Decomposition Analysis of Air Pollutants during the Transition and Post-Transition period in the Czech Republic

by

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Abstract: We examine the main driving forces of significant reductions in air pollutants that occurred during the transition of the Czech economy towards a market economy in the 1990s and how these driving forces affected emissions volumes across the post-transition period to 2016. Using Logarithmic Mean Divisia Index decomposition (Ang & Liu, 2001), we statistically decompose annual changes in the emission levels from large stationary emission sources of four types of air quality pollutants, including sulphur dioxide, carbon monoxide, nitrogen oxides and particulate matters over the period 1990–2016. While most of previous decomposition studies have been decomposing emissions into scale, structure and emission intensity factors, a unique environmental dataset allows us to further decompose the emission per output effect into [i] the emission-fuel factor, [ii] the fuel-mix factor, and [iii] the fuel-intensity factor, yielding a 5-factor decomposition. We find that the largest drop in emissions of all four pollutants occurred up to 1999 when the emissions decreased cumulatively by 74 % at least. In this period, the firms faced new competitive environment and were exposed to strict new command and control regulation – as a result, negative emission-fuel factor was the key driver of the emission reduction. However, the fuel-intensity effect contributed most to reduction of SO_2, NOx and PM emission in the first 3 years after the Velvet revolution (1990-1992). Since 2008, activity, structure, fuel-intensity and emission-fuel factors have contributed to emission changes by similar magnitudes, but in different directions. In the last two years, the emission-fuel factor effect has become important again, as the large stationary emission sources were required to comply with new emission limits set by the EU Industrial Emissions Directive. In order to examine the effect of the key LMDI parameters on the decomposition outcome, we perform a sensitivity analysis to decompose SO_2 emissions on different numbers of effects (3-, 4- and 5-factors) and when different sectoral detail is assumed.

1. Introduction

Whether economic growth is pollution-reducing or a pollution intensifier has remained under dispute. IPAT-based literature[1], following a famous pioneering study by Ehrlich & Holdren (1971) and, then, *Limits to Growth* by Meadows, Meadows, Randers, & Behrens (1972), has tended to see **P**opulation growth coupled with growing per capita income (i.e. **A**ffluence) as the primary forces driving adverse environmental **I**mpacts, while **T**echnology has been considered to be mostly neutral. The IPAT approach has been criticized due to its pessimistic perspective on technological progress, a lack of behavioural response to adverse impacts, and the quality of data used in assessments (Carson, 2010).

The second stream of literature based on the Environmental Kuznets Curve hypothesis, following the pioneering 1991 study by Grossman & Krueger (1995), relies on the stylized fact that environmental quality tends to be positively, not negatively, correlated with income, especially in developed countries (Carson, 2010). An inverted-U shaped relationship between per capita income and environmental quality has been tested in many studies utilising simple or improved econometric models and datasets (see Cavlovic, Baker, Berrens, & Gawande (2000) or Dinda (2004) for a review). However, the Grossman & Krueger (1991) study clearly highlights the limitations of such analyses. It has been particularly recognized that it is just the reduced-form nature of the EKC model that limits the policy implications of its results. In other words, we cannot tell through which channel the level of income per capita affects environmental quality, nor we can reveal the extent to which the income factor contributes to changes in environmental quality.

Further, as a reaction to criticisms of the EKC, other statistical techniques have been developed to better understand the mechanisms of changes in energy use (or emission volume). In particular, researchers were looking for ways to quantify the impact of structural shifts in production and changes in sectoral energy intensity on total energy demand. Since then, decomposition analysis, and in particular the index-based decomposition analysis, has been used hand-in-hand with econometric analysis to understand trends and underlying factors of changes in energy use and emissions (Ang and Zhang, 2000). Compared to the reduced-form analysis performed in the most EKC literature, a decomposition analysis can identify the channels through which environmental quality is affected, as noted in Tsurumi & Managi (2010). Others have found that results based on a decomposition model have better statistical properties than the standard EKC specification (Stern, 2002). The main criticism of

[1] The IPAT relates **I**mpact (e.g., pollution) to **P**opulation, **A**ffluence (proxied by per capita income), and **T**echnology, sometimes known as the Kaya identity.

decomposition analysis stemming from the fact that original approaches generated a residual term, which complicated interpretation of decomposition results, has been overcome by linking the decomposition to the Divisia index method.[2] Motivated by this discussion, we examine the main driving forces of significant reductions in the key air quality pollutants in a country that has faced dramatic political, economic and institutional changes over the past 29 years. In this paper, we conduct a Logarithmic Mean Divisia Index (LMDI) decomposition to examine the driving forces of change in air pollutants during the transition of the Czech Republic towards a market economy during the 1990s, becoming a member of the European Union in the 2000s, and complying with EU air quality and climate policy goals up to 2016. During the period analysed, the Czech economy evolved considerably in terms of its scale, structure, and institutions. The centrally-planned communist regime was replaced by a market economy governed by democratic institutions beginning with the Velvet Revolution of 1989. After a huge economic downturn due to the Revolution, it took the economy a decade to re-achieve its pre-market level. During the 1990s, the structure of the Czech economy changed significantly; industrial production declined from more than one third of GDP to one quarter, production in the mining and energy sectors decreased significantly, from 5% to 1.4%, and from 8% to 4% respectively, while market services, construction, trade and transport increased their outputs. The volume of air pollutant emissions fell tremendously, during 1990s (CENIA, 2005).

During the next decade, the Czech economy grew more than 40%, and since 2010 has increased by another 13%. These historical changes serve as a natural experiment, allowing us to investigate the key driving forces responsible for the huge drop in emissions of air pollutants. Our unique data set enables us to conduct a more refined index decomposition analysis (IDA) than prior studies have done. It also allows us to perform a set of sensitivity analyses of the LMDI method with respect to the number of decomposition factors used and the level of sector disaggregation.

We use a Logarithmic Mean Divisia Index to decompose the emissions of four air quality pollutants, specifically sulphur dioxide - SO_2, carbon monoxide - CO, nitrogen oxides - NO_x, and particulate matters - PM, into three to five factors: the activity effect, structure effect, fuel intensity effect, fuel mix effect, and emission-fuel intensity effect. The 5-factors decomposition enriches the existing literature, since the emission-fuel intensities have not been either available

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[2] Ang et al. (2002) defined four criteria for desired decomposition method that are factor-reversal, time-reversal, proportionality, and aggregation tests. Original approach based on Laspeyres index decomposition has been replaced by Divisia index decomposition mainly on the ground of a residual term that is generated by Laspeyres method.

or have been time invariant (based on average substance content) in all previous studies. In contrast to this commonly-used approach, our data contains information on the volume of each pollutant linked to each fuel used in the process, for instance, how much SO_2 is released per tonne of hard coal used in specific facility. This means that the emission coefficients we use in the analysis vary at the facility level as well as over time. Further, both emission volumes and fuel consumption are directly measured at the facility level. This provides more accurate data and a richer variation across facilities and time compared to emission values calculated based on time invariant chemical and technological parameters, which have been used in almost all previous studies.

The specific objectives of this paper are twofold: first, we identify the contribution of each of five factors affecting the emission level of four air pollutants in the Czech Republic during its transition and post-transition periods. Second, we perform a sensitivity analysis of the LMDI decomposition with respect to the number of factors and assuming different sector breakdowns of the Czech economy.

Institutional setting of the Czech Republic

Our analysis begins in the period of economic and political transformation in The Czech Republic[3] that started after the Velvet Revolution in 1989. The communist centrally planned economy was characterized by high energy and resource use accompanied by high pollution intensities due to a lack of environmental regulation and undercapitalization. In 1990, when economic and political transformation began, the Czech economy released around 16 tonnes of CO_2 per capita; an emission-output ratio six times higher than the ratio of the EU27 today. Because of high emissions of dust and sulphur released from insufficiently filtered power plants, the "Black Triangle" area (a region including northern Bohemia, southern Saxony and part of lower Silesia) was among the most polluted areas in Central Europe (Ürge-Vorsatz, Miladinova, & Paizs, 2006).

Already the first democratically elected government began to institute more environmental protections, and in order to comply with the Community Acquis of the EU, several policies to decrease pollution emission levels were introduced. The new Air Quality Act No. 309/1991 and related regulations, which required each existing large stationary emission source (power plants

[3] The Czech Republic was part of Czechoslovakia until 31.12.1992. Our data represents gross value added, fuel consumption and emissions in the Czech Republic only.

and industrial factories) to comply with strict emissions limits until 1998, were the main drivers of the large reduction in emissions of air pollutants in the Czech Republic during the 1900s.[4]

Following this Act, emissions limits were set in 1991 and have since been strengthened several times (1992, 1995, 1997 and 2002). This command-and-control regulation drove a large reduction in emissions of air pollutants in the Czech Republic during the 1990s, particularly SO_2, NO_x, and PM.

Newly introduced economic instruments aimed to reduce emissions in the 2000s were quite ineffective due to low tax rates (in the case of energy taxes) or because of over-allocation of CO_2 allowances within the first phase of the EU ETS (Ščasný & Máca, 2009). As a consequence, as all large emission sources fulfilled their emission limits by 1999, the emission levels of air quality pollutants decrease only slightly over the next decade. Integrated permits introduced under *Integrated Pollution and Prevention Control* and concentration limits on pollutants in flue gas were the only truly effective instruments that regulated airborne emissions released from large stationary emissions sources in the 2000s.

The European directive on industrial emissions 2010/75/EU has induced further strengthening of airborne emission regulation. However, The Czech Republic has negotiated a transition period for implementation of this directive up to the end of 2016. This means most of the current large emission sources had time to fulfil new emission limits until the end of 2016.

