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THE EFFECTS OF ADOPTING THE ANTI-SMOG RESOLUTION ON AIR QUALITY – THE CASE STUDY FROM KRAKOW

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ABSTRACT: We evaluate the impact of Krakow's Anti-Smog Resolution, which was passed on January 15, 2016, and prohibits the use of coal and wood within the city. We use random forest, interrupted time series, and Bayesian structural time series models to assess air quality gains in terms of PM10, PM2.5, and benzo(a)pyrene concentrations, predicting pollution levels if the legislation had not been implemented. The results show significant reductions in pollutant concentrations: PM10 fell by 23% to 39%, PM2.5 by 23% to 36% and benzo(a)pyrene in PM10 by 39% to 41%, with the highest declines occurring during the heating season. These findings indicate the efficacy of Krakow's legislative strategy, offering evidence-based benchmarks for policymakers and public health officials in other cities considering similar residential heating restrictions to achieve measurable air quality improvements.

KEYWORDS: anti-smog resolution, pollution, Krakow, random forest, interrupted time series, Bayesian STM

Introduction

Air pollution poses a significant health challenge for societies worldwide. Multiple studies have conclusively demonstrated that smog, a mixture of air pollutants mostly caused by human activity, represents a significant risk to human health and can even be life-threatening. According to Powdthavee and Oswald (2020), it has been found that air pollution plays a role in the development of respiratory illnesses, heart disease, cancer, and even memory issues. Research also suggests that apart from negative health consequences, air pollution adversely affects the overall well-being and life satisfaction of individuals who are exposed to it (Bernstein et al., 2004; Menz, 2011; Sanduijav et al., 2021). The majority of the pollutants that contribute to air pollution come from private households. Based on the estimation provided by Luo et al. (2022), it is estimated that their activities are accountable for around 3 million deaths on an annual basis. Data presented by the World Health Organisation shows that virtually the entire world population (99%) suffers from harmful substances exceeding standards set as permissible (World Health Organisation, 2024).

There are a number of organisations that conduct research on the extent of air pollution around the world. A report published by IQAir (IQAir, 2024), indicates that Asian countries experienced the most severe pollution levels in 2022. At that time, only 13 of the 131 countries and territories surveyed globally were able to provide their citizens with satisfactory air quality. The European Environment Agency is an additional organisation that conducts research on air quality (European Environment Agency, 2024). It provides a tool for determining the intensity of air pollution in 375 European cities during 2021-2022. According to the classification, Poland is the top producer of benzo(a)pyrene, a component of PM10 dust, in the European Union, which shows that twelve of the twenty most polluted cities during this period are located there (GIOS, 2022). In particular, poor air quality is estimated to have contributed to 6,700 premature fatalities in the country between 2015 and 2020 (Cakaj et al., 2023).

In recent years, various cities and provinces have introduced anti-smog resolutions. One of them concerns Krakow, the second largest city in Poland, both in terms of population and area, and the seventh city in the ranking of the 20 most polluted European cities. The city's presence on the UNESCO World Heritage List attracts tourists worldwide, eager to admire its beauty and historical wealth. The resolution passed on January 15, 2016, introduced a complete ban on coal and wood burning throughout the city from September 1, 2019. As a consequence of the resolution enactment and numerous assistance programs and subsidies for replacing heat sources in the city, almost all solid fuel furnaces have been eliminated (Rzeczpospolita, 2024). How has the implementation of the restrictive anti-smog resolution influenced air quality levels? We seek an answer to this question, providing a novel case study from Krakow. This research investigates the impact of a restrictive anti-smog resolution on air quality improvements in Krakow. We employed three models in our empirical analysis: the Random Forest algorithm, the Interrupted Time Series method, and the Bayesian Structural Time Series method. These techniques were chosen for their robustness in forecasting and interpreting complex environmental data, allowing for a comprehensive assessment of the resolution's effectiveness.

We predicted the levels of three air quality indicators, namely PM10, PM2.5, and benzo(a)pyrene concentration (referred to as BaP). We then compared our predictions with the actual values of these indicators. In our scenario, the forecasts depicted the potential outcomes without any legal modifications regarding the utilisation of solid fuel. Whatever the research methodology employed, our findings indicate that the levels of air quality indicators in Krakow would have been significantly elevated if the legislation implementing a prohibition on the utilisation of solid fuels had not been implemented in January 2016. The disparities are more pronounced during the winter season when temperatures are at their lowest. Among the three approaches used, the random forest demonstrates superior performance by yielding the lowest forecasting errors.

Our research makes three distinct contributions to the ongoing debate on air quality. First, in contrast to findings presented in Chen et al. (2013) and Zhang et al. (2016), which discuss temporary activities related to the Beijing Olympics, or the results on transportation limitations in Mexico City (Gallego et al., 2013; Liu & Kong, 2021), our study demonstrates that the restrictive anti-smog resolutions, implemented to lowering air pollution in the long term, were successful. This is evident in the steady decline in PM10, PM2.5, and BaP concentrations over time. Second, the scholarly literature on

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the effects of implementing various air quality limitations uses a diverse range of methodologies: regression (Davis, 2008, 2017; Gallego et al., 2013), difference-in-differences (Carrillo et al., 2016; Luo et al., 2022; Viard & Fu, 2015), and synthetic control methods (henceforth RF) (Huang et al., 2022; Zeng et al., 2021; Zhang et al., 2016). As far as we know, we are among the first to incorporate the interrupted time series (ITS) and Bayesian structural time series (BSTS) into this framework, alongside the RF. So far, both have been used primarily in medical research (see Chan et al. (2023); Hudson et al. (2019); Leung et al. (2024); Owen et al. (2024); Schaffer et al. (2021); Trinh et al. (2022) for the interrupted time series method or Chami et al. (2021); de Vocht (2016) for Bayesian structural time series). Recently, the BTS has frequently been utilized to examine the effects of lockdown measures on the progression of the COVID-19 pandemic, primarily as a result of the ongoing global health crisis (Barría-Sandoval et al., 2022; Feroze, 2020), the economy (Takyi & Bentum-Ennin, 2021), and the changes in the non-motorized modes of transport (Zhang & Fricker, 2021). Third, our investigation is focused on the geographical area that has received the least attention from researchers. The previously discussed studies primarily focus on cities located in Asia, South America, or North America. There is a knowledge gap in the available literature about European countries, and there is a major concern regarding the urgent need to mitigate air pollution. The purpose of our analysis is to fill this information gap. Within this framework, we are the first to examine the consequences of limitations on air quality in one of Poland's most renowned cities. This city not only ranks high in terms of tourist appeal but also in terms of air pollution levels.

The remainder of the paper is organised as follows. Section 2 summarises the literature review. Section 3 describes the methodology and data used in the study. Section 4 illustrates and discusses the empirical research. Section 5 presents concluding remarks.

An overview of the literature

In response to the increasing problems posed by smog, governments around the world have implemented a variety of air quality improvement strategies. Empirical studies seek to forecast the changes in CO2 pollution (Pérez-Suárez & López-Menéndez, 2015) and verify the efficacy of undertaken interventions. The aforementioned set of measures may encompass, among other things, the implementation of policies that limit the utilisation of cars. The findings of the research on this topic need to be more conclusive. Davis (2008, 2017) examined the impact of introducing this type of legislation for Mexico City residents on air quality. No evidence indicating improvements in terms of pollution was obtained. Gallego et al. (2013) proved that transportation restrictions cause only a short-term effect that disappears in less than a year. Liu & Kong (2021) also came to similar conclusions based on their study. In the mentioned case, the objects of the study were seven Chinese cities. However, there are also studies that support the validity of policies that restrict transportation. Carrillo et al. (2016) proved that reducing transportation in Quito resulted in a 9 to 11% decrease in carbon dioxide concentrations. Viard & Fu (2015), in turn, found that the decrease in pollution caused by limiting vehicle traffic in Beijing was as much as 21%. The ambiguity of the effect of traffic reduction on air quality is also pointed out by Wang et al. (2023), reviewing 24 studies related to the issue at hand.

