Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
COVID-19 regulations, culture, and the environment

Aatishya Mohanty*, Swati Sharma

Department of Economics, School of Social Sciences, Nanyang Technological University, 48 Nanyang Avenue, 639818, Singapore

ARTICLE INFO

JEL classification:
K20
Q53
Z18

Keywords:
COVID-19
Government policy
Environment
Pollution
Culture
Individualism

ABSTRACT

The economic and social disruptions caused by the COVID-19 pandemic are immense. Unexpectedly, a positive outcome of the stringent Covid restrictions has come in the form of air pollution reduction. Pollution reduction, however, has not happened everywhere at equal rates. Why are lockdown measures not producing this positive externality in all countries? Using satellite-based Aerosol Optical Depth data and panel analysis conducted at the country-day level, we find that the countries that have adopted stringent COVID-19 containment policies have experienced better air quality. Nonetheless, this relationship depends on the cultural orientation of a society. Our estimates indicate that the effect of policy stringency is lower in societies imbued with a collectivistic culture. The findings highlight the role of cultural differences in the successful implementation of policies and the realization of their intended outcomes. It implies that pollution mitigation policies are less likely to yield emission reduction in collectivist societies.

1. Introduction

Over and above the public health emergency, the COVID-19 pandemic has caused grave social and economic crises across the globe. The pandemic has caused global lockdowns and the implementation of stringent policies that curtail economic activity and human mobility. There, nonetheless, appears to be a positive outcome of the Covid restriction – air pollution reduction. In particular, the containment and lockdown measures put in place by most governments included the mandatory closure of businesses and schools, local and cross-boundary transport, tourism, air travel, and other business activities. The decline in such major economic activities has led to reduced energy demand (DNV GL, 2020; IEA, 2021) and curtailed fossil fuel use, and hence significant short-term reduction in air pollution and anthropogenic emissions (Helm, 2020).

Several early studies on COVID-19 have shown the positive impact of the lockdown on air quality in different regions across the world (see, e.g. Dutheil et al., 2020; Gautam, 2020; Kanniah et al., 2020; Tobias et al., 2020; Chen et al., 2020). In particular, Kanniah et al. (2020) show that Malaysia has witnessed approximately a 70 percent reduction in its urban aerosol optical depth value during the months of March–April 2020 compared to the same period in 2018 and 2019. Tobias et al. (2020) show that the atmospheric concentration of nitrogen dioxide decreased by half during the lockdown period in Barcelona between February–March 2020. European Space Agency (2020) also reported lower air pollution levels in major European cities, which coincided with the implementation of lockdown measures.

Most countries have adopted COVID-19 containment measures to curb the spread of the virus and break the chain of community transmission. However, air pollution has not been reduced in every country at equal rates. We, in this paper, aim to understand why the containment and lockdown measures are not producing this positive externality everywhere. We test the hypothesis that the impact of COVID-19 containment and control policies on air pollution may vary by the dichotomy between individualistic and collectivistic societies. In particular, the paper examines a novel dimension that suggests that the effective implementation of COVID-19 containment and closure measures might be dependent on the cultural orientation, specifically the individualism-collectivism cleavage of a society.

Several recent shreds of evidence show that the implementation of COVID-19 containment and closure has met with different challenges in different countries. First, public compliance with COVID-19 non-pharmaceutical interventions such as the use of face masks and staying-at-home orders have been challenging to achieve. It has even become a politically and socially contentious issue in many countries (Lyu and Wehby, 2020). Similarly, the lack of public support has impaired the effective implementation of government measures to identify and manage COVID-19 cases. For example, Lewis (2020) reports that while numerous countries have implemented contact tracing for patients with confirmed or probable COVID-19, only a handful of them have got it...
right. Along with technology, governance, and various other practical issues, public participation has proved to be a key factor for contact tracing efforts. In many countries, patients with confirmed COVID-19 cases are either not reachable for the contact tracing interview or have been unwilling to provide details of their close contacts. Other similar issues include patients’ unwillingness to self-isolate and follow stay-at-home recommendations.

The ability of policy measures to achieve its desired outcome not only depends on its effective implementation but a plethora of other factors such as political process including governance, social and cultural norms through public support and participation, and decision-making at the government and individual level (Bavel et al., 2020; Dasgupta and De Cian, 2018). Following a significant number of studies on this topic (Gorodnichenko and Roland, 2017; Sharma et al., 2021; Ang et al., 2020; Vu, 2020), we specifically focus to understand the role of cultural variations: are COVID-19 containment and closure measures likely to operate differently in individualistic and collectivistic cultures?

Several studies have associated individualism with better governance. Tanzi (1994) for example, describes the individualism-collectivism dichotomy in governance wherein policies are guided by objective reasoning and potential benefits in individualistic cultures. In contrast, they can be influenced by nepotism and personal relationships in a collectivistic society. In another study, Vu (2020) demonstrates that individualistic nations are better equipped to enforce stringent climate change policies due to their better quality of governance and greater female political representation.

It is to note that countries with an individualistic culture emphasize more on personal freedom and choice along with its other major characteristics such as self-reliance, affinity towards innovation, and humanitarian achievements (Snibbe and Markus, 2005; Kitayama et al., 2006; Gorodnichenko and Roland, 2012). Lesser preference for government interventions and greater ardor for individual actions is also the main feature of the individualistic culture. On the other hand, collectivistic societies value conformity, tend to interdepend on each other within a group, and live by the ideals of loyalty and solidarity (Triandis, 1995; Brewer and Chen, 2007).

Various other studies, specifically for environmental-related policies and actions, relate a higher degree of environmental actions and stringent policy implementation in individualistic countries with its citizen’s greater tendency towards environmentally conscious behavior (Rychlak, 1979). Halkos and Tzeremes (2013) find that countries with higher individualism have higher eco-efficiency levels and greater environmental consciousness. This may be because the national culture of individualist countries instigates a sense of responsibility by promoting individual accountability and self-empowerment. Similarly, a study by Eom et al. (2016) finds that individualism leads to more personal accountability towards the environment and a positive view on environmental action. Additionally, Ang et al. (2020) show that a higher degree of individualism is associated with greater adoption of clean energy technologies. Nevertheless, a few studies have shown that the collectivistic traits of valuing group goals over personal ones and cooperation lead to some positive environmental behaviors. For example, McCarty and Shrum (1994, 2001) show that collectivism has a positive impact on recycling behavior. Similarly, Kim and Choi (2005) find that collectivism is positively related to both environmental concerns and green purchasing behavior. Moreover, Deng et al. (2006) and Olofsson and Ohman (2006) demonstrate that collectivistic values are more consistent with an attitude in favor of preserving the environment. Several studies in psychology also argue that values imbibed in collectivistic societies are related to poor compliance issues stemming through collectivistic traits of lack of self-responsibility and tendency to be driven by the interests of ingroups, which might be further skewed by various other factors such as favoritism, and personal relationships, etc. Moreover, there might be historical and situational factors at play. For example, studies have shown that a farming legacy of rice cultivation led to the formation of a collectivistic culture (Talhelm et al., 2014; Zhu et al., 2019; Ang et al., 2021). The cultivation of rice is a labor-intensive process that requires in-group dependence and cooperation among farmers and family members thereby fostering and transmitting a more collectivistic culture as opposed to cultivating wheat which required comparatively much lower levels of interdependence. It follows from this line of reasoning that countries with collectivistic cultures would require much more social contact for the mere functioning of their economies and hence, less effective implementation and compliance of COVID-19 lockdown measures.