We find that the leading driver in the decrease of emissions during the 1990s is the emission-fuel intensity effect, not the structure effect, which is consistent with the findings of other studies from developed countries and transition economies. Although, the fuel intensity effect is the most important up to 1992. The emissions abatement was introduced as a consequence of a new regulation on the concentration of air pollutants which required large emission sources to satisfy certain limits by 1999. It suggests firms adjusted their environmental behaviour by improving their end-of-pipe technology rather than by switching type fuel or by improving of energy efficiency. This finding shows that command-and-control regulation, as introduced in the Czech Republic in the 1990s, did not motivate firms to decrease the amounts of fuel used or to change the composition of the fuels, which would have required changing significant

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[4] Act No. 309/1991 applies at the federal level (Czechoslovakia). Act No. 389/1991 applies to the national level (the Czech Republic). Act No.309 determines the emissions limits and deadlines to fulfil the requirement, while Act No. 389 defines administration of the process and competences for the relevant authority, Česká inspekce životního prostredí (the Czech Environment Inspectorate).

amounts of their technology, but rather it motivated firms to decrease their emission levels by improving their end-of-pipe type measures without changing their technology.

We find that, after satisfying the emission limits requirements by 1999, large emission sources in the Czech Republic decrease their fuel intensity. This is the main driver that allows keeping their emissions on steady level between 1999 and 2007, despite the strong economic growth. Since 2008, the magnitude of activity, structure, intensity and emission-fuel intensity effects get closer to each other. In 2015 and 2016, the emission-fuel intensity effect becomes important again, as the large stationary emission sources has to comply with new strict emission limits based on the directive on industrial emissions.

This paper is structured as follows. The next section reviews related literature. Section 1.2 introduces the methodology and section 1.3 describes data. Section 1.4 presents the result of LMDI decomposition and provides a sensitivity analysis of LMDI decomposition with respect to the number of decomposition factors and sector aggregation. The final section concludes.

1.1. Literature Review

Decomposition analysis has been applied as a reaction to criticism of the Environmental Kuznets Curve hypothesis (e.g. Stern, Common, & Barbier,1996). Stern (2002) finds that results from the decomposition model have better statistical properties than the standard EKC specification, and notes that the basic EKC model can be considered a nested version of a decomposition model. Studies of statistical decomposition of emissions development differ in various ways: by the decomposition method employed, the number of factors of the decomposition studied, the geographical regions covered by the analysis, aggregation of the data, and object of the analysis.

First, there are two main streams in which the index decomposition analyses are applied: the Laspeyres/Paasche index methods and the Divisia index methods. The Laspeyres/Paasche index can generate large unexplained residuals, especially in the case of large magnitudes of changes in the factors. The refined Laspeyres index method (Sun, 1998) extends the Laspeyres/Paasche method, and can achieve perfect decomposition (no residuals). However, the refined Laspeyres index method allocates the unexplained residuals among the factors arbitrarily. On the other hand, the Divisia index method overcomes the problem of unexplained residual terms, i.e. it satisfies the factor-reversal property of decomposition indexes. In particular, the refined Divisia index method by Ang & Choi (1997), the new log-mean Divisia index (LMDI), possesses all three desirable properties — time-reversal, circular and factor-reversal — and is currently the best recommended, index decomposition method (Ang, 2004).

Secondly, the number of factors into which emissions are decomposed differs across studies. Most studies perform the three-factor decomposition, examining the effects of the scale, the composition, and the intensity (or technology) factor. A few studies decompose emissions into more than three factors. This, however, requires computations of emission volumes for each type of fuel. Without carbon capture technology, the emission-fuel coefficients for CO_2 can be derived quite straightforwardly by using the typical carbon content of fuel and specific oxidation parameters. Sun (1999) uses the time invariant emission-fuel coefficients following Torvanger (1991), and then conducts a 4-factor decomposition analysis on the emission of carbon dioxide for the 24 OECD countries for 1960-1995. Deriving the emission-fuel coefficients for other airborne pollutants requires more information. Viguier (1999) calculates the emission coefficients based on the parameters of the substance content of fuels, the fraction of substances removed by pollution abatement, and the fraction of substances retained in ash, respectively. However, neither of these two studies used directly measured emission volumes per fuel. In this paper, both the emission volumes and fuel used are measured and reported at facility level, which means the data contain a richer variation across plants and time.

Third, the studies differ in geographical coverage. Most studies investigate the former EU-15 countries (e.g. Löfgren & Muller (2010)) and Asian countries, mainly China (e.g. Lin & Long, 2016) with some studies focusing on the USA and Canada or selected OECD and IEA countries (see Ang & Zhang, 2000). Only a few applications of decomposition analysis in African countries and Central and Eastern European (CEE) countries exist, and in this respect, our study aims to contribute to filling this gap in the literature. Viguier (1999), above, is one of the few studies which analyses emissions in CEE countries. Further, Cherp, Kopteva, & Mnatsakanian (2003) analyse the quality of air in Russia over the period 1990-1999. They claim that in Russia, a structural effect works positively on production of emissions and the intensity effect influences emissions production negatively, as a result of more environmentally friendly technologies.

Last, but not least, most of the studies mentioned are focused on CO2 or GHG emissions only. Ang (2015) finds that application of IDA has evolved from a focus on energy consumption prior to 1990, to more often focusing on energy-related CO2 emissions since 2000. Ang (2015) denotes air pollutant emissions as one of new areas in which IDA is applied. In recent literature, we have found studies only from Asian countries – mainly China – that investigate airborne emissions. In particular, He, Yan, & Zhou, (2016); Y. Wang, Wang, & Hang, (2016); Yang, Wang, Zhang, Li, & Zou, (2016) focus on SO2 emission; Chang et al., (2018) investigate SO2 and NOx emission; Ding, Liu, Chen, Huang, & Diao, (2017); J. Wang et al., (2018) analyse NOx emission; and Lyu et al., (2016); Zhang et al., (2019) focus on PM emission.

Our paper follows up a couple of studies conducted in The Czech Republic that have not been published in scientific journals: Brůha & Ščasný (2006) apply the Laspeyres method for a 3-factor decomposition analysis on air pollutant emissions in the Czech Republic for the period 1992-2003. A shortcoming of this method is that it generates the residuals. Ščasný & Tsuchimoto (2013) and Tsuchimoto & Ščasný (2012) overcome the problem with the residuals and conduct 3-, 4-, and 5-factor LMDI decomposition analyses of air pollutant emissions for the period of 1995-2007. The added value of this paper is that we use extended and more detail datasets, paying special attention to consistent classification of firms into economic sectors. We extend the time span to 1990-2016, paying special attention to consistent classification of firms into economic sectors, and we use eight categories of fuel instead of five. As a results we are able to identify significant role of fuel intensity effect in 1990-1992 and capture the fuel mix effect for CO emission from 2008 to 2016.

1.2. Methodology

According to Ang (2004), the method of decomposition should be chosen such that it passes both factor and time reversibility and circular tests (Ang & Zhang, 2000). The most important test is factor reversibility. It requires perfect decomposition – meaning with no residual term. The conventional Laspeyres index is not recommended due to huge residuals.

The method used in Brůha & Ščasný (2006) satisfies the critical points above; but their method is based on a logarithmic approximation and therefore the results are sensitive to a large magnitude of change.

We apply the logarithmic mean Divisia index (LMDI) approach, which satisfies the property of perfect decomposition (Ang & Liu, 2001). "The LMDI approach involves variations in three different dimensions: by method (LMDI-I versus LMDI-II), by decomposition procedure (additive versus multiplication decomposition), and by aggregate indicator (quantity indicator versus intensity indicator)"Ang, (2015, p. 235). LMDI-I is consistent in aggregation (Ang & Liu, 2001) and perfect in decomposition at subcategory level (Ang, Huang, & Mu, 2009).We decide to apply the LMDI-I method based on recommendation of Ang, (2004, 2005) recommends LMDI-I method.

We follow Ang & Liu, (2007), who also resolve the problem with zero value observation by substituting the zero values with a very small number (e.g. between e^{-10} and e^{-20}). Both multiplicative and additive decomposition can be applied with equal results.

Following Ang (2005), the general index decomposition analysis identity is given by

$$E = \sum_i E_i = \sum_i x_{1,i} x_{2,i} \ldots x_{n,i} \ ,$$

(1)

where E is emission, x_n are factors contributing to changes in E over time and subscript i denotes a sub-category of the aggregate for which structural changes is to be studied. The emission changes from $E^0 = \sum_i x_{1,i}^0 \, x_{2,i}^0 \ldots x_{n,i}^0$ in period 0 to $E^T = \sum_i x_{1,i}^T \, x_{2,i}^T \ldots x_{n,i}^T$ in period T. The multiplicative approach decomposes the ratio between E^T and E^0:

$$D_{tot} = \frac{E^T}{E^0} = D_{x_1} D_{x_2} \ldots D_{x_n},$$

(2)

The additive approach decomposes the difference between E^T and E^0:

$$\Delta E_{tot} = E^T - E^0 = \Delta E_{x_1} + \Delta E_{x_2} + \cdots + \Delta E_{x_n}.$$

(3)

The subscript tot denotes the total relative or absolute change from period 0 to period T, respectively, and the right-hand side terms give the effects associated with the respective factors. The general formulae of LMDI-I for the effect of the kth factor are:

$$D_{x_k} = exp\left(\sum_i \frac{L(E_i^T, E_i^0)}{L(E_T, E_0)} ln\left(\frac{x_{k,i}^T}{x_{k,i}^0}\right)\right)$$

(4)

for the multiplicative approach and:

$$\Delta E_{x_k} = \sum_i L(E_i^T, E_i^0) \ ln\left(\frac{x_{k,i}^T}{x_{k,i}^0}\right)$$

(5)

for an additive approach. $L(a, b)$ is the logarithmic average of the two numbers, a and b.[5]

[5] Specifically, $L(a, b) = \frac{a-b}{\log a - \log b}$, if a≠b, otherwise $L(a, b) = a$.

Since we analyse the emissions developments over the period of up to 27 years, when the magnitude of changes in emissions experiences a declining trend, we mainly focus on the additive LMDI-I, which has a more intuitive interpretation with regard to the magnitude of changes in emissions.

