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ESTIMATION OF THE EFFECTS OF MULTI-SOURCE POLLUTANTS ON HEALTH EXPENDITURE: THE CASE OF FRANCE

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Abstract: The objective of this study is to identify the main sectors that contribute to the emission of atmospheric pollutants (agricultural, industrial, residential, and transport) and to examine their effects on health expenditure in France. The partial least squares (PLS) regression method was adopted to obtain a reliable estimate, which focuses on six multi-source pollutants including nitrogen dioxide (NO_X), non-methane volatile organic compounds (NMVOC), ammonia (NH_3), sulphur oxides (SO_2), and particulate matter ($PM_{2.5}$ and PM_{10}) and on Health Expenditure (HE) as a dependent variable. The empirical results reveal several important findings. First, the models of the four sectors are all significant. Then, most pollutants negatively affect health expenditure, particularly the highest coefficient of NO_X, which accounts for 0.81 in the residential sector, a coefficient of 0.29 in the agricultural sector, that of SO_2 emissions (0.76) in the industrial sector, and particulate matter in the transport sector with coefficients of 0.29 and 0.28. It was found that France applied strict measures to reduce multi-source pollutants and succeeded in strengthening its health system.

Keywords: Ammonium, nitrogen dioxide, non-methane volatile organic compound, particulate matter, sulphur oxides.

Introduction

The research aiming at better understanding and mitigating the health effects of air pollution from multiple sources has a rich and interesting history. Air pollution can also have a significant economic impact through increased healthcare costs, lost productivity, and damage to property and infrastructure (OCDE, 2016).

According to sociologist Phil Brown's 2007 definition, health issues related to environmental pollution are "the health impacts induced by toxic substances present in people's immediate or adjacent environments (air, soil, food, water, household goods)". Identifying different environmental health concerns and establishing a causal relationship between environmental pollution and its effects on human health is a challenging task. Therefore, environmental health problems are usually characterised by ambiguity, which makes it difficult to draw clear conclusions.

The prevalence of air pollution and possible short- and long-term health effects make it a critical issue. Since each of the major air pollutants nitrogen dioxide (NO_X), ozone (O_3), sulfur (SO_2), carbon monoxide (CO), and particulate matter (PM) has a distinct effect, the majority of empirical studies on the health effects of air pollution have concentrated on understanding the effects of these pollutants. Given that people are constantly exposed to a variety of air pollutants that are closely connected, it is important to consider the phenomenon of multiple pollutants (Billionnet *et al*., 2012). The need to determine the relationship between health problems and the presence of a broader mixture of several pollutants has recently been highlighted to protect public health better and to facilitate decision-making in the management of the quality of air (Davalos *et al*., 2017).

The effects of environmental pollution on human health include not only the impact on life quality but also on health care expenses, the loss of income, and productivity. However, costs direct and indirect influence of environmental retraction on public health can be deducted (Badulescu *et al*., 2019). According to Magazzino *et al*. (2020), the transport sector which is highly dependent on petroleum products (mainly gasoline and diesel), is the main emitter of PM in France, the critical levels of which lead to adverse effects on the health of urban residents. The health consequences of air pollution linked to the transport sector constitute one of the main sources of concern for the sustainability of this sector. In urban areas, transport contributes heavily to air pollution and affects a large part of the population due to the high number of motor vehicles and urban population (Zeiri *et al*., 2021). So, the research question is: Which sector has the greatest impact on public health and, consequently, on healthcare spending?

The objective of this study is to identify the main sectors (agricultural, industrial, residential, and transport) which contribute to the emission of atmospheric pollutants and to examine their effects on health expenditure in France, over the period 1990-2020. The primary hypothesis is that a relationship exists between air pollution originating from the four sectors and healthcare expenditure. The partial least squares (PLS) regression is used in this study to accept or reject this hypothesis. In this paper, the following work plans are adopted. The second section reviews the literature on the chosen topic. The data and empirical methodology used are described in the third section. The fourth section explains the main results of the study. Finally, the results of the study were discussed before concluding.

Literature Review

For decades, many researchers and other stakeholders have been interested in the effects of pollutants from multiple sources on human health. We propose a systematic literature review on air pollutants from different sources and their effects on the health of living creatures. Pope and Dockery (2006) studied the effect of air pollution by PM on human health. They demonstrated that fine particles have a direct relationship with cardiovascular disease and cardiopulmonary morbidity and mortality. Using panel data from 8 OECD countries from 1980 to 1999, Narayan and Narayan (2008) found that the emissions of nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO_2) are negatively associated with the healthcare status. Further, they suggest that the health policy should be formulated considering the quality of the environment for the well-being of the community.

Moreover, Billionnet *et al*. (2012) discuss the statistical methods used in studying the effect of multiple pollutants. The authors found that 18 studies on the effect of multiple pollutants have been conducted, with 10 on outdoor pollution, 5 on indoor pollution, and 3 statistical methodologies applied to outdoor pollution. At the same time, the other studies discussed only the statistical methodologies. They summarise that using methods providing risk assessments should be emphasised in public healthcare. Human exposure to the particles, especially the $PM_{2.5}$, may cause chronic respiratory and cardiovascular diseases in addition to some cancers and low birth weight (Hoek *et al*., 2013; Pedersen *et al*., 2013; Beelen *et al*., 2014; Stafoggia *et al*., 2014). Nitrogen dioxide correlates with respiratory disorders such as asthma, especially in children (Jacquemin *et al*., 2009; Hoek *et al*., 2013).

Deng *et al*. (2016) reported that air pollutants from the industrial sector embedded in consumer and commercial goods in China increased during the years 1995-2009. The most air pollutant emissions are carbon dioxide (CO_2), while emissions of methane (CH_4), carbon monoxide (CO), sulphur oxides (SO_2), non-methane volatile organic compounds (NMVOCs), nitrogen oxides (NO_X), ammonia (NH_3) and nitrous oxide (NO_2) at a medium level. Traditionally, air pollution studies focused on the relationship between individual air pollutants and health outcomes. Associations between individual pollutants are often estimated by adjusting the other pollutants present in the mixture to account for potential confusion linked to pollutants. Davalos *et al*. (2017) identified new and innovative statistical methods to analyse the risks associated with exposure to multiple pollutants through extensive documentary research, with an emphasis on statistical approaches currently used in epidemiological studies about short-term exposures to the main air pollutants (i.e., particulate matter, carbon monoxide, sulfur dioxide, nitrogen dioxide, and ozone).

Wei *et al*. (2018) sought to identify the main sectors that contribute to air pollution emissions and verify the regional heterogeneity characteristics of air pollution in China using PLS regression. They demonstrated that air pollution comes mainly from coal consumption, coke production and electricity generation in non-key areas. The main air pollutants in urbanised areas are mainly nitrogen oxides (NO_X), sulfur oxides (SO_X), volatile organic compounds (VOCs) and particulate matter (PM). Under certain weather conditions, these air pollutants are transformed into $PM_{2.5}$ after a complex chemical reaction process. This situation further aggravates the pollution and the consequences on human health.

During the period 1995-2017, Moosa (2019) studied the impact of environmental degradation on health expenditure in Australia. It showed that carbon dioxide (CO_2) emissions have negative effects on the health of the citizens, which leads to the need for higher levels of health expenditure. The growth of the industrial sector, transport and urbanisation is at the origin of these negative effects. Using panel data from 20 Asian countries and using the dynamic ordinary least squares method, Ullah *et al*. (2020) examined the relationship between health and environmental quality indicators (carbon dioxide emissions, sulfur dioxide emissions and particulate concentrations) in the long term. They showed that air pollution worsens human health in developing Asian countries, as the CO_2, SO_2 and $PM_{2.5}$ pollutants have a negative effect on health.

Khojasteh *et al*. (2021) found evidence of the effect of carbon monoxide and nitric oxide on respiratory mortality by studying the daily variations in mortality and respiratory disease caused by air pollutants in Ahvaz Iran, for nine years. Furthermore, the sensitivity analysis and the ADF test results show that the other pollutants (SO_2, NO_2, O_3, PM_{10}) have no significant influence on total respiratory morbidity and mortality. Zeiri *et al*. (2021) studied the effect of pollutants from road transport in particular on health in France during the period 1990-2020 with ARDL modelling. They revealed that the pollutants SO_2, NO_X, PM10, NMVOC and CH_4 have statistically significant effects on short-term life expectancy and that PM_{10} is the most threatening to health in France.

Abulude *et al*. (2022) evaluated air quality in 253 urban and suburban cities in Nigeria using a one-day monitoring method. Data on six air pollutants particulate matter ($PM_{2.5}$, PM_{10}), ozone (O_3), nitrogen dioxide (NO_2), carbon monoxide (CO), and sulfur dioxide (SO_2) were collected by the authors. The study found that air quality in Nigeria is generally poor with elevated levels of $PM_{2.5}$ and PM_{10}, and urban areas have worse air quality compared to suburban areas.

