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Content

Pollution and its Fiscal Echo: Quantifying the Impact of Environmental Factors on Government Debt

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Abstract

In Mongolia, the postal and telecommunications sector is transitioning from a state service monopoly to a market characterized by perfect competition. Following the Covid-19 pandemic, there has been a surge in demand for delivery and dispatch services. Specifically, revenue within the postal industry witnessed a notable upswing, with increases of 26 percent in 2020, 39 percent in 2021, and 37 percent in 2022, respectively. This surge underscores a sharp rise in demand for parcel, shipping, and delivery services within the postal sector. Hence, within the postal sector of Mongolia, there exists a challenge to the expansion of e-commerce delivery services, the integration of novel electronic technologies, the enhancement of logistical service standards, and the systematic elevation of sectoral competitiveness. The primary objective of this research is to examine the factors influencing the competitiveness of companies within the postal sector by employing M. Porter's Diamond model. Additionally, the study aims to identify the pivotal success factors crucial for enhancing the competitiveness of the postal sector in Mongolia. In assessing competitiveness, the study employs the comprehensive methodology of the Diamond model, which encompasses resource factors, demand factors, company strategy, structure, and organization, as well as related and supporting industry factors. Through this framework, the competitiveness of Mongolia's postal industry is analyzed across seven dimensions, comprising a total of 119 indicators. These dimensions include government support, human resources, and opportunities, among others. Subsequently, the findings are disseminated to reveal the outcomes of the assessment. The results revealed that the opportunity factor is the major important factor, on the other hand, the government factor was the less important factor for boosting the competitiveness of the postal company.

Keywords: air pollution, PM10, government debt, public healthcare expenditures, correlation analysis.

Introduction

Pollution in the form of greenhouse gas emissions, chemical substances, or other contaminants is emerging as an increasingly pressing global issue, which has significant negative impacts on our planet. In recent years, this issue has become one of the most discussed topics at the global level, especially due to the growing awareness of the detrimental impacts on both public health and economic stability.

Deteriorating air quality, for example higher concentration of particulate matter (PM2.5) and nitrogen oxide (NOx) emissions, leads to increased morbidity and mortality rates. This results in higher healthcare expenditures and reduced labour productivity, thereby undermining the fiscal stability of countries (Gao et al., 2021). Moreover, these costs associated with air pollution may exacerbate public debt, as governments are often required to finance mitigation efforts and address pollution-related health issues (Han et al., 2023). The expenditures include e.g. the treatment of respiratory and cardiovascular diseases, which are directly attributable to the exposure of pollutants (Wang et al., 2022). Empirical studies show that rising pollutant concentration can elevate public spending by several percentage points per year, contributing to a growth in public debt (Fareed et al., 2022).

Governments are increasingly compelled to allocate substantial funds to environmental measures, which often contributes to the escalation of public debt, especially in countries under pressure to meet the emission goals of the European Union. The EU has outlined ambitious objectives, including the transition to a carbon-neutral economy by 2050, which necessitates large-scale investments in renewable energy resources and infrastructure modernization (European Environment Agency, 2022). The primary goal of these investments is to reduce air pollution and improve citizens´ quality of lifel (Irfan et al., 2021). However, this financial burden can further strain public finances, especially when they are not effectively managed and if these projects are debt-financed by the state (Kickhöfer et al., 2018).

Elevated levels of sovereign debt increase economic vulnerability to external shocks and crises, which limits the effectiveness of both fiscal and monetary policy. Governments borrowing in order to fund green investments may often face the risk that in times of economic downturn or unforeseen crisis, they will have to raise taxes or cut spending in other areas to meet debt servicing obligations (Ogbeifun & Shobande, 2020).

Like other EU member states, the Czech Republic has been investing annually in projects aimed at reducing dependence on fossil fuels and promoting renewable energy sources. However, these measures represent a significant financial burden, which may have long-term implications for the country´s economic stability.

The issue of environmental pollution began to gain prominence when people started to intensively use natural resources for personal and industrial needs, often without regard for the consequences on ecosystems (Pattanaik, 2024). This leads to significant degradation of the natural environment and poses a serios threat to the quality of life on our planet.

Environmental pollution encompasses the presence of harmful substances in air, water, and soil, primarily resulting from human activities such as industrial production, transportation, agriculture, or improper waste management (Atavullayeva, 2024; Fowler et al., 2020). These activities contribute not only to biodiversity loss but also lead to the emergence of new health issues within human population. According to Omer (2024), developing countries are particularly vulnerable to these impacts, as weak regulatory frameworks and rapid industrialization often result in uncontrolled release of pollutants in the environment. Dibley et al. (2021) also point to the fact that wealthier states frequently externalize their environmental burdens by shifting them to poorer countries, thereby exacerbating global environmental inequalities.

Air pollution represents a serious contemporary environmental problem. It involves the presence of harmful substances in the atmosphere, including particulate matter (PM2.5, PM10), nitrogen oxides (NOx), sulphur dioxide (SO_2), and ozone (O3), which are primarily generated through the combustion of fossil fuels, industrial activities, transportation, and other anthropogenic sources (Atavullayeva 2024; Bahrami et al., 2024).

For instance, a study by Sakib et al. (2023), employing time series analysis with ARIMA and SARIMAX models, identified seasonal trends and long-term trends in PM10 and PM2.5 concentrations in the capital of Bangladesh. The results revealed a significant decline in air quality during periods of elevated industrial and transport-related emissions. Similarly, Istiana et al. (2023) examined the relationship between PM2.5, other air pollutants (PM10, CO, NO2), and meteorological factors in Jakarta. Pearson correlation coefficient revealed the existence of linear relationship, while the application of the Convergent Cross Mapping (CCM) identified stronger non-linear causal relationships, particularly during the period December-February and March-May, with PM10 ($\rho = 0.74$) and wind speed ($\rho = 0.52$), exerting the strongest influence on PM2.5 levels. Similarly, Liang et al. (2021) analysed the impact of meteorological conditions on air quality in Beijing using Pearson correlation. Their findings showed that PM2.5 levels were negatively correlated with the temperature and wind speed but positively correlated with relative humidity. These studies underscore the significant role of seasonal dynamics, meteorological variables, and the complexity of interactions affecting air pollution levels. Li et al. (2021) found that public interest in air pollution measured using the Baidu Index, correlates with the concentrations of PM2.5, particularly during smog-heavy winter months. The study highlighted that while the public is highly responsive to current pollution levels, there is comparatively lower awareness or interest in long-term prevention strategies. However, since Pearson correlation assumes both linearity and normally distributed data, these assumptions must be tested using Shapiro-Wilk test prior to application. The test was used e.g. by Papadaki et al. (2023), who examined water pollution and found that most water quality indicators, such as dissolved oxygen (DO), total nitrogen (TN), and E. coli concentrations, did not follow a normal distribution ($p <$ 0.05).