The standard, three factor IDA identity for emission level of the pollutants from industry is:

$$E = \sum_i E_i = \sum_i Q \frac{Q_i}{Q} \frac{E_i}{Q_i} = \sum_i Q S_i I_i,$$

(6)

where E is the total level of emissions from the industry, subscript i denotes sector, $Q(= \sum_i Q_i)$ is total industrial activity level, $S_i(= \sum_i Q_i/Q)$ and $I_i(= \sum_i E_i/Q_i)$ are, respectively, the activity share and emission intensity of sector i. The change in total emissions from time 0 to T is then:

$$\Delta E_{tot} = E^T - E^0 = \Delta E_{act} + \Delta E_{str} + \Delta E_{int}.$$

(7)

The subscripts act, str and int denote the effect associated with the overall activity level (scale), activity structure and sectoral emission intensity, respectively.

In addition to the emission level in each sector i, our data set contains information on consumption of fuel j in sector i and also on how much pollutant is emitted by each type of fuel: $E_{i,j}$. Using the richer information outlined above, we conduct not only the conventional three-factor decomposition analysis, but also four and five-factor analysis:

Four-factor: $$\Delta E_{tot} = E^T - E^0 = \Delta E_{act} + \Delta E_{str} + \Delta E_{int} + \Delta E_{em}, \quad (8)$$

Five-factor: $$\Delta E_{tot} = E^T - E^0 = \Delta E_{act} + \Delta E_{str} + \Delta E_{int} + \Delta E_{mix} + \Delta E_{emf}. \quad (9)$$

In four-factor decomposition, the subscripts act, str, int, and em denote the activity (scale) effect, structure effect, energy intensity effect, and emission coefficient effect related to total energy consumption, respectively.

In five-factor decomposition, the subscripts act, str, int, mix and emf denote the activity (scale) effect , structure effect, energy intensity effect, fuel mix effect and emission coefficient effect related to each individual fuel, respectively. The additive LMDI-I formulae for this five-factor emission decomposing between year 0 and T are:

$$\Delta E_{act} = \sum_{i,j} L(E_{i,j}^T, E_{i,j}^0) \ln\left(\frac{Q^T}{Q^0}\right),$$

$$\Delta E_{str} = \sum_{i,j} L(E_{i,j}^T, E_{i,j}^0) \ln\left(\frac{S_i^T}{S_i^0}\right),$$

$$\Delta E_{int} = \sum_{i,j} L(E_{i,j}^T, E_{i,j}^0) \ln\left(\frac{I_i^T}{I_i^0}\right),$$

$$\Delta E_{mix} = \sum_{i,j} L(E_{i,j}^T, E_{i,j}^0) \ln\left(\frac{M_{i,j}^T}{M_{i,j}^0}\right),$$

$$\Delta E_{emf} = \sum_{i,j} L(E_{i,j}^T, E_{i,j}^0) \ln\left(\frac{U_{i,j}^T}{U_{i,j}^0}\right),$$

(10)

where $L\left(E_{i,j}^T, E_{i,j}^0\right) = \frac{E_{i,j}^T - E_{i,j}^0}{lnE_{i,j}^T - lnE_{i,j}^0}$, $Q(= \sum_i Q_i)$ is total industrial activity level, $S_i(= \sum_i Q_i/Q)$ and $I_i(= \sum_i F_i/Q_i)$ are, respectively, activity share and energy intensity of sector i, $M_{i,j}(= \sum_{i,j} F_{i,j}/F_i)$ represents the share of fuel j on total fuel consumption in sector i and $U_{i,j}(= \sum_{i,j} E_{i,j}/F_{i,j})$ is the emission-fuel intensity of fuel j in sector i.

1.3. Data

1.3.1. Emission and energy data

Emission and energy data used in this study was obtained from the Air Pollution Emission Source Register (REZZO – Registr emisí a zdrojů znečištění ovzduší).[6] The REZZO data on emissions attributable to stationary emission sources can be further divided into two broad categories. The first category covers emissions generated from fuel combustion, and the second covers emissions generated by various types of chemical reactions in technological processes. Our dataset is based on emissions generated from fuel combustion of facilities larger than 5MW of installed thermal capacity (termed REZZO 1).

For the fuel combustion processes in REZZO 1 facilities, our data set contains unique information about how much emissions are produced by which type of fuel, e.g., how much SO_2 is generated by the combustion of brown coal. While our database on combustion processes allows us to derive emissions per fuel type used for each unit, the emissions from technological processes do not contain information on the attribution of a specific fuel. That is why we particularly focus on emissions generated by REZZO 1 combustion processes (R1comb) in this paper.

The emissions released from the combustion processes of large stationary emissions sources (R1comb) represent a large share of the total aggregate level of emissions, about 80% of total SO_2 and NO_x emission over almost the entire period. The share of particulate matters (PM) from R1comb on total PM decreases across time due to a strict abatement introduced in large sources. Large combustion sources contribute only small amounts to emissions of CO, 5% to 8%. The heat and power sector (NACE rev.2 code 35) represents the majority of fuel consumption and emissions production in our dataset (R1comb) – it represents 70-80% of NOx and SO2 emissions with increasing trend, its share PM emissions decreases from initial 52 %

[6] The REZZO database, maintained by the Czech Hydro-Meteorological Institute, distinguishes four broad categories of emission sources in which data are stored: REZZO1 and REZZO2 include large and medium-sized emission sources, grouped by their thermal output amounts which are larger or smaller than 5MW respectively; REZZO3 reports the emissions released by local units, including households and area sources, while R4 reports emissions from mobile sources. In the case of large emission sources (REZZO1), data are gathered at the facility level. Data for medium-sized sources (REZZO2) are reported at the firm level.

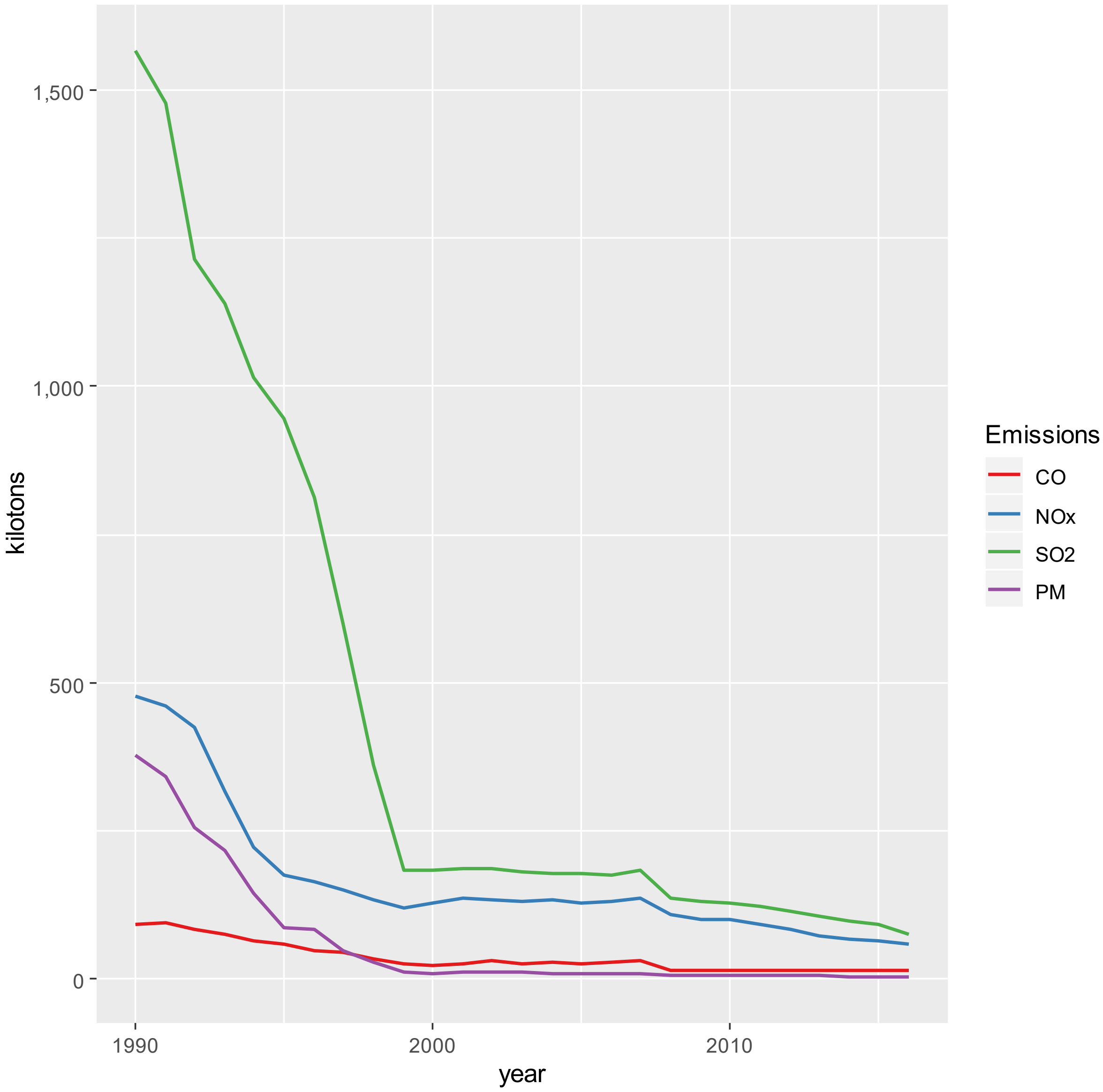
to 33% in 1994 and then increase up to 87 % in 2014. The heat and power sector´s share on fuel consumption on our dataset increases from 65 % to approximately 80 % since 2011.

Figure 1 shows development of emissions levels of CO, NOx, SO2 and PM in our data set from 1990 to 2016. There is an inconsistency between 2007 and 2008. The NACE classification changed from NACE rev.1 to NACE rev.2 in this period. The NACE rev.2 offers more detail than NACE rev.1 and as a consequence, a part of emissions reported in the R1comb database shifted to purely technological processes, while a part of the fuel consumption remained in R1comb – our datasets. As a result, we can observe a drop in all emissions between these two years that is reflected in energy intensity and emissions factor effects. Therefore, we do not interpret the change of emission levels between 2007 and 2008.