The literature also contains empirical studies concerning the impact of the organisation of major international events on air quality. The organisation of such events is associated with numerous actions undertaken by state authorities to improve air quality by the time of the event. These involve relocating or closing production facilities, replacing furnaces or controlling traffic. Such empirical studies include the 2008 Summer Olympics in Beijing (Chen et al., 2013; Zhang et al., 2016). Their results show that the authorities' actions had the intended effect of improving air quality, but this effect was short-lived, disappearing after a maximum of two years after the event. Restrictive policies aimed at improving air quality were also associated with the G20 summit in Hangzhou. The results on the impact of this policy on air quality testify to its success. Air quality in those cities improved in the short and long term (Huang et al., 2022; Wu et al., 2019; Zeng et al., 2020, 2021).

Due to the COVID-19 pandemic and the numerous restrictions implemented around the world, air quality also changed. Based on the results of empirical studies, global pollution levels improved significantly during the lockdown. Saha et al. (2022), through an extensive review of related litera-

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ture, show that levels of major air pollution indicators such as NO2, SO2, CO, PM2.5, and PM10 declined sharply during the COVID-19 pandemic.

Empirical studies on air quality also apply to Krakow. Zaręba and Danek (2022) analysed the migration of pollutants in the city during the lockdown associated with the COVID-19 pandemic. Based on the results obtained in the study, it can be concluded that neighbouring cities, from which hazardous substances are carried by the wind, are also largely responsible for air pollution in the city. In another analysis, Flaga-Maryańczyk and Baran-Gurgul (2022) studied the impact of the anti-smog resolution on air quality in Krakow. The decrease in pollution over the study period was estimated using nonparametric linear regression. The results showed that the rate of decrease in PM10 and benzo(a)pyrene in PM10 is significantly higher in Krakow than in other cities in Lesser Poland Voivodeship. A similar analysis was made by Kleczkowski and Kotarba (2020). Using linear regression and average values of PM10, PM2.5, benzo(a)pyrene and nitrogen dioxide concentrations, they calculated the percentage decrease in pollutant concentrations in Krakow and the area of Lesser Poland Voivodeship (excluding Krakow). The results showed that the rate of air quality improvement in Krakow is higher than in neighbouring cities in the province. Adamkiewicz et al. (2021) compared air quality in Krakow with other cities in Poland. He used random forest to normalise PM10 concentrations with meteorological factors, namely, to divide the measurement results into weather-dependent and weather-independent. The results showed that the biggest improvement in air quality due solely to human activity was in Krakow. Six cities in Poland, including Krakow, were also analysed by Filonchyk et al. (2021). These authors examined what effect the lockdown resulting from the COVID-19 pandemic had on air quality. Comparing the concentration levels of PM2.5, PM10, NO2 and SO2 before and during the lockdown, they found that air quality improved significantly during this period.

Our study seeks to innovate beyond the traditional models employed by Carnevale et al. (2018) and discussed in Petropoulos et al. (2022). While they utilise a range of data-driven models, including linear, nonlinear, and time-variant methods to predict air quality across more than 100 monitoring stations in Northern Italy, our approach integrates a variety of models such as random forest, interrupted time series, and Bayesian structural time series models. This diversification in methodologies allows us to propose novel empirical evidence with advanced methodologies.

Research methods

The starting point for the empirical study was the collection of air quality data in Krakow from the period before and after the enactment of the anti-smog legislation. Daily data were used for PM10 and benzo(a)pyrene (BaP) concentrations; however, for BaP measurements at one monitoring station, data were collected every other day over a two-year period. In the case of PM2.5 particulate matter, hourly data were available from a larger number of stations than daily data, so it was necessary to aggregate the hourly measurements to daily levels before calculating the monthly averages. Their selection was dictated by the fact that the main source of their emissions in Poland is the municipal and household sectors (GIOS, 2022). Based on the collected daily data from the period 2010-2022, we calculated the averages for each month. The final year was 2022, as at the time of the study, this was the last available period.

For each indicator, average values were calculated from all measurement stations available in Krakow during the period. Details regarding these stations are provided in Table 1.

Table 1. Measurement stations used in the study.

Address	Station type	Station classification	Operating time range
Kraków, Krasiński Avenue	traffic	stationary container	01.01.2011-31.12.2012
Kraków, Prądnicka Street	background	stationary container	01.01.2010-28.02.2010
Kraków, Bujaka Street	background	stationary container	01.01.2010-31.12.2022
Kraków, Bulwarowa Street	industrial	stationary container	01.01.2010-31.12.2022

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Address	Station type	Station classification	Operating time range
Kraków, Piastów Street	background	standalone dust sampler	01.01.2016-31.12.2022
Kraków, Telimeny Street	background	standalone dust sampler	01.01.2017-01.06.2018
Kraków, Lusińska Street	background	standalone dust sampler	01.01.2019-31.12.2022
Kraków, Wadów Estate	industrial	stationary container	01.01.2017-31.12.2022
Kraków, Złoty Róg Street	background	standalone dust sampler	01.01.2016-31.12.2022

Source: authors' work based on GIOS (2024).

The data was taken from the database of the Chief Inspectorate of Environmental Protection – Measurement Data Bank (GIOS, 2024). In accordance with the PN-EN 12341:2014 standard, suspended particulate matter (PM) concentrations were measured using the gravimetric method. The measurements were conducted following the Regulation of the Minister of the Environment dated September 13, 2012, on the assessment of substance levels in the air (Journal of Laws 2012, item 1032). These procedures ensured the collection of at least 90% valid data annually, with a measurement uncertainty not exceeding 25%. The results of the measurements collected this way are shown in Figure 1. Based on that, it can be concluded that air pollution is characterised by seasonality. The highest values for individual indicators can be observed in the winter months, i.e. during the intensive and widespread use of solid fuels for heating buildings, while the lowest values dominate in summer when heating is not needed. The date of enactment of the anti-smog resolution, 15th of January 2016, was taken as the moment of the intervention (and marked on the plot by the vertical dashed line). This is because solid fuel boilers were removed from the outset, even though replacement of heating furnaces was required over the next three years. According to the data, more than 14,000 coal and wood boilers were replaced between 2016 and 2018 (Rzeczpospolita, 2024).

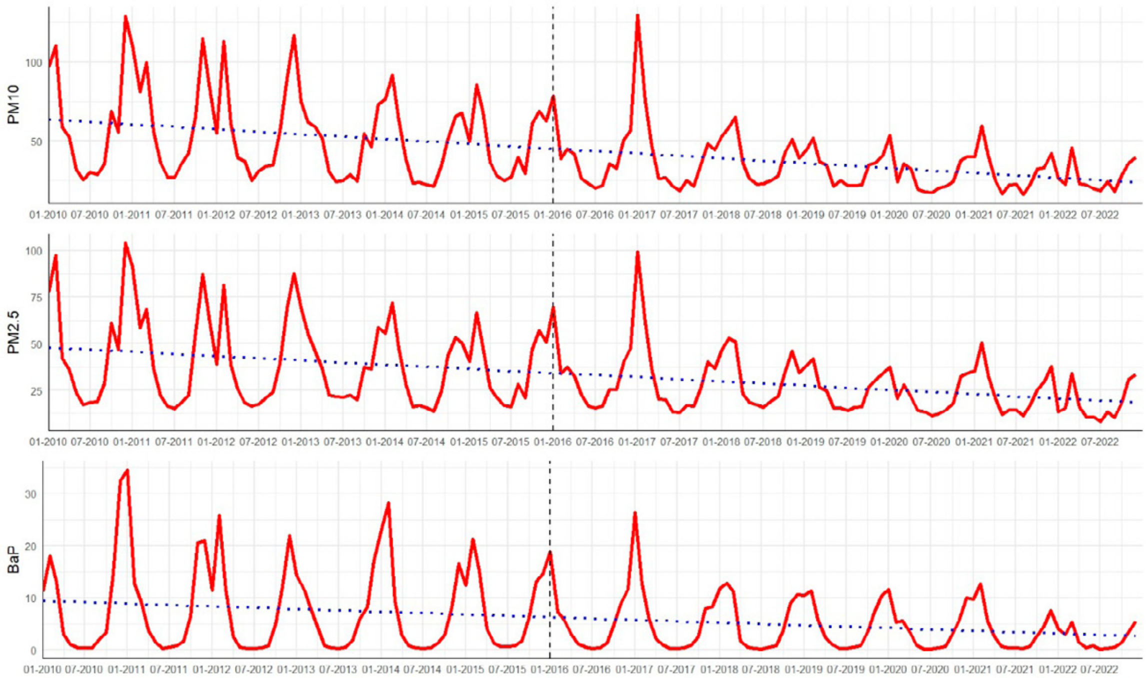

Figure 1. The average monthly concentration of PM10, PM 2.5 and BaP in Krakow within the period 01.2010-12.2022

Source: authors' work based on GIOS (2024) and IMGW (2024).

