Differential Impacts of US-China Trade War and Outbreak of COVID-19 on Chinese Air Quality

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Abstract

Purpose: Over the last couple of years, Chinese manufacturing sector was affected by the onset of US-China trade war and the outbreak of COVID-19. In such a scenario, air quality in China has encountered a shock, and the impacts of these two incidents are unknown. In this study, we analyze the convergence of air quality in China in presence of multiple structural breaks, and how the impacts of these two events are different from each other.

Design/methodology/approach: In order to assess the nature of shocks in the presence of multiple structural breaks, Clemente-Montañés-Reyes (1998) with two structural breaks and Bai and Carrion-i-Silvestre (2009) with five structural breaks are employed.

Findings: Our results reveal that air quality in China is showing the sign of convergence, and it is consistent across 18 provinces, which are worst hit by the outbreak of COVID-19. In presence of transitory shocks, the impact of COVID-19 outbreak is found to be higher, whereas the impact of US-China trade war is found to be more persistent. Lastly, outbreak of COVID-19 has been found to have more impact on pollutants with higher severity of health hazard.

Originality: To the best of our knowledge, this is the first study that contributes to the empirical literatures in terms of investigating the convergence of overall air pollution and individual air pollutants taking COVID-19 and trade war into account.

Keywords: China; Trade War; COVID-19; AQI; Convergence

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1. Introduction

Over last few years, the Chinese economy has experienced shocks because of two major mutually exclusive events, i.e., trade war between the USA and China, and another is the outbreak of Novel Coronavirus, popularly known as COVID-19. The USA is the largest single market for Chinese goods, but trade barriers imposed by USA forced China's growth rate below 7% in 2018 and 2019, first time since 1990 (Morrison 2018, McDonald 2020). According to National Bureau of Statistics of China, the manufacturing Purchasing Managers Index (PMI) of China remained in negative territory for about straight 6 months in 2019, because of the trade barriers imposed by the USA. Subsequent to this, the Chinese economy was hit again with the outbreak of COVID-19 in Chinese city of Wuhan in December 2019 (Zhu et al. 2020). The country's manufacturing PMI fell sharply to 35.7% in February 2020 from 50% in January 2020, with production index taking the hardest hit. The composite PMI output index also fell to 28.9% in February 2020 from 53% in the previous month.

First, during last few decades, while being world's largest manufacturer, environmental quality of China has taken a toll, as energy intensive and polluting industries continued to increase (Morrison, 2018). Owing to the US-China trade war and outbreak of COVID-19, manufacturing and other economic activities in China were hit, and it impacted the air quality of China. Due to the lockdown of traffic and power plants, the concentration of NO_2 and other pollutants have decreased (NASA, 2020). As people continued to postpone and avoid air-travel and unneeded commutes to work, carbon emissions have dropped by 25% in China alone (Myllyvirta, 2020). Given this situation, the nature of shock to air quality of China by these two incidents needs to be analyzed, as these shocks are permanent or transitory in nature. Moreover, following the latent observations in the recent works on the impact of COVID-19 outbreak on air quality of China by

He et al. (2020) and Le Quéré et al. (2020), it might be possible that air pollutants in China might show a sign of convergence.

Second, the reason to analyze these two apparently separate events is because of their similar impacts on the level of air quality across the Chinese cities. On the one hand, much of the pollution in Chinese cities can be traced back to the production of commodities for the consumption of other countries, notably USA and Europe (Helm, 2020). The recent trade war between China and USA has imposed a great concern for the Chinese economic growth which has slowed down compared to the past decades (Swift, 2019). But at the same time, this trade war has helped the Chinese economy improve its air quality as several manufacturing companies have shifted their production services from China which in turn reduced the energy consumption, a leading source of anthropogenic air pollutants (Wang, 2019). On the other hand, the COVID-19 emerged amidst the trade war and with the shutdown of factories and production, the air quality benefitted even more significantly. Hence, due to these two events which are structurally different, the air quality in Chinese cities experienced similar outcome on its environment. To accommodate these similar outcomes, this study makes an attempt to demonstrate the effects of these separate events on the air quality. However, the two mentioned incidents are structurally different, and therefore, they might have differential impacts on air pollutants. The US-China trade war is characterized by a series of political events, which had an indirect impact on manufacturing activities, while the outbreak of COVID-19 had a direct impact on manufacturing and allied economic activities. Coal powered industries are the major sources of air pollution in China. But as a result of the trade war, USA's imports of Chinese coal and petroleum products fell by nearly 70% in 2018, while coal output fell by 6.3% in the first two months of 2020, as the outbreak of COVID-19 affected mining activities (Bekkers and Schroeter 2020, NBS 2020). Impacts of these two events may also differ based on the nature of individual air pollutants. Power plants and construction activities cause spike in NO_2, CO, $PM_{2.5}$, PM_{10} and SO_2, while O_3 is formed through vehicular NOx and VOCs (Feng et al. 2015). Trade war is largely associated with reduction in manufacturing activities and hence reduction in air pollutants that result specifically from industrial pollution. Outbreak of COVID-19, on other hand, has been discouraging travel and transport activities across the nation, along with the postponement of other economic activities. Therefore, the nature of impact exerted by these two incidents might differ from one another. Moreover, as both of these activities severely impacted the energy consumption and consequential ambient air pollution, hence it might be noteworthy to observe the difference of impacts between these two events, given the evolutionary impacts of these two events might be different from each other. A major reason behind this argument is that while the US-China trade war is majorly politically driven and it can have an impact on the anthropogenic activities limited by international borders, the impact of COVID-19 might not depend on the international borders and it might have a different impact on the anthropogenic activities. It can be expected that this difference might be arising out of the duration of the impact, or the type of pollutant these events can impact. Irrespective of this nature, it can be logically assumed that there might exist certain difference between the impacts exerted by these two events.

Third, the air pollutants prevalent in atmospheric environment of China differ based on their level of severity, which is determined by their molecular size and half-life. Based on the level of economic and human activities, atmospheric concentration of these pollutants differs. In continuation with the previous argument, given the structural difference between the US-China trade war and outbreak of COVID-19, their impacts on the Chinese air quality are expected to be different, and this difference might be reflected on the various types of pollutants differed by severity. For example, Cole et al. (2020) found that NO_2 fell by 63% in Wuhan during the lockdown period, while no significant fall in SO_2 or CO emissions was observed during that period. Hence, it might be expected that the impacts of US-China trade war and outbreak of COVID-19 differ based on the nature of pollutants.

Given this background, it can be said that the US-China trade war and the outbreak of COVID-19 had substantial impacts on Chinese air quality, and these impacts might be different. Moreover, the nature of shocks to air quality of China is still unknown. These two aspects bring out the objective of the study. The present study intends to look into (a) whether the impacts of US-China trade war and the outbreak of COVID-19 on Chinese air quality are different from each other, and (b) how these two impacts differ from each other. These research objectives can help in determining the change in air quality in presence of two different and mutually exclusive events. From a broad outlook, this study can help the policymakers with certain recommendations, as this study isolates and analyzes the impacts of a political event and a pandemic on the air quality of China. Looking at the scenario from the lens of environmental sustainability, outcomes of this study might shed light on the areas of economic and environmental policy realignment in the event of political or health hazards. As the study by Sofia et al. (2020) gives an idea about strategic landscaping of sector-level emission reduction, it also provides an idea about the possibilities of differential impact on nature of pollutants, and our study has drawn inferences from the particular findings of that study. The present study sheds light in this area by analyzing the convergence of air quality index in China for the last six months (September 2019 to March 2020) and covering 18 Chinese provinces, which have been affected the most by the outbreak of COVID-19. Using Clemente-Montañés-Reyes (1998) unit root test with two structural breaks and Bai and Carrion-i-Silvestre (2009) with five structural breaks, convergence of air quality index (AQI) components (particulate matter, ozone, nitrogen dioxide, sulfur dioxide, and carbon monoxide) across the 18 cities are analyzed. We have found that the AQI and its individual components are showing a sign of convergence, and thereby demonstrating the betterment of air quality in China. The shocks to the air quality were found to be transitory, while the impact of COVID-19 outbreak was higher and the impact of US-China trade war was more persistent. Lastly, pollutants with higher severity of health hazard were more affected by the outbreak of COVID-19, whereas coarse pollutants with lower severity of health hazard were more affected by US-China trade war.