Recently, several studies have examined the relationship between CO_2 emissions and health expenditure in a group of countries, including a study by Hamid and Wibowo (2023) that used regression analysis of panel data to analyse five ASEAN countries. Their results indicate a significant positive relationship between CO_2 emissions and health expenditure. The study argues that this correlation may be attributed to the adverse health impact of air pollution resulting from CO_2 emissions. Air pollution can cause various health issues such as respiratory infections, heart disease, and cancer, leading to escalated healthcare expenses for individuals and governments. Indeed, Zeiri *et al*. (2023) examined the impact of economic growth and pollution on healthcare expenditures in G7 countries from 1990 to 2020 and employed the partial least squares (PLS) regression technique. Their findings reveal that GDP has a positive influence on healthcare spending in all nations except for Canada.

Additionally, CO_2 emissions adversely affect healthcare expenditures in all countries, except Japan. In addition, the impact of MR on healthcare spending is negative in France, Italy, the United States, and the United Kingdom. Similarly, the study conducted by (Weng *et al.,* 2023) investigates the effects of clean air measures on public health expenditure in China. The research indicates that these measures significantly improved health outcomes and reduced medical expenses related to air pollution. Furthermore, the study concludes that enhanced air quality mitigated health expenditure inequalities in low-income and under-resourced areas of Chinese cities.

Data and Methods

Data

Our study aims to examine the health impact of pollutants from four sectors (transport, agriculture, industry, and residential activities) in the case of France over the period (1990-2020). The data come from the National Institute of Statistics and Economic Studies (INSEE) and the Interprofessional Technical Center for the Study of Air Pollution (CITEPA).

Equation (1) shows the chosen variables of our study based on the literature.

$$HE = f(NOX, NMVOC, NH3, SO2, PM2.5, PM10) \quad (1)$$

Health Expenditure (HE)

According to the (DRESS, 2023)[1] (Research, Studies, Evaluation and Statistics Department), health expenditure measures the consumption of medical care and goods (CSBM) including hospital care (public and private sector hospitals), ambulatory care such as medical transport, ambulatory medicines and other medical goods such as vehicles for the physically handicapped. For our study, we are interested in the CSBM, which represents three-quarters (INSEE, 2020)[2] of the current health expenditure in France.

In 2019, the CSBM increased by 2.1% in value (the same as for the volume), of which the public hospital sector explains 0.8 points. There has been a noticeable decline in the dynamism of the CSBM value during the period between 2014 and 2019, as compared to the period between 2009 and 2014. The increase in value over the last five years has averaged 1.8%, whereas the value had increased at 2.3% during the previous years. The slowdown in terms of volume has been even more pronounced since 2017. This slowdown has been predominantly attributed to the evolution of hospital care consumption, as indicated by Figure 1.

Nitrogen Oxide (NO_X)

Major parts of nitrogen oxide emissions are two molecules (nitrogen monoxide NO and nitrogen dioxide NO_2). These emissions are related to human activities like industry (burning fossil fuels, making glass, cement, and metals), sea transport, and road transport because of exhaust gases.

According to CITEPA (2022)[3], the sector that emits the most NO_X is road transport. As early as 1966, it was responsible for 63% of total NO_X emissions in 1990. Since 1993, studies have shown that emissions from this sector have been detraction despite the excess in the number of vehicles and traffic. The agriculture sector comes after with a percentage of 14% in 2019, followed by the industrial sector, which rose from 11% in 1990 to 13% in 2019 of total NOX emissions (Figure 2). Zeiri *et al*. (2021) show that nitrogen dioxide emissions from road transport decreased by (16%) between 2019 and

1 https://data.drees.solidarites-sante.gouv.fr/pages/accueil/.
2 https://www.insee.fr/fr/statistiques/1288568?sommaire=1288637.
3 https://www.citepa.org/fr/2022_01_a02/.

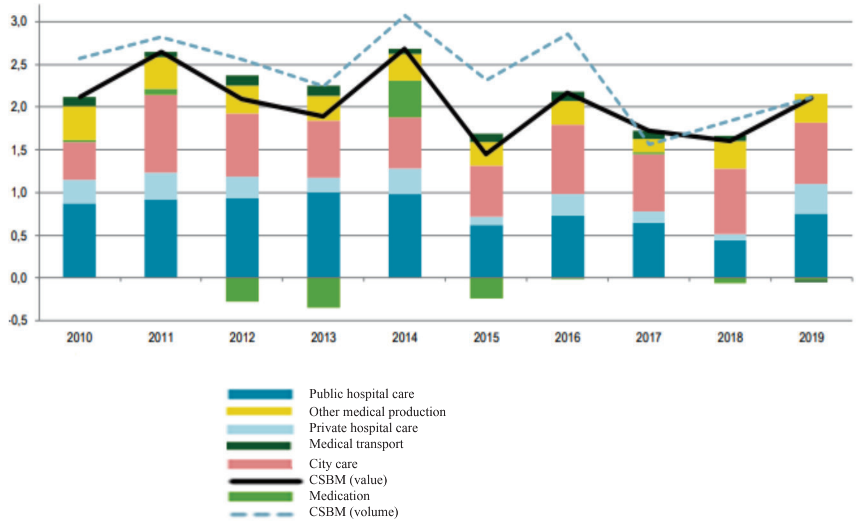


Figure 1: Evolution of CSBM in value with its main components and in volume from 2010 to 2019 for France (in %)
Source: DREES, comptes de la santé

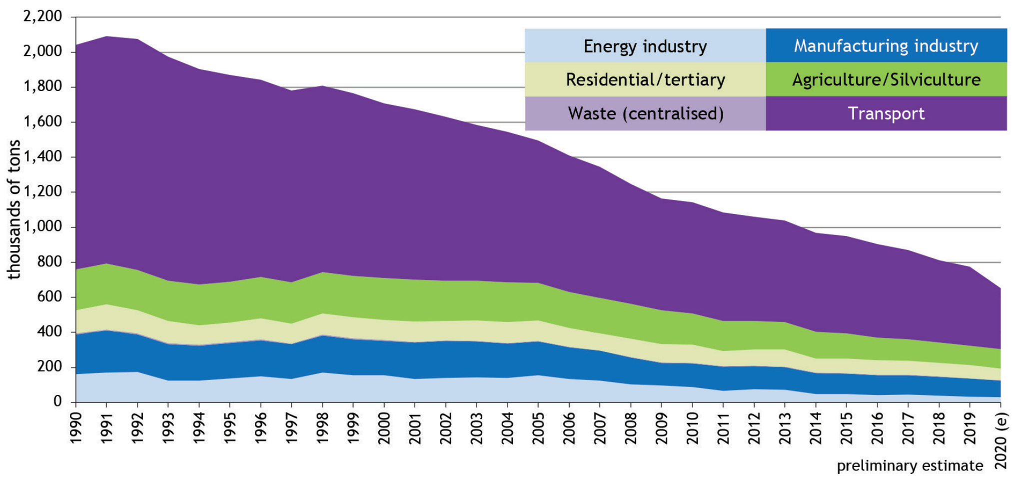


Figure 2: Evolution of NO_X emissions into the air since 1990 in France
Source: Citepa (2020)

2020. This overall decrease in emissions from the transport sector is related to the implementation of European emission standards since 1970.

Non-methane Volatile Organic Compounds (NMVOC)

The NMVOC correspond to emissions of non-methane volatile organic compounds. They form a complex and heterogeneous group of substances resulting from very different sources such as combustion, the use of solvents and some industrial processes based on alcoholic fermentation or vegetation.

According to Figure 3, the transport sector accounted for 33% of the total non-methane volatile organic compound (NMVOC) emissions in 1990, followed by the tertiary or residential sector at 25%, the industry sector

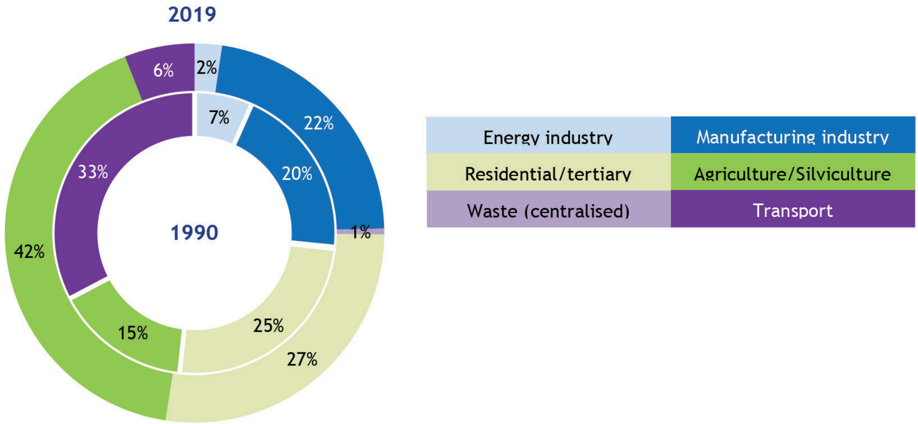


Figure 3: Breakdown of NMVOC emissions by sector in France (in %)
Source: Citepa (2020)

at 20%, and the agriculture sector with 15%. However, as of 2019, the highest amounts of NMVOC emissions were recorded in the agricultural sector, which contributed 42% of the total emissions, followed by the residential sector with 27% and the industrial sector with 22%.

Ammonia

Ammonia is a hazardous waste for the environment and health. It can cause burns and lung irritation. It is essentially a pollutant of agricultural origin emitted during the spreading of slurry from livestock and also but also during the manufacture of ammonia fertilisers.