The second characteristic visible in Figure 1 is a downward trend observed in concentration levels of all pollution indicators, both before and after the adoption of the anti-smog resolution. This

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applies primarily to the winter months. The highest rate of decrease over the period under review is characterised by the concentration of PM10, while the lowest rate of decrease is found for benzo(a) pyrene in PM10.

The literature often indicates that the concentration of air pollutants and thus air quality is highly dependent on weather conditions (Anh et al., 1997). Therefore, in addition, we used meteorological data on a monthly average as predictor variables in the analysis. These are data on temperature (in ° C) wind speed (in m/s), air pressure (in hPa), and relative humidity (in %) taken from the database of the Institute of Meteorology and Water Management (IMGW, 2024) for the Krakow-Balice station.

To investigate the relationship between the studied time series of PM10, PM2.5 and benzo(a) pyrene concentrations and meteorological data, correlations between these variables were calculated (see Figure 2).

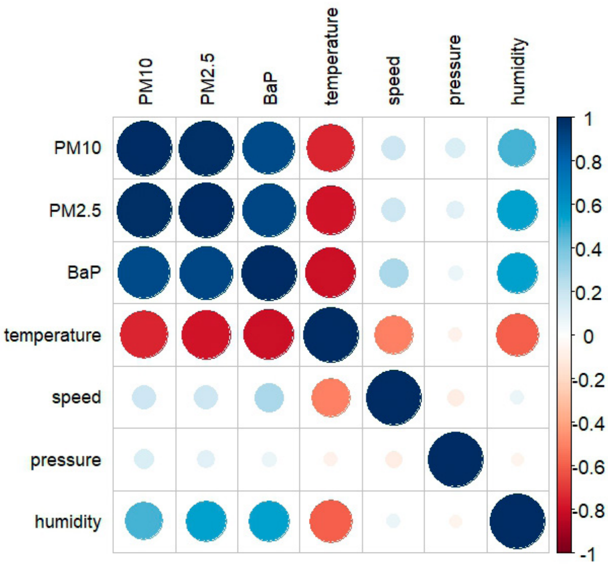

Figure 2. Correlation coefficients between the variables used in the study
Source: authors' work based on GIOS (2024) and IMGW (2024).

We find a strong positive correlation between the indicators corresponding to air pollution used in the study. The concentrations are also strongly correlated with air temperature. The relationship with average humidity, wind speed and atmospheric pressure is weaker. Temperature and humidity have a significant impact on air quality. Temperature influences chemical reactions and the dispersion of pollutants, while humidity affects the deposition of particulate matter and the formation of aerosols. Accounting for these factors in the study allows for better control of their effects and more accurate assessment of the outcomes of anti-smog measures. Seasonal variations in temperature and humidity may obscure the true changes in pollution levels. Table 2 shows the most important descriptive statistics on the variables studied before and after the policy intervention was entered. Appendix H also presents box plots illustrating the distributions of the individual variables used in the study. Based on the results, it can be concluded that air quality, as measured by the concentrations of PM10, PM2.5 and benzo(a)pyrene, improved significantly during the period under study. Noteworthy is the fact that the average air temperature has also increased. Given the strong negative correlation between the variables in question, it can be assumed that the decrease in PM10, PM2.5 and BaP concentrations may be partly related to higher temperatures. The methods used in the study should answer the question of to which of the noted changes are due to human activity – the enactment of anti-smog legislation in Krakow.

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Table 2. Descriptive statistics of the variables used in the study

Variable	Unit	Before 15th of Jan 2016			After 15th of Jan 2016			Growth rate
		Mean	Min	Max	Mean	Min	Max	
PM10	μg/m^3	54.33	21.33	128.48	34.41	16.14	129.26	-36.66%
PM2.5	μg/m^3	40.61	13.80	104.05	26.56	8.06	99.22	-34.59%
BaP	μg/m^3	7.84	0.22	34.50	4.40	0.19	26.30	-43.92%
Temperature	°C	8.88	-7.00	21.50	9.64	-5.70	22.30	8.61%
Wind speed	m/s	3.12	2.20	4.60	3.12	2.10	4.80	0.01%
Air pressure	hPa	987.60	978.20	998.90	988.90	979.20	997.90	0.05%
Humidity	%	79.74	63.60	91.20	77.62	51.70	92.30	-2.66%

Source: authors' work based on GIOS (2024) and IMGW (2024).

The first method used in the study was random forest (hereafter denoted as RF) (Breiman, 2001; Calderoni et al., 2015; Tong et al., 2003). It is a combination of decision trees, an ensemble method of machine learning. At each successive iteration in the process of building this model, a bootstrap sample is taken at random. This is done by drawing n times with the return of objects from a training sample of N observations. For each sample drawn in this way, a decision tree is built. At each of its nodes, m (out of M available in the study) of the drawn non-returned predictor variables are taken into account. Each tree constructed in this way is used to predict the level of the dependent variable. The final prediction is the arithmetic mean of the results obtained in this way for all the trees that make up the random forest. This procedure guarantees more stable and accurate results than those obtained from a single decision tree.

We have trained the random forest models to determine average monthly concentrations of PM10, PM2.5 and BaP. The meteorological data, namely temperature, speed, pressure and humidity, and the month number were used as predictor variables. Each random forest was constructed based on 1,000 trees. For the construction of each tree, two predictor variables were randomly selected (rounded down to the root of the number of variables). The training sample consisted of observations from January 2010 to December 2015. The resulting random forest was then used to predict the level of the studied concentrations in the period after the anti-smog legislation was passed in Krakow. The results obtained in this way correspond to the air quality that would have occurred in Krakow if the legislative changes had not taken place. The calculations were performed using the R rmweather package (Grange et al., 2018). This methodology has so far mainly been used to assess the impact of the COVID-19 pandemic restrictions on air quality (Cao et al., 2022; Fenech et al., 2021; Grange et al., 2021).

The second method used in the study is the interrupted time series (ITS) method. It belongs to the group of quasi-experimental methods. It is used to study the effect of an intervention introduced at one point in time. The time series studied must include observations before and after the intervention. A segmented regression model is estimated based on the data collected in this way. In a standard analysis, it can be represented as:

$$Y_t = \beta_0 + \beta_1 T + \beta_2 X_t + \beta_3 T X_t \tag{1}$$

where T describes the time elapsed since the beginning of the period under review, X_t is a binary variable indicating the period before the intervention (with value 0) or after that (value of 1), β_0 represents the initial level of the examined phenomena, β_1 shows the slope, the change of the output resulted from the time elapsed (trend before the intervention), β_2 represents the change in the level of the phenomenon under study as a result of the intervention, while β_3 is responsible for the change in slope that occurs after the date of intervention (Bernal et al., 2017; Turner et al., 2021). In the present study, the dependent variables in the estimated models were PM10, PM2.5 and BaP concentration levels. Due to the non-stationarity and seasonality of the studied series, the analysis uses an integrated ARMA model (ARIMA) that allows for capturing seasonality in the case of integrated series.

Within this approach, we estimate two models. The first one is a model with the 7 binary variables assuming the value of 1. Then, a second model is estimated in which this variable is zero, meaning there is no intervention (in the case of this study, this means that the anti-smog resolution in Krakow did not come into force). The latter is used to predict the concentration levels of the tested air pollutants from January 2016, which would have occurred in Kraków without the introduction of the ban on burning solid fuels. The R Forecast package was used to estimate the relevant models (Hyndman & Khandakar, 2008).

The final method used in the study is Bayesian Structural Time Series (BSTS), which is increasingly seen as an alternative to ITS. The BSTS are the state-space models for time series data (Gianacas et al., 2023; Scott & Varian, 2014). The basic idea behind BSTS is that the modelled time series is treated as a combination of different components, each with its own parameters. The model can be represented as follows:

$$y_t = \mu_t + \tau_t + \beta_t x_t + \varepsilon_t \tag{2}$$

where y_t is the value of the time series under study at the time of t, μ_t is the trend component, τ_t is the seasonality component, and $\beta_t x_t$ is the regression component. The parameters of the model are estimated based on the available data. This is most commonly done using Monte Carlo Chain Monte Carlo (MCMC) sampling.

