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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 generalized difference-in-differences approach and real-time data on air quality and transportation, we estimate that levels of sulfur dioxide, nitrogen dioxide and particulate matter increased 5 - 12 percent relative to 2017 - 2019. We demonstrate that this counterintuitive finding is likely due to a shift in preferences for mode of transport away from public transportation and towards personal automobiles. Similar COVID-19 prevention behaviors in regions or countries emerging from lockdowns could likewise result in an increase in air pollution.

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A data appendix is available at http://www.nber.org/data-appendix/w27604

1. Introduction

In order to reduce the spread of COVID-19 many countries have implemented significant restrictions on business operations and the mobility of consumers (Cheng et al., 2020).[1] For example, stay-at-home orders and social distancing reduce travel and limit the ability of individuals to work and shop. 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 have affected air quality, as the associated findings have important implications for public health and environmental policy.

For many years, researchers have sought to determine how both transportation and industrial activity affect air quality. This is particularly true in cities, where emissions from internal combustion engines constitute the primary source of air pollution (EU Science Hub, 2015). COVID-19 restrictions serve as a natural experiment allowing researchers to link changes in air pollution to reductions in automobile use, and formulate transportation and urban mobility policies to improve air quality (Baldasano, 2020).

Measurements of pollution reduction from restrictions are also important to the evaluation of mobility limits and other policies intended to stop the spread of COVID-19. Several recent studies have shown that short-term exposure to high levels of air pollution is associated with higher COVID-19 mortality (e.g., Persico and Johnson, 2020; Isphording and Pestel, 2020). If restrictions are effective in reducing air pollution they have the potential to not only directly reduce the likelihood of infection, but indirectly reduce the severity of COVID-19 infections.[2]

[1] Cheng et al. (2020) provides a comprehensive review of the policies implemented in different countries to combat COVID-19.
[2] Isphording and Pestel (2020) cites literature demonstrating that short-term pollution exposure increases the inflammatory response to viruses and lowers the body's immune response.

Finally, measurements of the reduction in air pollution from COVID-19 and associated mitigation strategies are important to the pursuit of the dual public health goals of reducing morbidity and mortality from both viruses and modifiable environmental factors. Between December 30, 2019 and July 8, 2020 there have been 545,728 (recorded) COVID-19 deaths worldwide, with annual deaths on pace to be roughly double this number (JHU CSSE, 2020). In comparison, outdoor air pollution causes approximately 3.4 million death per year (Ritchie and Roser, 2019). Therefore, both COVID-19 and air pollution represent significant threats to global health, and it is important to monitor the effects of both simultaneously so that policies designed to mitigate one threat do not worsen the other. For example, there is concern that rollbacks of environmental regulations intended to lesser the economic effects of COVID-19 could lead to longer term worsening of deadly air pollution (Persico and Johnson, 2020; Gardiner, 2020). In addition, industrial production could intensify relative to pre-coronavirus as businesses seek to recover from COVID-19-related production shocks, and pollution-related corporate social responsibility initiatives might decrease (Gardiner, 2020). COVID-19 could also worsen pollution through changes in individual behaviors, and these new sources of pollution should be taken into account when formulating mitigation strategies (Brackett, 2020; Hinson, 2020).

Recent studies that investigate the effect of the coronavirus pandemic on air pollution generally find that the lockdowns imposed to combat the virus improved air quality. However, these studies do not explore the specific mechanisms responsible for the reduction in pollution[3] and they do not consider how individual prevention behavior may affect levels of air pollution after the lockdowns are lifted. We seek to fill this gap in the literature by investigating the impact of COVID-19 in Taiwan,

[3] An exception is Dang and Trinh (2020) which used Google Mobility Reports to show that mobility was lower in places where government policies were more stringent.

which did not impose any mobility restrictions on residents or mandate business closures. Using real-time data on air quality and transportation in the two largest cities in Taiwan, we find that reductions in the use of public transportation and increases in automobile use worsened air quality during the COVID-19 pandemic.