We can identify three periods with different patterns of emissions development. In the first period, from 1990 to 1999, all emissions dropped rapidly – on average CO, NOx, SO2 and PM by 14, 14, 21 and 32 percent per year. In the second period, from 2000 to 2007, emissions varied around constant levels or even increased slightly. In the last period, from 2009 to 2016, CO emissions varied, and increased on average by 2 % per year, and NOx, SO2 and PM emissions declined again.

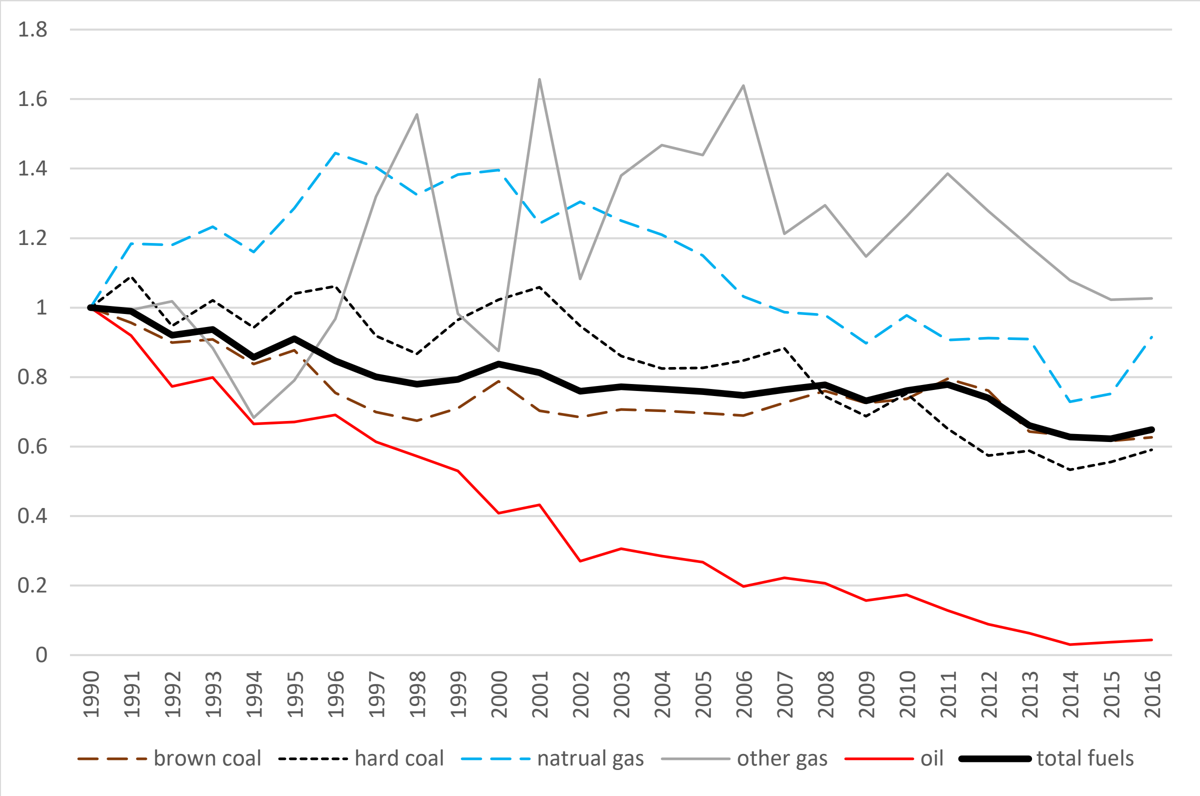
SO2 emissions experienced the largest absolute decrease across the whole period, decreasing from 1575 kt in 1990 to 74 kt in 2016. Therefore, we present the sensitivity analysis of LMDI decomposition on SO2 emissions in section 1.4.2.

Figure 1 Emission levels of CO, NOx, SO2 and PM, 1990–2016 for R1comb [kt]



We conduct the decomposition for eight categories of fuel: (1) brown coal, (2) biomass, (3) biogas, (4) hard coal, (5) natural gas, (6) oil, (7) other gases and (8) other solids. Figure 2 depicts relative development of total fuel consumption and five main fuels in in our dataset from 1990 to 2016. During this period, total fuel consumption has decreased by more than 35%.

Figure 2 Fossil fuels and total energy use , 1990–2016 for R1comb (1990 level = 1.0)



Note: The figure does not depict development of biogas, biomass and other solid fuels, they are included in total fuels, since use of these fuels was very low in the 1990s and grow then rapidly after 2000. Biogas use has started to be reported since 1997. In 2016, use of biogas, biomass and other solid fuels is 21-, 10- and 6-times larger than in 1990 or 1997, respectively.

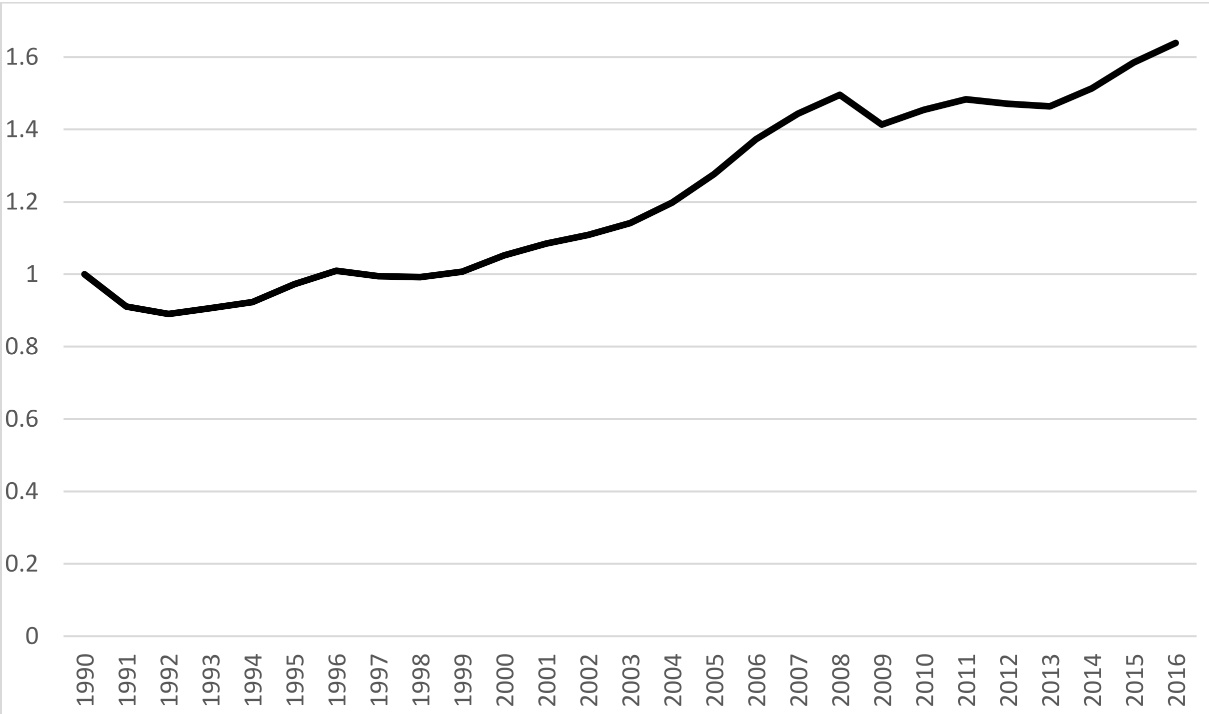
1.3.2. Activity data and aggregation of sectors

We use the Gross Value Added (GVA) as a proxy for economic activity. The GVA is obtained from the Supply and Use Tables (SUT) conducted by the Czech Statistical Office. Unfortunately, the sector classification in SUT is not constant in time. From 1990 to 1994, SUT are reported only in the simple structure of a NACE rev.2 sector classification (38 sectors) and only since 1995 have the SUT been reported in full level 2 NACE rev.2 classification (88 sectors). The GVA is expressed in real 1995 prices calculated based on the current and previous year's prices in the SUT.

The REZZO database contains information on the economic sector of facilities in NACE rev 1.1 till 2007 and only since 2008 in NACE rev.2 classification.

In order to compile a consistent dataset, we have to convert all sector classifications into the same classification structure. There is no one to one match between NACE rev.1.1 and NACE rev.2. First, we convert the REZZO database to aggregation of NACE rev.2 classification. As a result, we have a dataset aggregated to 44 sectors covering all large combustion sources in R1comb, consistent from 1995 to 2016. Second, we combine this 44 sector aggregation with the simple structure of NACE rev.2. and obtain a dataset aggregated to 26 sectors from 1990 to 2016. Figure 3 depict the relative development of Czech GVA from 1990 to 2016. During this period, the GVA in constant prices of 1995 has increase by almost 64 %.