2. Data and Methodology

2.1 Data description

The daily data for AQI and its six components of 18 Chinese cities[2] over a period of 6 months (October 01, 2019 to March 16, 2020) have been collected from World Air Quality Index (WAQI) project available on Air Quality Index China (AQICN)[3]. The project collects daily data of air pollutants concentrations and then illustrates them in real time for over 100 countries. This project compares the data released by different stations, embassies and environmental protection agencies with that of Chinese cities. This project converts raw concentrations to AQI using US Environmental Protection Agency's instant cast (i.e., Instant AQI) scale. AQI measures the air quality based on six pollutants, i.e., particulate matter ($PM_{2.5}$ and PM_{10}), Ozone (O_3), Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2) and Carbon Monoxide (CO) emissions. Measurements are based on 1 hour reading and hence an AQI reported at 10PM indicates that measurement was done from 9PM to 10PM. Composite AQI has been calculated based on the following formula:

[2] Beijing, Changsha, Chengdu, Fuzhou, Guangzhou, Hangzhou, Hefei, Jinan, Kunming, Nanchang, Nanjing, Nanning, Shanghai, Shenyang, Shijiazhuang, Wuhan, Xian, and Zhengzhou

[3] World Air Quality, "Real-time Air Quality Index (AQI)". Available at: https://aqicn.org.

$$AQI = \max\left(AQI_{PM2.5}, AQI_{PM10}, AQI_{03}, AQI_{NO2}, AQI_{SO2}, AQI_{CO}\right) \quad (1)$$

Where $AQI_{PM2.5}$, AQI_{PM10}, AQI_{O3}, AQI_{NO2}, AQI_{SO2}, and AQI_{CO} are partial indices of individual air pollutants.

$$AQI_p = \left[\frac{AQI_{ph} - AQI_{pl}}{C_{high} - C_{low}}\right] * \left(C_p - C_{low}\right) + AQI_{pl} \quad (2)$$

Where, AQI_p is the partial index of air pollutant p, C_p is the daily average concentration of p. C_{high} and C_{low} are threshold concentrations of air pollutant at air quality grade. AQI_{ph} and AQI_{p1} correspond to C_{high} and C_{low} and they represent threshold partial indices of p at air quality grade (Zhang et al., 2019).

2.2 Stationarity test

We have first analyzed the convergence in air quality through unit root tests by Clemente-Montañés-Reyes (1998) with two structural breaks and Bai and Carrion-i-Silvestre (2009) with five structural breaks. Following this, we have analyzed the convergence of individual components of air quality index (AQI) across the 18 cities, and we have analyzed the size of impacts of those two incidents by the number of structural breaks appearing for each of pollutants across the cities. A detailed scheme of the methods is illustrated in Appendix 1.

In order to assess the nature of shocks in the presence of multiple structural breaks, Bai and Carrion-i-Silvestre (2009) unit root test has been employed. The empirical design of the model is as per the following:

$$X_{it} = \alpha_i Z_{it} + \beta_i Y_{it} + \varepsilon_{it} \quad (3)$$

Here, X_{it} is the stochastic process differential, Z_{it} is the matrix of exogenous covariates with coefficients a_i, Y_{it} is a (L x 1) vector of common factors denoting the presence of cross-sectional dependence, β_{it} is a (L x 1) vector of factor loadings, and ε_{it} is the stochastic error term. Using principal component analysis and controlling for the cross-sectional dependence, the stationary matrix version of Eq. (3) can be written as:

$$\mathbf{x}_i = \boldsymbol{\alpha} z_i + \boldsymbol{\beta}_i y_i + \varepsilon_i \tag{4}$$

$$\begin{cases} \mathbf{x}_i = (\Delta x_{i2}, \dots, \Delta x_{iT})' \\ \boldsymbol{\alpha} = (\Delta\alpha_2, \dots, \Delta\alpha_T)' \\ \boldsymbol{\beta}_i = (\Delta\beta_{i2}, \dots, \Delta\beta_{iT})' \\ \beta_{it} = (1, DM_{1,it}, \dots, DM_{si,it})' \end{cases}$$

Here, *DM* is the dummy variable denoting the presence of any structural break TB^i in *i*-th time series, such that $DM_{it} = 1$, if $t > TB^i$, else $DM_{it} = 0$. For j number of unknown structural breaks, $DM_{j,it} = 1$, if $t > TB_j^i$, else $DM_{j,it} = 0$. Now, provided the estimated values of $\boldsymbol{\alpha}$, z_i, $\boldsymbol{\beta}_i$, and y_i to be $\widehat{\boldsymbol{\alpha}}$,$\hat{z}_i$, $\widehat{\boldsymbol{\beta}}_i$, and $\hat{y}_i$, the cumulative residual vector can be defined as $\hat{r}_{it} = \sum_{n=2}^{t} \hat{\mathbf{x}}_{i,s} - \widehat{\boldsymbol{\alpha}} \hat{z}_{i,s} + \widehat{\boldsymbol{\beta}}_{i,s} \hat{y}_{i,s}$. According to modified Sargan and Bhargava (1983) (thereafter MSB) approach, the MSB statistics can be defined as:

$$MSB_i(\pi_i) = (T^{-2} \textstyle\sum_{t=1}^{T} \hat{r}^2{}_{i,t-1}) / \hat{\varphi}_i^2 \tag{5}$$

Here, $\pi_{i,j} = TB_j^i / T$, $\hat{\varphi}_i^2$ is the variance of $\hat{r}_{i,j}$, and T is the length of the time series.

For enhancing the explanatory power, Bai and Carrion-i-Silvestre (2009) suggested the average individual statistic to be:

$$Z = \sqrt{C}\{\overline{MSB(\pi)} - \bar{\tau}\}/\gamma \rightarrow N(0,1) \tag{6}$$

Here, $MSB(\pi) = \sum_{i=1}^{C} MSB_i(\pi_i)/C$, $\tau = \sum_{i=1}^{C} \tau_i/C$, $\gamma_i = \sum_{i=1}^{C} \gamma_i^2/C^2$, and C is the breadth of the cross-sections. The Fisher-type test statistics are given by:

$$P = -2 \textstyle\sum_{i=1}^{C} \ln(\mu_i) \rightarrow X_{2C}^2 \tag{7}$$

$$P_m = \{-2 \textstyle\sum_{i=1}^{C} \ln(\mu_i) - 2C\}/\sqrt{4C} \rightarrow N(0,1) \tag{8}$$

Here, μ_i are the respective probability values of individual MSB_i assessments.

3. Results

Before we talk about the impact of US-China trade war and outbreak of COVID-19 on Chinese AQI, it is necessary to mention about the caveats and assumptions. Following the recent study by Hu et al. (2021) on four pandemic hotspots in four Asian countries divulge that the transformations in the AQI might be attributable to other exogenous factors. The inherent pollution characteristics of the cities are also responsible to this transformation, as the cities prone to higher pollutions might show a sign of reversal in the air quality during the post-COVID scenario. On the other hand, the cities prone to lower pollutions might show a sign of continuous improvement in the air quality during the post-COVID period. These structural attributes of the chosen cities are not incorporated in the analysis. A major reason behind this assumption is that the study period has not covered the post-COVID scenario, and therefore, we assumed these characteristics not to have a major impact in the study outcomes. With this assumption stated, we begin the discussion of the study outcomes.

3.1. Convergence of AQI

First, stationarity of AQI is checked using Clemente-Montañés-Reyes (1998) unit root test with two structural breaks, and the results reported in Table-1 show that most of structural breaks are appearing in February 2020, followed by January 2020 and December 2019. The AQI is demonstrating stationarity at level, and thereby, demonstrating the convergence in emissions pattern. The evidence of convergence divulges that the shocks to AQI are transitory. We can see that the prominent structural breaks found from this test correspond to the time when the Chinese economy was suffering from COVID-19. In order to dig deeper into this issue, we have checked stationarity of AQI using Bai and Carrion-I-Silvestre (2009) unit root test with five structural breaks, and the results are reported in Table-1. While showing the evidence in support of convergence, the structural breaks came out to be different than the former one. Using this test, October 2019 was found to be the month with the maximum number of structural breaks, followed by February 2020, January 2020, and December 2019. This also gives an indication that we should not restrict the analysis to two structural breaks, and therefore, Bai and Carrion-I-Silvestre (2009) unit root test will be used for further analysis.

