

# COVID-19 prevention, air pollution and transportation patterns in the absence of a lockdown

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## ABSTRACT

Recent studies demonstrate that air quality improved during the coronavirus pandemic due to the imposition of social lockdowns. We investigate the impact of COVID-19 on air pollution in the two largest cities in Taiwan, which were not subject to economic or mobility restrictions. Using a difference-in-differences approach and real-time data on air quality and transportation, we estimate that anthropogenic air pollution from local sources increased during working days and decreased during non-working days during the COVID-19 pandemic. This led to a 3–7 percent increase in CO, O<sub>3</sub>, SO<sub>2</sub>, PM<sub>10</sub> and PM<sub>2.5</sub>. We demonstrate that the increase in air pollution resulted from a shift in preferred mode of travel away from public transportation and towards personal motor vehicles during working days. In particular, metro and shared bicycle usage decreased between 8 and 18 percent, on average, while automobile and scooter use increased between 11 and 21 percent during working days. Similar COVID-19 prevention behaviors in regions or countries emerging from lockdowns could likewise result in an increase in air pollution. Taking action to reduce the transmissibility of COVID-19 on metro cars, trains and buses could help policymakers limit the substitution of personal motor vehicles for public transit, and mitigate increases in air pollution when lifting mobility restrictions.

## 1. Introduction

In order to reduce the spread of the SARS-CoV-2 virus that causes COVID-19, many regions and countries have implemented significant restrictions on business operations and the mobility of consumers (Cheng et al., 2020a). For example, stay-at-home orders and social distancing reduce travel and provide barriers to employment and the acquisition of consumer goods. The closure of restaurants, retail establishments, and non-essential businesses likewise limit movement and reduce economic output. There is significant interest in determining how these unprecedented restrictions and the associated behavioral responses affected air quality.

Studies of changes in air pollution initially focused on the strict lockdown of Wuhan and mobility restrictions put in place throughout China thereafter. For example, Xu et al. (2020), Wang and Su (2020), Shi and Brasseur (2020), Cole et al. (2020), Fan et al. (2020), and Almond et al. (2020) all find that lockdowns and restrictions on economic activities in the city of Wuhan and other regions of China significantly

reduced air pollution. Shi and Brasseur (2020) calculates that surface PM<sub>2.5</sub> and NO<sub>2</sub> levels decreased by 35 % and 60 %, respectively, in northern China during the pandemic, while Wang et al. (2021) finds reductions in six ambient air pollutants in the Beijing-Tianjin-Hebei region and Yangtze River Delta.<sup>1</sup> Most studies also find that O<sub>3</sub> increased by as much as a factor of 2 due to reductions in nitrogen oxides. Despite the offsetting effects of these pollutants, both He et al. (2020) and Chen et al. (2020) estimate that the improvement in China's air quality could lead to as many as 36,000 fewer premature deaths per month.

Investigations of the association between COVID-19 restrictions and air pollution in Europe (Baldasano, 2020; Menut et al., 2020; Bauwens et al., 2020; Collivignarelli et al., 2020), Egypt (Mostafa et al., 2021), South Korea (Bauwens et al., 2020) and India (Mahato et al., 2020), are generally consistent with those from China. For example, Menut et al. (2020) estimates reductions in NO<sub>2</sub> pollution across locations in Western Europe of 30 %–50 %, and reductions in PM<sub>10</sub> and PM<sub>2.5</sub> of 5 %–15 %. Mahato et al. (2020) finds a 53 % drop in NO<sub>2</sub> and reductions of 60 %

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<sup>1</sup> Hua et al. (2021) note that while the lockdown in the Beijing area resulted in large reductions in NO<sub>2</sub> and PM<sub>2.5</sub>, a large fraction of the surface concentrations of these pollutants was offset by meteorology, allowing haze pollution in Beijing to persist.

and 39 % in PM<sub>10</sub> and PM<sub>2.5</sub>, respectively, during the lockdown in Delhi, India. In addition, Mahato et al. (2020) finds concomitant increases in ground-level ozone in Delhi, as does Menut et al. (2020) in Western Europe.

Estimates from U.S. data are more mixed than in other countries. Brodeur et al. (2020) determines that stay-at-home orders reduced levels of PM<sub>2.5</sub> by 25 %, while Bauwens et al. (2020) reports reductions of NO<sub>2</sub> in the northeastern cities of New York, Philadelphia, and Washington D. C. of 21 %–28 %. In contrast, Bekbulat et al. (2020) does not find that PM<sub>2.5</sub> and O<sub>3</sub> concentrations in the U.S. fell outside the normal range of statistical variability. Zangari et al. (2020) likewise reports no significant differences in PM<sub>2.5</sub> and NO<sub>2</sub> during the 2020 New York City shutdown relative to the same weeks in 2015–2019.

Finally, Dang and Trong (2020) compiles data from 178 different countries and confirms the finding from most individual country or city studies that lockdowns decreased air pollution. They also conclude that decreases in mobility following the lockdowns likely reduced air pollution. Elsaid et al. (2021) conducts a similar worldwide review, and finds that lockdowns dramatically decreased CO<sub>x</sub>, NO<sub>x</sub>, SO<sub>x</sub> and PM emissions, but increased O<sub>3</sub> due to reductions in nitrogen emissions.

While studies hypothesize reductions in industrial production, transportation and other human activities are responsible for the lower levels of ambient air pollution that occurred during COVID-19 lockdowns, they typically do not make a direct link to specific activities. Exceptions include Sahraei et al. (2021) which shows that in 12 countries with lockdowns there was a concurrent decrease in public transit usage, and Dang and Trong (2020), which used Google Mobility Reports to show lower mobility in locations where government policies were more stringent. Likewise, Zeng and Bao (2021) finds that much of the decrease in PM<sub>10</sub>, PM<sub>2.5</sub> and NO<sub>2</sub> that occurred during lockdowns was due to lower levels of human migration. Hua et al. (2021) shows that NO<sub>2</sub> emissions in Beijing gradually increased as traffic volumes escalated following the start of the lockdown and Cicala et al. (2020) predicted a decline in CO<sub>2</sub> in a simulation study based on decreased vehicle traffic in the U.S.

We contribute to this literature by examining changes in air pollution in Taipei and New Taipei City, the two largest cities in Taiwan, which were not subject to the strict lockdowns imposed in many other major cities. As a result, we are able to examine how air quality changed during the early stages of the pandemic due to residents' attempts to avoid a COVID-19 infection. Using a difference-in-differences framework and real-time data on both air pollution and transportation, we draw a direct link between higher pollution levels and changes in transportation patterns that we ascribe to the COVID-19 prevention behavior of residents.