One of the most significant consequences of air pollution is the rise in healthcare expenditures. Prolonged exposure to elevated concentrations ofPM2.5 and PM10 is associated with chronic respiratory and cardiovascular diseases, which require substantial and ongoing medical treatment (Bahrami et al., 2024; Zhang et al., 2022). Globally, air pollution ranks as the fourth leading risk factor for mortality among all health threats (Murray et al., 2020). In Europe, air pollution is responsible for up to 790,000 premature deaths annually, with 40% to 80% of these deaths attributed to cardiovascular diseases (Lelieveld et al., 2019). A study conducted by Xia et al. (2022), employing Spearman correlation analysis alongside the GeoDetector method, examined the impact of air pollution on public healthcare expenditures in China. The results revealed that a 1 $\mu g/m^3$ increase inPM2.5 o 1 $\mu g/m^3$ concentration can lead to a rise in healthcare spending of up to 2.94%.

Velásquez & Lara (2020) employed Gaussian process regression to examine the relationship between air pollution (NO2, PM2.5) and the incidence of COVID-19 in Lima. Their findings indicated that pollution levels in industrial zones were significantly associated with higher infection rates, highlighting the influence of environmental actors on public health.

Jalaludin et al. (2021) applied basic statistical methods (mean, median, and standard deviation) to describe the level of air pollution during pregnancy, focusing on PM10, PM2.5 and O3 concentrations. These descriptive statistics provided an overview of pollutant exposure and serve as a foundation for a regression analysis assessing the impact of air pollution on prenatal health risks. However, the results of the study did not reveal a statistically significant association.

In the Czech Republic, air pollution is particularly severe in industrial regions, such as the Ostrava region. According to research by Volná et al. (2024), the primary sources of pollution include household emissions from burning solid fuels such as coal and emissions from industrial facilities, both of which contribute to increased morbidity and rising healthcare costs. Another major contributor is transport, with particularly older vehicles posing a significant problem. These factors collectively impact not only health but also economy. Although the CR remains one of the least indebted countries in the European Union, government debt has increased in recent years, particularly during the COVID-19 pandemic, which contributed to a rise in the structural deficit (Tomášková, 2023).

Research by Wang et al. (2022) also demonstrated that morbidity related to air pollution leads to a decline in labour productivity. Han et al. (2023) found that higher concentrations of particulate matter in the air are associated with an increase in local government debt. Their study revealed that a rise in PM2.5 concentration resulted in approximately a 3% increase in local government debt, primarily due to higher costs of healthcare and environmental measures. Similarly, Tan et al. (2021) showed that elevated levels of air pollution increase the cost of financing corporate debt. Specifically, they found that an increase in pollution intensity by one standard deviation led to a 16% rise in bond yield spreads. These findings were based on panel regression analyses that involved more than 200 enterprises in China.

Socioeconomic factors, such as GDP, the level of industrialization, and government policy, play an important role in the issue of air pollution and government debt. Xia et al. (2022) found that GDP, in combination with SO_2 emissions, contributes to increased healthcare expenditure, thereby putting pressure on public finances. According to Boly et al. (2022), a 1% increase in the public debt-to-GDP ratio leads to 0.74% increase in CO_2 emissions per capita, which highlights the conflict between fiscal and environmental goals. In a study by Bréon et al. (2017), the annual growth rate was used to analyse year-on-year changes in CO2 emissions. The results showed that GDP was one of the main drivers of emission growth, while annual meteorological factors (e.g., heating and cooling demand) had a smaller but notable effect, particularly in mid-latitude countries.

Within economic policy, environmental regulation and the allocation of public finances play a key role in combating pollution. Xie et al. (2023) found that local governments in China with high levels of debt often refrain from implementing stricter environmental regulations, leading to higher emissions from factories. Zhao et al. (2024) also state that rising local debt hampers the development of the green economy, distorts resource allocation, and limits investment in green technologies.

An effective solution to reduce air pollution is investment in green technologies. As stated by Li & Qiu (2024), the introduction of green innovations offers an effective way to address environmental issues by promoting economic growth while minimizing emissions and waste. Studies by Chen et al. (2022) and Han et al. (2023) also show that investment in industrial modernization can reduce greenhouse gas emissions, improve air quality, and contribute to long-term public finance stability. However, the implementation of such measures must be carefully managed to avoid a disproportionate increase in public debt (Nordhaus, 2017). Another effective solution is the investment in green technology. Further research using machine learning methods, such as artificial neural networks (ANN), was conducted by Chang & Tseng (2017), who accurately identified the impact of industrial and agricultural activities on PM2.5 levels. According to Halkos & Papageorgiou (2018), one of the key tools to mitigate the negative impacts of air pollution on public finances is the introduction of environmental tax reforms. For example, the introduction of a carbon tax in countries such as Sweden has shown that a tax increase by 1EUR per tonne of CO_2 can reduce annual emission per capita by up to 11.58 kg, while also supporting long-term fiscal stability (Hájek et al. 2019). Fodha et al.

(2018) also examined the impact of environmental tax reforms (ETR) on government debt levels. Using the overlapping generations (OLG) model, they found that revenues generated from such taxes can cover the higher healthcare costs of pollution-related diseases while helping to reduce public debt. Similar conclusions were made by Barrage (2020), who analysed optimal carbon tax in combination with fiscal policy. Using the COMET model and data from the International Monetary Fund, the study found that the optimal carbon tax could be up to 24% lower if other distortionary taxes are already in place.

The current goals of the Czech government include reducing the budget deficit and supporting eco-innovations that could improve air quality and reduce long-term healthcare costs. According to Hájek et al. (2019), introducing a higher carbon tax in the CR could help lower CO_2 emissions and encourage investment in renewable energy sources.

Nevertheless, quality research requires accurate and relevant data. Content analysis, both inductive and deductive, is particularly useful due to its effectiveness in secondary data processing (Kibiswa, 2019). Secondary data provide a comprehensive view of the issue; however, their reliability depends on the quality of the original resources. Their main advantages are availability and time efficiency compared to primary data collection (Renbarger et al., 2019), which makes them particularly suitable for this purpose. As stated by Kleinheksel et al. (2020), such data enable the identification of key patterns and relationships, thus improving planning and decision—making. Despite this, the data can be limited by inaccuracy.