While two tests on same AQI endows with different set of structural breaks, it is possible that individual components of AQI across the 18 Chinese provinces might demonstrate different structural breaks. In order to look into the issue, individual components of AQI need analyzing. In this pursuit, individual components of AQI are checked for their convergence on the presence of maximum five structural breaks, and the results are reported in Table-2. All six components of AQI demonstrate the evidence of convergence, and thereby, divulging that the shocks to these components are transitory in nature. The wholesome distribution of the structural breaks is depicted in Figure-1. However, the structural breaks appearing for those indicators are different.

3.2. Analysis of AQI components

The overall structural breaks appearing for PM2.5 are majorly clustered around February 2020, December 2019, and January 2020 (see Figure-2). Out of 18 provinces, 11 provinces have demonstrated the presence of structural breaks in February 2020, 10 provinces have demonstrated the presence of structural breaks in December 2019, and 8 provinces have demonstrated the presence of structural breaks in January 2020. There are provinces, which have demonstrated single structural breaks. For example, Nanning is the only province to demonstrate two structural breaks in February 2020, whereas January 2020 is the only structural break for Beijing. On the other hand, structural breaks for PM10 are comparatively different from that of the case of PM2.5. The structural breaks are majorly visible on October 2019, November 2019, December 2019, and January 2020 (see Figure-3). Out of 18 provinces, 14 provinces have demonstrated the presence of structural breaks in October 2019, 11 provinces have demonstrated the presence of structural breaks in November 2019, 10 provinces have demonstrated the presence of structural breaks in December 2019, and 12 provinces have demonstrated the presence of structural breaks in January 2020. In case of Wuhan, the structural break has appeared in March 2020. As source of PM2.5 and PM10 are largely the same, therefore, it is expected that the structural breaks appearing for PM2.5 will be lagged by PM10, as the finer particulate matters stay longer in the atmosphere. The shrinkage in the manufacturing sector due to the trade war with the United States caused the initial structural breaks in PM10 appearing during October 2019, and this was the time, when PM10 encountered the first significant transitory shock during the study period. With the gradual rise in the manufacturing sector, the second transitory shock to PM10 was visualized in November 2019. However, the sudden outbreak of COVID-19 has brought a shock to the ongoing economic activities in China, and alongside manufacturing sector, transportation and allied sectors also encountered a slowdown. Therefore, PM10 arising out of these sectors encountered a third transitory shock, and the third structural break in December 2019 was experienced. This was the time, when the first significant structural break for PM2.5 appeared, as along with economic activities, other household activities consistently started declining. With the lockdown in Wuhan starting from January 23, 2020, the economic activities experienced a further decline, and the PM2.5 demonstrated the second structural break on January 2020. With the rise in lockdown period and further decline in economic and human activities in the preceding month, PM2.5 encountered the third structural break on February 2020.

The structural breaks appearing for SO_2 emissions are majorly clustered around January 2020, October 2019, November 2019, and February 2020 (see Figure-4). Out of 18 provinces, 10 provinces have demonstrated the presence of structural breaks in October 2019, 8 provinces have demonstrated the presence of structural breaks in January 2020, and 7 provinces have demonstrated the presence of structural breaks in November 2019. Just like in the case of PM2.5, it can be seen that there are provinces which have demonstrated single structural breaks. For example, the only structural break for Hefei appeared in September 2019, whereas it was October 2019 for Changsha. In case of Kunming, two structural breaks appeared in January 2020. Following trade war with the United States, sudden shrinkage in manufacturing sector caused the initial structural breaks in SO_2 appearing during October 2019, as it was a transitory shock to SO_2 emissions pattern. Subsequent to this event, the sudden outbreak of COVID-19 brought forth a slump in the economic activities in China, and this transitory impact resulted in the structural breaks in January 2020. On the other hand, structural breaks for NO_2 are nearly similar to that of the case of SO_2. The structural breaks appearing for NO_2 emissions are majorly clustered around January 2020, September 2019, and October 2019 (see Figure-5). Out of 18 provinces, 12 provinces have demonstrated the presence of structural breaks in January 2020, 11 provinces have demonstrated the presence of structural breaks in September and December 2019, and 10 provinces have demonstrated the presence of structural breaks in October 2019. Beijing is the only province, which has demonstrated single structural break in December 2019. At the onset of the US-China trade war, air traffic activities started declining from September 2019 and as a result, vehicular emissions experienced significant reduction/fall as well. This reduction in vehicular emissions increased with the slump in manufacturing activities in the preceding month, and due to this incident, SO_2 and NO_2 experienced the structural breaks in October 2019. With the detection of first COVID-19 case in December 2019, vehicular movement within and across provinces started reducing again, and thereby causing a transitory shock in NO_2 emissions in December 2019.

The structural breaks appearing for CO emissions are majorly clustered around January 2020, and November 2019 (see Figure-6). Out of 18 provinces, 17 provinces have demonstrated the presence of structural breaks in January 2020, and 12 provinces have demonstrated the presence of structural breaks in November 2019. No structural breaks were found beyond January 2020. Following the US-China trade war, a fall in the vehicular sales caused the reduction in CO in November 2019, and it appeared as a transitory shock for CO emissions. In January 2020, the outbreak of COVID-19 caused not only a slump in manufacturing and other economic activities, but also started reducing the community concentrations. These had the second transitory shock on CO emissions. However, the scenario for O_3 is quite different. The structural breaks appearing for O_3 emissions are majorly clustered around October 2019, November 2019, and September 2019 (see Figure-7). Out of 18 provinces, 14 provinces have demonstrated the presence of structural breaks in October 2019, 12 provinces have demonstrated the presence of structural breaks in November 2019, and 11 provinces have demonstrated the presence of structural breaks in September 2019. Data for O_3 emissions in Nanjing was not found, and hence no structural are reported for this province. Wuhan has reported only one structural break in November 2019. The results show that the outbreak of COVID-19 did not have a major transitory shock on the O_3 emissions, as the structural breaks are appearing during the period of US-China trade war. Because of the slowdown of manufacturing activities and vehicular transportation, it appears that O_3 emissions encountered transitory shocks.

3.3. Analysis of cities

The overall structural breaks appearing across the cities are clustered around January 2020, followed by October 2019, and November 2019 (see Figure-8). While Fuzhou, Hangzhou, Hefei, and Nanchang encountered the most number (= 18) of structural breaks, Nanjing encountered the least number (= 10) of structural breaks. We tried to find out any possibility of the appearance of structural breaks with the average AQI level of the cities, and we observed no significant pattern between these two aspects. For example, both Kunming and Shijiazhuang have encountered 17 structural breaks each, when Kunming has the lowest average AQI and Shijiazhuang has the highest AQI. Nanjing has encountered 10 structural breaks, when its average AQI is the closest to the average AQI of the entire sample. Therefore, we could not obtain any significant association between the structural breaks and average AQI level for the cities.

However, it is surprising to find out that most of the structural breaks appeared during the period, when temporary lockdown was declared in China. This was the time when the cities encountered a total of 71 structural breaks, with Nanchang and Shanghai leading with 7 structural breaks each on January 2020, followed by Hangzhou with 6 structural breaks. The standard deviation in the impacts on the cities came out to be 1.697, which shows that AQI of all the cities were not equally impacted by the outbreak of COVID-19. On the other hand, the impact of US-China trade war is visible in the structural breaks appearing in October and November 2019. During these two periods, AQI of the sample cities were affected with standard deviations of 0.858 and 1.056, respectively. A brief summary of the findings is provided in Table 3.