## 2. Materials and methods

### 2.1. Data

We compiled data from several administrative sources in order to conduct our analysis. We collected data on confirmed cases of COVID-19 from the Taiwan Center for Disease Control (CDC); several air quality measures from the Environmental Protection Agency (EPA); metro usage from the Taipei Rapid Transit Corporation; shared bicycle usage from the Taipei City Government, and motor vehicle traffic data from the Ministry of Transportation and Communication.<sup>2</sup> Our study period is January 1 - March 31, 2017–2020.

<sup>2</sup> Our data cover the most popular methods of commuting in Taipei and New Taipei City. Based on commuting patterns in 2014–2016, scooters are the most widely used form of commuting (30 %), followed by buses (22 %), cars (19 %), the metro (17 %), walking (6 %), and bicycles (3 %) (Ministry of Transportation and Communications, 2018).

#### 2.1.1. COVID-19 case counts

The first confirmed case of COVID-19 in Taiwan was identified in Taipei City on January 22, 2020. We compiled the number of the confirmed cases of COVID-19 registered in both Taipei and New Taipei City during each day between January 22, 2020 and March 31, 2020. Confirmed cases are those that have been validated by medical testing, whereas unconfirmed cases are suspected by physicians to be COVID-19 based on patient-reported symptoms. We use the former because confirmed cases are listed on the CDC website and reported to the public during CDC press conferences. From these data we created two variables to measure COVID-19 cases. The first is a binary indicator for the period when confirmed COVID-19 cases existed in Taiwan (=1 if January 22 - March 31 of 2020; = 0 otherwise), while the second is a continuous measure of the cumulative number of the confirmed cases in each day of the sample period in each of the two cities.

For the analysis of all outcome variables we defined the treatment and control groups in 2020 and 2017–2019, respectively. In each year, the post-treatment period corresponds to January 22 - March 31 and the pre-treatment period is January 1 - January 21.

#### 2.1.2. Air quality measures

We obtained measures of air quality from 19 air quality monitoring stations located across Taipei and New Taipei City (see Fig. 1, panel A) and two monitoring stations on islands under the control of Taiwan (Matsu and Kinmen County) that are just off the coast of mainland China (see Fig. 1, panel B). The stations monitor major pollutants, including PM<sub>2.5</sub>, PM<sub>10</sub>, CO<sub>x</sub>, NO<sub>x</sub>, SO<sub>2</sub>, O<sub>3</sub>, and hydrocarbons. Due to the direction of prevailing winds and the close proximity of Taiwan to mainland China, residents of Taipei and New Taipei City are often subject to significant air pollution from China (Lee et al., 2020). It is therefore important to account for pollution from China when investigating the effect of behavioral change among residents of northern Taiwan on localized air pollution.

We analyzed the same criteria pollutants regulated by the EPA under the U.S. Clean Air Act, with the exception of lead, which is not monitored. These include PM<sub>10</sub>, PM<sub>2.5</sub>, NO<sub>2</sub>, SO<sub>2</sub>, CO, and O<sub>3</sub>. The level of each pollutant is calculated as the average concentration at the given station over a 24-h period. We used the pollution measures derived from monitoring stations in Taipei and New Taipei City as outcome variables in our empirical models and pollution measures from the two stations near China as control variables. We merged the COVID-19 variables into the air quality dataset using city and date. In total, the air quality data from Taipei and New Taipei City consist of 5,741 station-day observations across both the treatment and control periods, of which 1,190 occurred in the 2020 post-treatment period (i.e., the period corresponding to the COVID-19 outbreak).

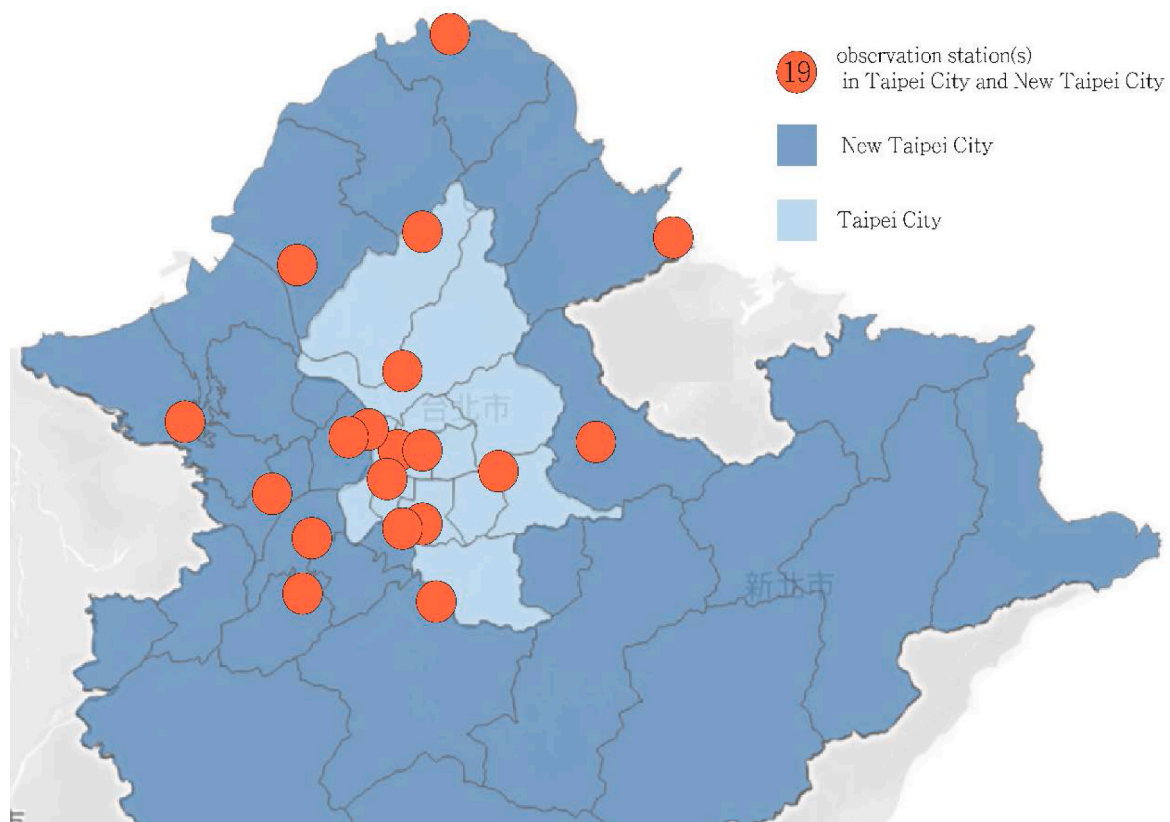
#### 2.1.3. Metro ridership and U-bike rentals

The Taipei metro system includes 119 stations that serve all sections of Taipei and New Taipei City. We excluded 11 stations from our analysis because they opened on January 31, 2020, right after the beginning of our treatment period. For each of the remaining 108 stations, we collected data on the number of people who departed from and exited the station on every day during our treatment and control periods. In total, our sample of metro ridership contains 38,772 station-day observations, of which 7,452 occurred in the 2020 post-treatment period.