The method uses information on the time series of the outcome variable, the date of the intervention, the seasonal component, and one or more time series of the explanatory variables. These additional time series of predictor variables are essential to the analysis, should be aligned with the time series of the outcome being studied, and should not be affected by the intervention being analysed.

As with the interrupted time series method, BSTS provides a counterfactual outcome time series (i.e. if no intervention had taken place) and the effect of the intervention is estimated as the difference between the counterfactual and the observed outcome after the intervention. In the study described, the outcome variable was the concentration levels of PM10, PM2.5 and BaP, while the additional predictor variables were the time series of meteorological data described above. The components of the model included in the study were responsible for local linear trend, monthly seasonality, and regression for control variables. The regression component was modelled using a spike-and-slab prior, composed of a Bernoulli distribution and a Gaussian distribution. For the trend and seasonality components, we employed Inverse-Gamma priors. Model estimation was performed using 1000 samples of Markov Chain Monte Carlo (MCMC).

The results of a sensitivity analysis on the number of MCMC iterations are presented in Supplementary Appendix A. The analysis indicates that increasing the number of iterations does not substantially affect the estimated results. The R CausalImpact package was used to estimate suitable models (Brodersen et al., 2015). The CausalImpact function relies on the R package bsts, which performs Bayesian inference using Gibbs sampling. Due to the use of conjugate prior distributions (e.g., the Inverse-Gamma distribution for variances), the proposal distributions are not explicitly defined, as parameter values are sampled directly from their full conditional distributions. A single MCMC chain was used in the analysis. To assess the impact of the number of chains, the CausalImpact() function was manually executed multiple times using different set.seed() values. The results of this multi-chain analysis (chains 1 to 5) are presented in Supplementary Appendix B. The results show that the average effect estimates remain consistent across chains, and the confidence intervals are very similar, suggesting that a single chain provides reliable inference for the dataset and model in question. The burn-in period is automatically set to 10% of the total number of iterations. Additionally, trace plots for the MCMC samples were generated as part of the analysis and are included in the supplementary material (Appendix C, D and E). These plots demonstrate that the chain effectively explores the posterior distribution, further supporting the reliability of the results.

The three methods applied – Bayesian Structural Time Series (BSTS), Interrupted Time Series (ITS) with SARIMA models, and Random Forests – differ in terms of transparency, policy relevance, predictive accuracy, and data assumptions. BSTS (Bayesian Structural Time Series) offers high interpretability and is particularly useful in the context of public policy. It decomposes the effect into trend, seasonality, and the impact of explanatory variables, while also providing credible intervals. These features make it well-suited for causal inference. However, it requires correct model specification and may be sensitive to the choice of priors. Interrupted Time Series (ITS) with SARIMA models is a transparent method grounded in classical statistical principles. It produces results that are straightforward to interpret and communicate, especially for linear data. Nonetheless, it relies on assumptions such as stationarity and correct model fitting. Its effectiveness can decline in the presence of structural changes or nonlinear patterns. Random Forests excel at capturing complex nonlinear relationships and interactions, often achieving high predictive accuracy. However, they are less transparent, which complicates causal interpretation and communication with non-technical stakeholders. Moreover, they typically require larger datasets and greater computational resources. In summary, BSTS and SARIMA provide greater transparency and policy relevance, whereas Random Forests prioritise predictive performance at the expense of interpretability. There is, therefore, a trade-off between model complexity and clarity. Employing multiple methods helps to triangulate the findings and enhance the credibility of the results.

Results of the research

First, for the three previously mentioned air quality indicators – PM10, PM2.5 and BaP concentrations – a random forest was used in the study. The models obtained using this method were characterised by determination coefficients of 78.2%, 81.4% and 66.5%, respectively, and prediction errors (expressed by the RMSE error) of 5.21, 13.70 and 10.70, respectively. The values of the coefficients responsible for fitting are high, which indicates a good predictive ability of the built models. Figure 3 presents how the concentration of PM10, PM2.5 and BaP has historically developed and the forecast values obtained using estimated random forests. These forecasts describe what the situation would have looked like since January 2016 if anti-smog regulations had not been adopted in Kraków.

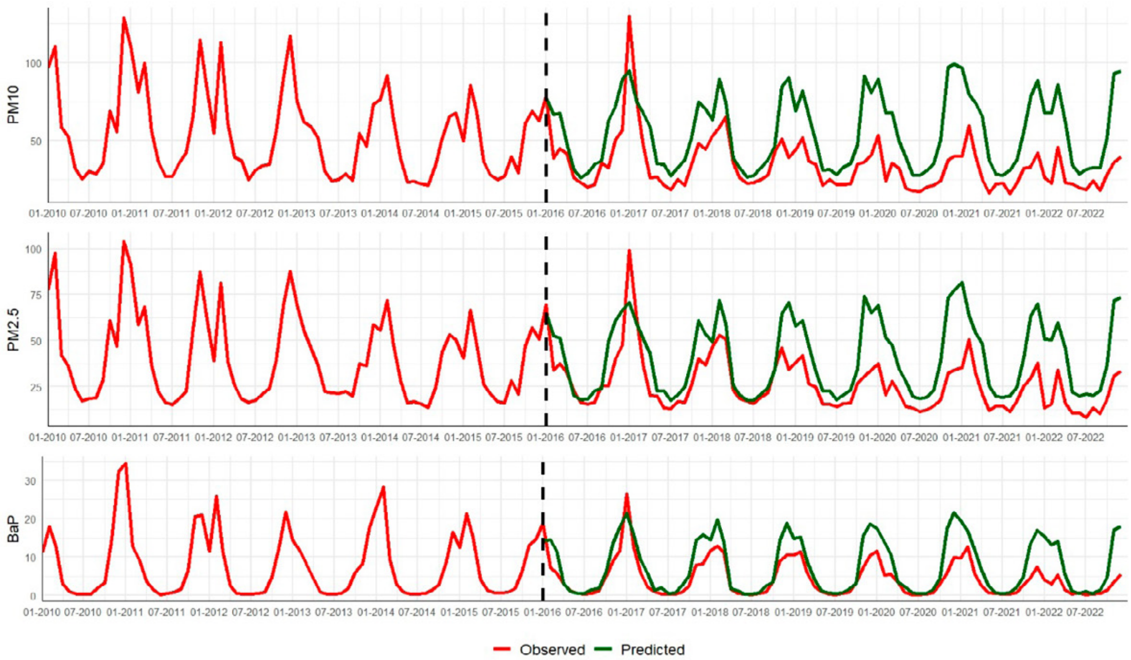

Figure 3. Average monthly concentration of PM10, PM 2.5 and BaP in Krakow and values forecast by random forest

Source: authors' work based on GIOS (2024) and IMGW (2024).

In the second step of the study, an analogous analysis was carried out using the interrupted time series method. Integrated autoregressive models with seasonality were selected based on the Akaike information criterion. Thus, the following models were estimated:

- for PM10 – SARIMA(2,0,0)(2,1,0) with RMSE = 7.41,
- for PM2.5 – PM10 SARIMA(2,0,0)(2,1,0) with RMSE = 5.28,
- for BaP PM10 – SARIMA(1,0,0)(2,1,2) with RMSE = 2.04.

The results of the relevant residual diagnostic tests for the ITS and ARIMA models are presented in Appendix F. Using these models, forecasts for air quality in Krakow were determined if the anti-smog resolution was not implemented. The corresponding results are shown in the Figure 4.