For the purposes of this paper, secondary data will be used and processed through content analysis in order to identify relevant information related to air pollution and public healthcare expenditures in the Czech Republic. Time series, along with linear regression and basic descriptive statistics such as mean, median, and standard deviation, will provide a general overview of the data. The year-on-year growth rate will also be used to gain insight into the dynamics of key indicators. To analyse the relationships between variables and verify data normality, the Shapiro-Wilk test will be applied. Pearson correlation will be used for normally distributed data, while Spearman correlation will be applied in the case of non-linear relationships. Based on the results, the formulated research questions will be gradually addressed.

The objective of the paper is to assess the impact of air pollution and investments in its mitigation on the public finances of the Czech Republic during the period 2012–2022. The analysis focuses on pollution trends, developments in healthcare expenditures, and the impact of government investment on fiscal stability.

Based on this objective, the following research questions are formulated:

The first question will analyse the overall trends of air pollution in the CR in the period from 2012 to 2022. These data will be further used for the third research question.

- RQ1: What were the trends in air pollution (PM10) in the Czech Republic during the period 2012–2022?

The second question aims to analyse the overall development of public healthcare spending in the CR over the monitored period. The data will also be used for the third research question.

- RQ2: How did public healthcare expenditures evolve in the Czech Republic during the period 2012–2022?

By answering this question, it will be determined whether there is a relationship between the level of pollution (PM10) and public spending on healthcare, or how the increase in pollution affects spending in this sector.

- RQ3: Is there a relationship between air pollution levels (PM10) and public healthcare expenditures in the Czech Republic during the period 2012–2022?

The aim of the following question is to explore how PM10 pollution affects the development of government debt in the period 2012–2022. The obtained data will be used for a deeper understanding of the economic implications of environmental challenges on public finances and informing policy aimed at mitigating these negative effects.

- RQ4: What is the impact of PM10 air pollution on the public debt of the Czech Republic during the period 2012–2022?

Methods and Data

For all formulated research questions, content analysis will be used, which will enable an in-depth analysis of the secondary data.

Research question RQ1
To answer the first research question (RQ1), data on air pollution in the CR obtained from the Czech Hydrometeorological Institute (ČHMÚ, 2023) will be analysed, specifically, average annual concentrations of PM10 for the period from 2012 to 2022. The data will be examined using time series analysis, basic descriptive statistics, and the year-on-year growth rate.

First, a time series analysis will be conducted to identify the long-term development of pollution levels. The data will be visualized in the form of a line graph, with individual years displayed on the X-axis and the average annual PM10 concentrations (μg/m^3) on the Y-axis. This graph will provide a general overview of whether the PM10 concentration levels in the CR showed an increase, decrease, or remained stable.

For a more detailed analysis, linear regression will be applied, modelled according to the following equation (Zvára, 2019):

$$PM_{10}(t) = \beta_0 + \beta_1 t + \epsilon_t \quad (1)$$

where:
β_0 – is the constant indicating the initial level of pollution at the beginning of the monitored period [μg/m^3]
β_1 – the trend coefficient indicating whether pollution increases or decreases over time [μg/m^3 per year]
ϵ_t – random error accounting for unpredictable deviations [μg/m^3]
t – time variable [year]

The coefficient β_1 indicates how the level of pollution changes over time. If $\beta_1 > 0$, it suggests that pollution is increasing each year, which reflects a deterioration in air quality. Conversely, if $\beta_1 < 0$, pollution levels are decreasing, indicating an improvement in air quality. A time series graph created in MS Excel will be used to visualize these trends.
In the next stage, a basic statistical analysis of the data will be conducted in order to provide a more accurate description of their characteristics. First, the average value of PM10 concentrations for the entire observed period will be calculated using the following formula (Hindls, 2018):

$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n} \tag{2}$$

where:
n – number of years
X_i – average PM_{10} concentration in individual years.
Subsequently, the variance (σ^2) will be calculated to determine the extent to which annual values deviate from the mean. The following formula will be applied:

$$\sigma^2 = \frac{\sum_{i=1}^{n} (X_i - \bar{X})^2}{n} \tag{3}$$

Standard deviation (σ) will be calculated as a square root of the variance:

$$\sigma = \sqrt{\sigma^2} \tag{4}$$

The standard deviation reflects the average deviation of annual values from the mean, providing an indication of the stability of PM_{10} concentration values over time. Finally, the minimum and maximum values of PM_{10} values will be identified to determine the range of fluctuations throughout the monitoring period.

Following the descriptive analysis, the year-on-year growth rate will be calculated using the formula below (Majaski, C., 2024):

$$Growth = \left(\frac{Value_t - Value_{t-1}}{Value_{t-1}}\right) \times 100 \tag{5}$$

where:
$Value_t$ – concentration of air pollution (PM_{10}) in the current year [μg/m^3]
$Value_{t-1}$ – concentration of air pollution (PM_{10}) in the preceding year [μg/m^3]
$Growth$ – percentage change in pollution concentration between two consecutive years [%]

The results of the year-on-year growth rate will be visualised using a bar graph, with the individual years displayed on the X-axis and percentage change in the Y-axis.

If the result is positive, i.e., $Growth > 0$, it indicates that the pollution concentration increased compared to the preceding year. A negative result, i.e., $Growth > 0$, suggests a decrease in pollution levels. If the result is zero, the concentration remained unchanged year-on-year. The results will be visualised using a bar graph in MS Excel. With individual years shown on the X-axis and the percentage change in concentrations displayed on the Y-axis.

This research question will further contribute to addressing the third and fourth research questions (RQ3 and RQ4).

Research question RQ2

To address the second research question (RQ2), which focuses on monitoring the year-on-year trend of healthcare expenditures in the CR in the period from 2012 to 2022, data obtained from the Czech Statistical Office will be analysed (CSO, 2023). The data will be processed using content analysis, which allows for the systematic evaluation of available secondary information.

The analytical approach will mirror the methods applied in response to RQ1. Initially, a time series analysis will be conducted to identify long-term trends in public healthcare expenditures. The data will be visualised using a line graph, where individual years will be displayed on the X-axis and annual healthcare expenditures (in billions of CZK) represented on the Y-axis.

Next, a linear regression model will be used in the same form as in RQ1.

As in the case of RQ1, basic statistical analysis will be conducted, including the calculation of the mean annual expenditures, variance, and standard deviation, as well as identification of minimum and maximum expenditures during the monitored period.

To compare the year-on-year changes, the annual growth rate will be applied to determine the percentage change in expenditures between two consecutive years. The calculation will be carried out in the same way as in RQ1. All results will be presented using MS Excel. The second research question will serve as the basis for addressing the third research question (RQ3).