4. Discussion

The shocks to AQI of the sample Chinese provinces have been found to be transitory, but the extent and persistence of shocks were different in nature. As each of the manufacturing, transport, logistics, and tourism sector of China is highly dependent on fossil fuel consumption, the outbreak of COVID-19 appeared as a shock to energy consumption pattern in these sectors, and thus, the negative environmental externality exerted by these sectors also encountered a similar shock. Moreover, due to lockdown, several corporate offices were closed, and hence the vehicular congestion also came down. This also resulted in a sudden shock in the vehicular emission pattern. These shocks appeared as structural breaks in unit root tests applied on AQI of the sample Chinese cities. This shock was not persistent, as the number of structural breaks across the sample cities got reduced in the subsequent months, i.e., February and March 2020. On the other hand, US-China trade war also took a toll on the manufacturing sector of China, and therefore, the negative environmental externality exerted by this sector was also affected. Now, though this impact was transitory, the impact was visible for nearly two consecutive months, i.e., October and November 2019. Therefore, in terms of persistence, the impact of US-China trade war on AQI of sample Chinese cities has been greater compared to the impact of COVID-19 outbreak. Considering the case of US-China trade war, the studies by Fuchs et al. (2019) and He et al. (2020) have focused majorly on the negative impacts of agricultural and deforestation dimensions, while the results of the present study have revealed the impact on air quality indicators. However, the environmental impact of the US-Mexico cross-border trucking dispute was different compared to impact of US-China trade war. Following the study by Alexander and Soukup (2010), the impact of the US-Mexico trade war had a negative impact on the environmental quality, as the trucking companies did not adhere to the U.S. safety and environmental standards. Consequently, this trade war deteriorated the environmental quality in both Mexico and the US. A similar kind of environmental impact was also experienced in case of US-Canada trade war. Following the study of Devine (1987), it can be found that the deterioration of the environmental quality stemmed from the deforestation caused by the trade war. Compared to these two trade wars, the US-China trade war had a different impact on the environmental quality. The restoring of environmental equilibrium in this case of trade war falls in the similar lines with the theoretical analysis of Copeland (2000).

Saying this, it should be remembered that the number of shocks on AQI was higher in case of the COVID-19 outbreak, and in this view, the number of shocks can be considered as the size of the impact. From this perspective, the impact of COVID-19 outbreak on AQI of the sample Chinese cities was higher compared to the impact of US-China trade war. The study by Zhang et al. (2020) and Elobeid et al. (2021) have mentioned about the reduction in ambient emissions by these two activities, results of the present study complement the findings obtained by Zhang et al. (2020) by carrying out the comparative impact assessment of these two events.

Following COVID-19 outbreak, the air quality in the Chinese cities is showing a sign of convergence, and it signifies an improvement in air quality, as polluting industries were hard hit by the pandemic. The impact on the air quality in China started during the US-China trade war period, and the impact has been different in terms of size. Moreover, all components of AQI have been impacted differently by these two major incidents. O_3, PM_{10}, and NO_2 have been more impacted by US-China trade war, whereas $PM_{2.5}$ and CO have been more impacted by the outbreak of COVID-19. The impacts of both of the incidents on SO_2 have been nearly similar. From the results, it can be inferred that the sudden reduction in economic and human activities have made a transitory impact on $PM_{2.5}$ and CO, whereas the reduction in manufacturing activities have made a transitory impact on O_3, PM_{10}, SO_2, and NO_2. Therefore, the coarse particulates and pollutants with low half-life are impacted by the US-China trade war, whereas the finer particulates and pollutants with high half-life are impacted by the outbreak of COVID-19 (for discussion on half-life, see Struttmann et al. 1998, Wade III et al. 1975, Wilson and Suh, 1997). Therefore, in terms of improvement in air quality, it can be said that the outbreak of COVID-19 has been more effective than the US-China trade war, as the former has been able to converge the finer particulates and pollutants with high half-life, which are more harmful than the coarse particulates and pollutants with low half-life.

5. Conclusion

By far, we have analyzed the impacts of US-China trade war and outbreak of COVID-19 on AQI and its components for 18 Chinese provinces over September 2019 to March 2020. In this pursuit, we have analyzed the convergence of AQI and its components through the unit root test by Clemente-Montañés-Reyes (1998) with two structural breaks and by that of Bai and Carrion-I-Silvestre (2009) with five structural breaks. The results show that (1) AQI and its components across the 18 Chinese provinces demonstrate convergence, which illustrates the betterment of air quality during the study period, (2) the impact of US-China trade war is more persistent than the impact of the outbreak of COVID-19, whereas the size of the impact of the latter event is more compared to the former one, and (3) the impact of the outbreak of COVID-19 is more visible on the finer particulates and pollutants with high half-life and more severity in terms of health hazards. These findings fulfill the research objectives of the study.

Given these findings, certain policy implications for the Chinese policymakers emerge. Anthropogenic activities result in majorly two types of pollutants, namely with high and low risk of health hazards, and any major economic activity might impact both these pollutants differently. Slowing down of the economic and anthropogenic activities might reduce the intensity of these pollutants, but the intensity might differ based on the source of the slowdown, and there the role of policy intervention might come. Any activity resulting in a sudden and large slowdown might reduce the intensity of pollutants with more severe health hazards, while activities resulting in a persistent slowdown might reduce the intensity of pollutants with less severe health hazards. It is the role of the policymakers to assess the nature of impact over a period of time by analyzing the convergence structure of the impact. For activities with sudden large impact, the focus should be on reducing the impact of more severe pollutants, as the effort from the policymakers by setting the proper environmental regulations might have a multiplier effect by complementing impact of that particular activity. Occurrences of such incidents will also give an idea to the policymakers about the possible source of the pollutants by tracing the slowdown patterns of the economic and anthropogenic activities, and setting the environmental policy targets accordingly to reduce the further negative environmental externality exerted by those particular activities. The present study sheds light on this particular aspect of policymaking through the convergence analysis of the AQI components of China in the wake of the US-China trade war and the outbreak of COVID-19.

In theoretical terms, this study has shown the way to isolate and analyze the impacts of two mutually exclusive events, which might cause the differential betterment of environmental quality. Bringing two consecutive and different political and pandemic events within a same empirical framework have allowed us to isolate the impacts of these events, and thereby, to differentiate the impacts on different components of air quality. Findings of this study might not only be important from the perspective of policymaking, but also might be important from the theoretical aspects of epidemiology studies, which aim at analyzing the environmental impact of a pandemic outbreak.

Saying this, it is also needed to state the limitations of the study. The study has been conducted on the 18 Chinese cities for 6 months, and the unavailability of data has been a major challenge for the study. Moreover, bringing spatial dimension in the analysis could have brought forth additional insights in the study. While mentioning the limitations, it also needs remembering that this study can be considered as a baseline approach for analyzing the differential impacts of any two events on the air quality of any nation, and there lies the contribution of the study. Future studies on this direction can be carried out at the cross-country level for bringing out a comparative scenario about the differential impact of such events, along with carrying out the analysis by considering the spatial dimensions of the pollutants.