From the 1990s, the main sector responsible for NH_3 emissions was agriculture. This sector was responsible for 95% of total NH_3 emissions in 1990 with 628,000 tonnes. In 2020, this figure decreased to more than 553,000 tonnes to reach a 94% share of total ammonia emissions (Figure 4).

Sulphur Dioxide

Sulphur dioxide emissions are one of the historical substances of air pollution. They lead to the deposition of sulphates and sulfuric acids, which disrupt ecosystems. SO_2 releases come from many sources (domestic heating and diesel vehicles) as well as larger point sources such as

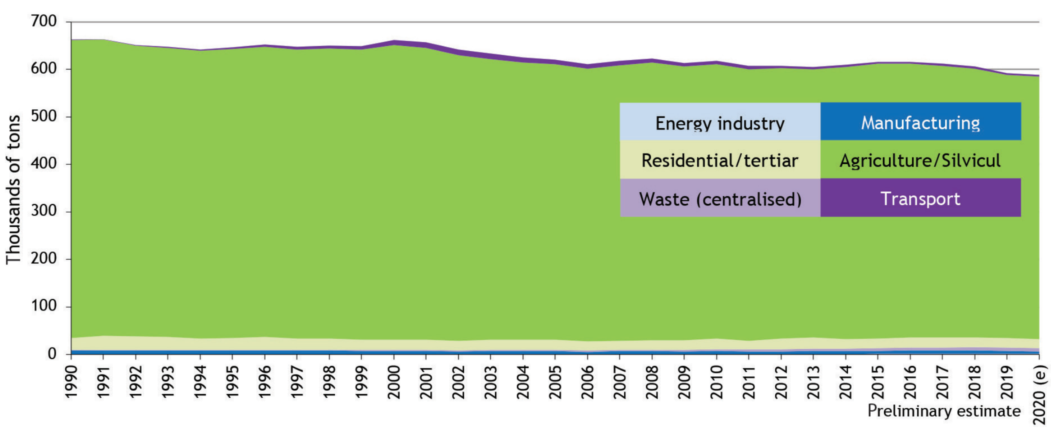


Figure 4: Evolution of NH_3 air emissions since 1990 in France
Source: Citepa (2020)

power or steam power plants, and district heating plants. Besides, some industrial processes produce sulfur effluents such as sulfuric acid production, and petroleum refining.

As shown in Figure 5, the sector that emits the most sulfur dioxide emissions is the industry, with a share of 55% in 2019. In fact, over the period 1990-2019, SO_2 emissions have decreased by 91%. In 2019, the release of 114 kt of SO_2 was the lowest level reached for almost half a century and the strongest downward trend that began in the mid-1970s. It was interrupted in 1991 and 1998 due to particular circumstances. This is mainly due to the reduction in the sulfur content of petroleum fuels and the increasing share of low-sulphur fuels (CITEPA, 2022).

Particulate Matter

Particulate matter also called ultrafine, fine and coarse particles have been classified into different size categories, such as $PM_{0.1}$, $PM_{2.5}$, and PM_{10}. The particles in question are generated through the combustion of diesel and gasoline in motor vehicles, solid domestic fuels, industrial activities, automobile traffic, agricultural or mining activities, and excavation work. The focus of the study is on PM10 and PM2.5, as these particles are known to pose a greater risk to human health compared to others. It is important to understand the impact of these particles on human health.

According to a study conducted by Ullah *et al*. (2020), the largest anthropogenic sources of PM emissions in France in 2019 were the tertiary (residential) sector, which contributed 53% of $PM_{2.5}$ and 32% of PM_{10}, while the manufacturing industry and construction represented 27% of PM_{10} and 18% of $PM_{2.5}$. Other sectors such as agriculture, transport, and energy production, also made significant contributions ranging from 10% to 25% (Figure 6). The study further highlights that these particles not only have adverse effects on human health, such as premature death but they also damage plants and crops by causing acid rain when mixed with moisture.

Methods

In this work, the effect of pollutants from the transport, agriculture, industrial and residential sectors was examined on health expenditure in France using the PLS method. The choice of this method is explained by the existence of a multicollinearity problem between the explanatory variables (see the autocorrelation matrices), the low number of observations (31 observations) and the presence of missing data in our database. The PLS method was proposed by Herman Wold (1966) as part of the modelling

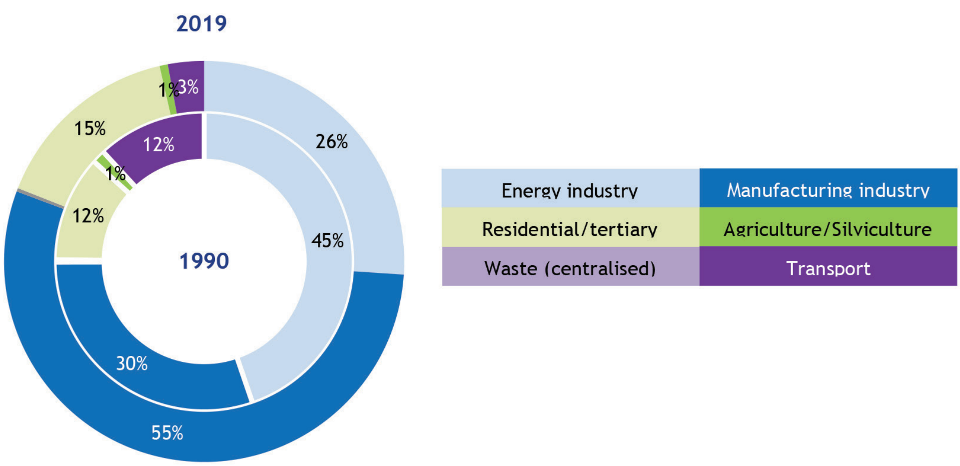


Figure 5: Breakdown of SO_2 emissions by sector in France (in %)
Source: Citepa (2020)

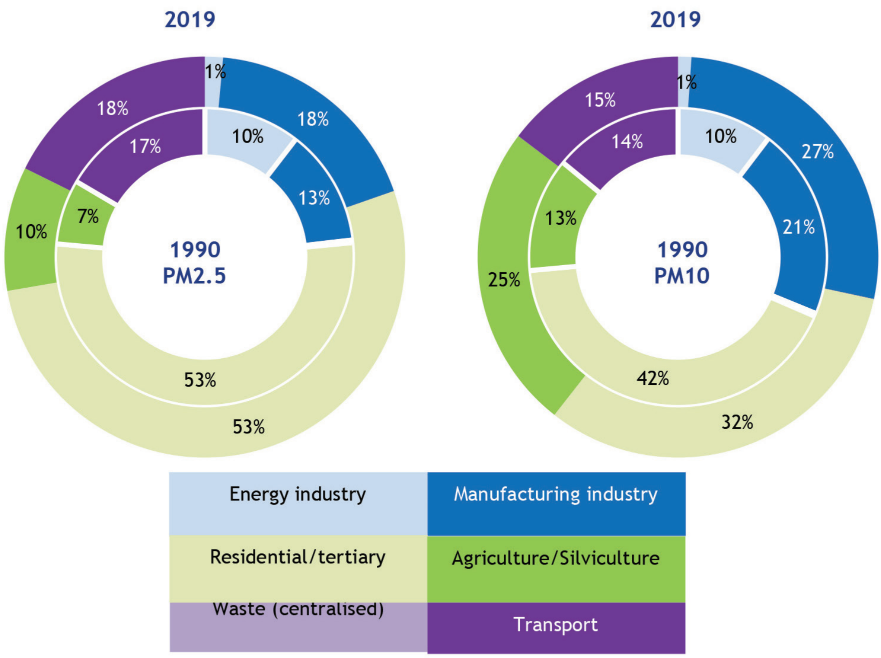


Figure 6: Breakdown of $PM_{2.5}$ and PM_{10} emissions by sector in France (in %)
Source: Citepa (2020)

of structural relationships on latent variables for the analysis of several blocks of variables observed in the same individuals. Wold and Harold (1983) then developed this method for application in chemometrics.

The PLS regression method is indeed a dimensionality reduction technique used when working with high-dimensional data and when there is strong collinearity between variables. In this case, the PLS technique is suitable because it reduces the dimension and ensures that the composite variables are not correlated. It thus makes it possible to distinguish a binary or nominal continuous dependent variable with K modalities from a matrix of quantitative or mixed continuous explanatory variables. PLS regression aims at combining features of principal component analysis (PCA) and regression to achieve a trade-off between maximising the variance explained by the variables.

In the article "PLS Regression and Applications" and his research notebook "New PLS Regression", Tenenhaus (1998) presented the PLS method with its algorithm, equations, as well as its main components and graphical interpretations. This PLS regression is performed in three steps. The first step is to calculate the orthogonal components of the blocks of explanatory variables X. The second is the regression of Y on the PLS orthogonal components most correlated to Y (see appendix). The third is the expression of the regression equation as a function of X (Desbois, 2002).

According to Tenenhaus (1998), partial least squares regression is based on the following iterative algorithm,

Step 0: we start from the initial tables X and Y.