On the other hand, it is also plausible that more stringent policies will have a feeble impact in individualistic societies due to prominent individualistic values such as emphasis on personal choice and freedom, lesser affinity towards government interference, and free-rider mindset instead of cooperation in group situations (Wagner, 1995). Ultimately, by focusing on an explanatory variable that represents the interaction between COVID-19 containment and closure policies and level of collectivism in a society, we set out to understand the impact of COVID-19 containment measures on air pollution gets mitigated or strengthen in societies with collectivistic values.

In particular, we examine the issue using satellite-based aerosol load data from NASA (Platnick et al., 2015b) and the COVID-19 policy response data from the Oxford COVID-19 Government Response Tracker (OxCGRT) of Hale et al. (2020), which are monitored daily, over the period January 1, 2020 to June 30, 2020. Collectivism is proxied by country-level data based on the individualism vs. collectivism index of Hofstede (1980). Hofstede’s index measures the individualistic-collectivistic orientation of societies by focusing on their major characteristics and is based on survey responses collected in around 101 countries.

Using nearly fifteen thousand observations for 89 countries, our panel analysis shows that the adoption of more stringent response policies amid the COVID-19 pandemic period improves air quality. However, the ability of response policy in improving air quality is mitigated if a society is imbued with collectivistic values. Our findings are generally in agreement with the findings from previous studies that collectivistic societies are ill-equipped to implement stringent environmental policies and display lower levels of environmental consciousness (e.g., see, Halkos and Tzeremes, 2013; Eom et al., 2016; Ang et al., 2020).

The causal interpretation of our results may be limited by the omitted variables correlated with both aerosol load and policy stringency. We address this concern by using the following strategies. First, we include a set of control variables that may confound the results. It includes macroeconomic variables (urbanization rate), demographic structure (population density and fraction of old-aged dependents), and climatic factors (temperature and precipitation). Our results are robust to the consideration of these factors. Second, we provide an instrumental variable estimation by exploiting the cumulative number of COVID-19 cases across time and space as the instrument for policy stringency. In addition, we also use the rice to wheat suitability ratio as an instrument to exploit the exogenous variation in collectivism. Reassuringly, these estimates provide consistent results.

In essence, we show that emission mitigation policies are less likely to yield emission reduction in collectivistic societies. Our findings contribute to an enriched understanding of policies’ effectiveness in curbing global emissions and underline the role of cultural differences in the successful implementation of public policies. This study is a novel contribution to the evolving literature studying the impacts of COVID-19 on air pollution.
We provide global estimates of the COVID-19 impact on air quality in 89 countries during its severe outbreak period of January to June 2020, right after most countries implemented a set of containment measures and the World health organization (WHO) declared COVID-19 a global pandemic.

We use a variety of real-time data sources for in-depth analysis utilizing satellite-based daily data on air pollution for wider spatial coverage and to account for the time-space dynamics of air pollution. For robustness, we take our air pollution data from several satellite sources of NASA. We combine the air pollution data with daily data of COVID-19 stringency measures in each country in our sample. The data is sourced from the Oxford COVID-19 Government Response Tracker (OxCGRT)- a distinctive database measuring policy responsiveness to the pandemic. With a comprehensive database and distinct data sources, our study provides a time-variant analysis of comparable policy impact across different countries in the world. Our findings have implications for the formulation of environmental policies.

The paper proceeds as follows. The next section provides the empirical specification and describes the data. The empirical estimates are presented and analyzed in Section 3. Several robustness checks are also performed. In section 4, we carry out some additional estimations by using data on individual response policies, consider the heterogeneous effects of institutional factors and investigate the role of compliance measures. Section 5 performs in the instrumental variable estimations. The last section summarizes and concludes with policy implications.

2. Regression model and data

2.1. Regression specification

The following model will be estimated:

\[ AOD_i = \alpha + \beta Stringency_{i,t-1} + \gamma Stringency_{i,t-2} \times COLL_i + \delta CV_i + \Theta_i + \sigma_i + u_i \]

(1)

where \( AOD \) is an index of aerosol optical depth, \( Stringency \) (lagged by one day) is a policy stringency index which measures the rigor of government-imposed containment and closure actions, \( COLL \) is collectivism, which is proxied by a country-level individualism vs. collectivism index of Hofstede (1980). \( CV \) is a set of control variables included in regressions to allow for the influence of some climatic, macroeconomic and demographic effects (interacted with \( Stringency \)). This set of control variables includes the country’s temperature, precipitation, urbanization rate, population density, and the share of the elderly population (aged 65 years or above).\(^2\)

These variables capture differences in the geographical and macroeconomic environment of countries, which could affect the air quality through channels other than the one we are interested to understand.\(^3\) The specification also allows for country fixed effects (\( \Theta_i \)) and time dummies (\( \sigma_i \)). Country fixed effects absorb unobserved country-specific time-invariant factors of the air quality whereas time dummies control for country-invariant time-specific differences in the air quality that are common across countries (e.g., seasonal variations in air quality). Since \( COLL \) is time invariant, it is absorbed by country fixed effects and thus not included as a separate regressor. Eq. (1) will be estimated using daily data over the period January 1, 2020 to June 30, 2020 \( (t) \) for 89 countries \( (i) \). Our sample consists of 13,255 observations. The panel is unbalanced because of the presence of some missing observations in the datasets. We expect \( Stringency \) to have a negative effect on \( AOD \) \((\beta < 0)\), but this effect will be mitigated or strengthened by an orientation towards a collectivistic culture \((\gamma > 0 \text{ or } \gamma < 0)\).