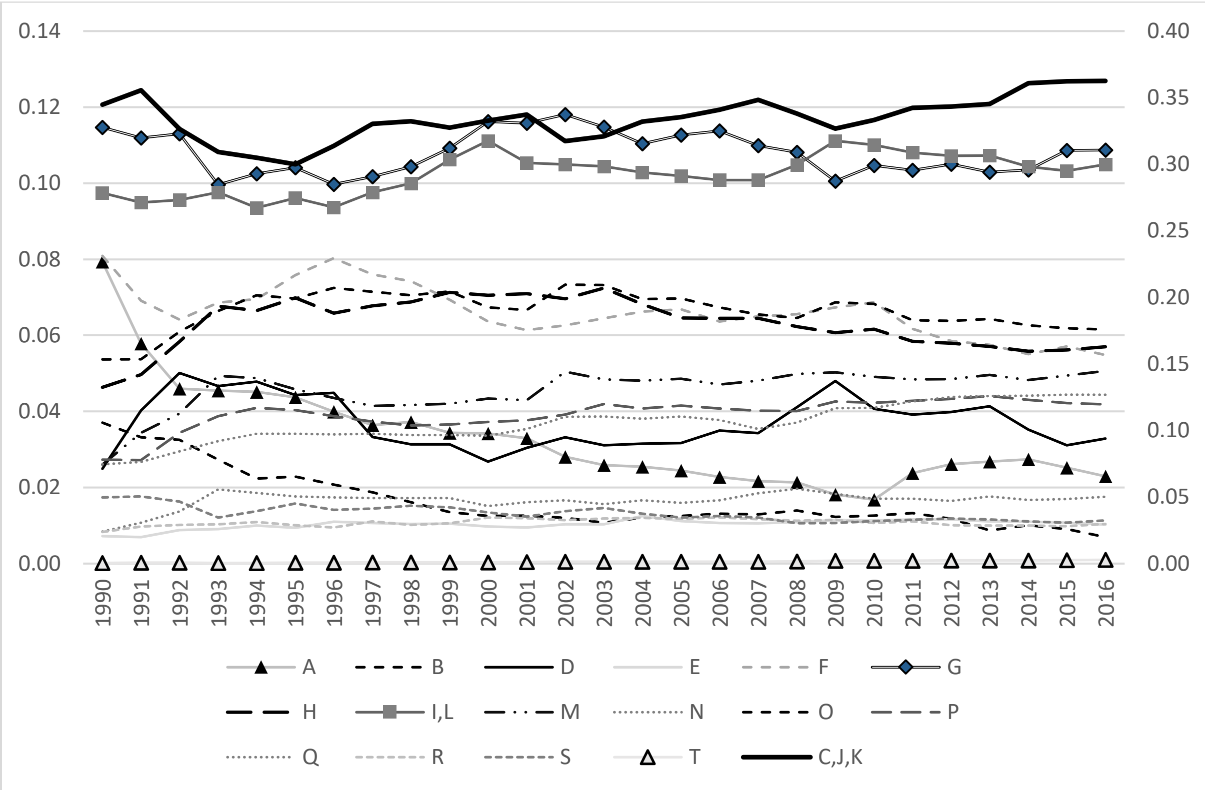
Figure 3 Gross value added, 1990–2016



We apply the LMDI decomposition to both datasets and also aggregate our dataset to 18 sectors to test the effect of sectoral aggregation on the precision of the LMDI method. Figure 4 depicts shares of economic sectors in 18 sector aggregation on total GVA from 1990 to 2016. Share of heat and power sector (D) involves counter-cyclically. Agriculture (A) and Mining and quarrying (B) from 8 to 2 and from 4 to less 0.7 percentage share on total GVA, respectively. Other sectors vary around their initial values. Figure 5 focuses on the C,J,K sector that has share of approximately 35 % GVA and depicts shares of its subsectors on total GVA.

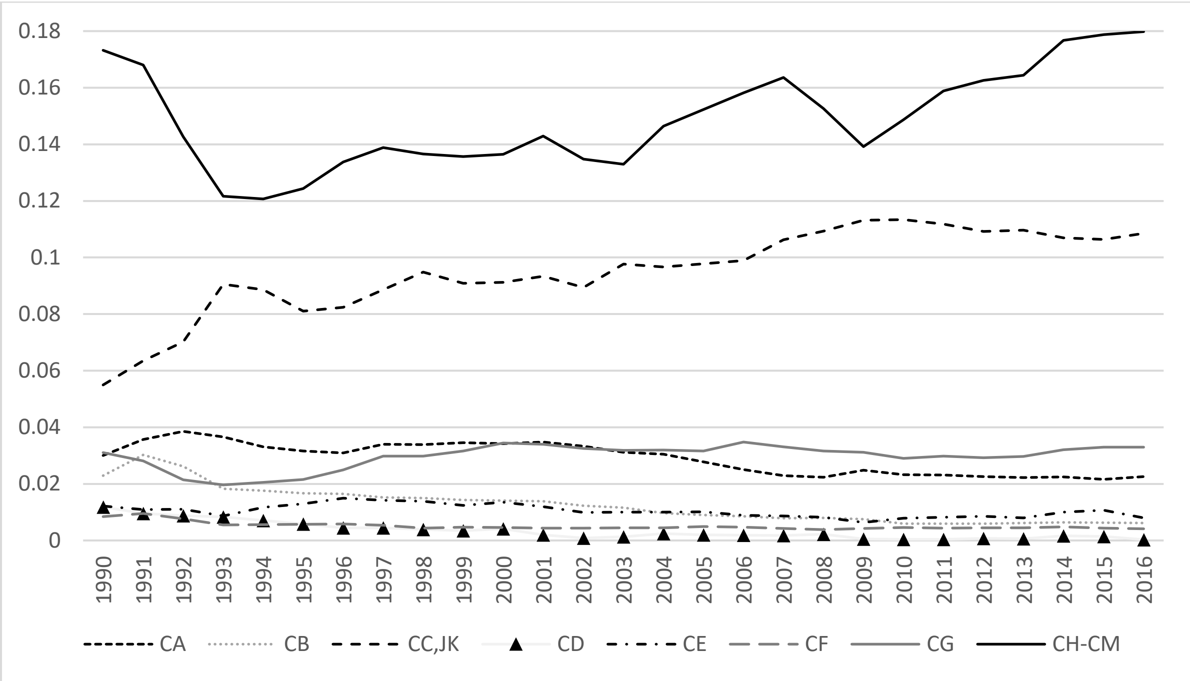
Table 4 in Appendix provides the sectoral aggregation in all three cases.

Figure 4 Share of sectoral GVA on total GVA, 1990–2016 (18 sectors)



Note: C,J,K sector (NACE codes 10-33 and 58-66) are on the right axis.

Figure 5 GVA share of C,J,K subsectors on total GVA, 1990–2016



1.4. Results

We apply the 5-factor LMDI decomposition in order to analyse the five underlying factors of air quality emissions in the Czech Republic from 1990 to 2016. Specifically, we quantify the amounts each of these five factors (scale, structure, fuel intensity, fuel-mix and emission-fuel intensity) were contributing to changes in the volumes of these emissions over this period. Then, we perform sensitivity analyses of the LMDI decomposition with respect to the number of decomposition factors (3F and 4F compared to 5F) and sectoral breakdown of the economy.

The decomposition is always performed on a year-by-year basis, though we report the results for a particular year if a cumulative effect is reported for a period. We also note that fuel use and emissions are measured for the large emission stationary sources and for combustion processes, setting aside emissions stemming from technological processes, medium-size and small stationary emission sources and mobile sources.

Due to a revision in NACE classification, the data are not fully consistent around 2007-2008.[7] As a consequence of this inconsistency, there are visible sharp hikes in the 2008/2007 annual

[7] As a consequence of the NACE revisions, some facilities were reclassified into a different economic sector and/or moved from the category of stationary emission sources combusting fuels (addressed in this paper) to sources

changes in all figures below. Due to this inconsistency in data, the 2008/2007 annual changes cannot be compared and readers should overlook them.

1.4.1. Five factor decomposition of air quality emissions for 1990–2016

This section provides the results of the 5F LMDI decomposition of SO2, NOx, PM and CO emissions performed for each year for the period of 1990–2016. This decomposition is performed with the economy breakdown into 26 economic sectors and eight different types of fuels. This means the decomposition works with 26 x 8 different emission-fuel intensities gathered for each year. Since the economic data are available in finer sectoral disaggregation from 1995 only, the LMDI decomposition with a 44 sector-breakdown can be carried out from 1995 on. How finer sectoral breakdown affected the decomposition outcome during the period 1996–2016 is therefore discussed in next subsection.

Figures 6–13 display the results from the 5F LMDI decomposition, in which we show the contributions of factors to emission changes in tonnes (on the left, in figures with even numbers) and then in percentage points (on the right, in figures with odd numbers). In each of the figures it is visible that, although the patterns of emission reductions and their drivers vary across the four pollutants analysed, there are two factors that are responsible for the largest portion of emissions reductions of each pollutant during nearly the entire period analysed. These two factors are the fuel intensity and the emission-fuel intensity.

Table 1 provides the results for the three periods (1990-1999, 1999-2007 and 2008-2016), but even here the decomposition is always performed on a year-by-year basis.[8] From left to right, we report the total changes that occurred before the end and the beginning of each particular period in kilotons and percentages. For instance, emissions of SO2 were reduced by 1,391 kt between 1990-1999, which amounted to a reduction of 88 %. In following period of 1999 - 2007, SO2 emissions were stable. In the 2008-2016 period, these emissions decreased further, by about 61 k, amounting to a 45 % reduction. The remaining five columns display overall

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releasing emissions from technological processes or to small emissions sources (neither of which is considered in this work).

[8] As Löfgren & Muller (2010) emphasized, "summing the effects of one factor over all years usually does not reveal a reliable overall effect of the factor in question" (Löfgren & Muller, 2010, p. 230). Hence, a decomposition that is based on the first and last years of a certain period exhibits similar problems as summing the effects of one particular factor over years. It implies that "results from decomposition analysis of changes over several years based on the first and the last year only or reporting sums over all years should be used very cautiously" *(ibid.)*..

whether and how much a given factor contributed more positively (increasing emissions) or negatively (decreasing emissions). Again, in the case of SO_2 emissions and for the first period (1990-1999 with 9 year-by-year changes), there were one more positive effects of the scale factor than negative (+1). For the same period and the same pollutant, the fuel mix factor affected emissions seven times more negatively than positively, and emission-fuel intensity constantly reduced emissions (i.e. the effect of this factor was always negative).