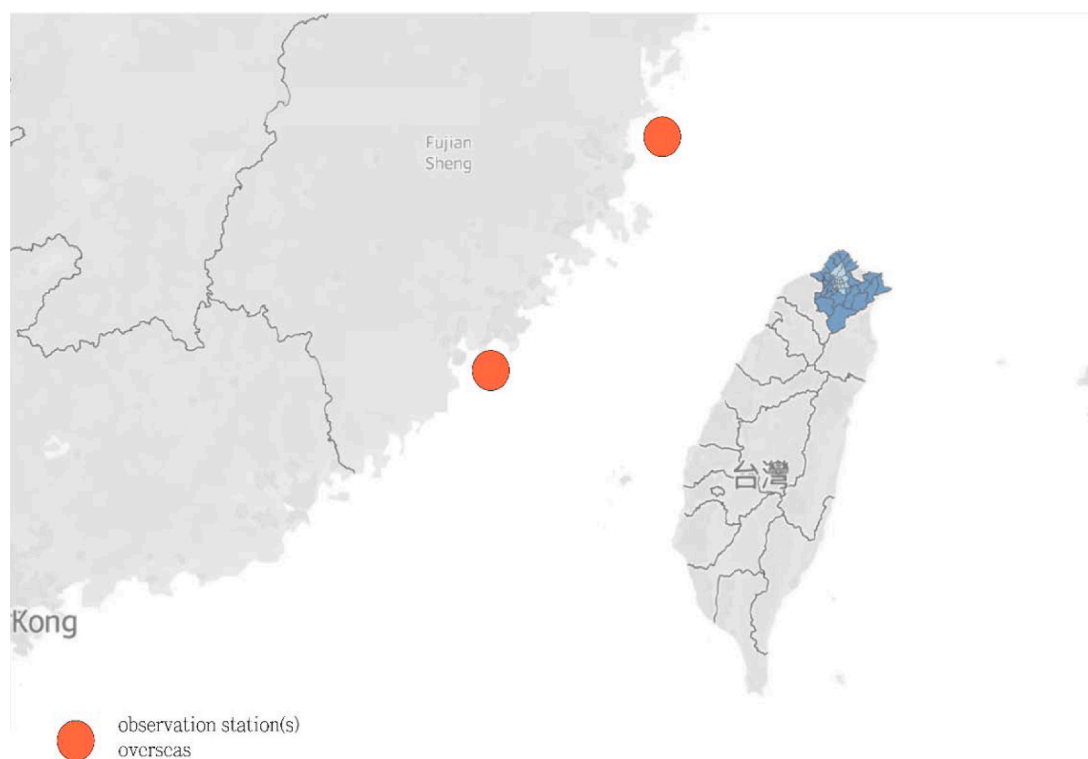
From the same metro database we created several indicator variables to measure characteristics of the stations and their surroundings. These include variables that indicate whether the station is a terminal station, connected to other metro lines, on an airport route or at an airport, connected to a high speed rail station, and whether a school or a traditional night market is near the station.

In 2011 the Taipei city government created a bike sharing system called U-bike to provide transportation to and from public transportation. The program has grown to 966 stations that serve most of Taipei and New Taipei City. U-bike stations are located at metro stations

Panel A. Nineteen stations in Taipei and New Taipei City.



Panel B. Two stations near mainland China.

**Fig. 1.** Geographic location of the air quality monitoring stations.

and bus stops as well as strategic locations near places of business and high density residential areas. The initial cost of bike rental is only five New Taiwan dollars, making the use of U-bikes very popular among metro and bus users.<sup>3</sup> In May 2020 the turnover rate of U-bikes was 5.6 times per bike per day (Cheng et al., 2020b). We excluded 10 stations that were opened in 2020. For the remaining 956 stations, we collected data on the number of departures and exits from each U-bike station (i.e. U-bike rentals) in each day of our treatment and control periods as well as information on the characteristics of U-bike stations. The latter include the year the station opened and the number of bike docks at each station. There are 222,007 rental-day observations in the U-bike data, 48,540 of which occurred in the 2020 post-treatment period.

#### 2.1.4. Automobile and scooter traffic

There are 35 traffic monitoring stations along the main bridges that connect Taipei and New Taipei City. Since many people live in New Taipei City and work in Taipei, the monitors effectively capture commuting patterns for all types of motor vehicles. We collected information on the number of cars, vans/trucks/buses and scooters passing through each traffic monitor during every hour of the treatment and control periods.<sup>4</sup> In total, our motor vehicle samples contains 309,400 station-hour observations, of which 60,460 are in the 2020 post-treatment period.

#### 2.1.5. Other variables

We collected additional data on three district-level characteristics that may explain variation in the outcome variables: the geographic area of each district, monthly population, the wind speed in each district, and the daily rainfall in each district.<sup>5</sup> For inclusion in our traffic analysis, we also collected information on the daily gasoline price, and for the air pollution models we collected data on the amount of coal used in power generation in metric tons per day.<sup>6</sup> Finally, we include in all of our models a control for the number of daily inbound visitors to Taiwan.<sup>7</sup>