2.2. Data

AOD. For measuring the overall air quality, the daily variations of aerosol optical depth (AOD) from January to June 2020 is considered. AOD is a measure of the extermination of the solar beam due to dust and haze particles. Contaminants in the atmosphere may block sunlight through absorption or scattering the solar rays. AOD measures how much direct sunlight is blocked from reaching the ground due to such pollution particles (National Oceanic and Atmospheric Administration, 2020). AOD may thus be considered as an indirect but precise measure of air pollution and consequently the air quality in a country. Relying on its appropriateness to proxy air quality, various studies have used AOD either to exclusively measure air pollution (see, for example, Hutchison, 2003; Chu et al., 2003; Engel-Cox et al., 2004) or to analyze health impacts of the air pollution (see, for example, Hu, 2009; Hu and Rao, 2009; Gutierrez, 2010).\(^3\)

Air quality is commonly measured using particulate matter 2.5 (PM2.5) (WHO Occupational and Environmental Health Team, 2000). In this research, we use satellite based AOD data instead for two reasons. First, the collection of PM2.5 data depends on the availability of ground-level monitoring stations, which is likely to vary significantly across countries due to geographic and economic reasons. AOD data derived from satellite instruments overcomes this limitation due to its wide spatial coverage, thus allowing us to perform an analysis of the time-space dynamics of air pollution (Kumar et al., 2007; Shi et al., 2018). Second, although the satellite-derived aerosol load data is an indirect measure of air quality, several studies conducted in different countries across the globe have demonstrated that there is a significant positive relationship between AOD, PM2.5 and PM10 (see Hutchison et al., 2005; Chu, 2006; Gupta et al., 2006; Khoshsima et al., 2014; Kong et al., 2016 among others). AOD also provides additional information on air quality since aerosols are also known to disrupt cloud formation, hydrological cycles, and atmospheric stability (Li et al., 2007; IPCC, 2013).

In light of these benefits, we collect daily data on satellite-based Aerosol Optical Depth (AOD) from NASA (Platnick et al., 2015b). Our data is drawn from the moderate resolution imaging spectroradiometer (MODIS) aboard NASA’s Terra satellite. In the robustness checks, we use alternative data sources from two other satellites – MODIS-Aqua and Ozone Monitoring Instrument (OMI)-Aura.

Stringency. The stringency policy index is taken from OxCGRT (Hale et al., 2020). The OxCGRT dataset compiled by the Blavatnik School of Government at the University of Oxford provides comprehensive information on the rigor of government-imposed containment actions using different lockdown measures. Daily data on the following controls are provided: 1) school closing, 2) workplace closing, 3) cancellation of public events, 4) restrictions on gatherings, 5) closure of public transport, 6) stay at home requirements, 7) restrictions on internal movement, 8) international travel controls, and 9) provision of public information campaigns. We use the overall stringency measure provided by OxCGRT, which is constructed based on all the above components. A larger value of the index corresponds to a higher degree of stringency. Fig. 1 shows the
evolution of Stringency over time (January to June 2020). The index shows a gradual increase from mid-January to mid-March, and increases dramatically over the next 30 days, before gradually declining from mid-April onwards.

**COLL.** Collectivism is measured using the individualism vs. collectivism index of Hofstede (1980). Hofstede’s index captures several cultural traits of individualism that include beliefs in the importance of personal freedom, outward orientation, small organizations, recognition and rewards, social networks, and non-conformity. The index was constructed by Geert Hofstede on the basis of over 117,000 survey responses in 40 countries. The data was further extended in Hofstede et al. (2010) and the Hofstede Center (www.hofstede-insights.com) to assimilate data in 101 countries. The index is on a scale of 0–100, with a higher value representing a greater level of individualism. In this study, we have rescaled the data to range from 0 to 1 such that a higher value reflects a greater degree of collectivism in a country. Fig. 2 shows the spatial distribution of collectivism across the globe. It is evident that the extent of collectivism differs widely across countries. In the robustness check

**Fig. 1.** Evolution of containment and closure policies (Stringency). Notes: The diagram shows the evolution of the stringency policy index over the first 6 months of 2020. The data is obtained from OxCGRT and are averaged across countries.

**Fig. 2.** Spatial distribution of the collectivism index (COLL).
Table 1
Summary statistics.

| Variable | Observations | Mean  | Std. Dev. | Min  | Max  |
|----------|--------------|-------|-----------|------|------|
| AOD      | 13,255       | 0.242 | 0.227     | 0.000| 4.551|
| Stringency | 13,255  | 0.476 | 0.352     | 0.000| 1.000|
| COLL     | 13,255       | 0.626 | 0.259     | 0.000| 1.000|

Notes: The descriptive statistics provided in the table include 133 countries used in the baseline regressions. Sources and definition of data are described in the text and the data appendix.

section, we show that our results are robust to the use of several alternative indices of collectivism.

Table 1 provides the summary statistics for the key variables used in the estimation. The mean value of AOD for 89 countries over the period 1 January – June 30, 2020 is 0.24. Figure A1 in the appendix shows the spatial variations in AOD and Stringency across our sample countries. The data are averaged over the period of January–June 2020. Noticeably, countries with stringent lockdown measures appear to have better air quality during that period. A few countries, however, are the exception. For example, most countries in South Asia (e.g., Bangladesh, Nepal), appear to have bad to moderate air quality even with stringent lockdown measures. Coincidentally, most of these countries’ manifest collectivist orientations. Conversely, mainly good air quality is recorded for most countries in Europe (e.g., Belarus, Sweden), which manifest individualist traits. Lockdown measures, however, were relatively less stringent in this continent.

3. Empirics

3.1. Main results

Table 2 provides the regression results for Eq. (1). First, we provide a basic specification to explore the relationship between AOD and Stringency while also controlling for the influence of temperature and precipitation, urbanization rate, population density, and the share of the elderly population (aged 65 or above) in column (1). Both the coefficients of Stringency and its interaction with COLL are statistically significant at the 1% level. In columns (2), and (3) we add country fixed effects and time dummies one at a time. The coefficients of Stringency and interaction term are stable. Column 4, finally, includes time dummies and country-fixed effects together along with all other control variables. This is the baseline specification that we use in the rest of the paper.

In sum, both the coefficients of Stringency and its interaction with COLL are statistically significant at the 1% level throughout all specifications. The coefficient of stringency and interaction term, however, have opposite signs. Note that the interaction term measures the differential impact of stringency measures in countries with varying degrees of collectivism. It shows that while Stringency has a mitigating effect on air pollution, this effect is weakened by a culture of collectivism. The results also remain robust to standard errors clustered at the country level (see Table A1 in the appendix). Fig. 3 visually displays the interaction effect by plotting mean predicted values of AOD at different levels of collectivism and containment policies. It further confirms that the mitigating effect of Stringency on air pollution is weakened by collectivistic culture. As the degree of collectivism goes up, the negative association between Stringency and air pollution starts getting weaker.

Overall, our finding that the stringency of policy response during the COVID-19 pandemic contributes to better air quality is largely consistent with the literature. However, our results strongly indicate that this effect is moderated by the presence of a collectivistic culture in a society. That is, a society that has a greater orientation towards being collectivistic is less effective in implementing and following stringent policy measures. These results lend some support to our hypothesis that the air quality can be predicted by the stringency of the COVID-19 response policy and its interaction with a culture of collectivism.

3.2. Robustness to alternative collectivism measures

While Hofstede’s index is the most widely used measure of the individualism–collectivism dimension of cultural differences, there are also other more commonly used indices of individualism–collectivism in the literature. These include the indices of Suh et al. (1998), Tang and Koveos (2008), Uz (2015), Kashima and Kashima (1998) and Gelfand et al. (2004), and Ang (2019). This section checks if our results are sensitive to the use of other measures of collectivism. The data appendix provides a description of these measures. All these indices have been rescaled (where applicable) so that higher values reflect greater collectivism. Table 3 reports the findings using these alternative measures. Reassuringly, in all cases, the results are consistent with our previous findings, suggesting that our estimates are robust to the use of a wide range of alternative collectivism measures.

