0710, ext.2873; e-mail: <u>halabadleh@wlu.ca</u>.
507 * M.L.: Phone: (519) 888-4567, ext.35503; e-mail: <u>mlysy@uwaterloo.ca</u>.
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- 515 Ontario, Canada. 2020.
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519 ASSOCIATED CONTENT

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521 Supporting Information Available

- Examples of earlier studies, Tables S1-S20, Figures S1-S10, additional details on methods. This
 material is available free of charge on the ACS Publications website at DOI: XXX
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