Research question RQ3

The third research question will be addressed through correlation analysis, using the data obtained in RQ1 and RQ2, i.e., the data on annual mean concentrations of PM10 and annual public healthcare expenditures in CR for the period 2012–2022 (ČHMÚ, 2023; CSO, 2023).

First, Shapiro-Wilk test will be performed to verify data normality (Hanusz et al. 2016):

$$W = \frac{(\sum_{i=1}^{n} a_i x_{(i)})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{6}$$

where:
$x_{(i)}$ *– data values arranged in ascending order (from the smallest to the larges)*
x_i *– initial values*
$\bar{x}$ *– arithmetic mean of the data set*

n – number of observations
a_i – weighting coefficients derived from the expected values of ordered samples from a normal distribution

To assess the statistical significance of the observed relationship, the null hypothesis regarding the distribution of annual mean concentrations of PM_{10} for the period 2012 – 2022 will be tested as follows:

H0: The data on annual mean concentrations of PM_{10} for the period 2012 - 2022 are drawn from a normal distribution.

H1: The data on annual mean concentrations of PM_{10} for the period 2012 - 2022 are not drawn from a normal distribution.

To assess the statistical significance of the relationship, the null hypothesis regarding public healthcare funding will be tested as follows:

H0: The data on healthcare funded by public budgets for the period 2012–2022 are drawn from a normal distribution.

H1: The data on healthcare funded by public budgets for the period 2012–2022 are not drawn from a normal distribution.

The level of statistical significance p was determined at 5% for both samples.

If both datasets follow a normal distribution, Pearson correlation will be employed to quantify the linear relationship between the concentrations of PM_{10} and public healthcare expenditures. If the assumption of data normality is not met for one or both datasets, Spearman correlation will be utilized, as it more effectively captures potential non-linear relationships.

Pearson correlation coefficient will be calculated as follows (Okoye, 2024):

$$r = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (y_i - \bar{y})^2}} \tag{7}$$

where:
x_i –PM_{10} pollution concentration in a given year [μg/m^3]
y_i – healthcare expenditures in a given year [billion CZK]
$\bar{x}$ – mean PM_{10} pollution concentration for all years
$\bar{y}$ – mean healthcare expenditures for all years

The value of the Pearson correlation coefficient ranges from -1 to +1. Values approaching +1 indicate a strong positive linear relationship between the variables (e.g., an increase in pollution levels is associated with an increase in healthcare expenditures), whereas values approaching -1 suggest a strong negative correlation. A coefficient value of 0 indicates no linear relationship between the variables. The significance level (α) is set at 5% (Akoglu, 2018).

To verify the statistical significance of the relationship, the null hypothesis will be tested as follows:

H0: There is a linear relationship between air pollution concentrations (PM_{10}) and public healthcare expenditures in the selected decade.

H1: There is no linear relationship between air pollution concentrations (PM_{10}) and public healthcare expenditures in the selected decade.

Spearman correlation coefficient will be calculated as follows (Hendl, J., 2012):

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{8}$$

where:
d_i – is the difference between the ranks of the PM_{10} concentration values (x) and the healthcare expenditure values (y) for each pair of observations
n – number of observations (number of pairs of values)

The value of the Spearman correlation coefficient ranges between -1 and +1. Values approaching +1 suggest a strong positive monotonic correlation, which means that as the value of one variable (e.g., PM_{10} concentration) increases, the value of the other variable (healthcare expenditures) increases as well. Conversely, values approaching -1 indicate a strong negative monotonic correlation, where an increase in one variable corresponds to a decrease in the other. A Spearman correlation coefficient of zero implies no monotonic relationship between the variables. The level of statistical significance (α) is set at 5% (0.05).

To verify the statistical significance of the relationship, the following null hypothesis will be tested:

H0: There is no monotonic relationship between air pollution concentrations (PM_{10}) and public healthcare expenditures in the selected decade.

H1: There is a monotonic relationship between air pollution concentrations (PM_{10}) and public healthcare expenditures in the selected decade.

If a statistically significant Pearson correlation is identified, linear regression will be performed as in the case of RQ1 and RQ2. All results will be presented in MS Excel charts.

Research question RQ4

To address the fourth research question, a content analysis of data on public healthcare expenditures (as identified in RQ2) and their relationship to the annual government debt levels of the Czech Republic for the period 2012–2022 will be conducted. The data on government debt will be obtained from the official statistics of the Ministry of Finance of the CR (MFČR, 2023). The analysis aims to determine whether higher healthcare expenditures contribute to the increase in government debt.

First, a time series analysis of government debt will be carried out, following the same procedure as applied in RQ1 and RQ2. The data will be visualized using a line graph, where the X-axis represents individual years, and the Y-axis displays the absolute value of government debt in billions of CZK. Linear regression will also be applied in accordance with the methodology used in RQ1 and RQ2

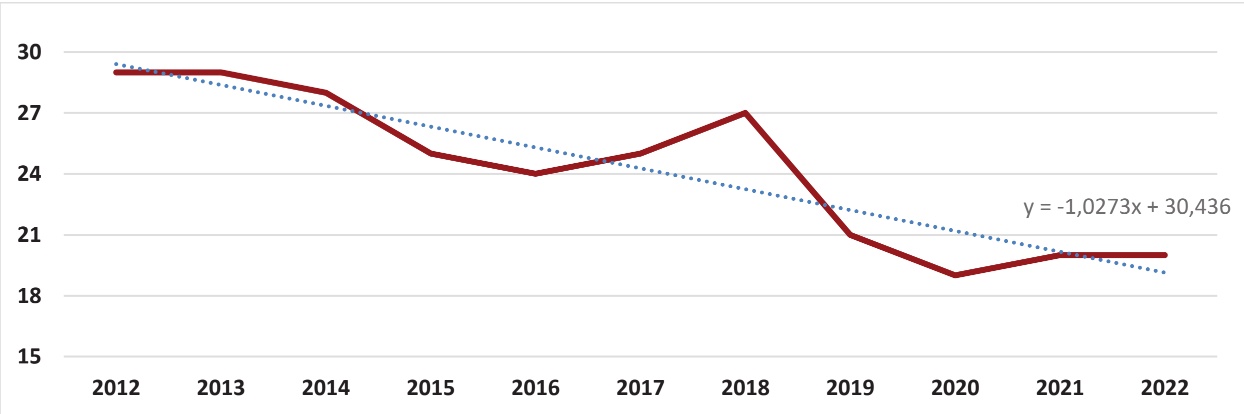
Subsequently, a descriptive analysis of government debt will be conducted, including the calculation of the mean, variance, and standard deviation, as previously done in RQ1 and RQ2. These descriptive statistics will help to better characterize the variability of debt over the observed period.