3.3. Robustness to using alternative satellite data for AOD and seasonal variations in air quality

In the main analysis, we have used data from NASA’s Terra satellite to generate the AOD measure. In this section, we check if our results are sensitive to the use of alternative satellite data. Two other satellites of NASA provide such data: Aqua and Aura. The Terra and Aqua satellites use the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument to measure the daily values of aerosols at a global scale in the atmosphere. MODIS uses eight spectral bands and an algorithm to estimate aerosol models that monitor spatial and temporal aerosol properties over land and ocean.

The orbital difference between the two satellites enables the MODIS instrument to capture the same region on the earth approximately 3 h apart. Terra crosses the equator from the north to south in the morning (approximately at 10:30am local time) while Aqua covers the same
locations in the afternoon (approximately at 1:30pm local time). The aerosol properties measured by the two satellites might vary due to this orbital difference which results in variation in the solar zenith, cloud coverage as well as the sensor view angles over the same region at different periods.

NASA’s Aura satellite uses a different instrument to measure the aerosol optical depth. It holds the Ozone Monitoring Instrument (OMI) whose spectrometer utilizes the sensitivity of the top of the atmosphere (TOA) upwelling radiances in the visible regions of the solar spectrum to estimate atmospheric aerosols. The algorithm used by OMI to measure aerosol optical depth also differs from the aerosol models in MODIS.

We choose Terra over Aqua and Aura since it allows us to generate the most data points over the sample period considered. Table 4(columns 1 and 2) reports the results using AOD data generated from these two alternative satellites: MODIS-Aqua and OMI-Aura. As is evident, our results are qualitatively similar. In both cases, the coefficients of Stringency and its interaction with collectivism are statistically highly significant and have signs consistent with our baseline findings reported in Table 2.

Table 3

| Dependent variable – AOD | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|--------------------------|-----|-----|-----|-----|-----|-----|-----|
| Stringency              | −0.156*** | −0.286*** | −0.325*** | −0.222*** | −0.511*** | −1.296*** | −0.123*** |
|                          | (0.042) | (0.047) | (0.048) | (0.034) | (0.071) | (0.095) | (0.037) |
| Stringency X COLL        | 0.113*** | 0.107*** | 0.245*** | 0.157*** | 0.058*** (0.010) | 0.192*** | 0.011*** |
|                          | (0.029) | (0.031) | (0.028) | (0.013) | (0.016) | (0.016) | (0.004) |
| Country fixed effects    | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time-period dummies      | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared                | 0.066 | 0.075 | 0.081 | 0.061 | 0.064 | 0.078 | 0.045 |
| No. of observations      | 6927 | 6876 | 6974 | 10,286 | 7739 | 7739 | 13,255 |
| No. of countries         | 47 | 43 | 53 | 65 | 52 | 52 | 89 |

Notes: This table reports fixed-effect estimates using data at the country-day level. Figures in the parenthesis are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The control variables are interactions of precipitation, temperature, urbanization rate, population density and the share of the elderly population with Stringency. Their estimates are not reported here for brevity.

We thank an anonymous referee of this journal for the suggestion.

3.4. Additional checks

We conduct some additional checks in this section. First, given the nature of our study (i.e., limited time duration of six months), analyzing cultural time trends based on analogous data is not feasible. We adopt an alternative approach for doing so. We divide our sample into two country groups based on their level of collectivism—those above the sample median and those below and re-run our baseline model. In this way, we can study the effects of time-variant factors separately in countries with a higher level of collectivism and those with a lower level of collectivism (i.e., individualistic societies). Additionally, we also include a collectivism time-trend whereby collectivistic countries have been divided in quartiles and interacted with the time-period dummy. The results are reported in columns (1)–(3) of Table 5. In all cases, the coefficients of Stringency and
10%, 5% and 1% levels, respectively. The control variables are interactions of precipitation, temperature, urbanization rate, population density and the share of the elderly population with its interaction with collectivism are statistically significant and have consistent signs. This finding is largely in line with the historical timeline of the lockdown measures, which were only strictly implemented in most countries since early March when many COVID-19 cases were reported worldwide.

Comparing all the results using data up to March 31, 2020, April 30, 2020, 31 May (for details, see columns (1) to (3) of Table A1 in the appendix) and June 30, 2020 (baseline model in Table 2) for which both the coefficients of Stringency and Stringency X COLL are significant, we can see that the total effect of stringency on \( AOD \) is waning. This result implies that while containment and closure policies are effective at reducing social mobility initially, which leads to better air quality, prolonged implementation of these policies may lead to a lower rate of compliance, which reduces the effectiveness of these policies.

### 4.2. Individual components of stringency

This sub-section provides further results using the sub-components of our stringency measure: school closing, workplace closing, public events cancellation, restrictions on gatherings, public transport closing, stay at home, restrictions on internal movements, international travel controls, and public information campaigns. This exercise allows us to check if the results are driven by specific components and identify which policy is most effective at containing air pollution. All sub-indices of the Stringency are re-scaled to take values between 0 and 1. Fig. 5 plots the point estimates of our main variables. The detailed results are reported in Table A3 in the appendix. The results indicate that all coefficients of Stringency remain statistically significant at the 1% level, suggesting that all containment and closure policies are effective at improving air quality. In line with the above findings, all coefficients of the interaction term between stringency and collectivism are also highly significant. Hence, the results do not appear to be driven by certain types of containment and closure policies.

### 4.3. Heterogeneity

In this section, we examine whether the interaction effect of policy

---

**Table 4**

Alternative satellite data for AOD.

| Dependent variable – AOD | (1) MODIS-Aqua | (2) OMI-Aqua | (3) AOD from 2019 values |
|--------------------------|---------------|-------------|-------------------------|
| Stringency X COLL        | –0.157***     | –0.156***   | –0.202***               |
|                          | (0.030)       | (0.059)     | (0.033)                 |

| Country fixed effects    | Yes           | Yes         | Yes                     |
| Time-period dummies      | Yes           | Yes         | Yes                     |
| R-squared                | 0.061         | 0.063       | 0.050                   |
| No. of observations      | 12,808        | 10,484      | 13,255                  |
| No. of countries         | 89            | 89          | 89                      |

Notes: This table reports fixed-effect estimates using data at the country-day level. Figures in the parenthesis are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The control variables are interactions of precipitation, temperature, urbanization rate, population density and the share of the elderly population with Stringency. Their estimates are not reported here for brevity.