2. Literature Review

There is a fast-growing literature on the impact of COVID-19 on air pollution across the world. Many studies analyze data from individual cities with air pollution monitoring stations (Xu et al., 2020; He, Pan and Tanaka, 2020; Baldasano, 2020; Almond, Du and Zhang, 2020; Collivignarelli et al., 2020; Brodeur, Cook and Wright, 2020; Mahato, Pal and Ghosh, 2020; Zangari et al., 2020, Cole, Elliot and Liu, 2020), while others analyze satellite imagery over countries or broad regions of the globe (Wang and Su, 2020; Shi and Brasseur, 2020; Fan et al., 2020; Bauwens et al., 2020). Some studies focus on different measures of pollution, so it is useful to begin by highlighting a few basic facts about air pollution.

There are numerous potential measures of pollution, but some are considered to be more closely related to human health than others. In the U.S., for example, the Clean Air Act regulates six common air pollutants, including particulate matter (PM_{10} and $PM_{2.5}$), ground-level ozone (O_3), carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen dioxide (NO_2) and lead.[4] The EU's air quality standards impose limits on these same pollutants (European Commission 2020).[5] While all of the six pollutants are harmful to humans and the environment, particle pollution and ground-level ozone are the most widespread (U.S. EPA, 2020). Worldwide, particulate matter is

[4] PM_{10} and $PM_{2.5}$ refer to atmospheric particles with a particle size of less than 10 and 2.5 ug, respectively.

[5] Ozone regulation in the EU is through a target rather than a limit, but the EU additionally limits benzene (European Commission, 2020).

responsible for more deaths than ozone (38.2/100K capita versus 6.2/100K capita in 2017), and consequently, many studies focus on measures such as $PM_{2.5}$ (Ritchie and Roser, 2019).

All of the above mentioned pollutants except O_3 and NO_2 are “primary pollutants” because they are emitted directly into the atmosphere from their source. In contrast, NO_2 is a “secondary pollutant” that is formed through the oxidation of NO by oxygen in the air. Likewise, O_3 is produced through chemical reactions between nitrogen oxides (NO_X) and volatile organic compounds (VOC) in sunlight and warm, stagnant air. While nitrogen oxides are a precursor to O_3, they can also suppress O_3 in colder weather (winter and nighttime) through NO_X titration (Jhun et al., 2015). As a result, there is sometimes an inverse relationship between nitrogen oxides, such as NO_2, and O_3. There are many different sources of pollution, including industrial production, vehicle emissions, the burning of fuel, and natural sources such as volcanoes or wildfires. For example, among pollutants regulated under the Clean Air Act, vehicle emissions contribute significantly to higher levels of CO, NO_2, PM_{10} and $PM_{2.5}$ (Zhang and Batterman, 2013).[6]

Because the coronavirus was first detected in China, and resulted in a strict lockdown of Wuhan followed by mobility restrictions throughout the country, more studies focus on air pollution in China than other countries. Xu et al. (2020), Wang and Su (2020), Shi and Brasseur (2020), Cole, Elliott and Liu (2020), Fan et al. (2020), and Almond, Du and Zhang (2020) all found that lockdowns and strict restrictions on economic activities in the city of Wuhan and other regions of China significantly reduced the level of major air pollutants. For example, Shi and Brasseur (2020) calculated that surface $PM_{2.5}$ and NO_2 levels decreased by 35% and 60%,

[6] Other pollutants from vehicles include CO_2, VOCs and hydrocarbons (Zhang and Batterman 2013).

respectively, in northern China during the COVID-19 pandemic. Such a large short-term drop in air pollution is unprecedented in China, with only the strict regulations put in place during the 2008 Beijing Olympics producing comparable reductions (American Geophysical Union, 2020). However, most of these studies also found that O_3 increased by as much as a factor of 2 due to reductions in nitrogen oxides. Despite the offsetting effects of these pollutants, He, Pan and Tanaka (2020) estimated that the improvement in China's air quality could lead to 24,000 – 36,000 fewer premature deaths per month. Chen et al. (2020) estimated a smaller total of 8,911 avoided NO_2-related deaths and 3,214 fewer deaths from $PM_{2.5}$ during the 34-day quarantine period from February 10, 2020 – March 14, 2020.