Following this, the Shapiro–Wilk test will be used to assess the normality of the data on public healthcare expenditures and government debt in the Czech Republic for the period 2012–2022. If the data meet the assumption of normality (p-value > 0.05), Pearson correlation will be used to determine the linear relationship between these variables. If the assumption of normality is not met (p-value ≤ 0.05), Spearman correlation will be employed, as it more accurately captures potential monotonic relationships. Based on the results of the correlation analysis, it will then be evaluated whether increased public healthcare expenditures potentially associated with air pollution may have contributed to the growth of government debt in the Czech Republic during the analysed period. The results will be presented in tables and charts generated using Microsoft Excel.

Results

Data on air pollution in the CR were collected on an annual basis for the period from 2012 to 2022. Information on PM_{10} concentrations was obtained from the Czech Hydrometeorological Institute (ČHMÚ, 2023).

Graph 6: Trend in yearly average concentrations of PM10 in the CR [μg/m3]



Source: Authors based on (ČHMÚ, 2023).

Graph 1 illustrates the annual trend in average concentrations of PM_{10} in the Czech Republic over the period 2012–2022. The data reveal a clear overall downward trend in air pollution, with average concentrations decreasing by approximately 1.03 μg/m^3 per year, as indicated by the linear regression equation. The highest concentrations were observed at the beginning of the monitored period (in 2012 and 2013), reaching 29 μg/m^3, while the lowest value (19 μg/m^3) could be seen in the years 2020 and 2021. This reduction may be partially attributed to exceptional measures implemented during the COVID-19 pandemic, which involved restrictions on transport, industrial production, and other activities affecting air quality. In the final years of the observed period (2021 and 202), the concentrations of PM_{10} stabilized at 20 μg/m^3.

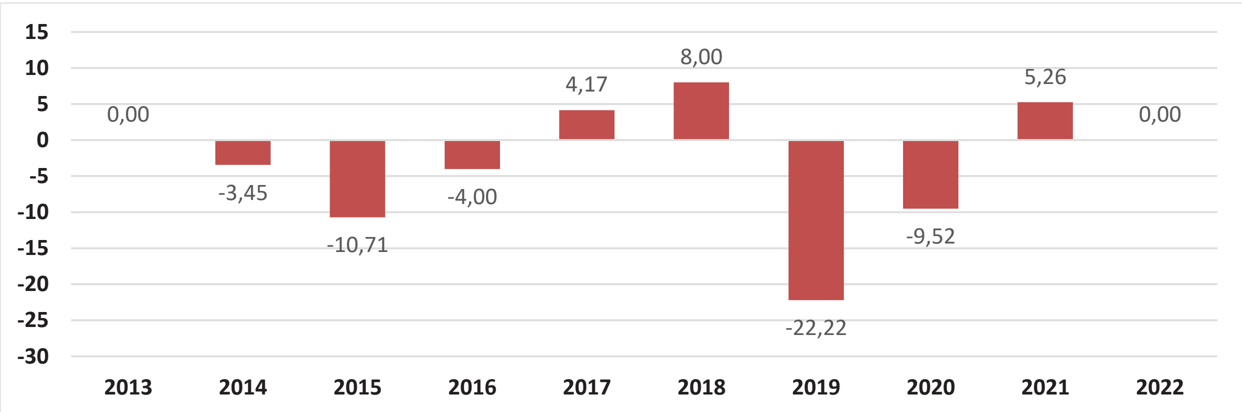
Tab. 1: Basic statistical analysis of PM10 concentrations in the CR (2012-2022)

Statistics	Value
Mean value ($\bar{X}$)	24.27 μg/m^3
Variance (σ^2)	12.93
Standard deviation (σ)	3.60 μg/m^3
Minimum value	19 μg/m^3
Maximum value	29 μg/m^3

Source: Authors based on (ČHMÚ, 2023).

Table 1 provides a basic statistical data analysis of PM10 concentrations in the Czech Republic for the period 2012–2022. The results indicate a mean value of 24.27 μg/m^3, with a variance of 12.93, and a standard deviation of 3.60 μg/m^3, suggesting relatively low variability in annual values. The lowest concentration (19 μg/m^3) was recorded in 2020 and 2021, while the highest value (29 μg/m^3) occurred in 2012 and 2013. These findings support the observed downward trend in air pollution levels in the CR.

Graph 7: Annual growth rate of PM10 concentrations (2012–2022)

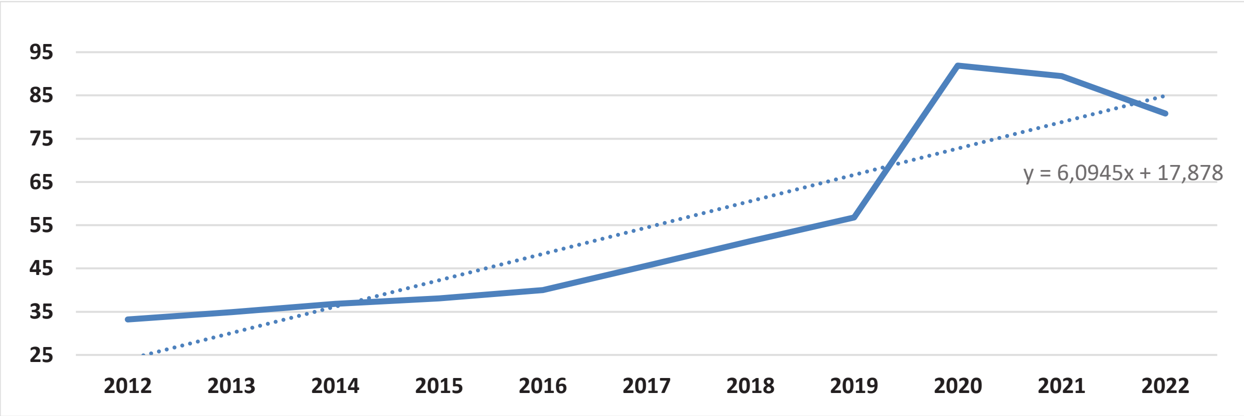


Source: Authors based on (ČHMÚ, 2023).

Graph 2 illustrates the annual percentage changes in PM10 concentrations in the Czech Republic. As the graph indicates, most of the year-on-year changes are negative, confirming the overall decline in PM10 levels over the observed period. The most significant decrease occurred between 2019 and 2020, when concentrations dropped by more than 22%, largely due to restrictions on emission-generating activities implemented during the COVID-19 pandemic. These findings are consistent with the results of previous analyses.