### 2.2. Econometric analysis

We use a difference-in-differences model (DiD) to identify the causal effect of confirmed COVID-19 cases on air quality, motor vehicle usage, metro usage, and U-bike rentals using panel data (Wooldridge, 2010). The pre-treatment period is January 1 – January 21 and the post-treatment period is January 22 – March 31. The control group is composed of observations in 2017–2019 and the treatment group is observations in 2020.<sup>8</sup> Because the air quality, public transportation and shared bicycle outcome variables are right-skewed, we implemented the following log-linear specification:

$$\log(y_{ijt}) = \alpha_1 + \gamma_1 \cdot \text{COVID}_{jt} + \beta_1' X_{ijt} + v_j + t_m + t_y + \varepsilon_{ijt}, \quad (1)$$

where  $y_{ijt}$  is the outcome variable for station  $i$  in city  $j$  during time  $t$ . Station is either air monitoring station, metro station or U-bike station, and time is day.  $\text{COVID}_{jt}$  is either our discrete or continuous measure of confirmed COVID-19 cases in city  $j$  at time  $t$ .  $X_{ijt}$  is a vector of the explanatory variables associated with the outcome variable,  $v_j$ ,  $t_m$ , and  $t_y$

are fixed effects for city, month and year, and  $\varepsilon_{ijt}$  is the random error term.<sup>9,10</sup>

In the case of motor vehicle traffic, all of the traffic monitoring stations are located on main bridges that connect Taipei and New Taipei City, which means that there is no city-level variation in the dependent variable. In addition, the outcome variable has some zero values, so we estimated the following DiD model:

$$y_{2it} = \alpha_2 + \gamma_2 \cdot \text{COVID}_t + \beta_2' X_{2it} + t_m + t_y + \varepsilon_{2it}. \quad (2)$$

In equation (2) the time index denotes the 1 hour period used to collect traffic data, and  $\text{COVID}_t$  is either our discrete or continuous measure of confirmed COVID-19 in both cities combined at time  $t$ .

In equation (1), 100 times the parameter  $\gamma_1$  is a semi-elasticity that measures the effect of COVID-19 on the outcome variable in percentage terms. In equation (2),  $\gamma_2$  measures the effect of COVID-19 on 100s of cars, vans/trucks/buses or scooters per hour traveling between Taipei and New Taipei City. Both  $\gamma_1$  and  $\gamma_2$  are identified by comparing differences in outcome variable before and after the advent of COVID-19 (or across the pre- and post-COVID-19 level of infections) within the same calendar month in the control period (2017–2019) and the treatment period (2020).<sup>11</sup> We computed the standard errors in all models using the two-way-cluster-robust variance approach proposed by Cameron and Miller (2015) to cluster on both station and day.

### 3. Results

In panel A of Table 1 we report the mean values of all of the outcome variables in the air quality, motor vehicle traffic, metro usage, and U-bike and models in the pre- and post-COVID-19 period in the treatment year (2020) and the control years (2017–2019). While the level of most air pollutants in 2020 increased in the COVID-19 period relative to the pre-period, air pollution also increased through the first quarter of the calendar year in 2017–2019. As a result, the unadjusted DiD estimates for all pollutants, with the exception of  $\text{SO}_2$  are negative. The unadjusted DiD estimates for air pollution coming from mainland China reported in panel B generally follow the same pattern as pollution in Taipei and New Taipei City.

The unadjusted DiD estimates for transportation measures reported in panel A of Table 1 indicate that the use of automobiles and scooters increased during the COVID-19 period, while metro and U-bike use decreased. We also note that rainfall during the COVID-19 period (Table 1, panel C) was 36 % higher than usual, which could have affected the popularity of metro transportation when paired with U-bike rental. Another notable change during the COVID-19 period was the 70 % reduction in inbound visitors to Taiwan that occurred as a result of travel restrictions imposed by the government.

#### 3.1. Air quality

We present semi-elasticity estimates in Table 2 from the full DiD model of air quality, as specified in equation (1), and full estimation results for the CO equation in Appendix Table A4.<sup>12</sup> These models control for the relevant measure of air quality from China as well as the other variables listed in panel C of Table 1. The estimates reported in panel A of Table 2 correspond to the full sample, while those in panels B

<sup>3</sup> The exchange rate of New Taiwan dollars (\$NT) to U.S. dollars (USD) on December 4, 2020 was \$NT 1 = 0.035 USD.

<sup>4</sup> We combine vans, trucks and buses into a single category. The scooter category also includes motorcycles, but the latter are relatively rare in Taiwan.

<sup>5</sup> There are 12 districts in Taipei and 29 districts in New Taipei City.

<sup>6</sup> Coal is the largest source of electricity generation in Taiwan (U.S. Energy Information Administration, 2020).

<sup>7</sup> Visitors are not captured in district population statistics and may use different forms of transport than residents.

<sup>8</sup> Our specification of the DiD model is similar to Leslie and Wilson (2020), which investigates the effect of directives to social distance during the pandemic on domestic violence.

<sup>9</sup> Specifications with an indicator variable for the week of Chinese New Year yield similar estimates to those with month and year fixed effects.

<sup>10</sup> We also report estimates from models with station, rather than city, fixed effects as a robustness check.

<sup>11</sup> In the case of equation (1), the variation in the continuous measure of confirmed COVID-19 cases between the pre- and post-COVID-19 periods is measured within each city due to the inclusion of city fixed effects.

<sup>12</sup> Full estimation results for the other pollution measures are available upon request from the authors.



**Table 1**

Sample statistics for air quality measures, transportation variables and explanatory variables in the air quality dataset.