Conflict of Interest

None

Table 1: Structural Breaks for AQI in Chinese Provinces

Provinces	Clemente-Montañés-Reyes (1998) [maximum two breaks]						Bai and Carrion-I-Silvestre (2009) [maximum five breaks]				
	Break 1	T-Statistic	Break 2	T-Statistic	ρ – 1		Break 1	Break 2	Break 3	Break 4	Break 5
Beijing	8-Feb-20	3.415[a]	11-Feb-20	-3.581[a]	-7.533		17-Jan-20	14-Feb-20	NIL	NIL	NIL
Changsha	25-Nov-19	3.447[a]	6-Feb-20	-5.047[a]	-4.999		30-Oct-19	29-Jan-20	NIL	NIL	NIL
Chengdu	31-Oct-19	7.988[a]	29-Feb-20	-2.774[a]	-4.423		27-Oct-19	1-Dec-19	NIL	NIL	NIL
Fuzhou	23-Jan-20	-2.832[a]	30-Jan-20	1.922[c]	-3.690		16-Jan-20	NIL	NIL	NIL	NIL
Guangzhou	6-Dec-19	3.976[a]	7-Jan-20	-8.796[a]	-3.654		16-Sep-19	17-Dec-19	5-Jan-20	NIL	NIL
Hangzhou	24-Sep-19	4.151[a]	19-Jan-20	-4.526[a]	-5.377		6-Oct-19	NIL	NIL	NIL	NIL
Hefei	14-Oct-19	5.654[a]	3-Feb-20	-4.461[a]	-8.325		11-Oct-19	NIL	NIL	NIL	NIL
Jinan	7-Dec-19	7.558[a]	6-Feb-20	-7.136[a]	-8.472		23-Jan-20	NIL	NIL	NIL	NIL
Kunming	4-Dec-19	1.193[a]	10-Feb-20	4.908[a]	-7.331		16-Sep-19	1-Oct-19	1-Nov-19	27-Dec-19	14-Feb-20
Nanchang	6-Oct-19	5.544[a]	24-Jan-20	-6.019[a]	-7.331		3-Oct-19	27-Nov-19	2-Feb-20	NIL	NIL
Nanjing	26-Oct-19	6.224[a]	3-Feb-20	-4.659[a]	-8.922		25-Sep-19	23-Oct-19	NIL	NIL	NIL
Nanning	31-Jan-20	-2.317[b]	20-Feb-20	0.760	-4.191		27-Oct-19	3-Feb-20	18-Feb-20	NIL	NIL
Shanghai	2-Dec-19	4.547[a]	1-Feb-20	-4.224[a]	-9.531		27-Nov-19	NIL	NIL	NIL	NIL
Shenyang	20-Dec-19	10.019[a]	29-Jan-20	-6.690[a]	-3.492		22-Dec-19	1-Feb-20	NIL	NIL	NIL
Shijiazhuang	22-Dec-19	8.401[a]	11-Feb-20	-6.405[a]	-4.314		3-Oct-19	29-Nov-19	6-Jan-20	14-Feb-20	NIL
Wuhan	2-Dec-19	4.547[a]	1-Feb-20	-4.224[a]	-9.531		27-Nov-19	NIL	NIL	NIL	NIL
Xian	30-Oct-19	10.597[a]	11-Feb-20	-5.674[a]	-3.559		27-Oct-19	19-Dec-19	10-Feb-20	NIL	NIL
Zhengzhou	23-Oct-19	8.648[a]	6-Feb-20	-4.127[a]	-8.242		16-Dec-19	3-Feb-20	NIL	NIL	NIL
							Z	1.4407[c]		Z*	2.1479[b]
							P_m	0.0767		P_m*	-1.4847[b]
							P	36.6511[a]		P*	23.4021

Table 2: Structural Breaks for different pollutants in Chinese Provinces

Provinces	*Pollutant*	*Break 1*	*Break 2*	*Break 3*	*Break 4*	*Break 5*
Beijing	PM2.5	16-Jan-20				
	PM10	29-Nov-19	14-Dec-19	21-Feb-20		
	SO_2	28-Sep-19	18-Oct-19	13-Nov-19	28-Nov-19	
	NO_2	27-Dec-19				
	O_3	30-Sep-19	25-Oct-19	14-Nov-19	1-Mar-20	
	CO	6-Dec-19	14-Jan-20			
Changsha	PM2.5	27-Nov-19	4-Feb-20			
	PM10	16-Oct-19	12-Dec-19	29-Dec-19	18-Jan-20	
	SO_2	29-Oct-19				
	NO_2	24-Sep-19	7-Jan-20			
	O_3	30-Sep-19	30-Oct-19	14-Nov-19	3-Feb-20	
	CO	1-Dec-19	30-Jan-20			
Chengdu	PM2.5	1-Dec-19	27-Jan-20			
	PM10	24-Oct-19	29-Nov-19	14-Dec-19		
	SO_2	28-Sep-19	13-Dec-19	6-Jan-20	27-Jan-20	
	NO_2	19-Sep-19	30-Oct-19			
	O_3	24-Sep-19	9-Oct-19	17-Nov-19	8-Jan-20	
	CO	30-Nov-19	30-Jan-20			
Fuzhou	PM2.5	24-Jan-20				
	PM10	23-Oct-19	18-Dec-19	4-Jan-20	5-Feb-20	21-Feb-20
	SO_2	28-Nov-19	6-Jan-20			
	NO_2	27-Sep-19	2-Nov-19	7-Dec-19	6-Jan-20	
	O_3	16-Sep-19	1-Oct-19	31-Oct-19	25-Nov-19	
	CO	20-Dec-19	10-Jan-20			
Guangzhou	PM2.5	16-Sep-19	9-Dec-19	4-Jan-20		
	PM10	25-Oct-19	16-Nov-19	4-Dec-19	1-Jan-20	
	SO_2	2-Feb-20	20-Feb-20			
	NO_2	30-Oct-19	14-Nov-19	6-Jan-20		
	O_3	28-Sep-19	30-Oct-19	17-Jan-20		
	CO	8-Nov-19	10-Jan-20			
Hangzhou	PM2.5	5-Oct-19	14-Jan-20			
	PM10	16-Oct-19	2-Nov-19	24-Nov-19	1-Jan-20	
	SO_2	14-Oct-19	22-Nov-19	13-Dec-19	2-Jan-20	
	NO_2	29-Oct-19	13-Nov-19	26-Jan-20		
	O_3	23-Sep-19	18-Nov-19	8-Jan-20		
	CO	25-Oct-19	27-Jan-20			
Hefei	PM2.5	26-Sep-19	19-Nov-19	4-Feb-20		
	PM10	19-Oct-19	23-Nov-19	18-Dec-19	20-Jan-20	
	SO_2	21-Sep-19				
	NO_2	22-Sep-19	19-Oct-19	16-Dec-19	6-Jan-20	
	O_3	23-Sep-19	28-Oct-19	31-Dec-19	1-Mar-20	
	CO	30-Nov-19	6-Jan-20			
Jinan	PM2.5	7-Dec-19	1-Feb-20			
	PM10	27-Sep-19	27-Oct-19	17-Nov-19	15-Dec-19	11-Jan-20
	SO_2	28-Oct-19	10-Dec-19			
	NO_2	26-Sep-19	13-Oct-19	30-Oct-19		
	O_3	3-Oct-19	7-Nov-19	18-Jan-20		
	CO	28-Nov-19	6-Jan-20			
Kunming	PM2.5	27-Oct-19	13-Feb-20			
	PM10	24-Sep-19	26-Oct-19	10-Nov-19	1-Feb-20	

	SO_2	6-Jan-20	27-Jan-20			
	NO_2	29-Sep-19	28-Nov-19	14-Dec-19	6-Jan-20	
	O_3	19-Sep-19	21-Oct-19	17-Feb-20		
	CO	13-Nov-19	23-Jan-20			
Nanchang	PM2.5	3-Oct-19	27-Nov-19	4-Feb-20		
	PM10	26-Nov-19	11-Dec-19	5-Jan-20	28-Jan-20	
	SO_2	2-Dec-19	2-Jan-20	27-Jan-20		
	NO_2	27-Sep-19	26-Oct-19	6-Jan-20		
	O_3	2-Oct-19	18-Nov-19	9-Jan-20		
	CO	28-Nov-19	10-Jan-20			
Nanjing	PM2.5	29-Sep-19	18-Dec-19			
	PM10	15-Oct-19	30-Oct-19			
	SO_2	27-Nov-19	19-Dec-19	4-Jan-20		
	NO_2	10-Dec-19				
	O_3					
	CO	13-Nov-19	20-Jan-20			
Nanning	PM2.5	2-Feb-20	17-Feb-20			
	PM10	15-Oct-19	2-Nov-19	20-Nov-19	11-Dec-19	
	SO_2	31-Oct-19	27-Nov-19			
	NO_2	22-Sep-19	23-Nov-19	8-Dec-19	6-Feb-20	
	O_3	2-Oct-19	27-Oct-19	12-Jan-20		
	CO	5-Dec-19	19-Jan-20			
Shanghai	PM2.5	1-Dec-19	4-Feb-20			
	PM10	27-Sep-19	11-Jan-20	27-Jan-20		
	SO_2	26-Oct-19	1-Jan-20	27-Jan-20	1-Mar-20	
	NO_2	14-Oct-19	6-Nov-19	14-Dec-19	19-Jan-20	
	O_3	18-Nov-19	8-Jan-20			
	CO	23-Nov-19	15-Jan-20			
Shenyang	PM2.5	23-Dec-19	2-Feb-20			
	PM10	25-Oct-19	20-Nov-19	28-Dec-19	20-Jan-20	
	SO_2	27-Sep-19	24-Jan-20			
	NO_2	31-Oct-19	17-Dec-19	6-Jan-20		
	O_3	30-Oct-19	16-Nov-19	26-Feb-20		
	CO	26-Nov-19	17-Jan-20			
Shijiazhuang	PM2.5	9-Oct-19	23-Dec-19	8-Jan-20		
	PM10	25-Oct-19	21-Nov-19			
	SO_2	27-Sep-19	24-Oct-19	26-Nov-19	24-Feb-20	
	NO_2	22-Sep-19	23-Nov-19	8-Dec-19		
	O_3	27-Sep-19	12-Nov-19	25-Dec-19		
	CO	22-Nov-19	18-Jan-20			
Wuhan	PM2.5	1-Dec-19	4-Feb-20			
	PM10	23-Oct-19	21-Jan-20	1-Mar-20		
	SO_2	30-Sep-19	23-Oct-19	14-Dec-19	6-Feb-20	22-Feb-20
	NO_2	30-Sep-19	31-Oct-19	31-Dec-19	25-Jan-20	
	O_3	6-Nov-19				
	CO	24-Nov-19	29-Dec-19			
Xian	PM2.5	9-Oct-19	20-Dec-19	26-Jan-20		
	PM10	4-Jan-20	20-Jan-20	26-Feb-20		
	SO_2	2-Oct-19	31-Oct-19	2-Feb-20		
	NO_2	14-Oct-19	6-Jan-20	8-Feb-20		
	O_3	26-Sep-19	6-Nov-19	1-Mar-20		
	CO	21-Nov-19	31-Jan-20			
Zhengzhou	PM2.5	16-Dec-19	6-Jan-20	4-Feb-20		