Table 1 Cumulative emissions change by period and indication of LMDI effects impacts

Pollutant	Period	Change (kt)	Change (%)	Activity	Structure	Fuel intensity	Fuel mix	Emission-fuel
CO	1990-99	-68.2	-73.8%	1	-3	-5	-5	-5
	1999-07	5.7	23%	8	-2	-6	0	0
	2008-16	3.9	29.3%	2	0	-2	2	2
NOx	1990-99	-358.5	-74.9%	1	-1	1	-3	-7
	1999-07	15.0	12.5%	8	2	-4	0	2
	2008-16	-52.2	-46.9%	2	0	0	-2	-8
PM	1990-99	-369.3	-96.9%	1	1	-1	-9	-7
	1999-07	-3.0	-25.6%	8	0	-4	-2	0
	2008-16	-1.8	-37.9%	2	0	0	-6	-4
SO2	1990-99	-1391.4	-88.3%	1	-1	1	-7	-9
	1999-07	-1.0	-0.6%	8	2	-4	0	0
	2008-16	-60.6	-44.9%	2	0	2	-4	-4

Note: In the last five columns we indicate how many times a given decomposition factor was either positive (increasing emissions), or negative (reducing emissions). The indicator is a sum of positive contributions (+1) and negative contributions (-1) across all years in the given period. For instance, zero indicates there were the same number of years with positive and negative direction of the factor effect for the given period. The decomposition is always performed on a year-by-year basis, so there are nine effects (one for each year) for the period 1990-1999, eight effects for 1999-2007 and another eight effects for 2008-2016

Table 1 clearly shows that the largest drop in emissions of all four pollutants occurred in the first period, from 1990 to 1999, when the emissions decreased by at least 74 %. In this period, the emission-fuel intensity factor was dominant in reducing emissions, followed by the fuel-intensity effect and the fuel-mix effect. In contrast, the activity and structure effects had positive impacts on emissions growth.

In the second period, from 1999 to 2007, emissions paths followed different patterns and even trends. Strong economic growth in this period resulted in a strong positive activity effect. The structure and fuel mix effects went in the same direction for all pollutants, but their effect was significantly lower than the activity effect. The fuel-intensity factor was the only negative one, and it reduced all four pollutants in this period. Thanks to its effect, overall emissions did not rise during this period. The effect of the emission-fuel intensity factor was both positive and negative during this period, as shown in Figure 7, Figure 9, Figure 11 andFigure 13. The emission-fuel intensity reduced emissions of PM, its effect was almost neutral for SO2 and it increased emissions of NOx and CO. Over the second period, CO and NOx emissions increased by 23 and 12 percent, while emissions of PM and SO2 decreased by 26 and 1 percent, respectively.

In the last period, from 2008 to 2016, the activity effect is positive, but its magnitude is lower than the effects of the other factors. The structure and fuel-intensity factors contributed negatively or positively at different magnitudes. As in the first period, the emission-fuel intensity is the most important factor in reductions of SO2, NOx and PM emissions. Overall, SO2, NOx and PM emissions followed a decreasing trend in this period. Emissions of CO rose and fell, but overall CO emissions rose, following the trend since 1999. In this case, while the activity, fuel-intensity and emission-fuel intensity factors mainly contributed to CO emissions increases, the fuel mix worked mainly in the opposite direction.

The magnitude and direction of the effect due to each factor is displayed in detail in figures 6–13. SO_2, NO_x and PM emissions shared a common decreasing trend over the whole period when the fuel mix effect was relatively low (up to -4, -2 and -6 percent, respectively) compared to the effects of other factors. CO emissions started at the lowest initial value of all four pollutants (see Figure 1). Their decline was relatively low in magnitude compared to other pollutants, and these reductions were realised mostly before 2000. Since then, emissions of CO rose and fell with the diverse directions of the effect of each factor, but the emission-fuel intensity was primarily responsible for reducing CO emissions, particularly before 2000.

In the first years after 1989, the Czech economy changed considerably in terms of its structure, and reduced its energy intensity. Still, the structure effect was very strong and positive, leading to increases, not decreases, in emissions of SO_2, NO_x and PM during the early years of economic transformation (1990-1992). Fuel intensity and activity factors worked in opposite directions in the first years after the Revolution, reducing emissions from large stationary sources by relatively large amounts and percentages. Emission-fuel intensity played a dominant role in reducing SO_2 and PM emissions until 1999 and 2000, respectively, due to installations of abatement technologies as a consequence of air emission control regulations introduced at the beginning of the 1990s. Between 2000 and 2014, the importance of the emission-fuel intensity factor lost its dominancy in reducing SO_2 and PM emissions, while the roles of fuel-intensity, structure and activity factors became at least as important as the emission-fuel intensity effect.

Figure 6: 5 factor decomposition of SO2 emission from 1990 to 2016 (t)

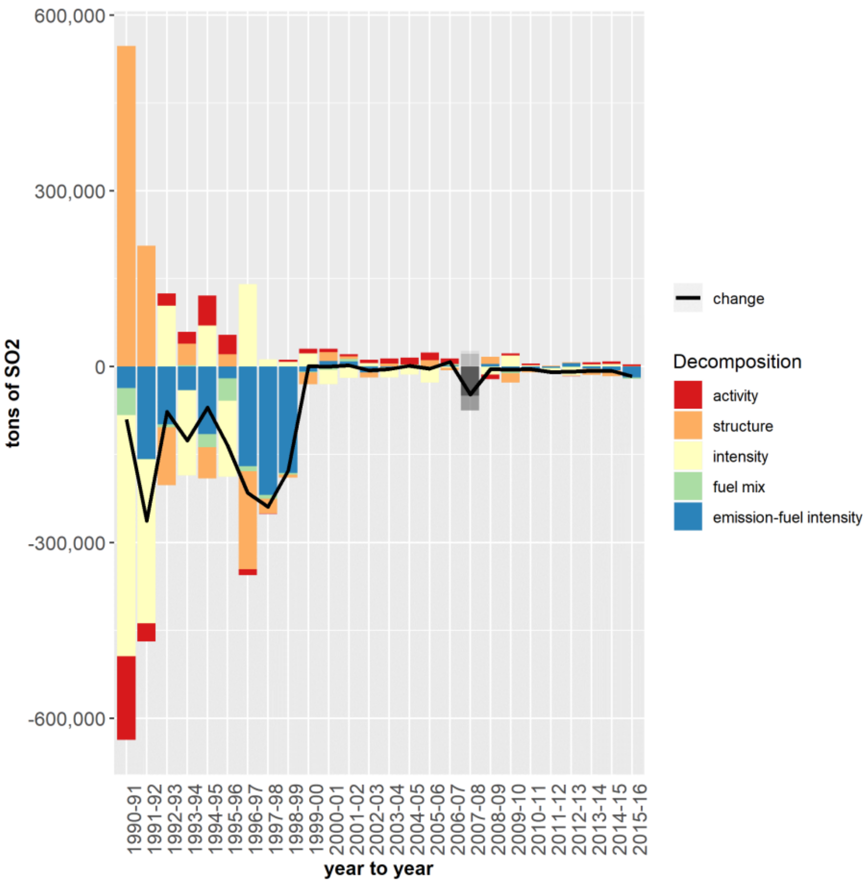


Figure 7: 5 factor decomposition of SO2 emission from 1990 to 2016 (percent)

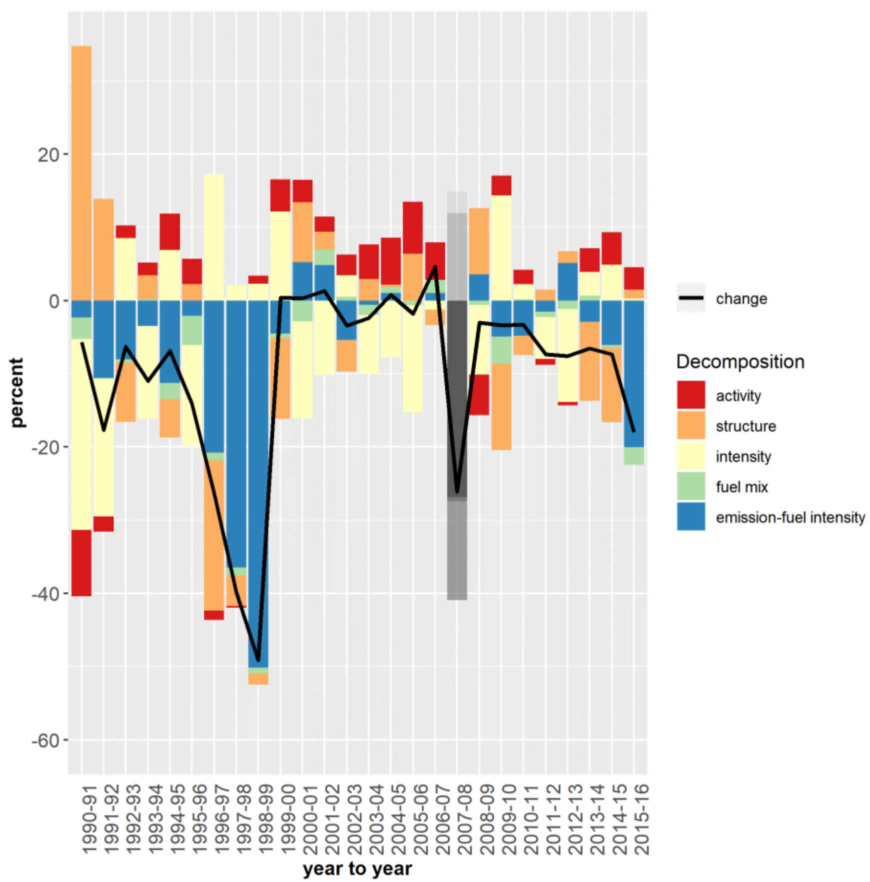


Figure 8: 5 factor decomposition of NOx emission from 1990 to 2016 (kt)