Step 1: we calculate the vector W_1:

$$W_{1j} = \mathrm{cov}(X_j, Y) \Big/ \sqrt{\sum_{j=1}^{p} \mathrm{cov}^2(X_j, Y)} \qquad (2)$$

Then, a linear combination t_1 of the explanatory variables X_j must be performed:

$$t_1 = w_{11}X_1 + \ldots + w_{1p}X_p \qquad (3)$$

The regressions of Y and X on t_1 are then:

$$X = tp_1^{'} + X_1 \quad (4)$$

$$Y = t_1 c_1^{'} + Y_1 \quad (5)$$

where X_1 and Y_1 are the vectors of the residuals.

Step 2: Two new components t_2 and w_2 were constructed which represent the linear combinations of the linear combinations of the columns of X_1 and Y_1 respectively. From where:

$$t_2 = w_{21}X_{11} + ... + w_{2j}X_{1j} + w_{2p}X_{1p} \quad (6)$$

$$W_{2j} = \mathrm{cov}(X_{1j}, Y) \Big/ \sqrt{\sum_{j=1}^{p} \mathrm{cov}^2(X_{1j}, Y)} \quad (7)$$

The regressions of Y and X were performed on t_1 and t_2:

$$X = t_1 p_1^{'} + t_2 p_2^{'} + x_2 \quad (8)$$

$$Y = t_1 c_1^{'} + t_2 c_2^{'} + y_2 \quad (9)$$

The same steps for the other components were repeated to construct the following regression:

$$Y = X \sum_{h-1}^{a} w_h c_h + Y_a \quad (10)$$

Results

The current study objective is to examine the effect of pollutants from the four sectors (agricultural, industrial, residential and transport) on health expenditure in France over 30 years, from 1990 to 2020, using SIMCA-P software.

Correlation Matrices

It was found that in the four sectors of agriculture, industry, residential and transportation, most of the variables are strongly correlated; otherwise, the results of the correlation matrix present a major problem of autocorrelation (Table 1).

The results illustrated in Figure 7 indicate that the coefficient of determination for the agricultural sector (R2Y = 0.985) surpasses 50%, which implies an excellent quality of fit. The model demonstrates global significance with two PLS components.

$$HE = 9.6 - 0.29NOX_a + 0.11NMVOC_a - 0.11NH3_a - 0.19SO2_a - 0.25PM10_a - 0.26PM2.5_a \quad (11)$$

According to Equation (11), the contribution of all pollutants from the agricultural sector

Table 1: Correlation matrices

Agriculture sector

	HECSBM	NOXA	NMVOCA	NH3A	SO2A	PM10A	PM2_5A
HECSBM	1	-	-	-	-	-	-
NOXA	**-0.991**	1	-	-	-	-	-
NMVOC	-0.584	0.590	1	-	-	-	-
NH3A	**-0.626**	**0.622**	**0.835**	1	-	-	-
SO2A	**-0.760**	**0.729**	0.501	0.385	1	-	-
PM10A	**-0.982**	**0.988**	0.544	0.542	**0.776**	1	-
PM2_5A	**-0.986**	**0.981**	0.522	0.520	**0.810**	**0.995**	1

Industry sector

	HECSBM	NOXI	COVNMI	NH3I	SO2I	PM10I	PM2_5I
HECSBM	1	-	-	-	-	-	-
NOXI	**-0.975**	1	-	-	-	-	-
COVNMI	**-0.945**	**0.930**	1	-	-	-	-
NH3I	0.077	0.005	-0.016	1	-	-	-
SO2I	**-0.964**	**0.961**	**0.942**	0.150	1	-	-
PM10I	-0.4248	0.486	0.464	0.290	**0.561**	1	-
PM2 5I	**-0.625**	**0.671**	**0.674**	0.524	**0.785**	**0.883**	1

Residential sector

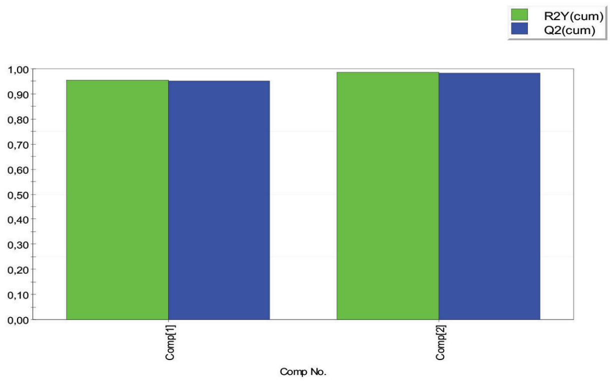
	HECSBM	NOXR	COVNMR	NH3R	SO2R	PM10R	PM2_5R
HECSBM	1	-	-	-	-	-	-
NOXR	**-0.898**	1	-	-	-	-	-
COVNMR	**-0.891**	**0.899**	1	-	-	-	-
NH3R	-0.299	**0.665**	0.460	1	-	-	-
SO2R	**-0.945**	**0.980**	**0.940**	0.569	1	-	-
PM10R	**-0.904**	**0.982**	**0.941**	**0.654**	**0.988**	1	-
PM2_5R	**-0.904**	**0.981**	**0.941**	**0.653**	**0.988**	**0.999**	1

Transportation sector

	HECSBM	NOXT	COVNMT	NH3T	SO2T	PM10T	PM2_5T
HECSBM	1	-	-	-	-	-	-
NOXT	**-0.928**	1	-	-	-	-	-
COVNMT	**-0.976**	**0.891**	1	-	-	-	-
NH3T	**-0.912**	**0.823**	**0.977**	1	-	-	-
SO2T	**-0.563**	**0.789**	0.487	0.413	1	-	-
PM10T	**-0.978**	**0.974**	**0.968**	**0.919**	**0.673**	1	-
PM2 5T	**-0.988**	**0.964**	**0.976**	**0.925**	**0.641**	**0.998**	1

Source: output of SIMCA-P software.

R2 Y = 0.985



Number of components	Q^2_{cum}	limit
1	0.952	0.05
2	0.981	0.05

Figure 7: Number of components for the agriculture sector
Source: Prepared by the authors (2023)

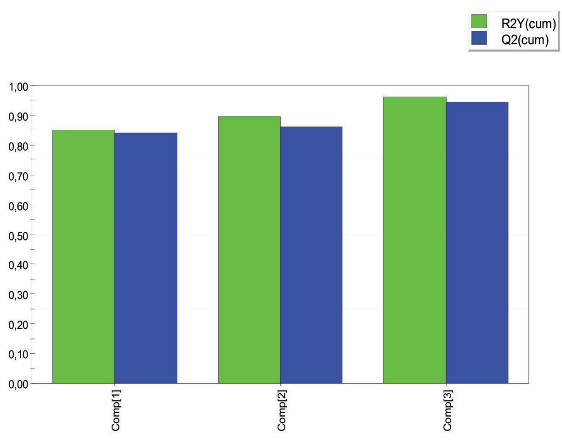
to health expenditure in France is low and negative (except for the NMVOC variable); the coefficients are: (–0.29) for dioxide emissions nitrogen, (–0.11) for ammonia, (–0.19) for sulfur dioxide emissions that vary between (–0.25) and (–0.26) for particulate matter. Figure 8: Number of components for the Industry sector. Source: Prepared by the authors (2023)

For the industrial sector, the coefficient of determination (0.963) shows a very good quality of adjustment with three PLS components (Figure 8).

$$HE_i = 9.6 - 0.47NOX_i - 0.22NMVOC_i - 0.03NH3_i - 0.76SO2_i + 0.34PM10_i - 0.18PM2.5_i \quad (12)$$

According to the Equation (12), the variables (NO_X, NMVOC, NH_3, SO_2) have a negative impact on health expenditure. The coefficients for these variables are (–0.47), (–0.22), (–0.03), and (–0.76), respectively. The analysis indicates that sulfur dioxide emitted by the industrial sector has a greater effect on health expenditure. Additionally, particulate matter (PM_{10} and $PM_{2.5}$) has a positive influence on the HE variable, with low coefficients of 0.34 and 0.18, respectively.

R2 Y = 0.963



Number of components	Q^2_{cum}	limit
1	**0.841**	**0.05**
2	**0.863**	**0.05**
3	**0.946**	**0.05**

Figure 8: Number of components for the industry sector
Source: Prepared by the authors (2023)

For the residential sector, the coefficient of determination is equal to 0.975. This indicates that the model is significant with three PLS components and a very good quality fit (Figure 9).

$$HE_r = 9.6 - 0.81NOX_r - 0.01NMVOC_r - 0.24NH3_r - 0.06SO2_r - 0.12PM10_r - 0.12PM2.5_r \quad (13)$$

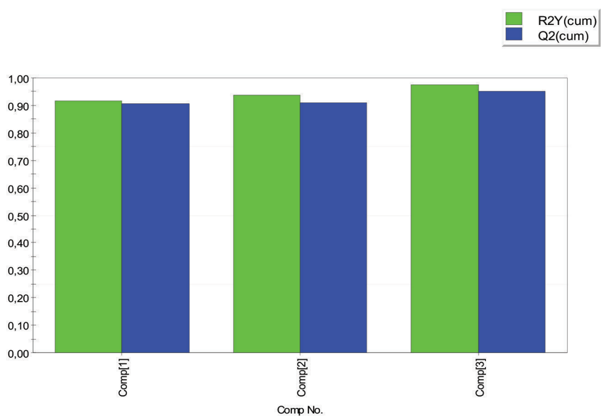
In Equation (13), sulfur dioxide (SO_2) and ammonia (NH_3) emissions positively affect the dependent variable (HE) with fairly low coefficients (0.24 and 0.06). It was observed that nitrogen oxide emissions from the tertiary sector affect health expenditure more with a very high coefficient (–0.81).