	PM10	26-Oct-19	20-Jan-20			
	SO_2	21-Oct-19	20-Nov-19	7-Feb-20	22-Feb-20	
	NO_2	19-Sep-19	5-Jan-20			
	O_3	25-Sep-19	29-Oct-19	1-Mar-20		
	CO	23-Dec-19	14-Jan-20			

Table 3: Summary of findings

Sl No.	*Findings*
1	AQI and its components across the 18 Chinese provinces demonstrate convergence
2	The impact of US-China trade war on AQI is more persistent than the impact of COVID-19 outbreak
3	The impact of COVID-19 outbreak on AQI is larger in size than the impact of US-China trade war
4	O_3, PM_{10}, and NO_2 emissions are impacted by the US-China trade war
5	$PM_{2.5}$ and CO emissions are impacted by the outbreak of COVID-19
6	Both the events have nearly similar impacts on SO_2 emissions

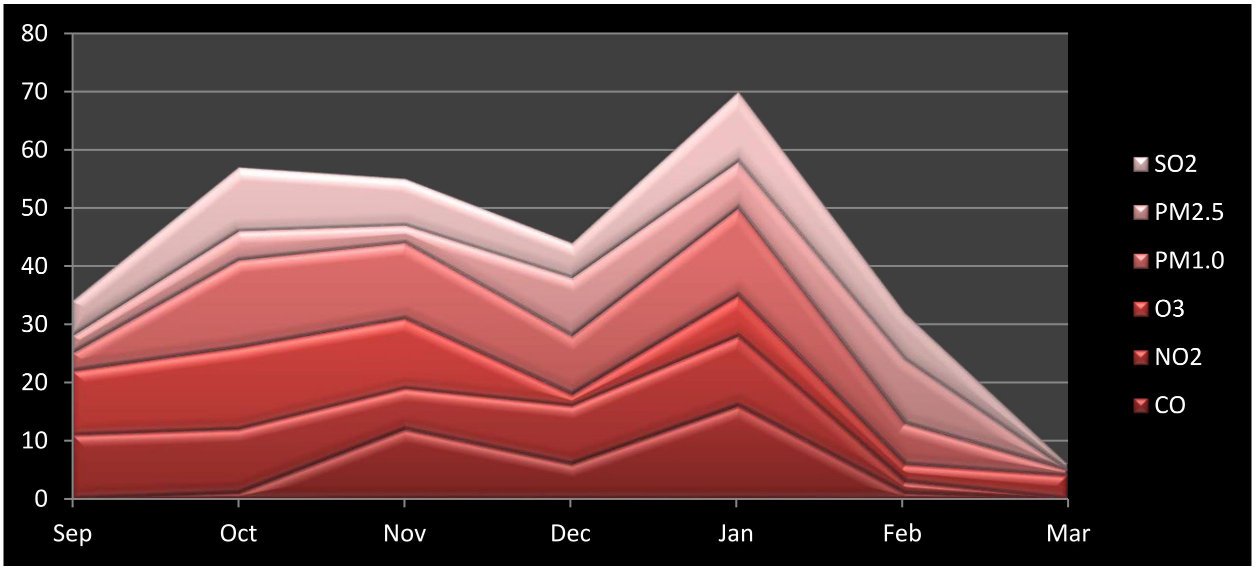


Figure 1: Distribution of Structural Breaks for different pollutants

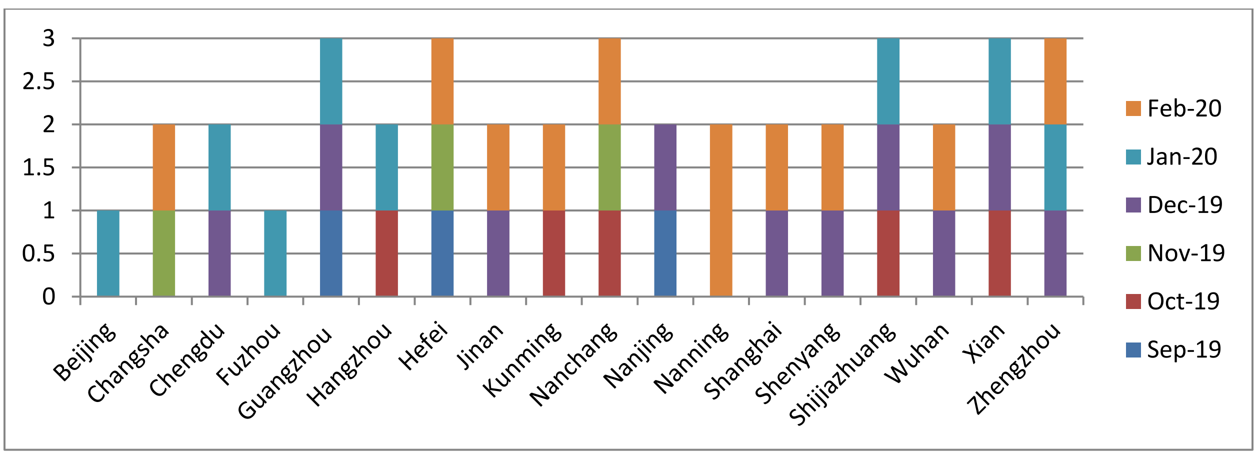


Figure 2: Distribution of Structural Breaks for PM2.5

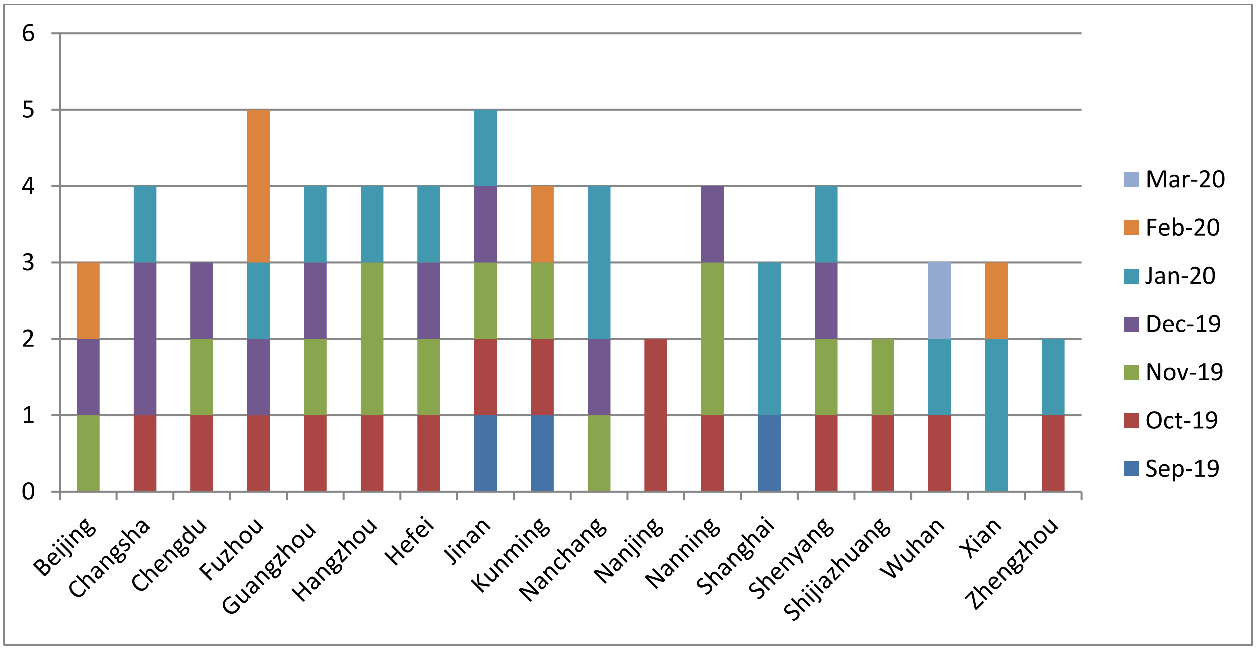


Figure 3: Distribution of Structural Breaks for PM10

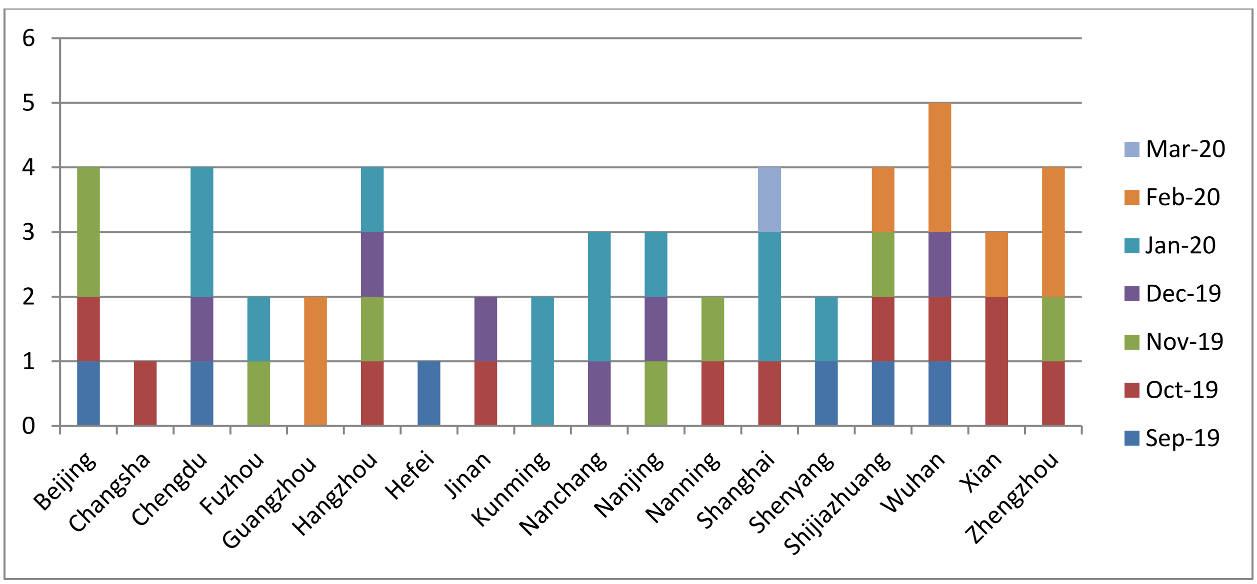


Figure 4: Distribution of Structural Breaks for SO_2