---

**Table 5**

Additional checks.

| Dependent variable – AOD | Collectivism - Low | Collectivism - High | Collectivism time trends | Social trust | GDP per capita (log) |
|--------------------------|-------------------|---------------------|--------------------------|--------------|----------------------|
| Stringency               | –0.096***         | –0.617***           | –0.289***                | –0.063*      | –0.201***            |
|                          | (0.030)           | (0.137)             | (0.035)                  | (0.038)      | (0.035)              |
| Stringency X COLL        | 0.194***          | 0.451***            | 0.368***                 | 0.026        | 0.213***             |
|                          | (0.023)           | (0.150)             | (0.030)                  | (0.043)      | (0.025)              |

| Country fixed effects    | Yes               | Yes                 | Yes                      | Yes          | Yes                  |
| Time-period dummies      | Yes               | Yes                 | Yes                      | Yes          | Yes                  |
| R-squared                | 0.091             | 0.080               | 0.056                    | 0.045        | 0.046                |
| No. of observations      | 7679              | 5576                | 13,255                   | 10,333       | 12,799               |
| No. of countries         | 54                | 35                  | 89                       | 67           | 89                   |

Notes: This table reports fixed-effect estimates using data at the country-day level. Figures in the parenthesis are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The control variables are interactions of precipitation, temperature, urbanization rate, population density and the share of the elderly population with Stringency. Their estimates are not reported here for brevity.

---

In our main analysis, we have chosen June 30, 2020 to be the cut-off date for the estimation. In this section, we examine how our results change with the use of different cut-off dates. Fig. 4 shows the coefficients of interest for using several alternative cut-off dates. The detailed results are reported in Table A2 in the appendix. The results show that, except for end-January and end-February, both the coefficients of Stringency and its interaction with COLL are highly significant and have consistent signs. This finding is largely in line with the historical timeline of the lockdown measures, which were only strictly implemented in most countries since early March when many COVID-19 cases were reported worldwide.
Stringency and collectivism is heterogeneous due to the institutional differences across countries. We divide the sample by constructing two country groups based on their dichotomy in institutional characteristics – those with institutional values above the sample median and those below. The following institutional variables are considered: political stability, government effectiveness, and rule of law. The political stability index assesses the extent to which political instability and politically motivated violence are likely to occur. Government effectiveness captures the government’s ability to formulate quality policies and its commitment to implement them. Hence, a government that is perceived to be effective is more likely to be able to successfully implement the lockdown measures.

We also allow for the effect of rule of law since countries that have stronger property rights protection and contract enforcement should be more competent in carrying out policy restrictions on social mobility. All variables are measured using data for 2018 from Kaufmann et al. (2010).

Table 6 shows that the mitigating effect of stringency is conditional upon collectivism regardless of institutional heterogeneity between states, which coincides with our baseline findings.

### 4.4. Compliance

In this section, we examine whether changes in compliance can help explain our findings. To measure compliance, we use data on mobility from the Google Community Mobility Reports on mobility reductions measured at retail areas, transit stations, and workplace mobility (Google, 2020). The data measures the changes in visits to places such as retail shops, train stations, and offices during the pandemic. The mobility reductions are measured daily compared to a baseline which is the median activity in that area on the same day of the week between January 3 to February 6, 2020. We also construct an average of the three variables. The results in Table 7 indicate that while mobility is reduced by increasing stringency, this effect is weakened by collectivism, thus consistent with our baseline findings.

## 5. Instrumental variable estimates

While the main results reported in Table 2 provide a first approximation of the main findings of this study, we cannot rule out the possibility that these estimates are plagued by endogeneity. Hence, we also estimate Eq. (1) by exploiting the variation in the cumulative number of COVID-19 cases across time and space as the instrument.\(^5\) All variables

---

\(^5\) The cumulative number of COVID-19 cases is expressed in natural logs. For those observations with zero entries, we assign a very small number (0.01) to preserve the sample size so that the results are comparable to the baseline estimates.
interacted with Stringency, including the control variables, are instrumented using this approach. The cumulative number of cases is a suitable instrument since lockdown regulations were often beefed up following a surge of new cases or after the number of cases had crossed a certain threshold, which caused significant concerns to policymakers. The number of COVID-19 cases is also unlikely to contribute directly to AOD changes, and hence is more probable of satisfying the exclusion restriction.

The instrumental variable results are reported in Table 8. In column (1), we use a cumulative number of COVID-19 cases lagged by 1 day as the instrument. The coefficients for Stringency and Stringency X COLL are found to be statistically significant and have signs consistent with our main findings. Considering that the government may need some time to foster and transmitting a more collectivistic culture as opposed to cultivating wheat which required comparatively much lower levels of cooperation among farmers and family members thereby rejecting the null hypothesis at the 1% level, providing evidence that the excluded instruments are statistically significant. These results suggest that the cumulative number of COVID-19 cases is a reliable instrument for our estimations.

In addition, we use the rice to wheat suitability ratio as an instrument to exploit the exogenous variation in collectivism. As discussed previously, the studies have shown that a farming legacy of rice cultivation leads to the formation of a collectivistic culture in a society (Talhelm et al., 2014; Zhu et al., 2019; Ang et al., 2021). Historically, the cultivation of rice is a labor-intensive process that requires in-group dependence and cooperation among farmers and family members thereby fostering and transmitting a more collectivistic culture as opposed to cultivating wheat which required comparatively much lower levels of interdependence. The IV-2SLS results reported in column (3) of Table 8 remain robust.

endogenous regressors at the 5% level of significance. Next, we also implement the Anderson and Rubin (1949) and Stock and Wright (2000) tests. These procedures test the coefficients of the excluded instruments to be jointly equal to zero. Both tests are robust to weak instruments. The tests reject the null hypothesis at the 1% level, providing evidence that the excluded instruments are statistically significant. These results suggest that the cumulative number of COVID-19 cases is a reliable instrument for our estimations.

In addition, we use the rice to wheat suitability ratio as an instrument to exploit the exogenous variation in collectivism. As discussed previously, the studies have shown that a farming legacy of rice cultivation leads to the formation of a collectivistic culture in a society (Talhelm et al., 2014; Zhu et al., 2019; Ang et al., 2021). Historically, the cultivation of rice is a labor-intensive process that requires in-group dependence and cooperation among farmers and family members thereby fostering and transmitting a more collectivistic culture as opposed to cultivating wheat which required comparatively much lower levels of interdependence. The IV-2SLS results reported in column (3) of Table 8 remain robust.