Data on public healthcare expenditures in the Czech Republic were also monitored on an annual basis during the period 2012–2022. This information was obtained from the Czech Statistical Office (ČSÚ, 2023).

Graph 8: Trend in public healthcare expenditures in CR [CZK billion]



Source: Authors based on (ČSÚ, 2023).

Graph 3 illustrates the annual public healthcare expenditures in the CR from 2012 to 2022. The data reveal a clear upward trend, with spending rising from CZK 33,2 billion in 2012 to CZK 80,8 billion in 2022. The most pronounced increase occurred between 2019 and 2020, likely reflecting additional costs related to the COVID-19 pandemic, including investments in healthcare infrastructure and preventive measures. Although a slight decline in expenditure followed after 2020, the overall level remained significantly higher than in the pre-pandemic years, suggesting a long-term policy shift towards increased investment in public healthcare. The linear regression depicted in the graph confirms this long-term upward trend in expenditure throughout the observed period.

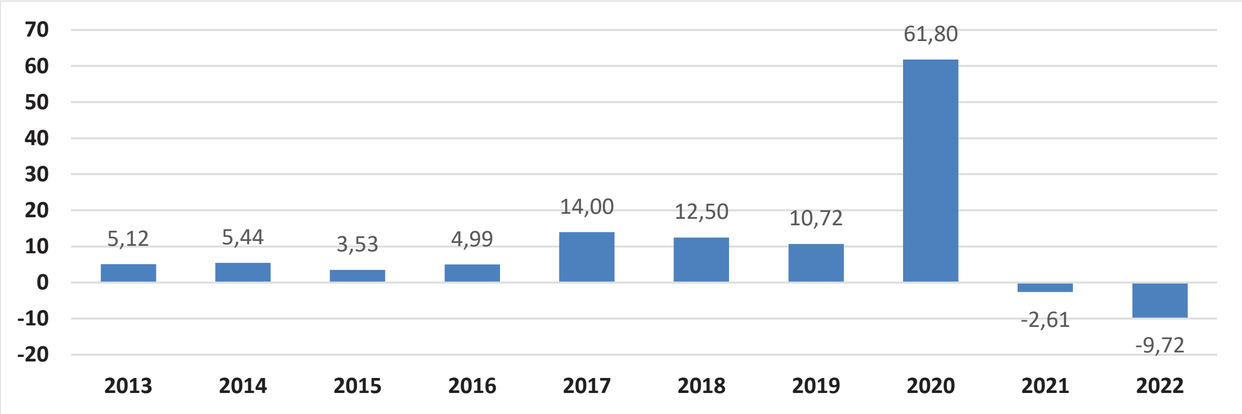
Tab. 2: Basic statistical analysis of public healthcare expenditures in the CR (2012–2022)

Statistics	Value
Mean value ($\bar{X}$)	CZK 54.45 billion
Variance (σ^2)	CZK 458.23 billion
Standard deviation (σ)	CZK 21.41 billion
Minimum value	CZK 33.20 billion
Maximum value	CZK 91.90 billion

Source: Authors based on (ČSÚ, 2023).

Table 2 provides a basic statistical analysis of public healthcare expenditure in the Czech Republic for the period 2012–2022. The results indicate that the average annual expenditure amounted to CZK 54.45 billion, reflecting substantial investment in the healthcare sector. The variance of CZK 458.23 billion^2 suggests a high degree of variability in annual spending, while the standard deviation of CZK 21.41 billion illustrates the average deviation from the mean. The lowest expenditure was recorded in 2012 (CZK 33.2 billion), whereas the highest occurred in 2020 (CZK 91.9 billion), likely due to the exceptional costs associated with the COVID-19 pandemic. These findings support the observed long-term increase in public healthcare investment in the Czech Republic.

Graph 9: Annual growth rate of public healthcare expenditures (2012-2022)



Source: Authors based on (ČSÚ, 2023).

Graph 4 illustrate the year-on-year changes in public healthcare expenditures in the CZ, expressed as percentages. The data show that until 2019, the annual growth in expenditures remained relatively stable, ranging from 3.53% to 14%, with the highest increase observed in 2017. A dramatic surge occurred in 2020, when expenditures rose by 61.80%, largely due to the extraordinary measures implemented during the COVID-19 pandemic. This period was followed by a decline in the growth rate. In 2021 and 2022, year-on-year expenditures decreased, with the most pronounced decrease by 9.72% being recorded in 2022. These findings confirm the exceptional impact of the pandemic on healthcare expenditure, followed by a return to more typical growth rate, although interrupted by short-term fluctuations.

Tab. 3: Results of Shapiro-Wilk test of data normality

Data	**Test statistics (W)**	**p-value**	**Data normality**
Average concentrations of PM_{10}	0.901470184	0.192638814	Yes
Public healthcare expenditures	0.822440207	0.018570257	No

Source: Authors based on (ČHMÚ, 2023; ČSÚ, 2023).

Table 3 presents the results of the Shapiro-Wilk normality test conducted on the data for average PM_{10} concentrations and public healthcare expenditures for the period 2012–2022. The test indicated that the PM_{10} concentration data follow a normal distribution, as evidenced by the test statistic $W = 0.9014$ and p-value of 0.193, which exceeds the 5% significance level ($p > 0.05$). Conversely, the data on public healthcare expenditures did not meet the assumption of normality, as shown by the test statistic $W = 0.0186$ and p-value 0.019 ($p < 0.05$).

In light of these results, the Spearman correlation analysis was selected for further investigation, as it is appropriate for data sets that do not meet the assumption of normality.

Tab. 4: Correlation of average PM10 concentrations and public healthcare expenditures