For the transport sector, the coefficient of determination (R2Y) is equal to 0.976. The model is globally significant with two PLS components (Figure 10).

$$HE_t = 9.6 - 0.28NOX_t - 0.09NMVOC_t - 0.24NH3_t - 0.26SO2_t - 0.28PM10_i - 0.29PM2.5_i \quad (14)$$

As Equation (14) shows, pollutants from transport have a negative effect on health expenditure in France where all the coefficients are low.

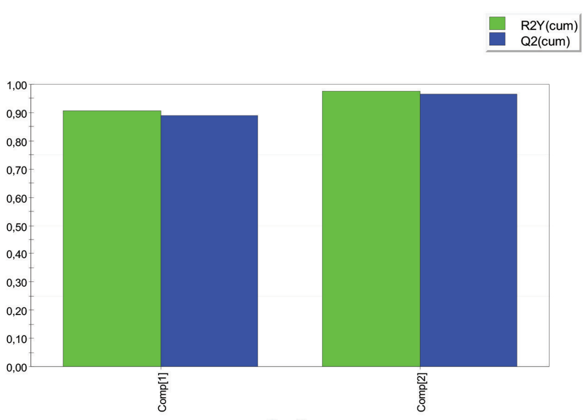
R2 Y = 0.975



Number of components	Q^2_{cum}	limit
1	**0.906**	**0.05**
2	**0.912**	**0.05**
3	**0.953**	**0.05**

Figure 9: Number of components for the residential sector
Source: Prepared by the authors (2023)

R2 Y = 0.976



Number of components	Q^2_{cum}	limit
1	**0.89**	**0.05**
2	**0.965**	**0.05**

Figure 10: Number of components for the transportation sector
Source: Prepared by the authors (2023)

The Importance of Variables

Figure 11 shows that in the agricultural sector, the variables NO_X, $PM_{2.5}$ and PM_{10} affect health expenditure more strongly as their VIP values are greater than 1, while the variables NMVOC and NH_3 present a VIP value less than 1. Thus, in the industrial sector, it was noted that sulfur dioxide emissions, nitrogen oxide emissions, fine particles and emissions of non-methane volatile organic compounds affect the HE variable more strongly (their VIP values are higher than 1) (Figure 12). Moreover, in the residential sector, NO_X, NMVOC, SO_2 and particulate matter are the most important variables in the construction of health expenditure (their VIP values are greater than 1) (Figure 13). Finally, in the transport sector, the sulfur dioxide (SO_2) emissions variable and that of non-methane volatile organic compounds (NMVOCs) have a less significant influence on health expenditure since their VIP value is less than 1 (Figure 14). In general, the variables of this study (in the four sectors) have a strong impact on health expenditure in France.

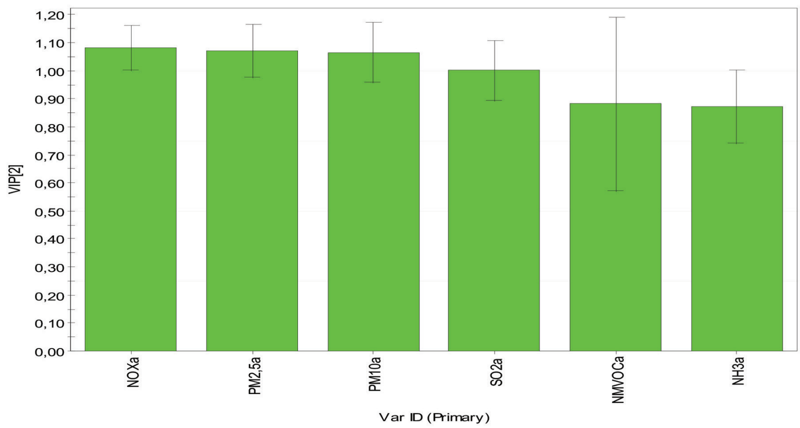


Figure 11: Importance of variables for the agriculture sector
Source: Prepared by the authors (2023)

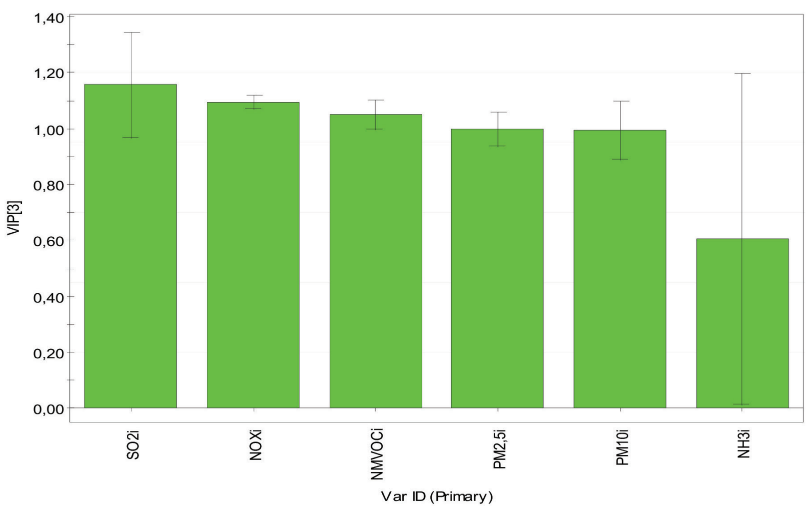


Figure 12: Importance of variables for the industry sector
Source: Prepared by the authors (2023)

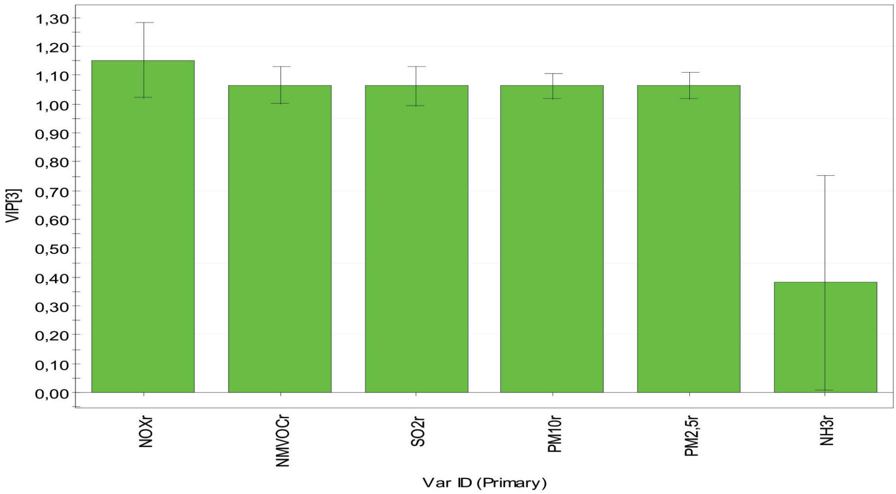


Figure 13: Importance of variables for the residential sector
Source: Prepared by the authors (2023)

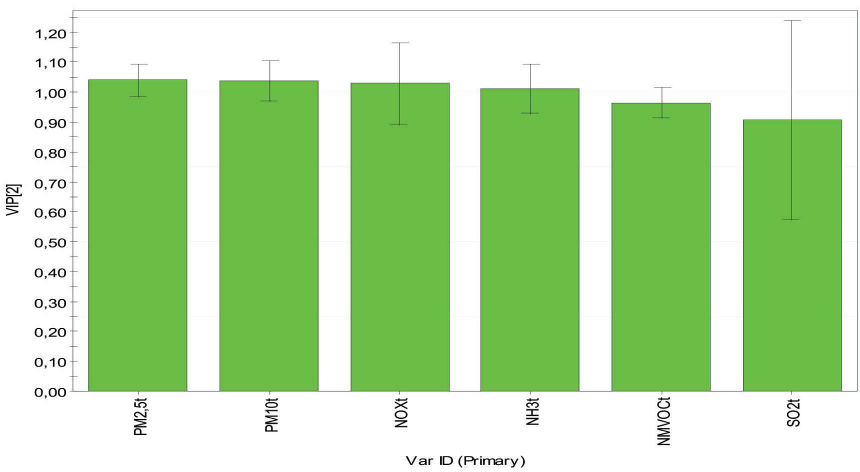


Figure 14: Importance of variables for the transportation sector
Source: Prepared by the authors (2023)

Observation Maps

The data presented in Figures 15, 16, 17, and 18 reveals that a majority of the observations lie within the ellipse, indicating homogeneity in characteristics across the four sectors, with the exception of the year 2003. Notably, the sector of agriculture and transport shows an outlier outside the ellipse, which can be attributed to the disruption of emissions in both sectors. Specifically, the analysis suggests a decrease in pollutants from agriculture, except for SO_2 emissions, which increased by 5% between 2003 and 2004, and NO_X emissions, which increased by nearly 0.5% during the same period (as shown in Figure 15). Moreover, the transport sector in Figure 18 depicts the year 2004 as being near an atypical point due to the sharp decrease in all pollutants, such as NMVOC emissions, which decreased by 11%.