Studies in Europe (Baldasano, 2020; Menut et al., 2020; Bauwens et al., 2020; Collivignarelli et al., 2020), South Korea (Bauwens et al., 2020) and India (Mahato, Pal and Ghosh, 2020), all of which implemented some form of economic and mobility restrictions, produced results that are generally consistent with those from China. For example, Menut et al. (2020) estimated reductions in NO_2 pollution across locations in Western Europe of 30% - 50%, and reductions in particle concentrations (PM_{10} and $PM_{2.5}$) of 5% – 15%. Mahato, Pal and Ghosh (2020) found a 53% drop in NO_2 and reductions on 60% and 39% in PM_{10} and $PM_{2.5}$, respectively, during the lockdown in Delhi, India. In addition, Mahato, Pal and Ghosh (2020) found concomitant increases in ground-level ozone in Delhi, as did Menut et al. (2020) in Western Europe.

Estimates from U.S. data are more mixed than in other countries. Brodeur, Cook and Wright (2020) used difference-in-differences methods to determine that stay-at-home orders reduced levels of $PM_{2.5}$ by 25% and Bauwens et al. (2020) reported reductions of NO_2 in the northeastern cities of New York, Philadelphia, and Washington D.C. of 21% - 28% based on satellite readings. Cicala et al. (2020) also predicted declines in primary air pollutants, but their estimates rely on simulations that extrapolate pollution reductions from measured decreases in traffic and electricity consumption. In contrast, Bekbulat et al. (2020) did not find that $PM_{2.5}$ and ozone concentrations in the U.S. generally fall outside the normal range of statistical variability. Zangari et al. (2020) likewise reported no significant differences in $PM_{2.5}$ and NO_2 in New York City (NYC), when using a linear time series model to compare pollutant levels following the NYC shutdown to the same weeks in 2015 - 2019. One consideration in the interpretation of estimates by Bekbulat at al. (2020) is that they analyzed data from across the U.S., where restrictions and compliance with federal directives was very heterogeneous.

Finally, Dang and Trinh (2020) compiled data from 178 different countries and confirmed the results from most individual country or city studies that lockdowns decreased air pollution. They also found that decreases in mobility following the lockdowns likely contributed to lower air pollution levels.

3. 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 of the Disease Control (CDC); several air quality measures from the Environmental Protection Agency (EPA); metro usage from the Taipei Rapid Transit Corporation; and car traffic data from the Ministry of Communication.

3.1. 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 treatment and control periods. The treatment period corresponds to January 22 - March 31 of 2020 and the control period includes these same dates in 2017, 2018 and 2019.

3.2. Air quality measures

We obtained measures of air quality from 19 air quality monitoring stations located across Taipei and New Taipei City. The stations monitor twelve different pollutants, including particle levels, carbon oxides, nitrogen oxides, sodium dioxide, ground-level ozone, and hydrocarbons. We analyzed the same pollutants regulated under the U.S. Clean Air Act, with the exception of lead, which is not monitored. These include PM_{10}, $PM_{2.5}$, NO_2, SO_2, CO, and O_3. The level of each pollutant is calculated as the average concentration at the given station over a 24-hour period. We merged the COVID-19 variables into the air quality dataset using city and date. In total, the air quality data consist of 5,119 station-day observations across both the treatment and control periods, of which 1,330 occurred during the treatment period.

3.3. Metro usage

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, in the beginning to 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 29,808 station-day observations, of which 7,452 occurred during the 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.

3.4. Car 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 by car. We collected information on the number of cars that pass each traffic monitor during every four hours of the treatment and control periods. In total, our sample contains 59,785 station-4-hour period observations, of which 15,368 are in the treatment period.

3.5. Other variables

We collected additional data on two district-level characteristics that may explain variation in the outcome variables: the geographic area of each district and monthly population.[7] For inclusion in our car 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.[8] Descriptive statistics for all explanatory variables are listed in Appendix Table A1.

[7] There are 12 districts in Taipei and 29 districts in New Taipei City.

[8] Coal is the largest source of electricity generation in Taiwan (U.S. Energy Information Administration, 2020).