Variable	Outcome	2017–2020		2020				2017–2019				DiD	DiD %
		Full sample		Before 1/22		After 1/22		Before 1/22		After 1/22			
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.		
Panel A. Measures of air quality and transportation in Taipei and New Taipei City													
CO <sup>a</sup>	Concentration of carbon monoxide (ppb).	0.47	0.22	0.47	0.19	0.46	0.22	0.47	0.20	0.48	0.23	−0.02	−3.6 %
O <sub>3</sub> <sup>a</sup>	Concentration of ozone (ppb).	32.60	10.78	29.98	7.45	33.42	10.49	28.20	9.49	33.85	11.16	−2.21	−6.8 %
SO <sub>2</sub> <sup>a</sup>	Concentration of sulfur dioxide (ppb).	2.05	1.05	1.61	0.75	1.71	0.82	2.19	1.12	2.18	1.09	0.11	5.3 %
NO <sub>2</sub> <sup>a</sup>	Concentration of nitrogen dioxide (ppb).	16.15	8.92	14.78	7.98	14.94	8.96	15.94	8.17	16.80	9.14	−0.70	−4.3 %
PM <sub>10</sub> <sup>a</sup>	Concentration of particular matter <10 (ug/m <sup>3</sup> ).	34.03	17.58	26.24	11.22	28.75	13.67	29.76	16.08	36.02	18.70	−3.74	−11.0 %
PM <sub>2.5</sub> <sup>a</sup>	Concentration of particular matter <2.5 (ug/m <sup>3</sup> ).	16.96	9.09	14.30	6.73	15.81	8.00	14.12	8.46	17.47	9.52	−1.84	−10.9 %
Car <sup>b</sup>	No. of hourly cars per station (100).	3.02	6.23	3.00	2.79	3.22	6.55	3.07	7.97	2.94	5.76	0.35	11.6 %
Van/truck/ bus <sup>b</sup>	No. of hourly vans/trucks/buses per station (100).	0.64	5.69	0.51	0.94	0.62	5.78	0.63	7.72	0.72	5.21	0.02	3.1 %
Scooter <sup>b</sup>	No. of hourly scooters/motorcycles per station (100).	1.11	10.95	0.93	7.16	1.20	13.02	1.11	12.68	0.96	9.88	0.42	38.0 %
Metro <sup>c</sup>	No. of daily departures & exits per station (10,000).	1.87	1.82	2.08	1.96	1.58	1.43	1.93	1.83	1.92	1.90	−0.49	−26.1 %
U-bike <sup>d</sup>	No. of daily departures & exits per station (100).	1.99	2.87	2.34	3.23	2.02	2.78	1.96	2.88	1.94	2.85	−0.30	−15.3 %
Panel B. Measures of air quality in mainland China													
CO_China	Concentration of carbon monoxide (ppb).	0.36	0.10	0.40	0.09	0.33	0.09	0.40	0.11	0.36	0.09	−0.02	−5.9 %
O <sub>3</sub> _China	Concentration of ozone (ppb).	41.21	10.62	35.76	7.88	41.32	10.42	34.08	10.26	43.79	9.89	−4.14	−9.5 %
Variable	Outcome	2017–2020		2020				2017–2019				DiD	DiD %
		Full sample		Before 1/22		After 1/22		Before 1/22		After 1/22			
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.		
Panel B. Measures of air quality in mainland China, con't													
SO <sub>2</sub> _China	Concentration of sulfur dioxide (ppb).	2.61	0.98	2.03	0.44	1.84	0.59	3.20	0.87	2.79	0.96	0.21	7.7 %
NO <sub>2</sub> _China	Concentration of nitrogen dioxide (ppb).	9.01	3.96	9.64	3.04	7.80	4.61	10.94	3.95	8.83	3.56	0.27	3.1 %
PM <sub>10</sub> _China	Concentration of particular matter <10 (ug/m <sup>3</sup> ).	49.84	22.96	39.34	13.17	36.99	18.55	53.42	24.08	54.63	22.78	−3.55	−6.5 %
PM <sub>2.5</sub> _China	Concentration of particular matter <2.5 (ug/m <sup>3</sup> ).	27.40	12.05	23.17	9.94	23.06	12.26	28.64	13.01	29.07	11.38	−0.54	−1.9 %
Panel C. Other explanatory variables in the air quality dataset													
COVID-19 (0/1)	If 1/22/20 - 3/31/20 (0/1).	0.07	0.26	0	0	0.36	0.48	0	0	0	0	−	−
COVID-19 cases	Daily cumulative number of COVID-19 cases.	0.24	1.04	0	0	1.15	2.05	0	0	0	0	−	−
Visitors	No. of daily inbound visitors (100,000 person).	1.26	0.45	1.48	0.13	0.58	0.55	1.34	0.15	1.47	0.17	−1.03	−70.1 %
Wind	Wind speed in district (km/hour).	2.37	1.40	2.38	1.36	2.19	1.32	2.52	1.46	2.39	1.41	−0.06	−2.5 %
Coal	Coal use (1 million mt/day).	0.07	0.01	0.05	0.00	0.06	0.00	0.07	0.00	0.07	0.01	0.01	14.4 %
Area	District area (km <sup>2</sup> ).	39.20	31.22	40.20	30.95	40.23	30.89	38.65	31.05	38.87	31.43	−0.18	−0.5 %
Population	District population density (10,000 person/km <sup>2</sup> ).	1.33	1.12	1.27	1.12	1.27	1.11	1.34	1.13	1.35	1.13	−0.01	−0.7 %
Rainfall	Rainfall in district (mm/hour).	0.69	1.26	0.62	0.70	0.75	1.77	0.75	1.14	0.64	1.07	0.23	36.3 %
Non-working day	Weekend day or holiday (0/1).	0.36	0.48	0.34	0.47	0.37	0.48	0.34	0.47	0.36	0.48	0.02	5.9 %
N-T		5741		354		1190		932		3265			

Note: The sample period is January 1 - March 31 in each year.

<sup>a</sup> Drawn from the air quality dataset.<sup>b</sup> Drawn from the motor vehicle traffic dataset (see Table A5).<sup>c</sup> Drawn from the metro use dataset (see Table A7).<sup>d</sup> Drawn from the U-bike rental dataset (see Table A8).

and C are sub-sample estimates for working days (Monday – Friday during non-holiday weeks) and non-working days (Saturday, Sunday, and holidays), respectively. In both panels A and B there is a statistically significant increase in CO, O<sub>3</sub>, SO<sub>2</sub>, and PM<sub>2.5</sub> levels in models with a COVID-19 treatment effect. The largest increase in pollution during the COVID-19 treatment period is a 8.7 % increase in SO<sub>2</sub>, followed by a 6.8 % increase in CO, both during working days.

When we estimate the DiD model with the continuous measure of COVID-19 cases, there are statistically significant increases in CO, O<sub>3</sub> and PM<sub>2.5</sub> in the full sample and during working days, as well as an increase in PM<sub>10</sub> during working days. O<sub>3</sub> is most responsive to changes in the COVID-19 case count, increasing by 2.3 % per additional confirmed case (overall and during working days). CO increased by 0.9 % per additional case, and both PM<sub>10</sub> and PM<sub>2.5</sub> increased by 0.4 % per

case during working days. The pattern of air pollution changes is fundamentally different for non-working days than working days. In particular, there are precisely estimated reductions in both NO<sub>2</sub> and PM<sub>10</sub> and no detectable changes in the other pollutants during non-working days.

We performed several specification and robustness tests of the DiD air quality models, which we describe more fully in Appendix A, Section 1. First, we tested whether the assumption of parallel pre-treatment trends in the air quality outcomes is met using the approach developed by Mora and Reggio (2012, 2015). We found that models for CO, O<sub>3</sub>, SO<sub>2</sub>, NO<sub>2</sub>, and PM<sub>2.5</sub>, but not PM<sub>10</sub>, are consistent with the null hypotheses of common parallel linear trends. We then conducted a falsification test by using the 2020 COVID-19 discrete indicator and case count variables as placebo treatments in 2019, 2018 and 2017, while

**Table 2**

Semi-elasticity estimates of the impact of COVID-19 on air quality.