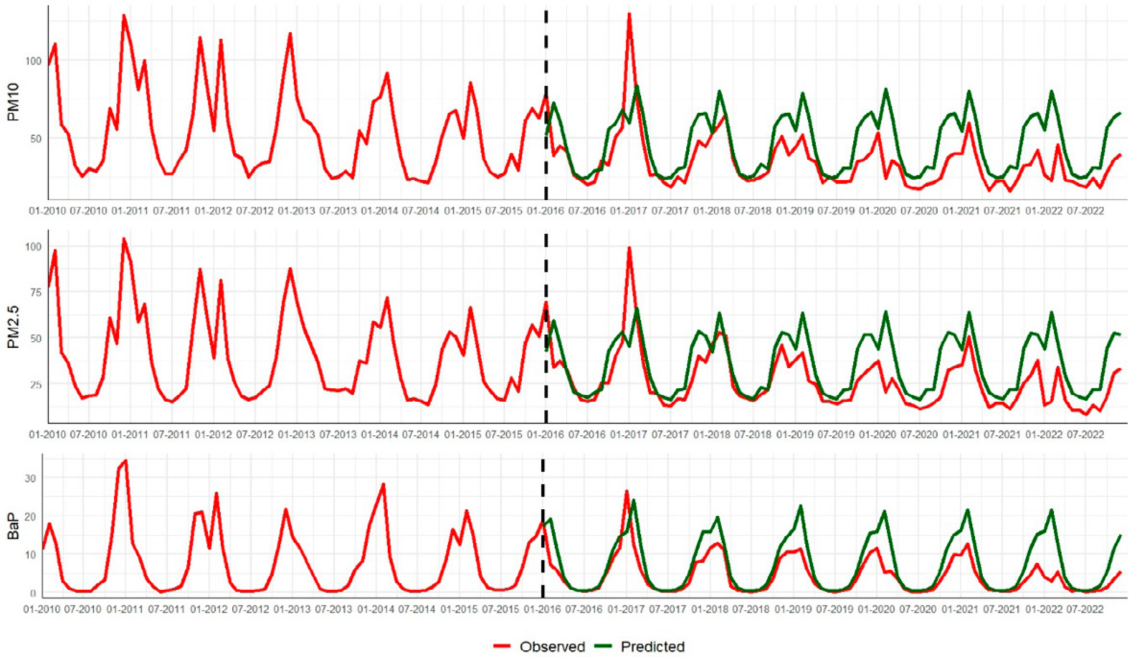

Figure 4. Average monthly concentrations of PM10, PM 2.5 and BaP in Krakow and values forecast using the interrupted time series method

Source: authors' work based on GIOS (2024) and IMGW (2024).

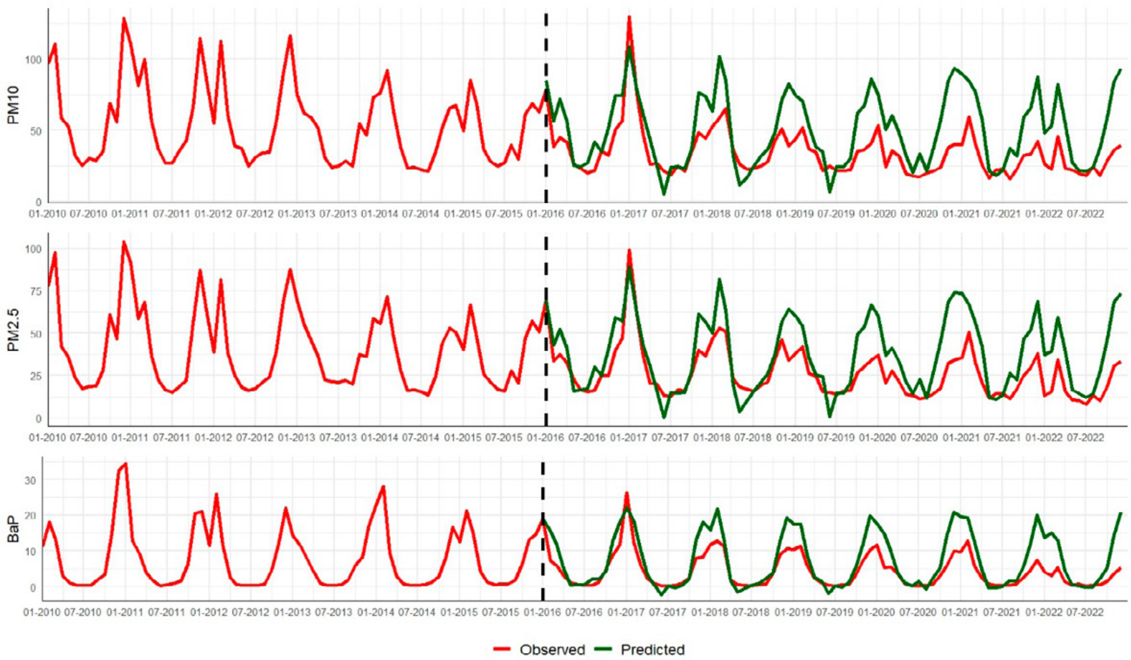

Figure 5. Average monthly concentrations of PM10, PM 2.5 and BaP in Krakow and values forecast using the Bayesian structural time series method

Source: authors' work based on GIOS (2024) and IMGW (2024).

The Bayesian structural time series method was used in the analysis's last step. The accuracy of the prediction was re-evaluated using the root mean squared error. For example, PM10 was 9.50, PM2.5 7.17, and benzo(a)pyrene 3.35. Figure 5 presents how the forecast values are shaping up against the background of the actual concentration of the discussed indicators, corresponding to the situation in Krakow without the introduction of a ban on the use of solid fuels.

Based on the presented Figures 3-5, it can be clearly stated that, regardless of the research method used, the level of PM10, PM2.5 and benzo(a)pyrene concentrations in Krakow would have been much higher if the regulations introducing a ban on the use of solid fuels had not been adopted in January 2016. The largest absolute differences in this aspect were estimated using random forest. According to the results obtained using this method, it can be concluded that the introduction of the ban in Krakow resulted in a decrease in the concentration of PM10 by 21.09 μg/m3, PM2.5 by 14.48 μg/m3, and benzo(a)pyrene by 3.21 μg/m3. Additionally, predictive intervals for the BSTS models were estimated, and the corresponding plot is included in Appendix G.

Comparing the obtained results with the average level of concentrations of the tested substances in the period preceding the entry into force of the anti-smog resolution, it can be concluded that the largest relative decreases occurred in the case of benzo(a)pyrene. Its concentration decreased in the study period by 41% (RF method), 39% (ITS method) and 39% (BSTS method), respectively. The biggest differences between the actual concentration of the tested substances and their forecasted level concern the winter months, and the smallest in the summer months.

The conclusions drawn from Figures 3-5 are summarised in Table 3. Monthly changes were averaged for three-time ranges: the whole year, the winter/heating season (October to March) and the summer season (April-September).

Table 3. Change in the average concentration of air quality indicators between the period 2016-2022 and the period 2010-2015

Method	Period	Air quality index		
		PM10	PM2.5	BaP
RF	Whole year	-21.09 (-38.81)	-14.48 (-35.66)	-3.21 (-40.93)
	Winter season	-30.17 (-39.54)	-21.45 (-36.06)	-5.62 (-38.83)
	Summer season	-12.00 (-37.09)	-7.51(-34.54)	-0.80 (-66.06)
ITS	Whole year	-12.46 (-22.94)	-9.28 (-22.85)	-3.08 (-39.24)
	Winter season	-18.96 (-24.84)	-13.67 (-22.99)	-5.62 (-38.85)
	Summer season	-5.97 (-18.45)	-4.89 (-22.48)	-0.53 (-43.83)
BSTS	Whole year	-16.26 (-29.93)	-11.14 (-27.44)	-3.06 (-39.09)
	Winter season	-26.79 (-35.10)	-19.23 (-32.33)	-5.98 (-41.32)
	Summer season	-5.73 (-17.71)	-3.06 (-14.05)	-0.15 (-12.42)

Changes in PM10, PM2.5, and BaP concentrations are presented in μg/m³, with percentage changes shown in parentheses
Source: authors' work based on GIOS (2024) and IMGW (2024).

To better highlight the difference between introducing regulations and not introducing these changes, we present Figure 6, which shows differences (commonly named as gaps, see Zeng et al. (2021); Zhang et al. (2016)) between the predicted values under the condition no change was observed and the actual values of PM10, PM2.5 and BaP. Each panel represents gaps obtained for three different approaches for a given measure.