4. Econometric Analysis

We use a generalization of the difference-in-differences model (DiD) to identify the causal effect of confirmed COVID-19 cases on air quality and metro departures using panel data (Wooldridge, 2010). Because both outcome variables are right-skewed, we implemented the following log-linear specification:

(1) $log(y_{1ijt}) = \alpha_1 + \gamma_1 \cdot COVID_{jt} + \beta_1{}'X_{1ijt} + \upsilon_j + t_m + t_y + \varepsilon_{1ijt}$,

where y_{1ijt} is the outcome variable for station i in city j during time t. Station is either air monitoring station or metro station, and time is day. $COVID_{jt}$ is either our discrete or continuous measure of confirmed COVID-19 cases in city j at time t. X_{1ijt} is a vector of the explanatory variables associated with the outcome variable, υ_j, t_m, and t_y are fixed effects for city, month and year, and ε_{1ijt} is the random error term.

In the case of car traffic, all of the traffic monitoring stations are located on 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 linear model with time fixed effects:

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

In equation (2) the time index denotes the 4-hour period used to collect car traffic data.

In equation (1), 100 times the parameter γ_1 is a semi-elasticity that measures the effect of COVID-19 on the outcome variable in percentage terms. The semi-elasticity is identified by comparing differences in the outcome variable between the two cities across the same month in the treatment and control periods. In equation (2), γ_2 measures the association between COVID-19 and 100s of cars per 4 hours travelling between Taipei and New Taipei City. In this case, the parameter is identified by comparing car travel during the COVID-19 period to car travel in the pre-COVID-19 period during the same calendar month. 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.

5. Results

In Table 1 we compare the mean values of all of the outcome variables in the air quality, metro usage and car traffic models in the COVID-19 treatment period (2020) and pre-COVID-19 control period (2017-2019). The average level of car traffic was 27% higher in the former than the latter. In addition, metro usage decreased 18% in 2020 relative to the pre-COVID-19 period, suggesting a shift in transportation preferences from public transport to personal car transport during the COVID-19 period. Despite the shift towards car travel, all six pollution measures decreased between 2% and 26% from 2017-2019 to 2020. These unadjusted means, however, could reflect long run decreases in air pollution over time (Cheng and Hsu, 2019).

5.1. COVID-19 and air quality

We present semi-elasticity estimates from the generalized DiD model of air quality in Table 2, and full estimation results for the SO_2 equation in Appendix Table A2.[9] The estimates in the left columns measure the change in air pollution during the COVID-19 period relative to the pre-COVID-19 period, while the estimates in the right columns measure the effect of an additional cumulative confirmed case of COVID-19 on air pollution. Consistent with the unadjusted means, CO and O_3 both decreased as a result of COVID-19, but SO_2, NO_2, PM_{10} and $PM_{2.5}$ all increased during the COVID-19 period. Furthermore, the 5% - 12% increase among the latter pollutants was larger in magnitude than the 3% increase in CO and O_3. Estimates

[9] Full estimation results for the other pollution measures are available upon request from the authors.

from the models using the number of the cumulative COVID-19 cases are consistent with the treatment effect models, although the impact of an additional case of COVID-19 is not statistically significant in the CO model. While O_3 decreased by 1% with an additional COVID-19 case, SO_2, NO_2, PM_{10} and $PM_{2.5}$ increased by 1.6%, 1.1%, 3.4% and 3.5%, respectively.

5.2. Car traffic and metro use under COVID-19

The DiD estimates of the effect of COVID-19 on air pollution are more consistent with the shift in transportation patterns identified in Table 1 than the unadjusted differences in pollutants. In order to further explore changes in transportation as a mechanism for the increase in air pollution, we turn to the car traffic model (Table 3). The estimates in Panel A confirm that car traffic increased 34% in the COVID-19 period relative to the same calendar month in the pre-COVID-19 period, after controlling for date variables, hour of travel, weekend day, and the price of gasoline (see Appendix Table A3 for all coefficient estimates). Likewise, an additional cumulative case of COVID-19 was associated with a 0.7% increase in car traffic, *ceteris paribus*.