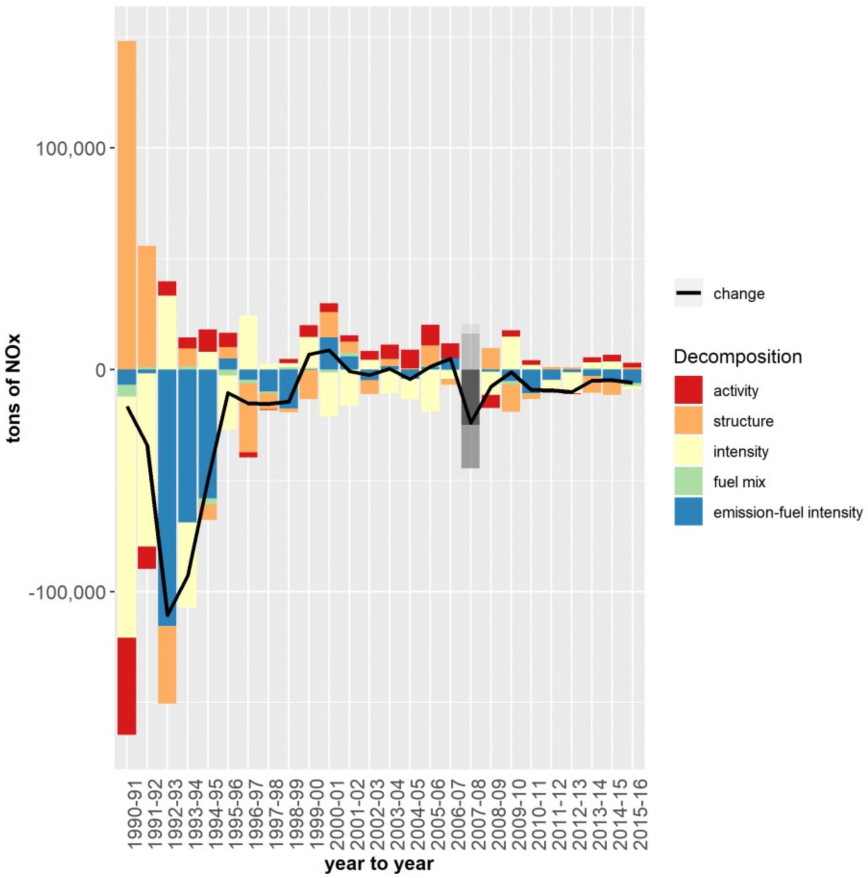


Figure 9: 5 factor decomposition of NOx emission from 1990 to 2016

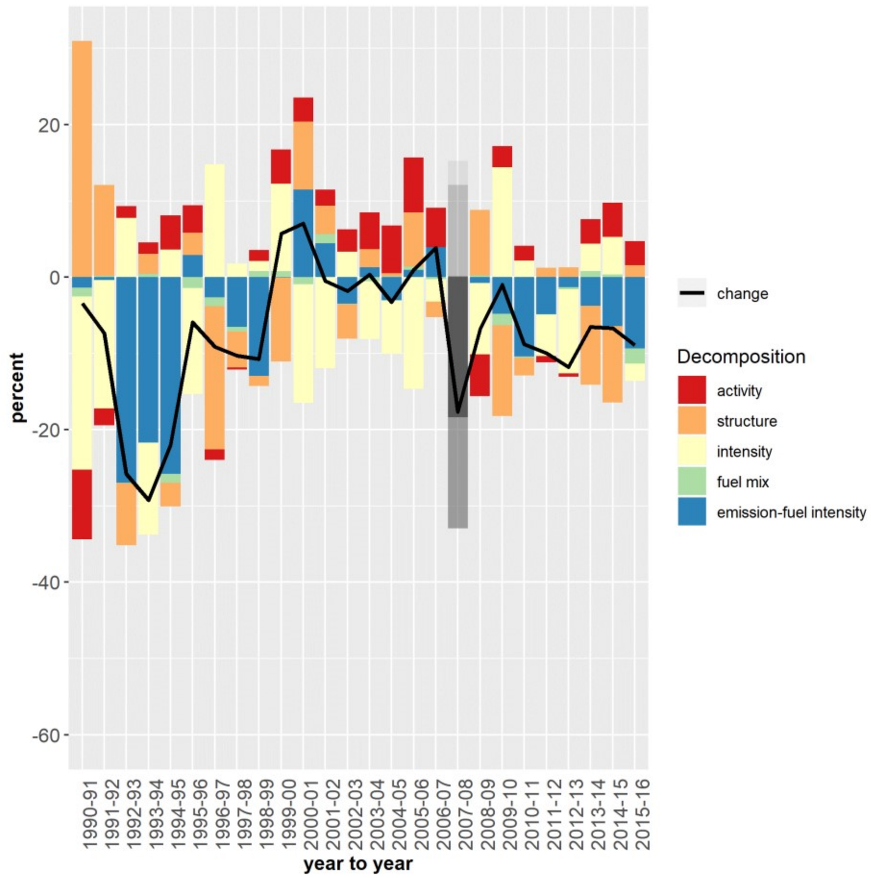


Figure 10: 5-factor decomposition of CO emission from 1990 to 2016 (kt)

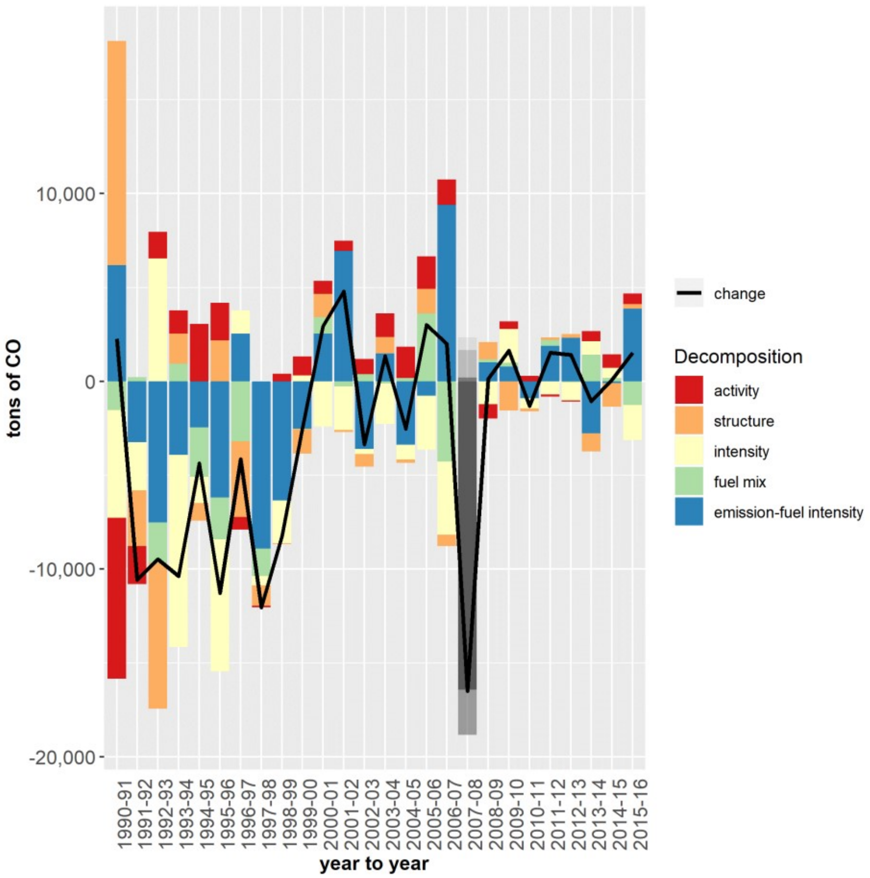


Figure 11: 5-factor decomposition of CO emission from 1990 to 2016

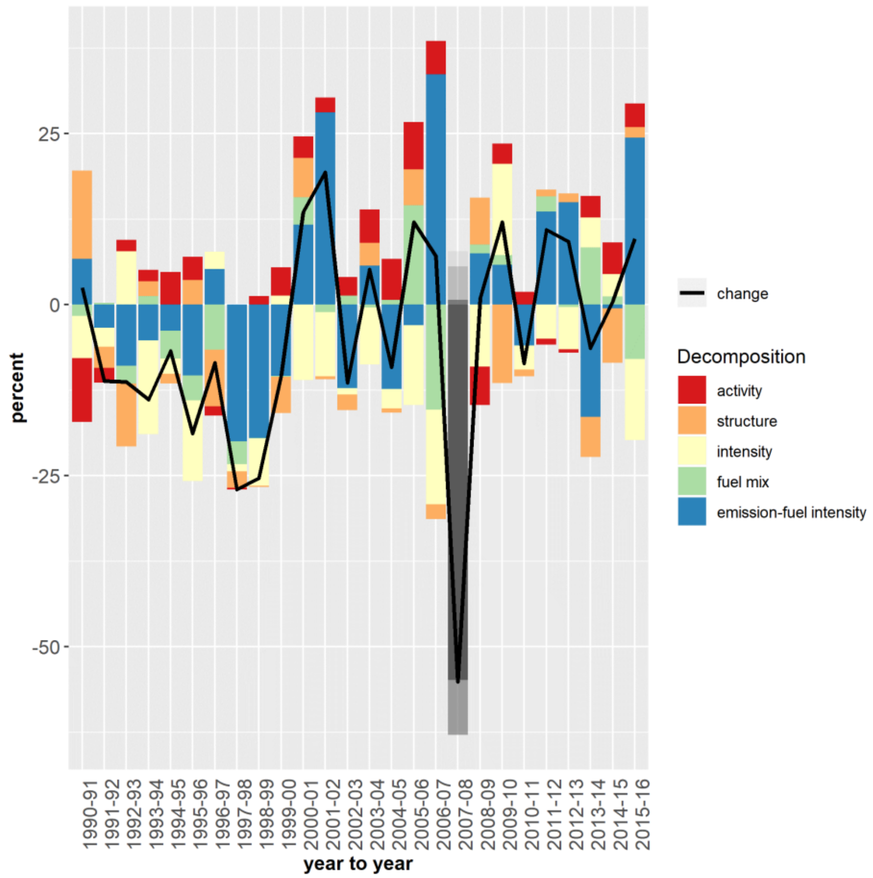


Figure 12: 5-factor decomposition of PM emission from 1990 to 2016 (kt)