Several diagnostic checks are in order. First, we perform the weak identification test of Cragg and Donald (1993). The results are compared against the critical values provided by Stock and Yogo (2005). The test rejects the null that our instruments are only weakly correlated with the

| Table 6 | Heterogeneity effects of institutional factors. |
|---------|-----------------------------------------------|
| Dependent variable – AOD | Low political stability | High political stability | Low government effectiveness | High government effectiveness | Low rule of law | High rule of law |
| Stringency | −0.441*** (0.092) | −0.189*** (0.038) | −0.344*** (0.088) | −0.191*** (0.039) | −0.265*** (0.081) | −0.112*** (0.042) |
| Stringency X COLL | 0.619*** (0.093) | 0.144*** (0.022) | 0.510*** (0.085) | 0.157*** (0.022) | 0.270*** (0.100) | 0.155*** (0.024) |
| Baseline controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time-period dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.115 | 0.058 | 0.099 | 0.060 | 0.099 | 0.051 |
| No. of observations | 4457 | 8798 | 4739 | 8516 | 5070 | 8185 |
| No. of countries | 28 | 61 | 30 | 59 | 31 | 58 |

Notes: This table reports fixed-effect estimates using data at the country-day level. Figures in the parenthesis are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The control variables are interactions of precipitation, temperature, urbanization rate, population density and the share of the elderly population with Stringency. Their estimates are not reported here for brevity.

| Table 7 | Compliance measures and stringency. |
|---------|------------------------------------|
| Dependent variable – stringency | (1) | (2) | (3) | (4) |
| | Retail mobility | Transit mobility | Workplace mobility | Avg. mobility |
| Stringency | −33.820*** (2.359) | −15.946*** (2.036) | −23.689*** (2.291) | −24.485*** (1.997) |
| Stringency X COLL | 11.668*** (1.724) | 8.398*** (1.488) | 8.378*** (1.674) | 9.481*** (1.460) |
| Baseline controls | Yes | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Time-period dummies | Yes | Yes | Yes | Yes |
| R-squared | 0.854 | 0.890 | 0.867 | 0.877 |
| No. of observations | 11,474 | 11,474 | 11,474 | 11,474 |
| No. of countries | 28 | 61 | 30 | 59 |

Notes: This table reports fixed-effect estimates using data at the country-day level. Figures in the parenthesis are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The control variables are interactions of precipitation, temperature, urbanization rate, population density and the share of the elderly population with Stringency. Their estimates are not reported here for brevity.

| Table 8 | Instrumental variable estimates. |
|---------|----------------------------------|
| Dependent variable – IV | IV – COVID-19 cases (t-1) | IV – COVID-19 cases (t-5) | IV – Rice-wheat suitability (for COLL) |
| | (1) | (2) | (3) |
| Stringency | −0.147*** (0.048) | −0.129*** (0.050) | −2.090*** (0.234) |
| Stringency X COLL | 0.207*** (0.029) | 0.191*** (0.030) | 3.202*** (0.407) |
| Baseline controls | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes |
| Time-period dummies | Yes | Yes | Yes |
| No. of observations | 12,532 | 12,091 | 11,513 |
| No. of countries | 89 | 89 | 72 |
| Cragg-Donald weak identification test | [5% c.v. = 19.86] | [5% c.v. = 23.689] | [5% c.v. = 19.86] |
| Anderson-Rubin test | 142.89 | 135.68 | 172.77 |
| Wald test | [p = 0.000] | [p = 0.000] | [p = 0.000] |
| Stock-Wright Wald test | 141.27 | 134.16 | 170.20 |

Notes: This table reports the IV results at the country-day level. t is time period (day). Figures in the parenthesis are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The control variables are interactions of precipitation, temperature, urbanization rate, population density and the share of the elderly population with Stringency. Their estimates are not reported here for brevity.
The economic and social disruptions caused by the COVID-19 pandemic are immense. Although the stringent Covid restrictions have produced a positive externality in the form of air pollution reduction, this reduction has not happened everywhere at equal rates. This paper hypothesizes that countries that adopt stringent containment and closure policies during the COVID-19 pandemic period are likely to experience better air quality, and this relationship depends on their cultural orientation. In view of the major characteristics of individualistic and collectivistic societies, and a multitude of other factors, it is theoretically ambiguous that COVID-19 containment policies will be more effective in which types of societies? More stringent containment measures will have a feeble impact on air pollution reduction in individualistic or collectivist societies?

Our regression estimates provide support for the second hypothesis. We find that stringent containment policies result in lower levels of satellite-derived aerosol loads. However, the strength of this effect is mitigated by the degree of collectivistic traits. These results still hold when we control for climatic, macroeconomic, and demographic factors. Moreover, our results indicate that a lengthy lockdown period appears to reduce the effectiveness of containment and closure policies.

Our findings should not be interpreted as an attempt to undermine the catastrophic impact of COVID-19 on public health and the economy. Rather, they advance an understanding of policy effectiveness in curbing global emissions, and above all, highlight the role of cultural differences in the successful implementation of policy and realization of desired outcomes using the COVID-19 pandemic as an exogenous event. We show that even during a global pandemic, stringent policies can control anthropogenic emissions. Cultural dimensions, however, may reinforce or curb these impacts to some extent. Hence, our results have implications for the formulation of environmental policies. It signifies that CO2 mitigation policies are less likely to yield emission reduction in collectivist societies.

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.

Acknowledgements

The authors thank the editor Sushanta Mallick, two insightful referees, Ian Bateman, Cheng Keat Tang and Christian A. Vossler for helpful discussions and comments. James B. Ang provided especially generous input.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2022.105874.

References

Anderson, T.W., Rubin, H. 1949. Estimation of the parameters of a single equation in a complete system of stochastic equations. Ann. Math. Stat. 46–63.

Ang, J.B., 2019. Agricultural legacy and individualistic culture. J. Econ. Growth 24, 397–425.

Ang, J.B., Fredriksson, P.G., Sharma, S. 2020. Individualism and the adoption of clean energy technology. Resour. Energy Econ. 61, 101180.

Ang, J.B., Madsen, J.B., Wang, W., 2021. Rice farming, culture and democracy. Eur. Econ. Rev. 136, 103778.

Bavel, J.J.V., Baicker, K., Boggio, P.S., Capraro, V., Cichocka, A., Cikara, M., Crockett, M.J., Crum, A.J., Douglas, K.M., Druckman, J.N., Drury, J., Dube, O., Eellemers, N., Finkel, E.J., Fowler, J.H., Gefen, M., Han, S., Haslam, S.A., Jetten, J., Kitayama, S., Mobbs, D., Napper, L.E., Packe, D.J., Pennycuick, G., Peters, E., Petty, R.E., Rand, D.G., Reicher, S.D., Schnall, S., Sharriff, A., Skitka, L.J., Smith, S.S., Sunstein, C.R., Taheri, N., Tucker, J.A., Linden, S.V.d., Lange, P.V., Weedon, R.A., Wohl, M.J.A., Zaki, J., Zion, S.R., Willer, R., 2020. Using social and behavioural science to support COVID-19 pandemic response. Nat. Hum. Behavior. 4, 460–471.

Bezuidenhout, S., De Grooth, H.L., Van Schalk, A.B. 2004. Trust and economic growth: a robustness analysis. Oxf. Econ. Pap. 56, 118–134.

Breuer, M.B., Chen, Y.-R., 2007. Where (who) are collectivists in collectivism? Toward conceptual clarification of individualism and collectivism. Psychol. Rev. 114, 151–162.

Chen, K., Wang, M., Huang, C., Kinney, P.L., Anastas, P.T., 2020. Air pollution reduction and mortality benefit during the COVID-19 outbreak in China. Lancet Planet. Health 4, e211–e212.