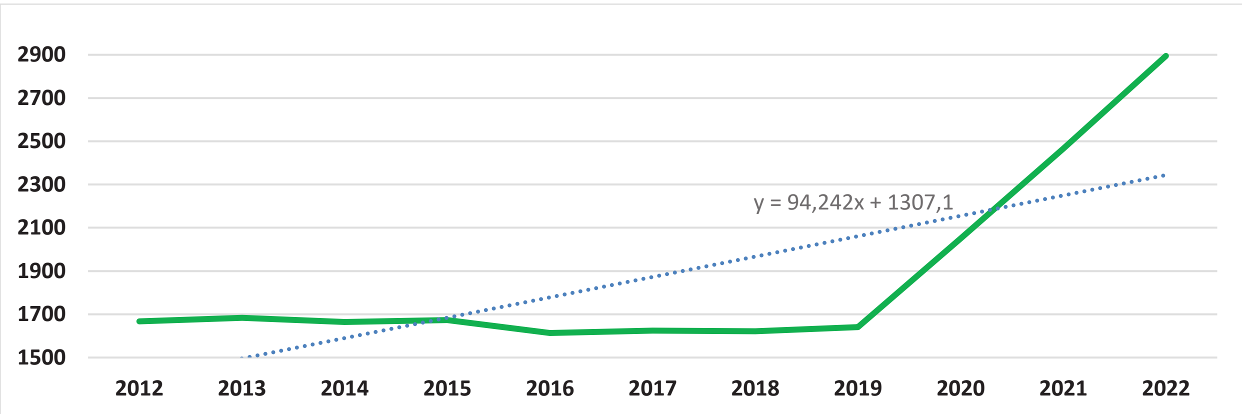
	Average concentrations of PM10	**Public healthcare expenditures**
Average concentrations of PM10	1	-0.91136364
Public healthcare expenditures	-0.91136364	1

Source: Authors based on (ČHMÚ, 2023; ČSÚ, 2023).

Table 4 presents the Spearman correlation coefficient, which was approximately -0.9114, indicating a strong negative monotonic relationship. This relationship suggests that as PM10 concentrations decreased, public healthcare expenditures tended to increase. The significance level was set at 5%, and the p-value obtained was considerably lower than this threshold, confirming the statistical significance of the relationship. Consequently, the null hypothesis H0, which assumed no monotonic relationship between the two variables, was rejected.

Additionally, data on government debt in the CR were monitored on an annual basis for the period 2012–2022. The data were obtained from the Ministry of Finance of the Czech Republic (MFČR, 2024).

Graph 10: Trend in government debt in the CR [CZK billion]



Source: Authors based on (MFČR, 2024).

Graph 5 illustrates the development of government debt in the Czech Republic between 2012 and 2022. The data reveal a substantial increase in government debt, rising from CZK 1667,6 billion in 2012 to CZK 2894,8 billion in 2022. The most significant increase occurred between 2019 and 2020, when the debt surged by over CZK 400 billion, followed by continued growth between 2020 and 2022. These increases can be largely attributed to extraordinary circumstances, particularly the economic consequences of the COVID-19 pandemic. The linear regression displayed in the graph confirms a long-term upward trend, with the average annual increase in government debt estimated at approximately

CZK 94,24 billion.

Tab. 5 Basic statistical analysis of government debt in the CR (2012–2022)

Statistics	Value
Mean value ($\bar{X}$)	CZK 1872.55 billion
Variance (σ^2)	CZK 183481.29
Standard deviation (σ)	CZK 428.35 billion
Minimum value	CZK 1613.4 billion
Maximum value	CZK 2894.8 billion

Source: Authors based on (MFČR, 2024).

Table 5 presents a basic statistical analysis of government debt in the Czech Republic for the period 2012–2022. The mean value of the government debt during this period was CZK 1872,55 billion, reflection the long-term level of indebtedness. The variance, amounting to CZK 183481,29, indicates considerable year-on-year fluctuations in debt levels. The standard deviation of CZK 428.35 billion further illustrates the average deviation from the mean. The lowest level of debt was recorded in 2016, at CZK 1,613.4 billion, while the highest value (CZK 2,894.8 billion) was reached in 2022. These findings confirm a rising trend in public debt, particularly in the latter years of the period, likely influenced by extraordinary events such as the COVID-19 pandemic.

Tab. 6: Shapiro-Wilk normality test

Data	Test statistics (W)	p-value	Data normality
Government debt	0.659685373	0.000142914	No
Mean concentrations of PM_{10}	0.901470184	0.192638814	Yes

Source: Authors based on (ČHMÚ, 2023; MFČR, 2024).

Table 6 presents the results of the Shapiro-Wilk normality test conducted on the data on government debt and PM10 air pollution in the CR for the period 2012–2022. The results indicate that the distribution of government debt data deviates significantly from normality, as confirmed by the test statistic W = 0.6597 and a p-value of 0.00014, which is well below the 5% significance threshold. In contrast, the data on average PM10 concentrations satisfy the assumption of normality, making them suitable for parametric statistical analyses.

Based on these results, Spearman’s rank correlation analysis was selected for further examination, as it is appropriate for data that do not meet the assumption of normality.

Tab. 7: Correlation between PM10 concentrations and government debt in the CR

	Government debt	**Average concentrations of PM_{10}**
Government debt	1	-0.36136364
Average concentration of PM_{10}	-0.36136364	1

Source: Authors based on (ČHMÚ, 2023; MFČR, 2024).

Table 7 presents the resulting Spearman correlation coefficient, which reached approximately -0.3614, indicating a weak negative monotonic relationship between the two variables. This suggests that a decrease in PM_{10} concentrations may be accompanied by a slight increase in national debt; however, the relationship is not statistically significant. The significance level was set at 5%, and the obtained p-value of 0.26171 exceeds this threshold ($p > 0.05$). Therefore, the relationship between PM_{10} concentrations and national debt cannot be considered statistically significant.

Discussion

Based on the obtained findings, the formulated research questions can be answered:

RQ1: What were the trends in air pollution (PM_{10}) in the Czech Republic during the period 2012–2022?

The results of the analysis revealed a downward trend in PM_{10} concentrations in the CR in the selected period. This decline can largely be attributed to technological modernization, improvements in industrial processes, and the implementation of stricter environmental regulations, including adherence to European emission standards. These findings are consistent with the conclusions of Chen et al. (2022), who underscore the role of technological innovation and investments in environmental protection as key factors in improving air quality. However, the sustainability of this downward trend remains uncertain. As noted by Halkos & Papageorgiou (2018), systemic reforms, such as the introduction of environmental taxes, could be essential for achieving log-term reduction in pollution and mitigating its economic impacts.

An interesting and unexpected development during this period was the influence of the COVID-19 pandemic, which had a significant effect on air quality. A sharp drop in PM_{10} concentrations was observed in 2020, coinciding with the peak of pandemic-related restrictions. Reduced transportation and industrial activity during lockdowns highlighted the sensitivity of air pollution levels to changes in human behaviour and economic operations. A similar pattern was reported by Sakib et al. (2023), who documented a comparable decline in emissions in Bangladesh during the pandemic.

However, the data also show notable fluctuations in PM_{10} concentrations, particularly in 2017 and 2018. These fluctuations may be due to seasonal factors and climatic conditions. Liang et al. (2021) emphasize that factors such as humidity, temperature, and wind speed can have a significant influence on air quality. Such variability indicates that both short-term and long-term dynamics must be considered when designing environmental policies, in order to ensure their effectiveness under a range of conditions.