The economic crisis of 2008 had a profound impact on all emissions from the agricultural, industrial, residential, and transport sectors. This resulted in a noticeable drop in emissions, particularly in 2009. However, with the resumption of activities in 2010, all sectors were able to return to their pre-crisis emission levels. It is important to note that agricultural activities are significant sources of air pollution that have a considerable impact on both health and the environment. In 2016, this sector was responsible for 94% of NH_3 emissions, 9% of $PM_{2.5}$ emissions, and 14% of soot carbon emissions at the metropolitan scale (CITEPA, 2020).

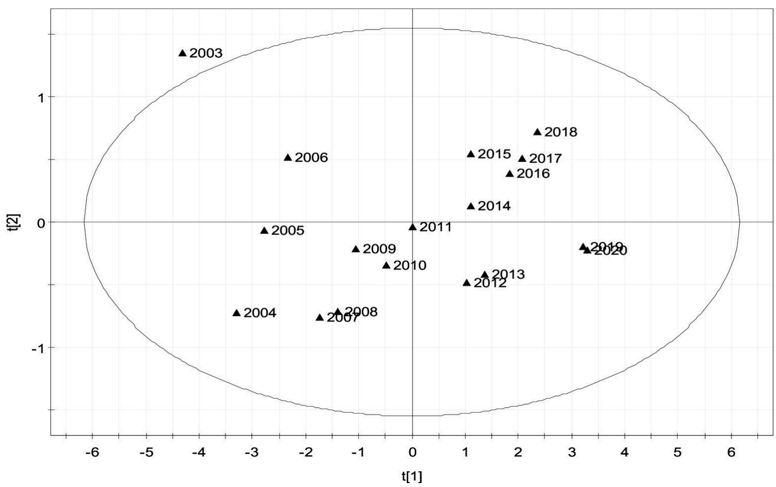


Figure 15: Map of observations for the agriculture sector
Source: Prepared by the authors (2023)

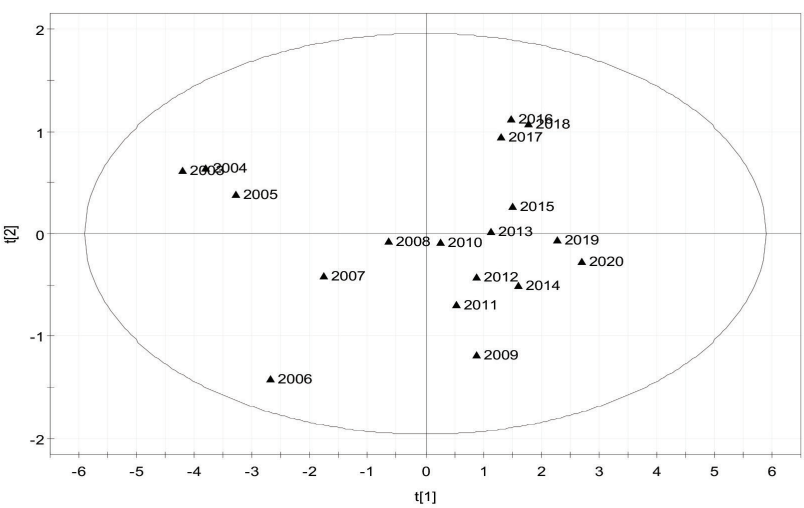


Figure 16: Map of observations for the industry sector
Source: Prepared by the authors (2023)

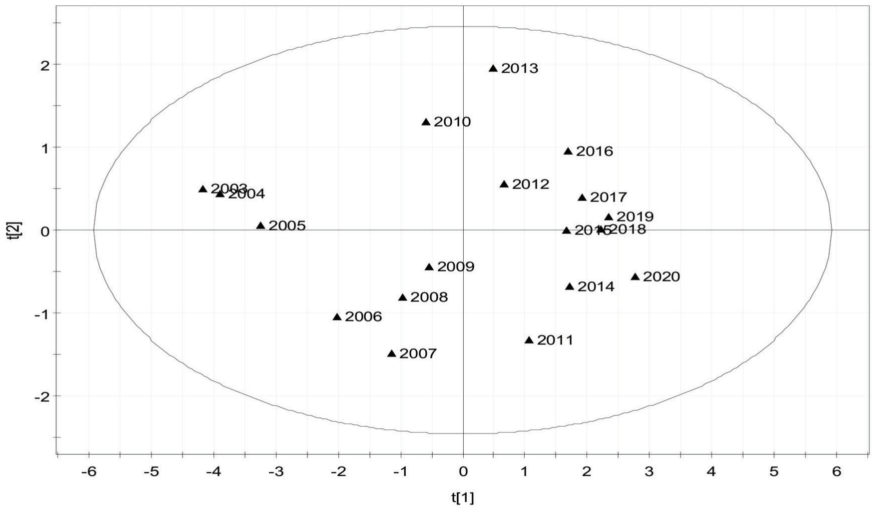


Figure 17: Map of observations for the residential sector
Source: Prepared by the authors (2023)

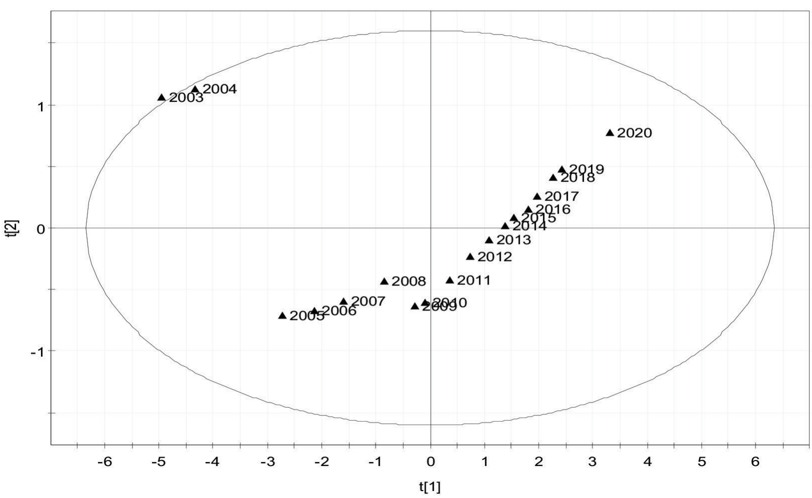


Figure 18: Map of observations for the transportation sector
Source: Prepared by the authors (2023)

Map of Variables

Figures 19, 20, 21 and 22 are the structure of the correlations between the dependent variable (HE) and the explanatory variables (NO_X, NMVOC, NH_3, SO_2, PM_{10} and $PM_{2.5}$) in the four sectors. All the explanatory variables were found far from the dependent variable. This confirms equations (11, 12, 13, and 14) of the PLS regression. Note that nitrogen oxide (NO_X) emissions negatively affect health expenditure in the 4 sectors. Similarly, fine particles have a bad influence on health expenditure (HE) in the transport, agriculture and residential sectors. In the same context, the agricultural sector admits a positive influence for emissions of non-methane volatile organic compounds (NMVOC) on HE (with a very low coefficient of 0.11). Furthermore, there is a poor contribution of ammonia (NH_3) and sulfur dioxide (SO_2) to the construction of health expenditure in the three sectors (agricultural, industrial and transport).

For the agriculture and transport sectors, emissions of nitrogen oxide and particulate matter have the highest coefficients compared to other pollutants (Figures 19 & 22). At the industrial sector level, sulfur dioxide (SO_2) emissions have the highest rate (76%) in determining health expenditures, while NO_X emissions strongly affect health expenditures with a rate of 81% in the residential sector (Figure 21).