Cho, Y.N., Tyrroff, A., Rapert, M.I., Park, S.-Y., Lee, H.J., 2013. To Be or not to Be green: exploring individualism and collectivism as antecedents of environmental behavior. J. Bus. Res. 66, 1052–1059.

Chu, D.A., 2006. Analysis of the relationship between MODIS aerosol optical depth and PM2.5 in the summertime US. Rem. Sens. Aero. Chem. Gases Mod. Simul./Assimil. Appl. Air Qual. 6299, 629903.

Chu, D.A., Kaufman, Y., Zibordi, G., Chen, J., Mao, J., Li, C., Holben, B., 2003. Global monitoring of air pollution over land from the earth observing system-terrestrial moderate resolution imaging spectroradiometer (MODIS). J. Geophys. Res. Atmos. 108.

Cragg, J.G., Donald, S.G., 1993. Testing Identifiability and Specification in Instrumental Variables Models. Econometric Theory, pp. 222–240.

Dasgupta, S., De Gaze, E., 2018. The influence of institutions, governance, and public opinion on the environment: synthesized findings from applied econometrics studies. Energy Res. Social Sci. 43, 77–95.

Deng, J., Walker, G.J., Swinnerton, G., 2006. A comparison of environmental values and preferences between Chinese in Canada and anglo-Canadians. Environ. Behav. 38, 22–47.

DNV GL, 2020. Energy Transition Outlook 2020. DNV GL AS., Høvik, Norway. Accessed at: https://www.dnv.com/energy-transition/impact-of-covid-19-on-the-energy-transition.

Dubhfil, B., Baker, J.S., Navel, V., 2020. COVID-19 as a factor influencing air pollution? Environ. Pollut. 263, 114466.

Engel-Cox, J.A., Hollomon, C.H., Costant, B.W., Hoff, R.M., 2004. Qualitative and quantitative evaluation of MODIS satellite aerosol data for regional and urban scale Air quality. Atmos. Environ. 38, 2495–2509.

Eom, K., Kim, H.S., Sherman, D.K., Inhi, K., 2016. Cultural variability in the link between environmental concern and support for environmental action. Psychol. Sci. 27, 1351–1359.

European Space Agency, 2020. Air Pollution Remains Low as Europeans Stay at Home. Retrieved on: 9 June 2020, Accessed at: https://www.esa.int/Applications/Observin_g_the_Earth/Copernicus/Sentinel-5P/Air_pollution_remains_low_as_Europeans_stay_at_home.

Gautam, S., 2020. The influence of COVID-19 on air quality in India: a boon or inutile. Bull. Environ. Contam. Toxicol. 104, 724–726.

Gelfand, M.J., Bhawuk, D.P.S., Nishii, L.H., Bechtold, D.J., 2004. Individualism and collectivism. In: House, R.J., Hanges, P.J., Javidan, M., Dorfman, P.W., Gupta, V. (Eds.), Culture, Leadership, and Organizations: The GLOBE Study of 62 Societies. Thousand Oaks, CA Sage Publications, pp. 457–512.

Google, 2020. COVID-19 community mobility reports. Accessed at: https://www.google.com/covid19/mobility/.

Gorodnichenko, Y., Roland, G., 2012. Understanding the individualism-collectivism cleavage and its effects: lessons from cultural psychology. In: Aoki, M., Kuran, T., Roland, G. (Eds.), Institutions and Comparative Economic Development. Palgrave Macmillan UK), London, pp. 213–236.

Gorodnichenko, Y., Roland, G., 2017. Culture, institutions, and the wealth of nations. Rev. Econ. Stat. 99, 402–416.

Guino, L., Sapienza, P., Zingales, L., 2006. Does culture affect economic outcomes? J. Econ. Perspect. 20, 23–48.

Gupta, P., Christopher, S.A., Wang, J., Gehrig, B., Lee, Y., Kumar, N., 2006. Satellite remote sensing of particulate matter and air quality assessment over global cities. Atmos. Environ. 40, 5880–5892.

Gutierrez, E., 2010. Using satellite imagery to measure the relationship between air quality and infant mortality: an empirical study for Mexico. Popul. Environ. 31, 203–222.

Hale, T., Webster, S., Petherick, A., Phillips, T., Kira, B., 2020. Oxford COVID-19 Government Response Tracker. Blavatnik School of Government.

Halkos, G.E., Trzemes, N.G., 2013. National culture and eco-efficiency: an application of conditional partial nonparametric frontiers. Environ. Econ. Pol. Stud. 15, 423–441.

Helm, D., 2020. The environmental impacts of the coronavirus. Environ. Resour. Econ. 76, 21–38.

Hofstede, G., 1980. Culture’s Consequences: International Differences in Work-Related Values. Sage Publications. Beverly Hills, CA.

Hofstede, G., Hofstede, G.J., Minkov, M., 2010. Cultures and Organizations: Software of the Mind. Revised and Expanded, third ed. McGraw-Hill USA, New York.

Hu, Z., 2009. Spatial analysis of MODIS aerosol optical depth, PM2.5, and chronic coronary heart disease. Int. J. Health Geogr. 8, 1–10.

Hu, Z., Ruo, K.R., 2009. Particulate air pollution and chronic ischemic heart disease in the eastern United States: a county level ecological study using satellite aerosol data. Environ. Health 8, 28.

Hutchinson, K.D., 2003. Applications of MODIS satellite data and products for monitoring air quality in the state of Texas. Atmos. Environ. 37, 2403–2412.

Hutchinson, K.D., Smith, S., Faruqui, S.J., 2005. Correlating MODIS aerosol optical thickness data with ground-based PM2.5 observations across Texas for use in a real-time air quality prediction system. Atmos. Environ. 39, 7190–7202.

IEA, 2021. Covid-19 Impact on Electricity. IEA, Paris’. https://www.iea.org/reports/covid-19-impact-on-electricity.
IPCC, 2013. Working Group I Contribution to the IPCC Fifth Assessment Report (AR5) Climate Change 2013: the Physical Science Basis. Intergovernmental Panel on Climate Change, Geneva, Switzerland.

Kanniah, K.D., Kamrarul Zaman, N.A.F., Kaskaoutis, D.G., Latif, M.T., 2020. COVID-19’s impact on the atmospheric environment in the southeast Asia region. Sci. Total Environ. 736, 139658.

Kashima, E.S., Kashima, Y., 1998. Culture and language: the case of cultural dimensions and personal pronoun use. J. Cross Cult. Psychol. 29, 461–486.

Kaufmann, D., Kraay, A., Mastruzzi, M., 2010. The Worldwide Governance Indicators: Methodology and Analytical Issues. The World Bank. Policy Research Working Paper Series 5430.

Khoshsima, M., Ahmadi-Givi, F., Bidokhti, A., Sabetghadam, S., 2014. Impact of meteorological parameters on relation between aerosol optical indices and air pollution in a sub-urban area. J. Aerosol Sci. 68, 46–57.