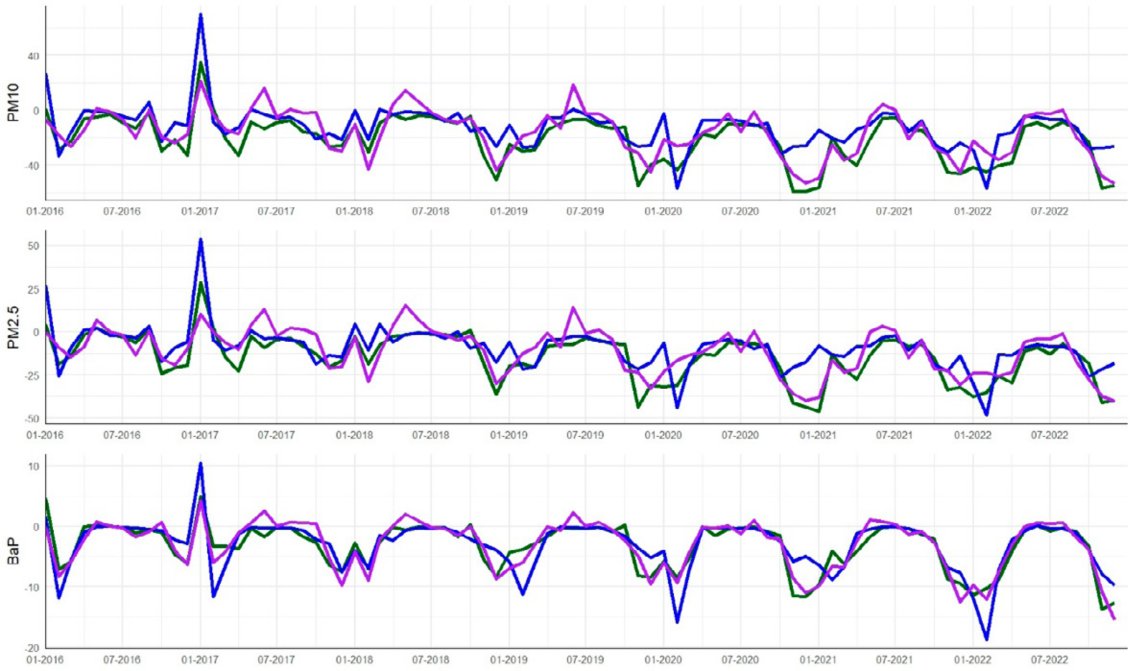

Figure 6. The gaps (differences) between the concentration of PM10, PM2.5 and BaP in Krakow and the forecasts made on the basis of three methods

Source: authors' work based on GIOS (2024) and IMGW (2024).

Note: Each of the three panels presents gaps for three methods. The top is for PM10, the middle is forPM2.5, and the bottom is for BaP. There are three different colours for each method – green colour is for RF, blue is for ITS and purple is for BSTS.

First of all, we observe seasonality in gaps – the forecast errors are lower in winter than in summer, regardless of the method used. Based on the presented results, it can be concluded that the ban on the use of solid fuels introduced in Krakow contributed to a much higher reduction of PM10, PM2.5 and benzo(a)pyrene dust during heating seasons than in summer seasons, which indicates a reduction in the impact of individual heating on air quality. Second, the gaps are slightly declining over time. Third, all three methods give similar results, which are indistinguishable visually. Therefore, we apply the Diebold-Mariano test to verify if any of the methods are better at forecasting pollution concentration than other methods. Table 4 shows the results.

Table 4. The Diebold-Mariano test statistics for the comparison of the forecasting errors of three dust measures

methods	PM10		PM2.5		BaP	
	DM stat	p-value	DM stat	p-value	DM stat	p-value
RF-ITS	3.413	0.001	2.532	0.013	-0.361	0,719
RF-BSTS	3.665	0.000	3.063	0.003	-0.592	0.555
ITS-BSTS	1.597	0.114	0.918	0.362	-0.133	0.895

Source: authors' work based on GIOS (2024) and IMGW (2024).

Note: DM stat stands for the Diebold-Mariano statistic. The null hypothesis in the test states that there is no difference in the predictive accuracy between the two forecasting methods being compared.

We find that at the significance level $\alpha = 0.05$, RF generate a better forecast than ITS and BSTS for PM10 and PM2.5. No differences are found in the case of ITS versus BSTS and for any method when BaP is taken into account.

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Conclusions

In this paper, we aimed to confirm whether and to what degree Kraków's air quality has improved as a result of the implementation of stringent anti-smog legislation. Random forest, interrupted time series, and Bayesian structural time series are the three models that are used. We evaluated the air quality using the following metrics: PM10, PM2.5, and benzo(a)pyrene concentrations. Based on the results, we can conclude that the adoption of legislative changes, such as the prohibition on the use of solid fuels in Kraków, contributes to a significant improvement in air quality. The results indicate that the largest relative decrease of 39 to 41% was related to the concentration of benzo(a)pyrene, while the smallest was related to the concentration of PM2.5 (decrease of 23 to 36%). The concentration of benzo(a)pyrene is especially noteworthy in this investigation because it is primarily emitted by household stoves. The reported improvement in air quality in Krakow during the heating season is noticeably greater than in the summer months. Despite the great achievements made through various initiatives, Kraków remains one of Europe's most polluted cities. It is critical to recognise that pollutants from adjacent towns that do not have strict anti-smog measures have a negative impact on air quality in Kraków.

From a policy perspective, these findings demonstrate that even under less favourable geographic situations, strong legislative frameworks can result in significant improvements in air quality. This is an important lesson for local governments and national policymakers, emphasising the need to speed up the replacement of outmoded heating systems. Currently, the European Union is adopting laws to reduce the use of fossil fuels in heating systems. By 2040, all fossil-fuel-based heating systems in buildings are scheduled to be banned. Although this legislation may impose large expenses, which may cause public concern, the long-term advantages to public health and environmental sustainability are apparent. Thus, this research aims to offer valuable insights that could guide the formulation of effective air quality strategies in other heavily polluted cities and regions across Europe.

Effective communication of the outcomes and benefits of anti-smog policies is essential to securing public acceptance. Resistance may particularly arise in the case of costly measures, such as the replacement of outdated heating systems. Therefore, messaging should emphasise not only the health and environmental benefits but also the long-term economic gains, such as reduced heating costs or increased property values. Targeted information campaigns that highlight tangible local effects – such as reductions in hospitalisations due to respiratory diseases or visibly improved air quality – have proven effective. Financial support mechanisms, including subsidies, preferential loans, or full cost coverage for low-income households, have been successfully implemented in cities such as Bucharest and Sofia. In these cases, public acceptance increased significantly when financial burdens were alleviated and the implementation timeline was clearly defined. The credibility and reach of the communication can be further enhanced through collaboration with trusted local institutions, such as schools, healthcare centres, and municipal offices. Engaging local communities through public consultations and participatory planning fosters a sense of agency and strengthens support for environmental policies

The main limitation of this study is the relatively short time horizon, as only seven years have passed since the implementation of the anti-smog legislation in Kraków. As more data becomes available in the future, it will be valuable to assess whether and how the effects of the legal intervention persist or diminish over time. Future research could also explore the long-term public health impacts of the policy, particularly in terms of respiratory and cardiovascular outcomes. Additionally, alternative methodological approaches – such as the synthetic control method using other Polish cities as comparators – could help control for external factors like weather variability. These avenues would contribute to a deeper understanding of the sustainability and broader applicability of local air quality regulations.

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The contribution of the authors

Conceptualisation, S.H., B.B-S. and A.P.; literature review, S.H., B.B-S. and A.P; methodology, S.H., B.B-S. and A.P; formal analysis, S.H., B.B-S. and A.P; writing, S.H., B.B-S. and A.P.; conclusions S.H., B.B-S. and A.P.

The authors have read and agreed to the published version of the manuscript.

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Appendix A. Effect Estimates (Mean and 95% CI) Across Different Numbers of MCMC Chains

Variable	Chains	MeanEffect	LowerCI	UpperCI
PM10	1 Chains	-16.26	-22.06	-10.40
	2 Chains	-16.26	-21.82	-10.41
	3 Chains	-16.26	-21.71	-10.43
	4 Chains	-16.26	-21.74	-10.44
	5 Chains	-16.26	-21.74	-10.44
PM2.5	1 Chains	-11.14	-15.70	-6.46
	2 Chains	-11.14	-15.67	-6.41
	3 Chains	-11.14	-15.62	-6.42
	4 Chains	-11.14	-15.59	-6.44
	5 Chains	-11.14	-15.59	-6.41
BaP	1 Chains	-3.06	-4.81	-1.26
	2 Chains	-3.06	-4.85	-1.25
	3 Chains	-3.06	-4.86	-1.20
	4 Chains	-3.06	-4.84	-1.21
	5 Chains	-3.06	-4.83	-1.20

Note: MeanEffect – the average estimated effect (mean of the AbsEffect values from individual runs). LowerCI – the lower bound of the confidence interval for the effect. UpperCI – the upper bound of the confidence interval for the effect.