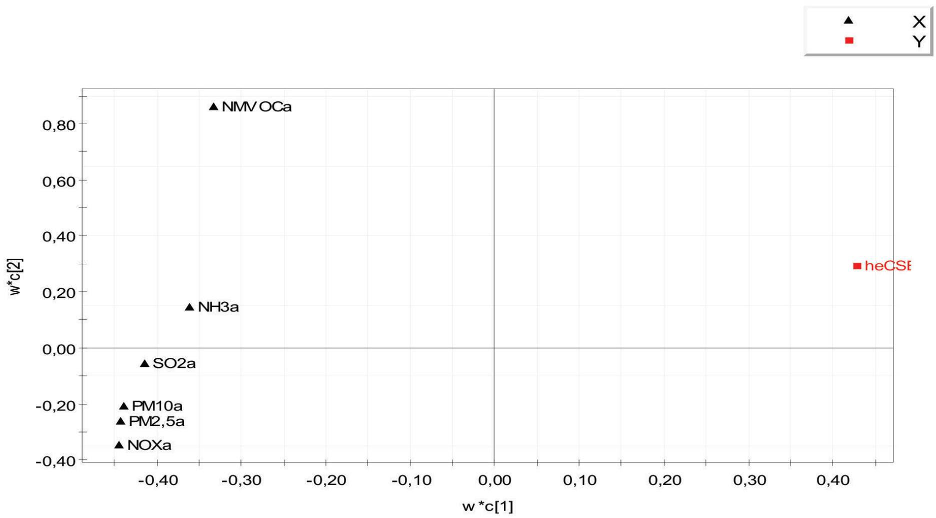


Figure 19: Map of variables for the agriculture sector
Source: Prepared by the authors (2023)

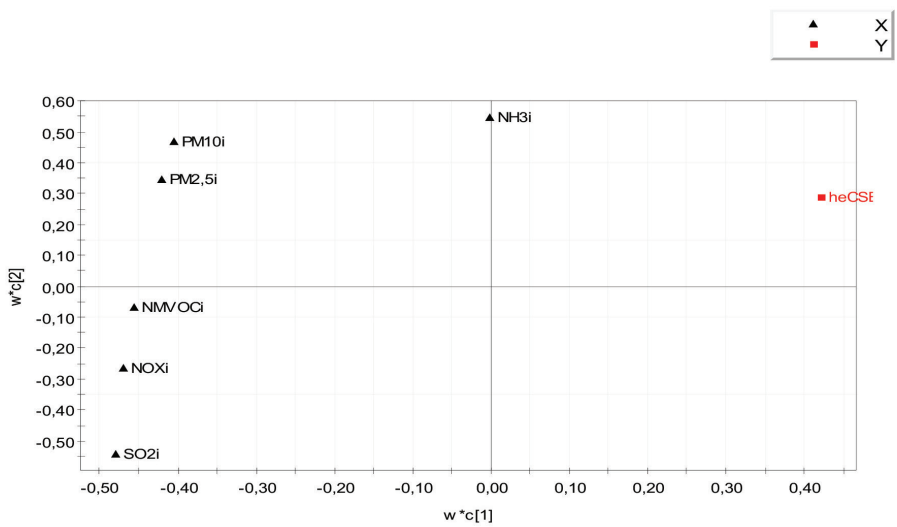


Figure 20: Map of variables for the industry sector
Source: Prepared by the authors (2023)

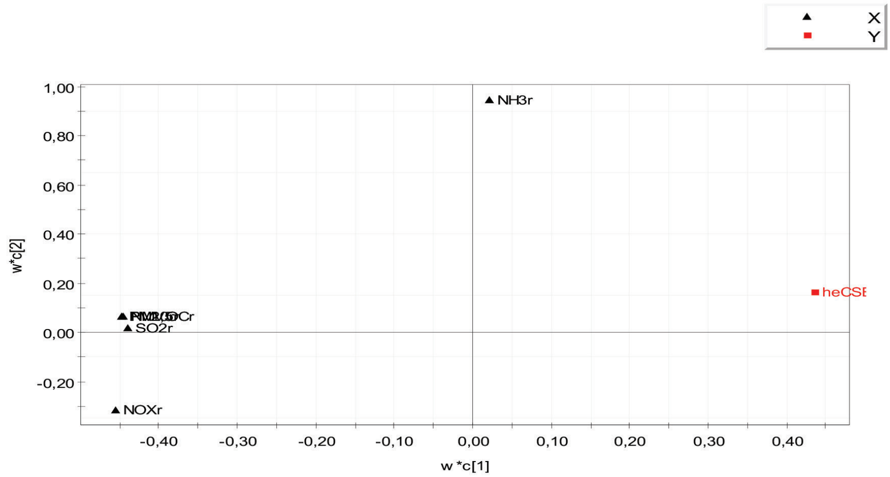


Figure 21: Map of variables for the residential sector
Source: Prepared by the authors (2023)

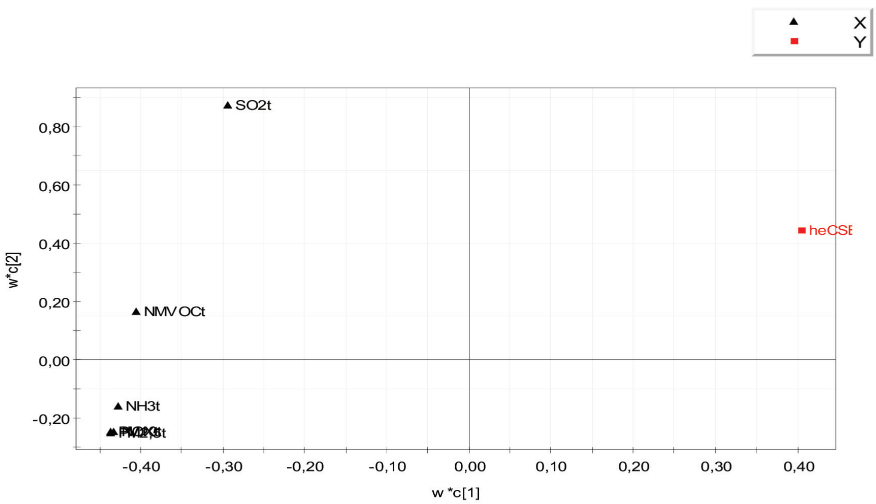


Figure 22: Map of variables for the transportation sector
Source: Prepared by the authors (2023)

Comparison between Y Observed and Y Predicted

Results in Figures 23, 24, 25 and 26 confirm this efficiency since the predicted and observed values are almost identical. Indeed, PLS regression provides a very effective solution and resolution. For the agricultural sector, the percentage of determining the R^2 is equal to almost 99% and for the transport sector to almost 98% with two PLS components. Similarly, in the industrial sector, the coefficient of determining R^2 is almost equal to 96% and in the residential sector is almost equal to 97% with three PLS components.

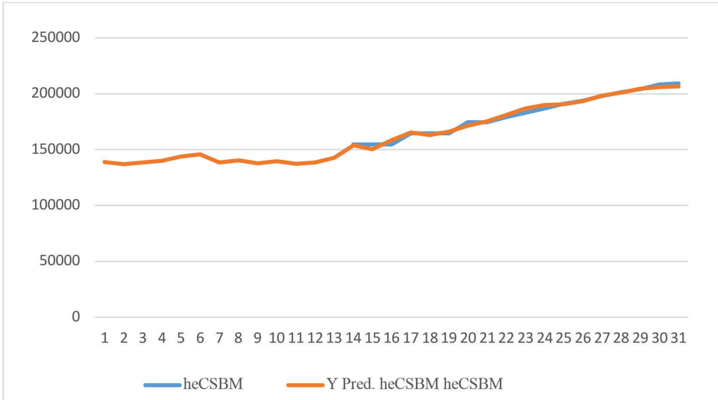


Figure 23: Map of observations for the agriculture sector
Source: Prepared by the authors (2023)

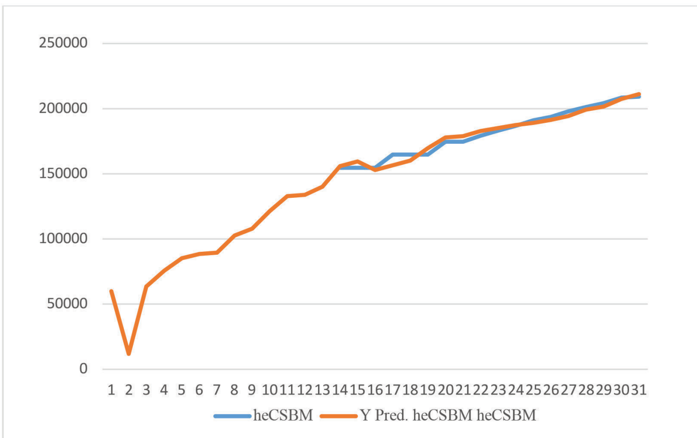


Figure 24: Map of observations for the industry sector
Source: Prepared by the authors (2023)

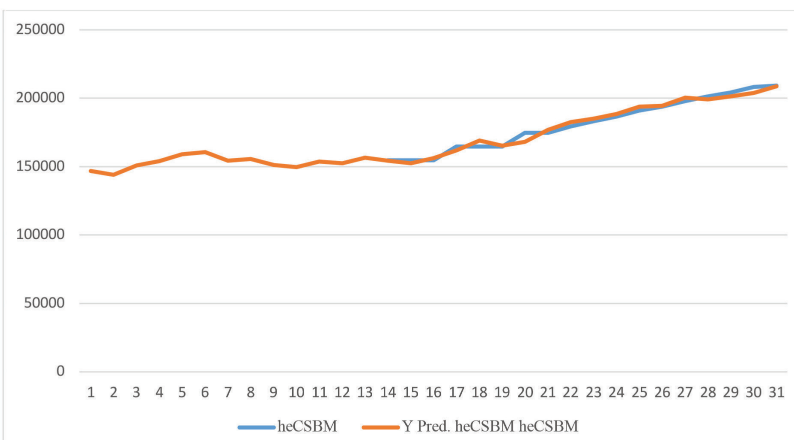


Figure 25: Map of observations for the residential sector
Source: Prepared by the authors (2023)