In Panel B we present estimates from a model estimated on just weekend (i.e. non-working) days, while Panels C and D contain analogous estimates for week (i.e. working) days, divided into typical commuting and non-commuting hours. We specify commuting hours as 6 – 10AM in the morning and 6 – 10PM in the evening. Interestingly, there is no statistically significant increase in car traffic during weekends in the COVID-19 period (the point estimate is negative), but a large increase in car traffic during week days. In the treatment effect model the magnitude of the increase during commuting hours (70%) is only marginally larger than the rest of the day (65%). The models with a continuous measure of COVID-19 cases are precisely estimated in Panels C and D, and they suggest that an additional case of

COVID-19 is associated with a 0.7% - 0.8% increase in car traffic. While the difference between the effect of COVID-19 in commuting and non-commuting hours is less than anticipated, this may be due to policies by employers that rotate employees across different shifts to achieve physical distancing.

In the case of metro departures and exits, we are able to estimate the generalized DiD model in equation (1). Panel A of Table 4 contains estimates for the full sample, while in Panels B and C we break the sample into week days and weekend days, respectively (Table A4 contains all coefficient estimates). Overall, metro use decreased 6.5% during the COVID-19 period, or 0.3% per additional confirmed case. While ridership was lower during both week days and weekends, the magnitude of the effect was larger for the latter. In particular, metro use was 13.8% lower on weekends due to COVID-19 and 3.6% lower during the work week. The analogous estimates for cumulative case counts are a 0.5% reduction in metro station departures and exits per case during weekends and a 0.2% decrease in departures and exits per case on week days.

5.3. COVID-19 and air quality by day of the week

Given that automobile use in the COVID-19 period only increased during week days, in order for car traffic to be one of the drivers of higher levels of NO_2, PM_{10} and $PM_{2.5}$, measures of these pollutants should also be higher during the work week.[10] We investigated this possibility by estimating our air pollution models separately on the samples of week days and weekends. The estimates in Table 5 for week days (Panel A) are all consistent in sign with those from the pooled sample in Table 2, but they are generally larger in magnitude. For example, COVID-19 leads to a 5%

[10] Since vehicles also emit CO, the observed decrease in CO must be due to another reason. Likewise, vehicle emissions are no longer a major source of SO_2 (Australia Department of Agriculture, Water and the Environment, 2020).

increase in NO_2 in the pooled sample, but a 12% increase on week days. However, there is no statistically significant change in most of the pollutants during weekends, with the exception of SO_2 and NO_2 for which there is a statistically significant *decrease*. Levels of SO_2 drop by 7% from COVID-19 during weekends, and NO_2 drops by 11%.

5.4. Robustness checks

One concern with our main analysis is that trends in air quality could be spuriously correlated with trends in the number of COVID-19 cases in our models. Although we included both month and year fixed effects to capture aggregate-level trends, we want to verify that the steady, long-term improvement in air quality is not spuriously correlated with the increase in cases of COVID-19, net of these controls. If such a correlation exists, it could increase the magnitude of the (negative) semi-elasticities for CO and O_3 or attenuate the (positive) semi-elasticity estimates for the other air quality measures. We investigated the potential for a spurious correlation by estimating our DiD models of air pollution using only the pre-COVID-19 period data from 2017-2019 by assigning the number of COVID-19 cases observed in 2020 to the same month and day in the 2017-2019 sample. The resulting semi-elasticity estimates, reported in Table 6, are statistically insignificant when using either measure of COVID-19, with the exception of the treatment effect in the NO_2 model, which is statistically significant at the 10% level.

While the presence of COVID-19 is an exogenous event that we don't expect to be simultaneously determined with air quality, there could be omitted variables that are correlated with the number of COVID-19 cases and the level of the air quality measures. For example, it is possible that unobserved differences in COVID-19 prevention behaviors across communities may result in different levels of air pollution. Such unobservables would need to vary over both time and place to bias our estimates since time-invariant factors across the two cities, and changes in aggregate trends over time that are common to both cities should be captured by city and time fixed effects.