Appendix B. Impact of MCMC Iteration Count on Estimated Average Effect and Confidence Intervals

Variable	Number of iterations	MeanEffect	LowerCI	UpperCI
PM10	1000	-16.26	23.35	78.02
	2000	-16.17	23.86	77.40
	3000	-16.14	24.28	76.93
	4000	-16.10	24.56	76.54
	5000	-16.12	24.41	76.61
	6000	-16.11	24.49	76.46
	7000	-16.12	24.71	76.40
	8000	-16.14	24.74	76.35
	9000	-16.15	24.83	76.31
	10000	-16.14	24.76	76.28
PM2.5	1000	-11.14	15.70	59.70
	2000	-11.11	16.23	59.19
	3000	-11.07	17.41	57.96
	4000	-11.08	16.69	58.61
	5000	-11.09	16.67	58.53
	6000	-11.10	16.76	58.46
	7000	-11.10	16.90	58.40
	8000	-11.10	17.24	58.00

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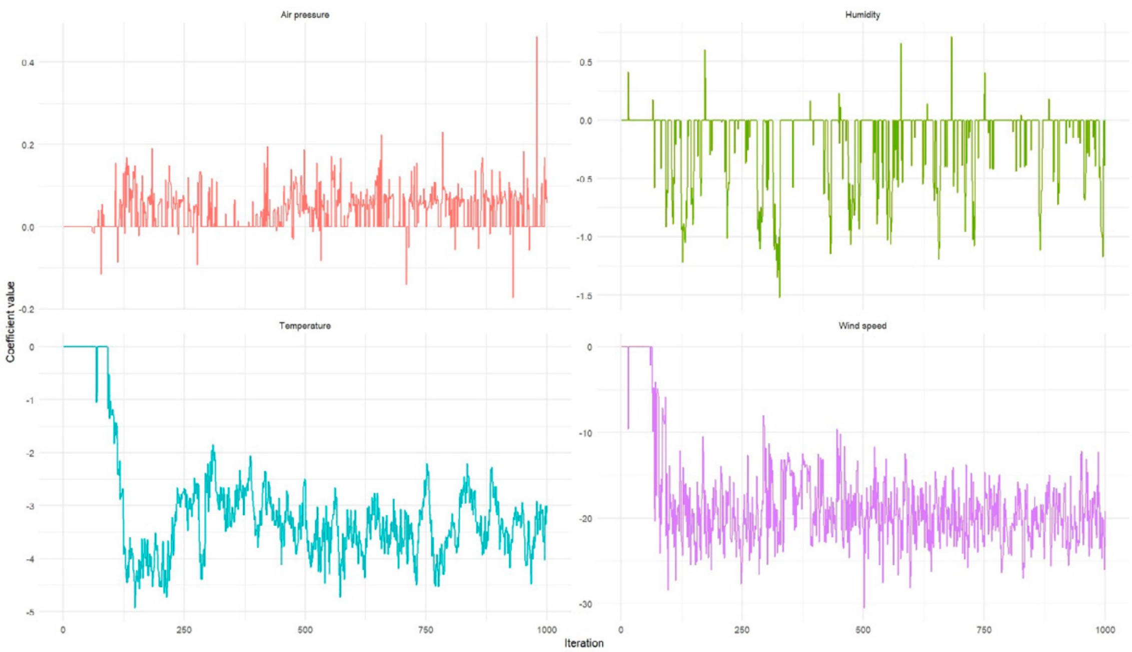
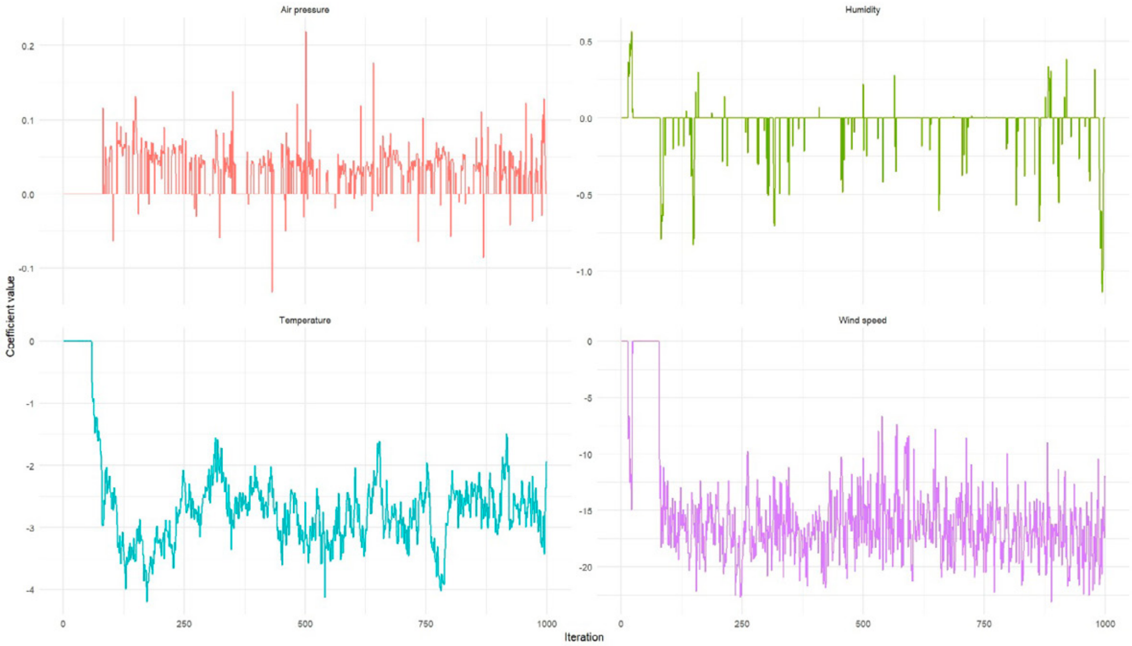
Variable	Number of iterations	MeanEffect	LowerCI	UpperCI
PM2.5	9000	-11.11	17.27	58.06
	10000	-11.10	17.29	57.99
BaP	1000	-3.06	-2.00	17.01
	2000	-3.05	-1.81	16.79
	3000	-3.04	-1.67	16.54
	4000	-3.03	-1.56	16.39
	5000	-3.02	-1.53	16.36
	6000	-3.02	-1.51	16.32
	7000	-3.03	-1.43	16.29
	8000	-3.03	-1.40	16.25
	9000	-3.03	-1.37	16.24
	10000	-3.04	-1.37	16.22

Note: MeanEffect – the average estimated effect, LowerCI – the lower bound of the confidence interval for the effect. UpperCI – the upper bound of the confidence interval for the effect.

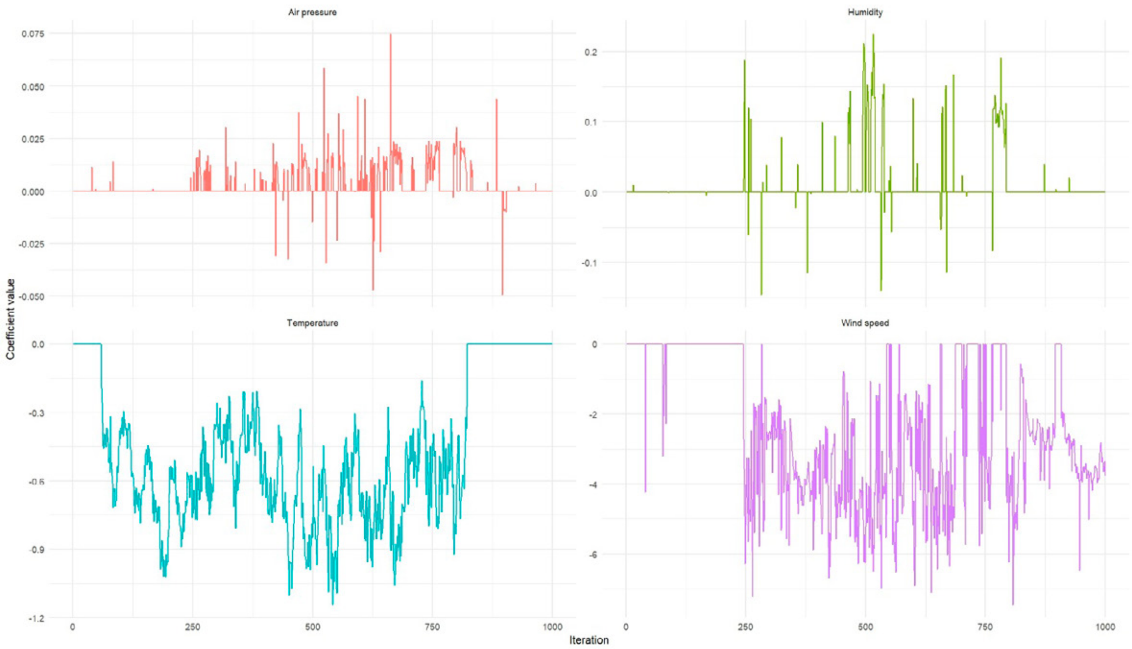
Appendix C. Trace Plots for Regression Coefficients in the PM10 Model