Kim, Y., Choi, S.M., 2005. Antecedents of Green Purchase Behavior: an Examination of Collectivism, Environmental Concern, and PCE. ACR North American Advances, Kitayama, S., Mesquita, B.I., Karasawa, M., 2006. Cultural affordances and emotional experience: socially engaging and disengaging emotions in Japan and the United States. J. Pers. Soc. Psychol. 91, 890–903.

Kong, L., Xin, J., Zhang, W., Wang, Y., 2016. The empirical correlations between PM2.5, PM10 and AOD in the beijing metropolitan region and the PM2.5, PM10 distributions retrieved by MODIS. Environ. Pollut. 216, 350–360.

Kumar, N., Chu, A., Foster, A., 2007. An empirical relationship between PM2.5 and aerosol optical depth in Delhi metropolitan. Atmos. Environ. 41, 4492–4503.

Lewis, D., 2020. Why many countries failed at COVID contact-tracing — but some got it right. Nature 580, 384–387.

Li, Z., Xia, X., Cribb, M., Mi, W., Holben, B., Wang, P., Chen, H., Tsay, S.C., Eck, T.F., Zhao, F., Dutton, E.G., Dickerson, R.E., 2007. Aerosol optical properties and their radiative effects in northern China. J. Geophys. Res. Atmos. 112.

Lyu, W., Wehby, G.L., 2020. Community use of face masks and COVID-19: evidence from SURFRAD aerosol optical depth. Retrieved on: 6 Jun 2020, Accessed at: https://giovanni.gsfc.nasa.gov.

Khaniah, K.D., Kamarul Zaman, N.A.F., Kaskaoutis, D.G., Latif, M.T., 2020. COVID-19’s impact on the atmospheric environment in the southeast Asia region. Sci. Total Environ. 736, 139658.

Kashima, E.S., Kashima, Y., 1998. Culture and language: the case of cultural dimensions and personal pronoun use. J. Cross Cult. Psychol. 29, 461–486.

Kaufmann, D., Kraay, A., Mastruzzi, M., 2010. The Worldwide Governance Indicators: Methodology and Analytical Issues. The World Bank. Policy Research Working Paper Series 5430.

Khoshsima, M., Ahmadi-Givi, F., Bidokhti, A., Sabetghadam, S., 2014. Impact of meteorological parameters on relation between aerosol optical indices and air pollution in a sub-urban area. J. Aerosol Sci. 68, 46–57.

Kim, Y., Choi, S.M., 2005. Antecedents of Green Purchase Behavior: an Examination of Collectivism, Environmental Concern, and PCE. ACR North American Advances, Kitayama, S., Mesquita, B.I., Karasawa, M., 2006. Cultural affordances and emotional experience: socially engaging and disengaging emotions in Japan and the United States. J. Pers. Soc. Psychol. 91, 890–903.

Kong, L., Xin, J., Zhang, W., Wang, Y., 2016. The empirical correlations between PM2.5, PM10 and AOD in the beijing metropolitan region and the PM2.5, PM10 distributions retrieved by MODIS. Environ. Pollut. 216, 350–360.

Kumar, N., Chu, A., Foster, A., 2007. An empirical relationship between PM2.5 and aerosol optical depth in Delhi metropolitan. Atmos. Environ. 41, 4492–4503.

Lewis, D., 2020. Why many countries failed at COVID contact-tracing — but some got it right. Nature 580, 384–387.

Li, Z., Xia, X., Cribb, M., Mi, W., Holben, B., Wang, P., Chen, H., Tsay, S.C., Eck, T.F., Zhao, F., Dutton, E.G., Dickerson, R.E., 2007. Aerosol optical properties and their radiative effects in northern China. J. Geophys. Res. Atmos. 112.

Lyu, W., Wehby, G.L., 2020. Community use of face masks and COVID-19: evidence from SURFRAD aerosol optical depth. Retrieved on: 6 Jun 2020, Accessed at: https://giovanni.gsfc.nasa.gov.

Zhu, J., Ang, J.B., Fredriksson, P.G., 2021. Raininess and climate change policies. Energy Econ. 101, 105414.

Shi, Y., Ho, H.C., Xu, Y., Ng, E., 2018. Improving satellite aerosol optical depth-PM2.5 correlations using land use regression with microscale geographic predictors in a high-density urban context. Atmos. Environ. 190, 23–34.

Snibbe, A.C., Markus, H.R., 2005. You can’t always get what you want: educational attainment, agency, and choice. J. Pers. Soc. Psychol. 88, 703–720.

Stock, J.H., Wright, J.H., 2000. GMM with weak identification. Econometrica 68, 1055–1096.

Stock, J.H., Yogo, M., 2005. Testing for weak instruments in linear IV regression. In: Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg. Cambridge University Press, Cambridge, pp. 80–108.

Suh, E., Diener, E., Oishi, S., Triandis, H.C., 1998. The shifting basis of life satisfaction judgments across cultures: emotions versus norms. J. Pers. Soc. Psychol. 71, 482–493.

Talhelm, T., Zhang, X., Oishi, S., Shimpin, C., Duan, D., Lan, X., Kitayama, S., 2014. Large-scale psychological differences within China explained by rice versus wheat agriculture. Science 344, 663–668.

Tang, L., Koveos, P.E., 2008. A framework to update Hofstede’s cultural value indices: economic dynamics and institutional stability. J. Int. Bus. Stud. 39, 1045–1063.

Tanzi, V., 1994. Corruption, Governmental Activities and Markets. IMF Working Paper 94/99.

Tobias, A., Carnerero, C., Reche, C., Massague, J., Via, M., Minguillon, M.C., Alastuey, A., Querol, X., 2020. Changes in air quality during the lockdown in Barcelona (Spain) one month into the SARS-CoV-2 epidemic. Sci. Total Environ. 726, 138546.

Triandis, H.C., 1995. Individualism & Collectivism. Westview Press, Boulder, Colorado.

Uz, I., 2015. The index of cultural tightness and looseness among 68 countries. J. Cross Cult. Psychol. 46, 319–335.

Vu, T.V., 2020. Individualism and Climate Change Policies: International Evidence. Available at: SSRN 3547076.

Wagner III, J.A., 1995. Studies of individualism-collectivism: effects on cooperation in groups. Acad. Manag. J. 38, 152–173.

WHO Occupational and Environmental Health Team, 2000. Guidelines for Air Quality. World Health Organization, Geneva.

Xiang, P., Zhang, H., Gong, L., Zhou, K., Wu, Y., 2019. Individualist-collectivist differences in climate change inaction: the role of perceived intractability. Front. Psychol. 10, 187.

Xue, W., Hine, D.W., Marks, A.D.G., Phillips, W.J., Zhao, S., 2016. Cultural worldviews and climate change: a view from China. Asian J. Soc. Psychol. 19, 134–144.

Zhu, J., Ang, J.B., Fredriksson, P.G., 2019. The agricultural roots of Chinese innovation performance. Eur. Econ. Rev. 118, 126–147.