In order to investigate the potential for omitted variables to bias our estimates we implemented the sensitivity analysis proposed by Oster (2019). Based on the assumption that selection on unobservable factors is proportional to selection on observable covariates, Oster (2019) derives an estimator, δ, for the degree of selection of unobservables relative to observables necessary to drive the coefficient on the treatment variable to a statistical null. We report estimates of δ in Table 7, which range from 1.6 – 8.9 for the COVID-19 treatment effect and from 1.3 – 6.9 for the cumulative number of confirmed cases. Across all models, the average level of δ is 3.6, suggesting a significant level of selection on unobservables would be needed to invalidate our results.

6. Discussion and Conclusions

We find that measures of four major pollutants (SO_2, NO_2, PM_{10} and $PM_{2.5}$) increased and two major pollutants (CO and O_3) decreased in the two largest cities in Taiwan as a result of the COVID-19 pandemic. The magnitude of the increase in pollution among the former measures was, on average, roughly three times larger than the decrease in pollution among the latter measures. Studies of the effect of COVID-19 in China (Xu et al., 2020; Fan et al., 2020; Shi and Brasseur, 2020), Milan, Italy (Collivignarelli et al., 2020) and Delhi, India (Mahato, Pal and Ghosh, 2020) have also found increases in NO_2 and other pollutants with concomitant reductions in O_3 (Xu et al., 2020; Fan et al., 2020; Shi and Brasseur, 2020). Ground-level ozone can be diminished by nitrogen oxides, so it is not uncommon to measure decreases in O_3 when levels of NO_2 rise (Jhun et al., 2015; Shi and Brasseur, 2020).

By examining data on transportation patterns, we find compelling evidence that a shift from metro use to car ridership contributed to higher levels of NO_2, PM_{10} and $PM_{2.5}$. Not only does car traffic increase with these pollution measures, but both the increase in traffic and levels of NO_2, PM_{10} and $PM_{2.5}$ only occurred during the work week. Because automobiles are no longer a significant source of sulfur oxides, the increase in SO_2 due to COVID-19 must have a different mechanism. In addition, it is unclear why measures of CO decrease when car traffic increases. While the increase in CO is relatively small, and only precisely estimated in the treatment effect model, automobiles are a major source of CO pollution (Zhang and Batterman, 2013).[11]

Given that the level of automobile use and reduction in metro ridership increased with the cumulative number of COVID-19 cases, 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 automobile than the confined space of a metro car. Furthermore, the decrease in both metro use and levels of SO_2 and NO_2 during weekends suggest that individuals were limiting their mobility on weekends to avoid contracting COVID-19.

Our findings have important implications for policy. Existing studies from China, Europe and elsewhere almost exclusively show that air pollution improved under government-mandated lockdowns. While Taiwan restricted international travel from countries with high rates of infection, the promotion of social distancing and mandatory use of masks 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, Ng

[11] One possibility is that there are other shifts in transportation patterns that we do not observe. For example, scooters and motorcycles emit more CO than cars (Platt et al., 2014; Carpenter, 2014). If scooters are complementary to public transportation, then reductions in metro and scooter use could have resulted and a shift in pollution that reduced CO. To the best of our knowledge, there are no sources of administrative traffic data on scooters in Taiwan.

and Brook, 2020).

Without the stricter lockdowns imposed in other parts of the world, we find that pollution in Taiwan worsened due to COVID-19 prevention behaviors. In particular, the fear of contracting COVID-19 while using public transportation appears to have resulted in a significant increase in car traffic and associated air pollution. As other regions or countries emerge from lockdowns, they should expect individuals to exhibit similar preferences for personal automobile use, which could lead to congestion and higher levels of pollution. Initiatives to improve the safety of public transportation could help avoid the shift that we observe in Taiwan. Furthermore, research suggests that individuals de-prioritize environmental protection following periods of high unemployment (Kenny, 2019). Our findings suggests that scaling back air pollution regulations due to a perceived tradeoff between environmental protection and economic growth could compound the deterioration in air quality.

In addition to having a direct negative impact on human health, higher levels of air pollution also increase COVID-19 mortality (Persico and Johnson, 2020; Isphording and Pestel, 2020). Our results imply that loosening mobility restrictions in countries with high COVID-19 infection rates, such as the U.S., could make it more difficult to reduce deaths from COVID-19 (all else equal) if individuals practice similar prevention behaviors to those we identify in Taiwan.