Key variable	COVID-19 (0/1)		COVID-19 cases	
Dependent variable (in log)	Semi-elas.	S.E.	Semi-elas.	S.E.
Panel A. Full sample (N*T = 5741)				
CO	0.039***	0.012	0.010***	0.002
O <sub>3</sub>	0.072**	0.032	0.023***	0.002
SO <sub>2</sub>	0.056*	0.031	0.005	0.008
NO <sub>2</sub>	−0.011	0.027	−0.006	0.004
PM <sub>10</sub>	0.001	0.026	0.007	0.005
PM <sub>2.5</sub>	0.032**	0.015	0.007*	0.004
Panel B. Working days (N*T = 3705)				
CO	0.068***	0.011	0.009***	0.002
O <sub>3</sub>	0.073***	0.011	0.023***	0.002
SO <sub>2</sub>	0.087**	0.036	0.003	0.008
NO <sub>2</sub>	0.015	0.020	0.005	0.004
PM <sub>10</sub>	0.019	0.019	0.004*	0.003
PM <sub>2.5</sub>	0.011**	0.004	0.004*	0.002
Panel C. Non-working days (N*T = 2036)				
CO	0.009	0.022	0.002	0.007
O <sub>3</sub>	0.055	0.041	0.020	0.035
SO <sub>2</sub>	0.014	0.052	0.016	0.012
NO <sub>2</sub>	−0.030*	0.015	−0.004*	0.002
PM <sub>10</sub>	−0.001*	0.000	−0.032***	0.007
PM <sub>2.5</sub>	−0.049	0.030	−0.009	0.006

Note: The full list of variables in each regression is composed of the relevant pollution measure in panels B and the explanatory variables in panel C of Table 1. Standard errors are clustered by day and air quality monitoring station. \*\*\*, \*\*, \* indicate significance at the 1 %, 5 % and 10 % level, respectively.

retaining the remaining 2 years as the control group. All models passed the falsification test except some formulations of PM<sub>10</sub> model. Finally, we increased the flexibility of our DiD specification to allow for differential linear pre-treatment trends across the two cities and estimated models with station fixed effects. Semi-elasticity estimates for all outcomes are robust across these different specifications. Overall, the sensitivity analyses suggest a small bias in the semi-elasticity estimates from the PM<sub>10</sub> models.

### 3.2. Motor vehicle, metro and U-bike use

Because motor vehicle traffic is a major source of pollution in Taipei and New Taipei City, we investigated whether the change in pollution levels due to COVID-19 could have resulted from a shift in transportation patterns. Table 3 contains marginal effect estimates from our DiD model for car, van/truck/bus, and scooter traffic.<sup>13</sup> For all three types of motor vehicles, the COVID-19 treatment effect and case count variables are statistically insignificant in the full sample, but these estimates mask heterogeneous effects across different types of days. In particular, behavioral change among city residents during the COVID-19 period reduced traffic during non-working days, but increased traffic during working days. Traffic decreased by 52.2 cars/hr (19.7 %) and by 20.2 scooters/hr (23.3 %) during non-working days, but increased by 62.5 cars/hr (16.4 %) and 21.6 scooters/hr (21.1 %) during the regular commuting hours of working days. Van, truck and bus traffic increased by 2.7 motor vehicles/hr (3.5 %) during commuting hours. COVID-19-related changes in transportation preferences also increased all types of motor traffic during the non-commuting hours of workdays, but to a lesser extent, particular in the case of scooters. Estimates from the models with the continuous measure of COVID-19 indicate that increases and decreases in motor vehicle traffic both increase in

<sup>13</sup> Descriptive statistics for the control variables in these models and full estimation results for the car traffic model are contained in appendix Tables A5 and A6, respectively.

**Table 3**  
Estimates of the impact of COVID-19 on motor vehicle traffic.

Variable	Full sample (N:T = 309,400)				Non-working days (N:T = 106,479)				Working days, 6–9AM & 5–8PM (N:T = 67,609)				Working days, 9AM–5PM & 8PM–6AM (N:T = 135,312)			
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Panel A. Cars																
COVID-19 (0/1)	0.108	0.070														
Effect in %	3.58 %				−0.522***	0.083			0.625***	0.187			0.318**	0.134		
COVID-19 cases					−19.69 %				16.38 %				10.92 %			
Effect in %			0.000	0.001			−0.003***	0.001			0.016***	0.004			0.002**	0.001
Effect in %			0.01 %				−0.11 %				0.43 %				0.06 %	
Panel B. Vans/trucks/buses																
COVID-19 (0/1)	0.013	0.476														
Effect in %	2.11 %				−0.024	0.016			0.027*	0.014			0.019*	0.011		
COVID-19 cases					−4.98 %				3.51 %				2.76 %			
Effect in %			0.000	0.003							0.001*	0.000			0.000	0.005
Effect in %			0.07 %				−0.10 %				0.09 %				0.06 %	
Panel C. Scooters																
COVID-19 (0/1)	0.182	0.134														
Effect in %	16.47 %				−0.202**	0.079			0.216***	0.065			0.195***	0.025		
COVID-19 cases					−23.32 %				21.07 %				14.69 %			
Effect in %			0.017	0.020			−0.009***	0.003			0.016***	0.004			0.021*	0.011
Effect in %			1.55 %				−1.06 %				1.59 %				1.60 %	

Note: The dependent variable is the number of vehicles in 100s during a 1-h period. The percentage magnitude of the COVID-19 effect is evaluated using the sample mean of the dependent variable in the full sample. The full list of explanatory variables in each regression is reported in Appendix Table A5. Standard errors are clustered by day and traffic monitoring station. \*\*\*, \*\*, \* indicate significance at the 1 %, 5 % and 10 % level, respectively.

magnitude with the number of confirmed cases in each city when the sample is split between working and non-working days.

While transportation by personal motor vehicle increases air pollution, the use of the metro system and U-bikes reduces pollution by decreasing the combustion of fossil fuels associated with vehicle travel. We present the results for the use of metro and U-bikes together because the latter are often used jointly with the metro in order to travel the first and last miles of a journey. Table 4 contains semi-elasticity estimates of COVID-19 on metro departures and exits and on U-bike rentals.<sup>14</sup> Using the full sample, we find that metro departures and exits decreased 17.7 % during the COVID-19 period and 0.2 % per additional confirmed case of COVID-19 (Table 4, panel A). When we split the sample into working and non-working days, we find that metro use decreased more during the latter than the former. In particular, metro departures and exits went down 25.2 % due to COVID-19 during non-working days, but only decreased by 11.2 % during working days.