RQ2: How did public healthcare expenditures evolve in the Czech Republic during the period 2012–2022?

Public healthcare expenditures in the CR in the selected period showed a downward trend, with the sharp increase between 2019 and 2020, which can be attributed to the COVID-19 pandemic. Overall, this trend reflects substantial investment in medical supplies, healthcare infrastructure, and preventive measures. Notably, even after the acute phase of the pandemic subsided, expenditure levels remained above the pre-pandemic ones in 2019. This may suggest structural shifts within the Czech healthcare system.

Similar trends were observed in other studies. For example, Velásquez & Lara (2020), who deal with the impact of the COVID-19 pandemic on healthcare systems in Lima, described how the pandemic prompted a considerable strengthening of healthcare infrastructure and preventive measures. Xia et al. (2022) explored the relationship between air pollution (particularly $PM_{2.5}$) and rising healthcare costs. Their findings suggest that improvements in air quality could contribute to long-term reduction in public healthcare expenditure.

These insights underscore the importance of long-term strategies that extend beyond short-term crisis management to include prevention, preparedness, and sustainable financing of the healthcare system. The observed growth in healthcare expenditure may therefore reflect broader policy shifts, with public health increasingly viewed as a central pillar in political decision-making.

RQ3: Is there a relationship between air pollution levels (PM_{10}) and public healthcare expenditures in the Czech Republic during the period 2012–2022?

Spearman correlation analysis revealed a strong negative monotonic relationship between PM_{10} concentrations and healthcare expenditures, suggesting that the decrease in PM_{10} levels was associated with an increase in healthcare expenditures. This finding is initially surprising, as a reduction in healthcare costs could be expected with improved air quality.

One possible explanation is the "delayed effect" of air pollution, where health issues associated with long-term exposure to poor air quality persist even after environmental conditions improve. Bahrami et al. (2024) emphasize that chronic diseases, such as respiratory and cardiovascular diseases, incur long-term costs that may not immediately decrease, even with a reduction in pollution levels.

The increase in healthcare spending may also be attributed to structural changes within the healthcare system. Improved air quality could have enabled governments to reallocate resources toward modernizing healthcare infrastructure or supporting preventive programs, which would contribute to long-term improvements in public health. Nevertheless, these findings align with the conclusions of Xia et al. (2022), who highlight the enduring health impacts of pollution that can persist even after air quality improves.

However, the COVID-19 pandemic likely played a crucial role, as the surge in healthcare spending during 2020 and 2021 may have contributed to the apparent negative correlation with declining PM_{10} levels. Velásquez & Lara (2020) suggest that the combination of reduced air pollution and increased healthcare expenditure during the pandemic could have distorted the perceived relationship between these variables. Paradoxically, while air quality improved during the lockdown, potentially lowering healthcare costs, the pandemic itself led to increased healthcare costs related to COVID-19 treatment and enhanced preventive measures.

This result underscores the complexity of the relationship between air quality and public healthcare spending. While lower PM_{10} concentrations may ultimately reduce healthcare costs in the long run, it should be considered that healthcare systems respond not only to current challenges but also to cumulative impacts from the past and broader societal changes.

RQ4: What is the impact of PM_{10} air pollution on the public debt of the Czech Republic during the period 2012–2022?

In the Czech Republic, government debt exhibited an upward trend over the analysed period, rising from CZK 1667,6 billion in 2012 to CZK 2894,8 billion in 2022. However, the Spearman correlation between PM_{10} concentrations and government debt indicated a weak negative monotonic relationship, which was statistically insignificant. These results suggest that, within the Czech context, the primary drivers of public debt were macroeconomic factors—such as pandemic-related healthcare expenditures, social support measures, and other crisis-related interventions—rather than the direct environmental impacts of air pollution.

Although the analysis did not show a statistically significant direct relationship between air pollution and government debt, studies such as Boly et al. (2022) point to possible indirect links. Their findings highlight that rising public debt may hinder the financing of environmental policies, while insufficient investment in environmental protection can, over time, lead to higher emissions and increased healthcare costs. Conversely, Han et al. (2023) argue that although investments in green technologies may raise public debt in the short term, they can deliver long-term economic and health benefit.

These insights underscore the complexity of the interplay between environmental and economic factors. While the impact of air pollution on government debt appears weak, indirect effects should not be disregarded. It is therefore essential that environmental policies be crafted in a manner that simultaneously promotes sustainable development and maintains fiscal responsibility.

Conclusion

The objective of this paper was to assess the impact of air pollution and investment in its mitigation on public expenditures in the Czech Republic in the period 2012–2022, with a focus on analysing air pollution trend, development of public healthcare expenditures, and the impact of government investment on financial stability. The set objective was achieved.

The analysis revealed that PM_{10} concentrations generally followed a decreasing trend over the observed period. At the beginning of the period, concentrations reached 29 μg/m^3, while by the end they had stabilized at 20 μg/m^3. The most significant decline occurred during the COVID-19 pandemic, likely due to restrictions on emissions from transport and industrial activities. Overall, the findings confirm an improvement in air quality during the decade, with the most notable progress occurring after 2019.

In contrast, public healthcare expenditures in the Czech Republic demonstrated a steadily increasing trend. Starting at CZK 33.2 billion at the beginning of the observed period, they peaked at CZK 91.9 billion in 2020. Although a slight decline followed, expenditures remained above pre-pandemic levels.

Correlation analysis revealed a strong negative monotonic relationship between PM_{10} concentrations and public healthcare expenditures over the selected decade. Spearman's correlation coefficient indicated that as air pollution decreased, health-related public spending increased. This relationship underscores the complex and possibly delayed impact of air quality on healthcare costs.

Government debt showed an upward trend in the observed period, rising from CZK 1667,6 billion in 2012 to CZK 2894,8 billion in 2022. The relationship between PM_{10} concentrations and the government debt was weaker. Spearman correlation coefficient showed a mild negative monotonic relationship, which was not statistically significant. These findings suggest that the impact of air pollution on government debt is rather indirect and may be influenced by other factors, such as economic shocks, pandemics, and structural changes in fiscal policy.

The main limitation of this study was the relatively short observation period and the restriction of available data to average annual values. Another limitation is the absence of direct measurements of health consequences of air pollution and their impact on individual components of government debt.

Further research could include analysis of extended period and incorporating data with greater temporal resolution. Moreover, it would be recommendable to consider regional differences in air quality, public healthcare expenditures, and government debt.

The results of this paper may support the development of policies aimed at improving air quality, enhancing the efficiency of healthcare spending, and promoting the long-term stability of publicfinances.

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