This study has several limitations that should be noted. 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 from all sources, so we cannot identify mechanisms that could be responsible for increases in air pollution other than a shift from metro to automobile use. Finally, our results may not generalize to other regions or countries if COVID-19 prevention behaviors in Taiwan differ from those exhibited elsewhere.

Despite these limitations, we believe this study makes an important contribution to the literature, as the first to find higher levels of several major air pollutants due to COVID-19. Moreover, our results may help policy makers in countries emerging from lockdowns to avoid spikes in air pollution by identifying a shift in preferred modes of transport with important implications for pollution levels, congestion and energy use.

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Table 1. Sample statistics for COVID-19 cases, air quality measures, and transportation variables.

		(1)		(2)		(3)		
		2017-2020		2020		2017-2019		(2) – (3)
Variable	Definition	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean
COVID	Cumulative number of confirmed COVID-19 cases.	7.82	26.03	31.29	44.67	0	0	-
CO	Concentration of carbon monoxide (ppb).	0.54	0.33	0.52	0.30	0.55	0.33	-5%
O_3	Concentration of ozone (ppb).	34.07	11.17	33.58	10.42	34.24	11.42	-2%
SO_2	Concentration of sulphur dioxide (ppb).	2.14	1.07	1.77	0.83	2.26	1.11	-22%
NO_2	Concentration of nitrogen dioxide (ppb).	17.97	10.77	16.53	10.02	18.47	10.98	-11%
PM_{10}	Concentration of particulate matter < 10 (ug/m^3).	36.51	18.74	29.09	13.55	39.06	19.58	-26%
$PM_{2.5}$	Concentration of particulate matter < 2.5 (ug/m^3).	17.74	9.28	16.13	8.05	18.30	9.61	-12%
Metro use	No. of daily departures & exits per metro station (10,000s).	1.83	1.80	1.58	1.43	1.92	1.91	-18%
Car traffic	No. of cars per 4-hours per station (100s).	4.70	18.59	5.60	20.98	4.39	17.68	27%

Notes: All measures are collected during each day of the sample period defined as January 22 - March 31 in each year. Car traffic is collected during every 4-hour period during the day.

Table 2. Semi-elasticity estimates of the impact of COVID-19 on air quality.

	COVID-19 period (0/1)			Cumulative number of COVID-19 cases		
Dependent var.	Semi-elas.	S.E.	Adjusted R^2	Semi-elas.	S.E.	Adjusted R^2
CO	-0.028 *	0.015	0.34	-0.003	0.014	0.34
O_3	-0.031 *	0.018	0.16	-0.010 **	0.004	0.16
SO_2	0.080 *	0.041	0.13	0.016 *	0.009	0.13
NO_2	0.050 **	0.020	0.34	0.011 *	0.006	0.34
PM_{10}	0.119 **	0.058	0.15	0.034 **	0.016	0.15
$PM_{2.5}$	0.099 **	0.047	0.07	0.035 **	0.015	0.08

Notes: The full list of variables in each regression is reported in Appendix Table A2. The number of observations (N·T) is 5,119. Standard errors are clustered by day and air quality monitoring station. ***,**, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 3. Estimates of the impact of COVID-19 on car traffic.

	Panel A: Full sample (N·T = 59,785)				Panel B: Weekend days (N·T = 21,291)			
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
COVID-19 period	2.255 *	1.275			-0.041	0.542		
Effect in %	34.13%				-1.05%			
COVID-19 cases			0.045 *	0.024			-0.024	0.018
Effect in %			0.68%				-0.63%	
Adjusted R^2	0.01		0.01		0.01		0.01	
	Panel C: Week days 6-10 AM & 6-10 PM (N·T = 12,808)				Panel D: Week days 10 PM - 6 AM & 10 AM - 6 PM (N·T = 25,686)			
COVID-19 period	4.966 **	2.232			4.167 *	2.345		
Effect in %	70.48%				65.23%			
COVID-19 cases			0.055 *	0.031			0.043 *	0.022
Effect in %			0.78%				0.68%	
Adjusted R^2	0.01		0.01		0.01		0.01	

Notes: The dependent variable is the number of cars in 100s during a 4-hour period. The percentage magnitude of the COVID-19 effect is evaluated at the sample mean of the dependent variable during the COVID-19 period. The full list of variables in each regression is reported in Appendix Table A3. Standard errors are clustered by day and traffic monitoring station. ***,**, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 4. Semi-elasticity estimates of the impact of COVID-19 on metro departures and exits.