U-bike rentals also decreased due to behavioral change among residents during the COVID-19 period, but to a lesser extent than the reduction in metro use. The overall decrease in U-bike rentals was 8.1 % during the COVID-19 period, or 0.1 % per confirmed case of COVID-19 (Table 4, panel B). Similar to metro use, U-bike rentals decreased more during non-working days than working days. In particular, rentals decreased 15.6 % due to COVID-19 during non-working days, but 3.1 %

**Table 4**  
Semi-elasticity estimates of the impact of COVID-19 on metro use and U-bike rentals.

Variable	Panel A. Metro use			
	Full sample (N·T = 38,772)			
	Semi-el.	S.E.	Semi-el.	S.E.
COVID-19 (0/1)	−0.177***	0.044	−0.002***	0.001
COVID-19 cases				
Working days (N·T = 25,272)				
COVID-19 (0/1)	−0.112***	0.018	−0.002***	0.000
COVID-19 cases				
Non-working days (N·T = 13,500)				
COVID-19 (0/1)	−0.252***	0.066	−0.002***	0.001
COVID-19 cases				
Panel B. U-bike rentals				
Full sample (N·T = 222,007)				
COVID-19 (0/1)	−0.081***	0.020	−0.001**	0.000
COVID-19 cases				
Working days (N·T = 144,757)				
COVID-19 (0/1)	−0.031***	0.006	−0.001***	0.000
COVID-19 cases				
Non-working days (N·T = 77,250)				
COVID-19 (0/1)	−0.156***	0.021	−0.005***	0.000
COVID-19 cases				

*Note:* The dependent variable in panel A is the log of daily departures and exits from each metro station in 10,000s. The full list of explanatory variables in each regression in panel A is reported in Appendix Table A7. The dependent variable in panel B is the log of daily departures and exits from each U-bike station in 100s. The full list of explanatory variables in each regression in panel B is reported in Appendix Table A8. Standard errors are clustered by day and metro or U-bike station. \*\*\*, \*\*, \* indicate significance at the 1 %, 5 % and 10 % level, respectively.

<sup>14</sup> Appendix Tables A7 and A8 contain descriptive statistics for the control variables in the metro and U-bike datasets, respectively, and full estimation results for the metro and U-bike models are reported in Tables A9 and A10, respectively.

during working days.

As a robustness check, we re-estimated all of our transportation models with station-level fixed effects using the full sample in each dataset. The estimates, reported in appendix Table A11, are similar to the main DiD estimates.

### 3.3. Sensitivity of air pollution results to manufacturing activity

The increase in motor vehicle use and decrease in metro and U-bike use that we identify is consistent with the increase in air pollution levels during working days in the COVID-19 period. In addition, the reduction in motor vehicle use during non-working days is consistent with the decrease in NO<sub>2</sub> and PM<sub>10</sub> we find during non-working days. However, it is possible that the changes in industrial pollution could have also affected air pollution. Because Taiwan did not impose a social lockdown or implement restrictions on business activities, we suspect that differences in industrial pollution across the pre- and post-COVID-19 period were minor. Nonetheless, industrial output could have been affected by shifts in demand during the pandemic. Most heavy industries in Taiwan are located in the southwestern part of the island, while Taipei and New Taipei City are in northern Taiwan. Prevailing winds move pollution from southern Taiwan into the Pacific Ocean, so the main sources of industrial pollution in Taipei and New Taipei City are located in China (which we control for) or from the limited industrial base around the two cities.

We investigated the sensitivity of our air pollution results to changes in manufacturing by re-estimating our DiD models while controlling for manufacturing sales in each city. Due to limitations on data availability, we could only access manufacturing sales data in 2020 and 2019. Therefore, we use observations in 2019 as the control group in these models. Table 5 contains our baseline estimates from Table 2 in panel A, and the semi-elasticity estimates from the models controlling for manufacturing sales in panel B. Both sets of estimates are very similar, with the only notable difference being that the impact of an additional COVID-19 case on PM<sub>10</sub> becomes statistically significant when controlling for manufacturing sales. Overall, the estimates suggest that our findings are unlikely to be affected by changes in industrial pollution.

## 4. Discussion and policy implications

Cars, vans, trucks, buses and scooters are a major source of air

**Table 5**  
Semi-elasticity estimates of the impact of COVID-19 on air quality controlling for manufacturing sales (2019–2020).

Key variable	COVID-19 (0/1)		COVID-19 cases	
Dependent variable (in log)	Semi-el.	S.E.	Semi-el.	S.E.
Panel A. Baseline model (2017–2020)				
CO	0.039***	0.012	0.010***	0.002
O <sub>3</sub>	0.072**	0.032	0.023***	0.002
SO <sub>2</sub>	0.056*	0.031	0.005	0.008
NO <sub>2</sub>	−0.011	0.027	−0.006	0.004
PM <sub>10</sub>	0.001	0.026	0.007	0.005
PM <sub>2.5</sub>	0.032**	0.015	0.007*	0.004
Panel B. Model w/ manufacturing sales (2019–2020)				
CO	0.042***	0.012	0.011***	0.002
O <sub>3</sub>	0.069***	0.010	0.024***	0.002
SO <sub>2</sub>	0.049**	0.021	0.003	0.008
NO <sub>2</sub>	−0.006	0.033	−0.004	0.005
PM <sub>10</sub>	0.003	0.022	0.006*	0.003
PM <sub>2.5</sub>	0.031**	0.012	0.006*	0.003

*Note:* The full list of variables in each regression is composed of the relevant pollution measure in panels B and the explanatory variables in panel C of Table 1 in addition to city-level manufacturing sales per 10 days during 1/1–3/31 in 2019 and 2020. The number of observations (N·T) is 3030. Standard errors are clustered by day and air quality monitoring station. \*\*\*, \*\*, \* indicate significance at the 1 %, 5 % and 10 % level, respectively.

pollution in many cities around the world. Collectively, they emit all of the primary pollutants we track in our study, and are major contributors to the formation of secondary pollutants (Union of Concerned Scientists, 2018; Zhang and Batterman, 2013; Platt et al., 2014). In Taipei and New Taipei City, scooters were the most popular method commuting to work prior to the pandemic, accounting for approximately 30 % of trips. Scooter engines emit significant amounts of carbon monoxide, nitrogen oxides and particulate matter (more per mile than cars), and they are regulated less stringently than other types of motor vehicles (Platt et al., 2014; Carpenter, 2014). Because the use of scooters increased the most due to COVID-19, they are likely the single largest source of increased air pollution that we identify during the pandemic.