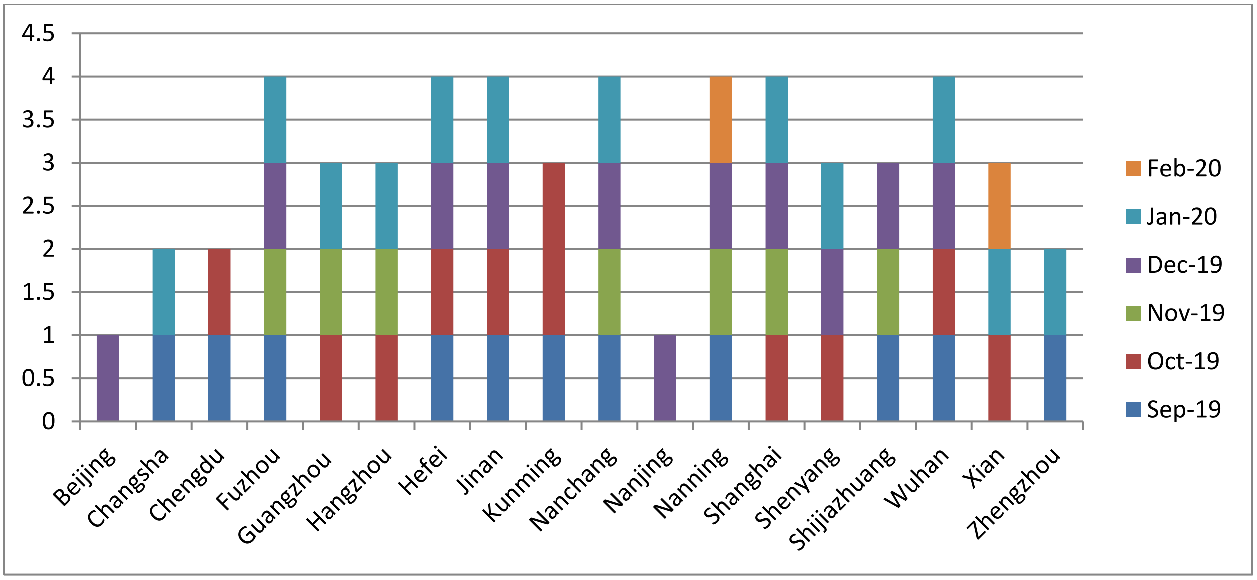


Figure 5: Distribution of Structural Breaks for NO_2

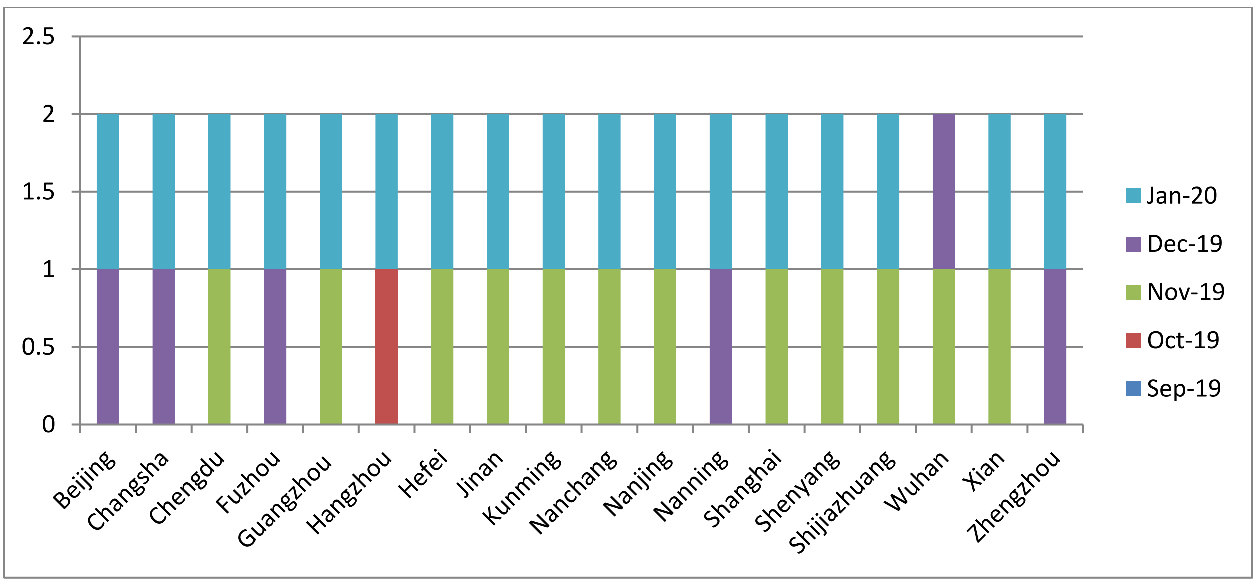


Figure 6: Distribution of Structural Breaks for CO

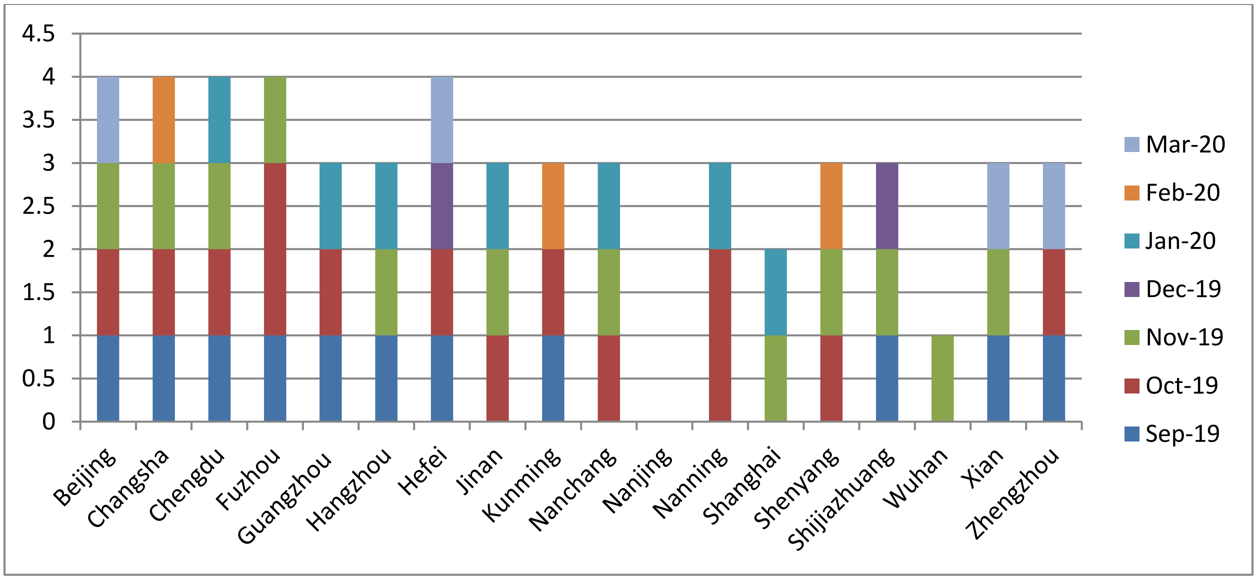


Figure 7: Distribution of Structural Breaks for O_3

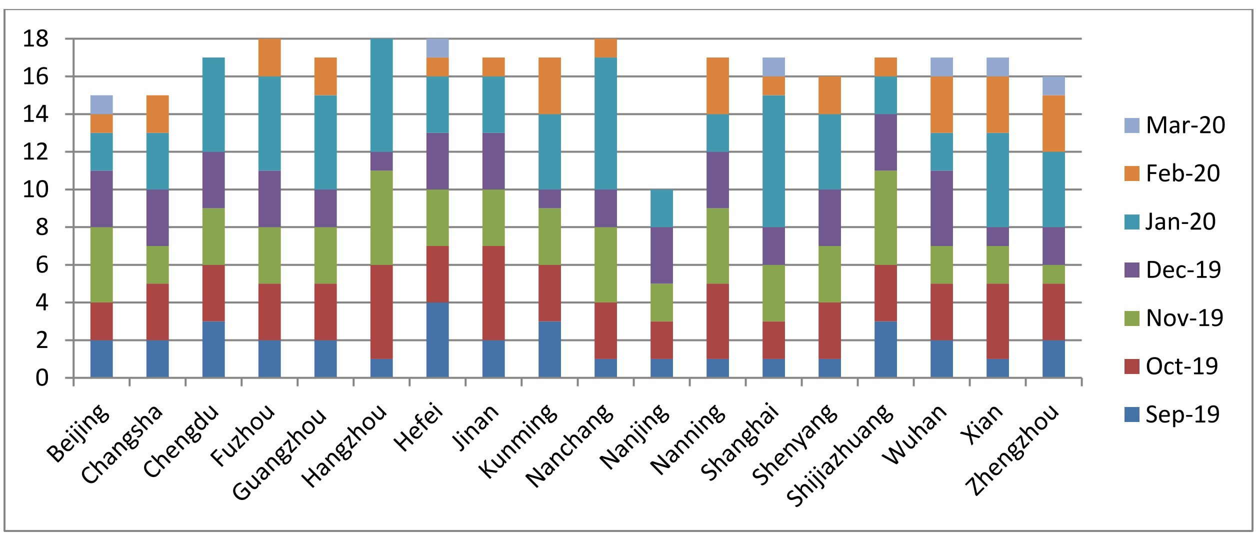
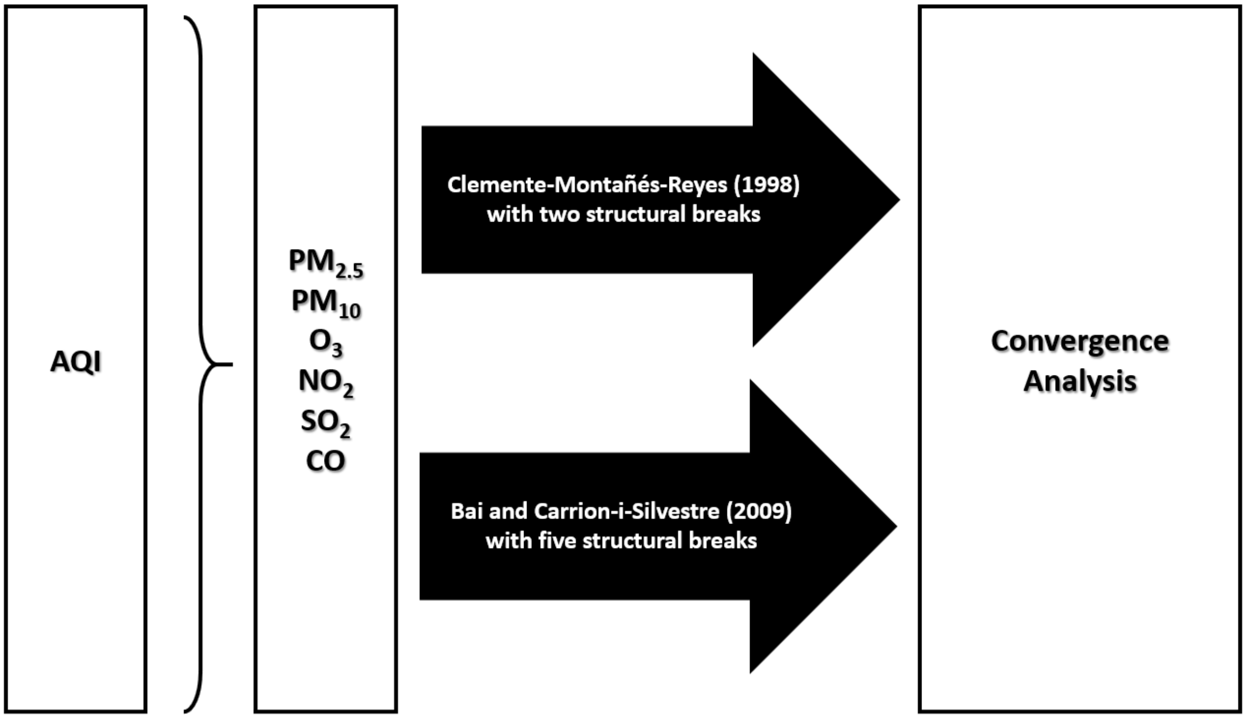


Figure 8: Distribution of Structural Breaks for the Cities



Appendix 1: Illustrative Scheme of Methods used

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