Appendix D. Trace Plots for Regression Coefficients in the PM2.5 Model



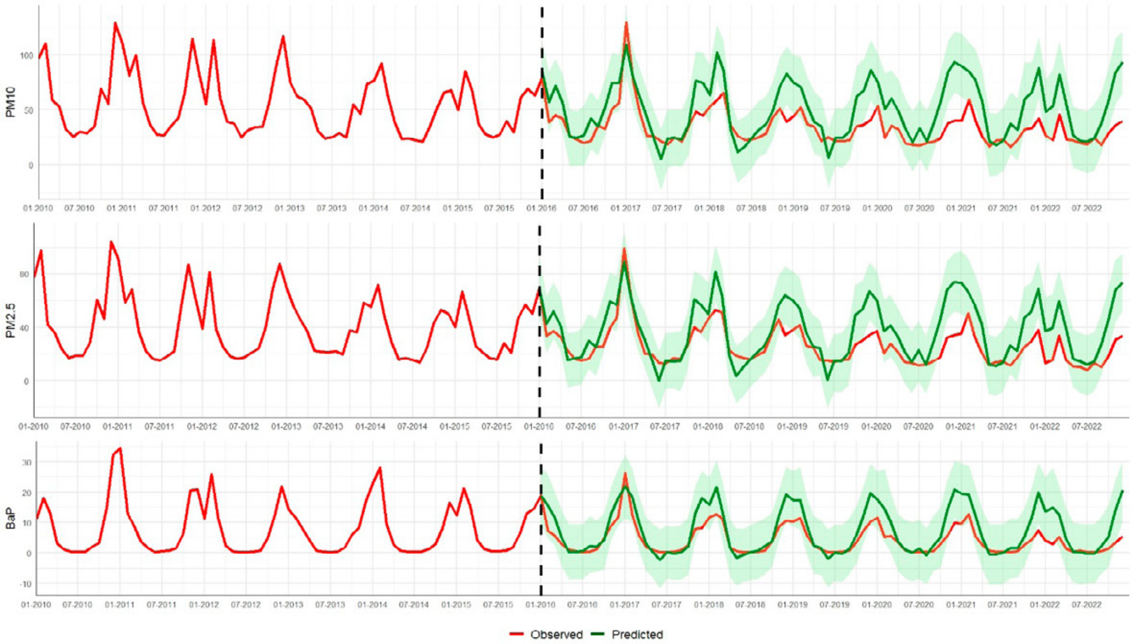
Appendix E. Trace Plots for Regression Coefficients in the BaP Model



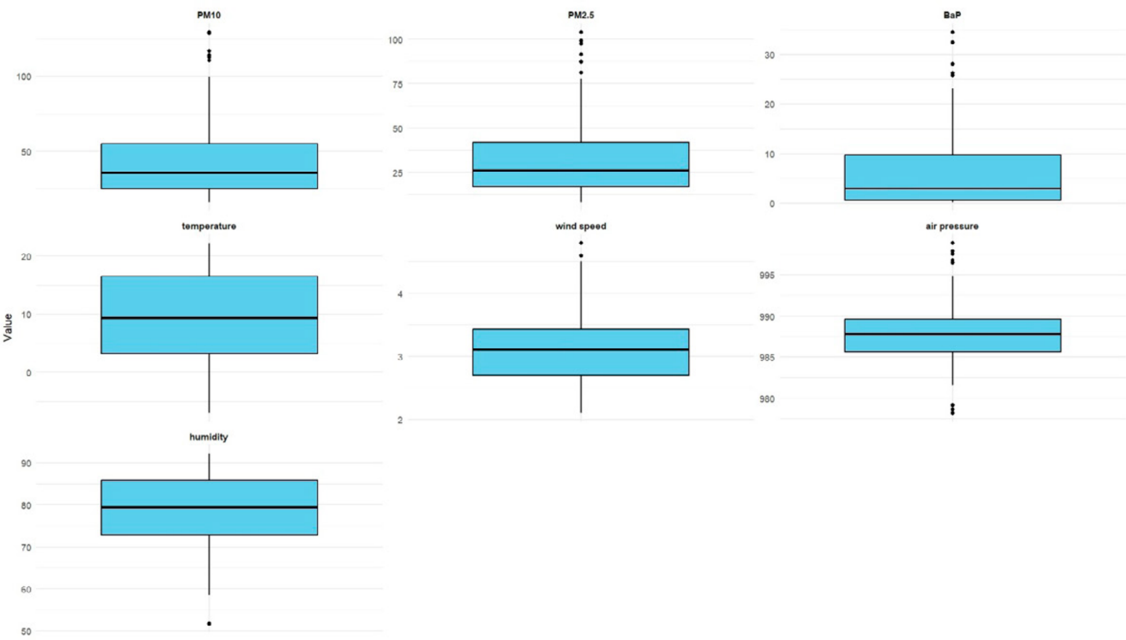
Appendix F. Diagnostic Test Statistics for PM10, PM2.5, and BaP Models: Box-Ljung, Shapiro-Wilk Normality, and ARCH Tests

Model	Box-Ljung test		Shapiro-Wilk normality test		ARCH test	
	test statistic	p-value	test statistic	p-value	test statistic	p-value
PM10	24.683	0.423	0.875	0,000	6.937	0.8618
PM2.5	28.836	0.226	0.871	0,000	14.397	0.2761
BaP	25.212	0.394	0.821	0,000	17.572	0.1293

Appendix G. Predictive Intervals for BSTS Models



Appendix H. Boxplots of the Seven Variables Used in the Analysis.



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SKUTKI PRZYJĘCIA UCHWAŁY ANTYSMOGOWEJ NA JAKOŚĆ POWIETRZA – STUDIUM PRZYPADKU KRAKOWA

STRESZCZENIE: Oceniamy wpływ krakowskiej uchwały antysmogowej, która została przyjęta 15 stycznia 2016 r. i zakazuje używania węgla i drewna na terenie miasta. Wykorzystujemy metodę lasu losowego, przerywanych szeregów czasowych i Bayesowskich strukturalnych szeregów czasowych do oceny poprawy jakości powietrza pod względem stężeń PM10, PM2,5 i benzo(a)pirenu, przewidując poziomy zanieczyszczeń w sytuacji, gdyby przepisy nie zostały wdrożone. Wyniki wskazują na znaczne obniżenie stężeń zanieczyszczeń: PM10 spadło od 23% do 39%, PM2,5 od 23% do 36%, a benzo(a)piren w PM10 od 39% do 41%, przy czym największe spadki miały miejsce w sezonie grzewczym. Wyniki te wskazują na skuteczność strategii legislacyjnej Krakowa, dostarczając opartych na dowodach punktów odniesienia dla decydentów politycznych i przedstawicieli służby zdrowia publicznego w innych miastach rozważających wprowadzenie podobnych ograniczeń dotyczących ogrzewania mieszkań w celu osiągnięcia wymiernej poprawy jakości powietrza.

SŁOWA KLUCZOWE: uchwała antysmogowa; zanieczyszczenie; Kraków; las losowy; przerywane szeregi czasowe; Bayesowskie strukturalne szeregi czasowe

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