Given the increase in the level of motor vehicle use and the reduction in both metro ridership and U-bike rentals during the COVID-19 period, it is likely that the shift in mode of transport was a strategy used by individuals to reduce their chances of contracting COVID-19. Clearly, the likelihood of infection is far lower in a personal motor vehicle than in the confined space of a metro car. Furthermore, the 25 % decrease in metro use and significant reductions in the levels of NO<sub>2</sub> and PM<sub>10</sub> during non-working days suggest that individuals were limiting their mobility on weekends to avoid contracting COVID-19. It is important to note that there were no capacity restrictions on metro operations during our study period, so the reduction in ridership was a direct result of lower consumer demand.

Our findings have important implications for policy. Existing studies from China, Europe and elsewhere almost exclusively show that air pollution improved under government-mandated social lockdowns. While Taiwan implemented entry restrictions for foreigners (which we control for) and a 14-day quarantine protocol for all inbound travelers, the promotion of social distancing and mandatory use of facemasks were the only domestic policies imposed by the government to limit the spread of the virus. As a result, the mobility of citizens within Taiwan was relatively unaffected during the initial month of the coronavirus pandemic (Wang et al., 2020).

As vaccines are deployed and other regions or countries emerge from lockdowns, they should expect individuals to exhibit similar preferences for personal vehicle use that we observe in Taiwan. This could lead to congestion and higher levels of pollution. Initiatives to improve the safety of public transportation and associated public information campaigns could help to limit the avoidance of such cleaner forms of transportation. In addition, research suggests that individuals deprioritize environmental protection following periods of high unemployment (Kenny, 2019) and there is evidence that rollbacks of environmental regulations intended to lessen the economic effects of COVID-19 could lead to longer term worsening of deadly air pollution and result in additional deaths (Persico and Johnson, 2021; Gardiner, 2020). Our findings suggest that scaling back air pollution regulations due to a perceived tradeoff between environmental protection and economic growth could compound the deterioration in air quality.

As the pace of worldwide vaccination effects increases, and COVID-19 infection rates begin to decline, governments will face mounting pressure to lift restrictions on economic activities intended to reduce the spread of COVID-19. For example, China has begun to lift COVID-19 restrictions in some provinces, while most countries in Western Europe are also lifting restrictions (IMF, 2021). However, if individuals, particularly those who are unvaccinated, do not feel safe traveling among the general population, they may engage in prevention behaviors similar to those we identify in Taiwan (Brackett, 2020). Fear of public transportation could also result in preferences for work-at-home arrangements, which could increase demand for residential energy (Hinson, 2020). The resulting increase in air pollution from personal motor vehicle use and greater time spent at home could compound a rise in air pollution from industrial sources as business seek to meet the pent-up demand for consumer goods resulting from months of limited access to retail outlets.

In order to reduce avoidance of public transportation, policymakers

can consider several actions. Scientific reviews indicate that physical distancing of 1m or more, facemask use, and eye protection all decrease the transmissibility of COVID-19 (Chu et al., 2020; Brooks and Butler, 2021). Mask mandates on public transportation are among the easiest policies to implement and enforce because they involve a low cost to the public, and compliance is observable. However, experts agree that physical distancing is the most effective public health measure to reduce the spread of COVID-19 (IDSA, 2020). Implementing physical distancing on metro/train cars and buses reduces the capacity of the public transportation system, but it could increase overall ridership if potential users feel safer. In addition, policy makers need to evaluate other initiatives to implement physical distancing without reducing system use, such as increasing (decreasing) fares during peak (off-peak) hours in order to smooth demand over the course of the day. Further, ventilation and higher rates of air circulation are known to reduce the risk of COVID-19 transmission (U.S. Environmental Protection Agency, 2021). Aside from opening windows of train cars and buses, transportation systems managers should evaluate this cost-effectiveness of air purification and ventilation systems.

By taking actions and implementing policies to reduce the risk of COVID-19 transmission during the use of public transportation, policy makers can limit the avoidance that we identify in Taiwan during the early stages of the coronavirus pandemic. Although some measures may result in additional costs, our findings suggest the reductions in air pollution from encouraging the use of public transport could be substantial. Not only does reducing air pollution lower future disease risks of otherwise healthy individuals, it also reduces COVID-19 mortality (Persico and Johnson, 2021; Ispording and Pestel, 2020).

## 5. Conclusion and research limitations

This study makes an important contribution to the literature as the first to link higher levels of several major air pollutants to a shift in transportation patterns from COVID-19 prevention behavior. After controlling for pollution from China, we find that measures of four major pollutants (CO, O<sub>3</sub>, SO<sub>2</sub>, and PM<sub>2.5</sub>) in the two largest cities in Taiwan increased as a result of the COVID-19 pandemic. Using data on mode of public and private transportation, we find strong evidence that the increase in pollution was due to a shift away from metro and shared bicycle use and an increase in motor vehicle use during working days. Although all types of transport in Taipei and New Taipei city decreased on non-working days due to COVID-19, leading to decreases in NO<sub>2</sub> and PM<sub>10</sub>, the net effect of the shift in transportation patterns was to increase air pollution during the pandemic.

This study has some limitations. Although we conducted several robustness checks that are consistent with a lack of endogeneity bias in our estimates, it is possible that there are omitted factors that are correlated with the number of COVID-19 cases and air pollution levels that could affect our results. In addition, we do not measure pollution directly from industrial sources, so we can only address the impact of industrial pollution on our results using a sensitivity test. Finally, our results may not generalize to other regions or countries if COVID-19 prevention behaviors in Taiwan differ from those exhibited elsewhere due to differences in infection rates or socioeconomic and cultural factors. For example, the number of COVID-19 cases per capita was relatively low in Taiwan during our study period, so avoidance behaviors could be stronger in other countries leading to larger increases in air pollution.

## Credit author statement

Hung-Hao Chang: Conceptualization, Methodology, Data curation and analysis, Software. Chad D. Meyerhoefer: Conceptualization, Validation, Writing – original draft, Writing – review & editing. Feng-An Yang: Investigation, Validation.



## 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.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jenvman.2021.113522>.

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