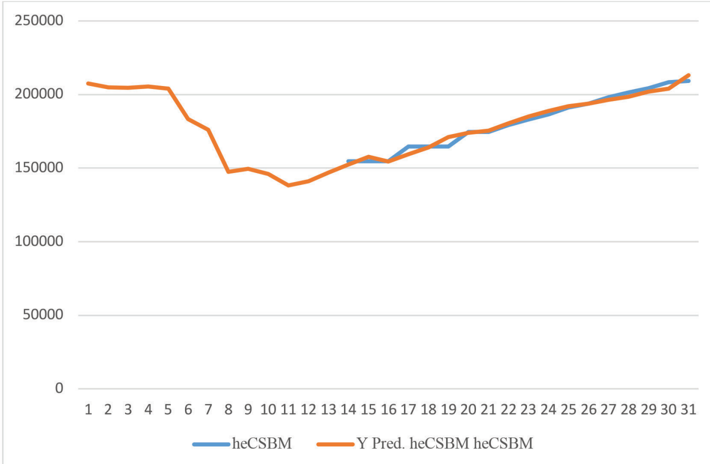


Figure 26: Map of observations for the transportation sector
Source: Prepared by the authors (2023)

Discussions

Overall, the results of the current study align with previous research regarding the detrimental effects of pollutants from various sources on health (Jacquemin *et al.*, 2009; Hoek *et al.*, 2013; Davalos *et al.*, 2017). However, our data analysis techniques differed from those of prior studies, as PLS regression was employed via SIMCA-P software on proprietary data from France. Additionally, this is the first study to examine the impact of pollutants from all four sectors. This study aligns with the results of previous research in the industrial sector conducted by Deng *et al.* (2016), Moosa (2019) and Li *et al.* (2020). Similarly, our findings in the residential sector are in line with those of Cooper (1980), Wei *et al.* (2018) and Yun *et al.* (2020). Indeed, the results of Beylot *et al.* (2018) showed that the residential sector increases air pollution, reinforcing our results. In the agricultural sector, our results are compatible with those of (Hu *et al.*, 2023). On the other hand, the research conducted by Selmi *et al.* (2016) provides evidence that trees in public green spaces within the city of Strasbourg, France, can efficiently remove atmospheric pollutants. In the transport sector, our study is consistent with the research by Magazzino *et al.* (2020) and Zeiri *et al.* (2021).

Air and water pollution causes a negative impact on human health. Bâ *et al.* (2015) found that no research has been conducted on the monetary valuation of agricultural pollution in France. Based on existing research, the authors estimated that agricultural externalities can cost up to 55 billion Euros. The externalities are separated into six categories: Air pollution, water pollution, soil pollution, greenhouse gas emissions, risks to human health, and impacts on biodiversity and landscapes. The estimate was determined through homogenisation, analysis, and selection of the most significant costs. Despite certain uncertainties related to the complexity of the monetary valuation of environmental damage, we can conclude that the pollution costs generated by intensive agriculture are far from negligible. According to Agreste (2014), they represent between 21% and 80% of the value of agricultural production in France (68.4 billion euros in 2010), an amount in any case greater than 11 billion Euros in subsidies for agriculture and agricultural products. According to the report of the European Environment Agency (Ineris *et al.*, 2021), the industrial sector is responsible for an annual cost of between 280 and 430 billion euros in health and environmental damage due to air pollution.

The transport sector is thus responsible for 43 to 46 billion euros in health costs per year for the Member States of the European Economic Area in 2019. In the case of France, air pollution costs an average of almost 1,000 Euros per person each year, and according to a study by the European Public Health Alliance, air pollution is mainly caused by the transport sector.

According to CITEPA (2020)[4], 93% of ammonia (NH_3) emissions come from the agricultural sector, 75% of sulfur dioxide (SO_2) emissions from the industrial sector, 63% of nitrogen oxide (NO_X) from the transportation sector and 46% of non-methane volatile organic compound emissions from the residential sector. According to data for the year 2021 from the Interprofessional Technical Center for Atmospheric Pollution Studies, annual NO_X emissions are around 651 kt (2020) and these emissions are decreasing (–62% between 1990 and 2019). Similarly, NMVOC emissions are close to 923 kt for 2020 and these are down 67% between 1990 and 2019. On the other hand, annual NH_3 emissions are around 589 kt (2020) and these emissions are decreasing (–11% between 1990 and 2019). As for annual SO_2 emissions, they are around 100 kt (2019); these emissions are shrinking (–92% between 1990 and 2019). Finally, PM_{10} and $PM_{2.5}$ emissions are respectively about 190.6 kt and 111.8 kt in 2020, they are decreasing between 1990 and 2019 by –62% and –71%. This reduction in all multi-source pollutants is explained by France's compliance with the Geneva Convention on Long-Range Transboundary Air Pollution in 1981 and the Stockholm Convention on Persistent Organic Pollutants (POPs) in 2004. Each year, according to the Public Health of France (2021)[5], nearly 40,000 deaths are attributable to exposure to multi-source pollutants for people aged 30 and over. Consequently, ambient air pollution is a major health risk factor in France, representing 7% of the total mortality of the French population attributable to exposure to fine particles.

Regarding the economic impact, the SENAT (2015)[6] Commission of Inquiry on the economic and financial cost of atmospheric pollution estimates the total cost between 68 and 97 billion Euros per year for France, of which a very significant part is related to health impacts. According to the Federation of Air Quality Monitoring Associations (Atmo 2021)[7], air pollution also has a significant financial cost, not to mention its impact on human health and the environment. On the one hand, it has a tangible health cost, i.e. a cost mainly measured through the health expenditure reimbursed by health insurance which covers the pathologies attributable to atmospheric pollution (cardiovascular diseases and respiratory). Expenditure linked to pollution is estimated at 3 billion Euros per year in France. On the other hand, it has an intangible annual health cost which was estimated in 2015 at 97 billion Euros, which is equivalent to 1,469 Euros per person each year. The French government has done well in strengthening the health system as it has increased its spending by almost 19.8% between 2010 and 2020 (from 174,694.16 million euros to 209,227.64 million euros), according to the data from the Direction de la Recherche, des Etudes, de l'Evaluation et des Statistiques (DRESS 2023)[8].

Our study shows significant links between air pollution and healthcare expenditures, which could strengthen the need for implementing stricter regulations to reduce air pollution in France. Policymakers may be inclined to adopt measures to decrease pollutant emissions from various sources and encourage investment in pollution prevention. To encourage discussions on the need for increased funding for healthcare services to address the growing demand caused

[4] https://www.citepa.org/fr/donnees-emissions/
[5] https://www.santepubliquefrance.fr/content/download/370060/3138468?version=1
[6] http://www.senat.fr/commission/enquete/cout_economique_et_financier_de_la_pollution_de_lair.html
[7] https://www.atmo-france.org/actualite/nouvelle-estimation-financiere-du-cout-de-la-pollution-en-europe
[8] https://data.drees.solidaritessante.gouv.fr/explore/dataset/organismes_complementaires_rapport_annuel/information/

by air pollution, to urge authorities to promote more sustainable modes of transportation, and to balance economic interests with public health concerns.

Conclusion

Generally, multi-source air pollution today is the result of rapid economic development, unsustainable production and consumption patterns, and unbalanced economic and energy structures. The agricultural sector (consumption of organic and mineral fertilisers, burning of agricultural residues), the industrial sector (consumption of coal, production of electricity), the residential sector (consumption of heating, domestic waste and burning, wastewater) and the transport sector (vehicle use) are the four main sources of air pollution at the national level. This study provides evidence of the significant impact of air pollution on health expenditure in France, particularly in the sectors with the greatest impact on human health. The findings suggest that policies to reduce air pollution could lead to significant savings in health expenditure.

Indeed, the empirical results of our study reveal several important findings. On the one hand, the models of the four sectors are all significant; in other words, all pollutants have a statistically significant impact on health expenditure in France. On the other hand, our results indicate that most pollutants negatively affect health expenditure, notably the highest coefficient of NO_X which represents (0.81) in the residential sector, a coefficient of SO_2 emissions (0.76) in the industrial sector, PM in the transport sector with coefficients of (0.29) and (0.28), and a practically low coefficient of NO_X emissions (0.29) in the agricultural sector.

The exposure-response relationship with total mortality seemed better explained by a combined index of PM_1, nitrogen dioxide, SO_2 and CO than by an individual air pollutant. In assessing the risks associated with air pollution, it is appropriate to consider all pollutants rather than measure individual pollutants' risk (Hong *et al*., 1999). Combating air pollution depends largely on countries' commitments to pollution control and energy consumption and generation technologies. In the long- term, the fundamental solution to effectively combat air pollution is to increase the use of renewable energy sources such as solar, nuclear, and wind. The French government should adopt strict emission standards and devote more funds to promoting the use of efficient treatment technologies to reduce further emissions of NO_X, NMVOC, NH_3, SO_2 and particulate matter to protect the environment and human health.

The findings are limited by the use of French data, which may restrict their applicability beyond French borders. The link between healthcare expenditure and air pollution may differ in regions with different levels of air pollution, socio-economic conditions or healthcare systems. Future studies should utilise data from multiple countries to investigate this relationship, as research focuses on the long-term effects of air pollution. These efforts will foster a more comprehensive understanding of the complete impact of air pollution on human health.

Conflict of Interest Statement

The authors declared that they have no conflict of interest.

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