Variable	Semi-elas.	S.E.	Semi-elas.	S.E.
	Panel A: Full Sample (N·T = 29,808)			
COVID-19 period	-0.065 **	0.027		
COVID-19 cases			-0.003 ***	0.001
Adjusted R^2	0.36		0.36	
	Panel B: Week days (N·T = 19,116)			
COVID-19 period	-0.036 *	0.022		
COVID-19 cases			-0.002 ***	0.0001
Adjusted R^2	0.34		0.34	
	Panel C: Weekend days (N·T = 10,692)			
COVID-19 period	-0.138 ***	0.024		
COVID-19 cases			-0.005 ***	0.0001
Adjusted R^2	0.33		0.33	

Notes: The dependent variable is the log of daily departures and exits from each metro station in 10,000s. The full list of variables in each regression is reported in Appendix Table A4. Standard errors are clustered by day and metro station. ***,**, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 5. Semi-elasticity estimates of the impact of COVID-19 on air quality by day of the week.

	COVID-19 period (0/1)			Cumulative no. of COVID-19 cases		
	Panel A: Week days (N·T = 3,305)					
Dependent var.	Semi-elas.	S.E.	Adjusted R^2	Semi-elas.	S.E.	Adjusted R^2
CO	-0.023 *	0.012	0.37	-0.002	0.015	0.04
O_3	-0.004 *	0.002	0.18	-0.008 *	0.004	0.18
SO_2	0.156 **	0.062	0.12	0.017 ***	0.004	0.12
NO_2	0.116 **	0.049	0.34	0.012 **	0.006	0.34
PM_{10}	0.135 *	0.080	0.14	0.036 **	0.017	0.14
$PM_{2.5}$	0.123 **	0.053	0.06	0.038 *	0.020	0.07
	Panel B: Weekend days (N·T = 1,814)					
CO	0.143	0.097	0.30	-0.033	0.044	0.30
O_3	0.113	0.068	0.16	0.028	0.022	0.16
SO_2	-0.069 *	0.039	0.15	0.002	0.003	0.15
NO_2	-0.109 *	0.053	0.35	-0.015 *	0.008	0.35
PM_{10}	0.062	0.197	0.19	0.002	0.008	0.19
$PM_{2.5}$	0.010	0.198	0.14	-0.009	0.008	0.14

Notes: The full list of variables in each equation is provided in Appendix Table A2. Standard errors are clustered by day and air quality monitoring station. ***,**, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 6. Falsification test of the effect of COVID-19 on air pollution measures using on the pre-COVID-19 sample (2017-2019).

	COVID-19 period (0/1)			Cumulative no. of COVID-19 cases		
Dependent var.	Semi-elas.	S.E.	Adjusted R^2	Semi-elas.	S.E.	Adjusted R^2
CO	0.013	0.025	0.34	-0.002	0.002	0.35
O_3	-0.050	0.044	0.16	0.002	0.002	0.17
SO_2	-0.035	0.045	0.11	0.000	0.001	0.11
NO_2	0.039 *	0.020	0.35	-0.002	0.005	0.35
PM_{10}	-0.130	0.083	0.12	0.002	0.002	0.12
$PM_{2.5}$	-0.083	0.086	0.08	0.001	0.002	0.08

Notes: The number of observations (N·T) is 3,789. Standard errors are clustered by day and air quality monitoring station. ***,**, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 7. Estimate of ratio of selection on unobservables relative to selection on observables (δ) needed to generate null effect of COVID-19 on air quality.

Dependent var.	COVID-19 period (0/1)	Cumulative no. of COVID-19 cases
CO	8.93	6.29
O_3	1.93	1.85
SO_2	4.83	5.94
NO_2	3.98	2.94
PM_{10}	1.60	1.30
$PM_{2.5}$	1.72	1.68

Notes: All models include city, month and year fixed effects, and other explanatory variables.