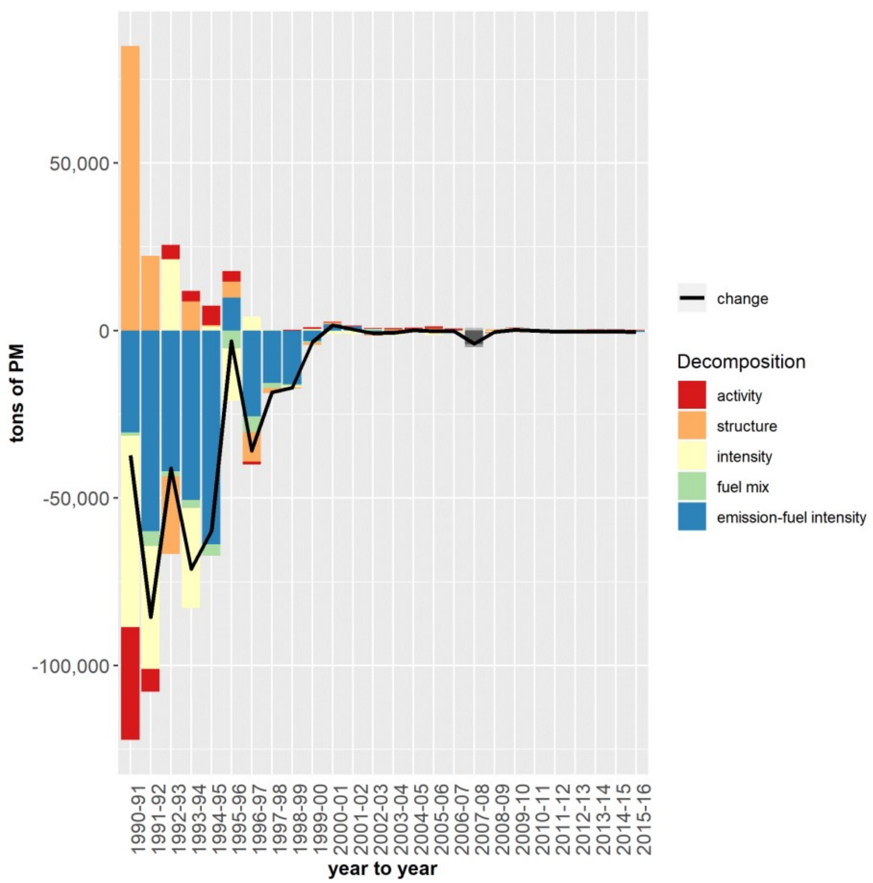
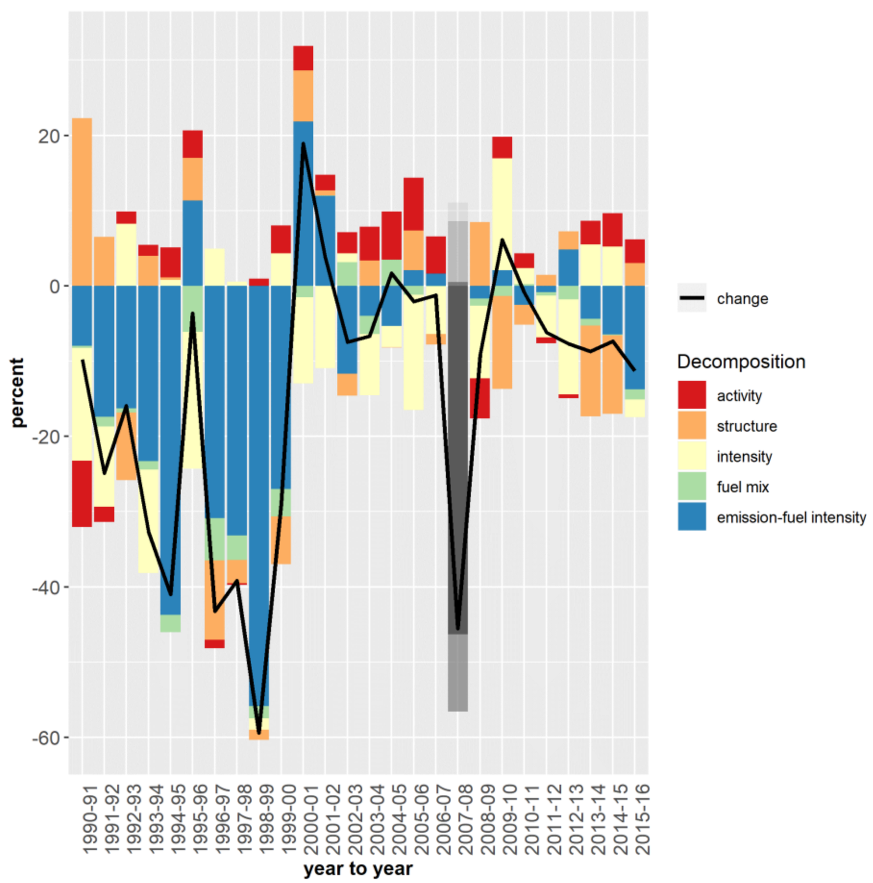


Figure 13: 5-factor decomposition of PM emission from 1990 to 2016



1.4.2. Sensitivity analysis of LMDI decomposition with respect to the number of decomposition factors and sectoral aggregation

We perform sensitivity analyses of LMDI decomposition on individual years in the period between 1995 and 2016, when we have the most detailed dataset of 44 sectors. We focus on the differences between the decompositions with respect to the number of decomposition factors and sectoral aggregation here, and present all figures in percentages.

1.4.2.1. Sensitivity analysis of LMDI decomposition with respect to the number of decomposition factors

Most literature applying LMDI decomposition performs a 3-factor decomposition. This distinguishes the activity effect of the whole economy, the structure effect and the emission intensity effect. The emissions intensity effect is the main driver of SO2 emissions reduction in the period from 1995 to 2016 (in sum and in 14 cases of 21), followed by the structure effect. The activity effect, on the other hand, is positive in 17 of 21 cases.

The emissions intensity effect captures three emissions abatement options together, i.e. it captures abatements through end-of-pipe technology, fuel switch and technological and/or product changes that can affect the energy intensity of production. This factor thus indicates the effects of the environmentally friendliness of production without distinguishing further through which channel the emissions were abated. Although these three channels can be either combined or counteract each other – as is clear from the emissions changes from 1996 to 1997 (second column in the figures) when the positive effects of energy intensity are outweighed by negative effects of emissions factor and partly by fuel mix factor too.

The 4-factor decomposition allows us to understand the underlying drivers of the emissions intensity effect – i.e. the energy intensity effect, the emissions factor effect aggregated for total energy consumption. We can see the energy intensity effect on SO2 emissions was positive ten times and negative ten times between 1995 and 2016, but over this period, the reductions in the energy intensity of the Czech economy helped to reduce SO2 emissions overall.

The 5-factor decomposition goes one step further and decomposes the emissions factor aggregated for total energy consumption to fuel mix effect and the emissions factor effect related to consumption of individual fuels. The fuel mix effect captures the effect of a change in fuel type on emissions. The emissions factor effect captures changes in the quality of fuel within the particular fuel (e.g. shift to coal with low content of SO2) and changes in technologies – mainly the introduction of end of pipe abatements – where the later channel of emissions reduction is dominant.

The new information on the role of fuel type changes on SO2 emissions (fuel mix effect) supports the emissions factor effect in 15 of 21 years analysed, but is always lover in absolute terms than the emissions factor effect.

Thanks to the definition of LMDI decomposition, adding fuel specific dimension – in the 5-factor decomposition – affects not only the last factor that is decomposed, but has a slight impact on the other effects as well (e.g. $\sum_{i,j} L(E_{i,j}^{T}, E_{i,j}^{0}) \ln\left(\frac{Q^T}{Q^0}\right)$ is not equal to $\sum_{i} L(E_{i}^{T}, E_{i}^{0}) \ln\left(\frac{Q^T}{Q^0}\right)$). Table 2 compares the activity, structure and intensity effects in 5-factor LMDI and with 3- and 4-factor LMDI decomposition effects. Introduction of fifth factor and the new dimension of specific fuel decrease all other LMDI effects in most cases.

Table 2 Impact of additional dimension in 5-factor LMDI on activity, structure and intensity effects

Factors compared:	5/3		5/4		
Effect	Activity	Structure	Activity	Structure	Intensity
1995-96	-0.2%	-0.5%	-0.2%	-0.5%	-0.2%
1996-97	-0.5%	-0.4%	-0.5%	-0.4%	-0.5%
1997-98	-0.2%	-0.1%	-0.2%	-0.1%	0.7%
1998-99	-1.0%	-3.1%	-1.0%	-3.1%	3.1%
1999-00	-0.4%	-0.1%	-0.4%	-0.1%	0.0%
2000-01	-0.5%	-0.2%	-0.5%	-0.2%	0.4%
2001-02	-0.6%	4.3%	-0.6%	4.3%	0.9%
2002-03	-0.9%	0.8%	-0.9%	0.8%	6.7%
2003-04	-0.6%	-2.5%	-0.6%	-2.5%	-2.5%
2004-05	-0.2%	0.4%	-0.2%	0.4%	0.0%
2005-06	-0.5%	-0.1%	-0.5%	-0.1%	-0.2%
2006-07	-0.6%	-0.6%	-0.6%	-0.6%	-7.9%
2007-08	-1.3%	-0.3%	-1.3%	-0.3%	0.3%
2008-09	-0.1%	0.1%	-0.1%	0.1%	-0.1%
2009-10	-0.3%	-0.3%	-0.3%	-0.3%	2.3%
2010-11	-0.2%	0.0%	-0.2%	0.0%	1.3%
2011-12	-0.2%	-0.6%	-0.2%	-0.6%	1.9%
2012-13	-0.2%	0.2%	-0.2%	0.2%	-0.6%
2013-14	-0.2%	0.2%	-0.2%	0.2%	1.7%
2014-15	0.0%	0.0%	0.0%	0.0%	0.0%
2015-16	-0.2%	2.6%	-0.2%	2.6%	-18.4%
Mean of absolute values	0.4%	0.8%	0.4%	0.8%	2.4%
Min	-1.3%	-3.1%	-1.3%	-3.1%	-18.4%
Max	0.0%	4.3%	0.0%	4.3%	6.7%

1.4.2.2. Sensitivity analysis of LMDI decomposition with respect to sectoral aggregation

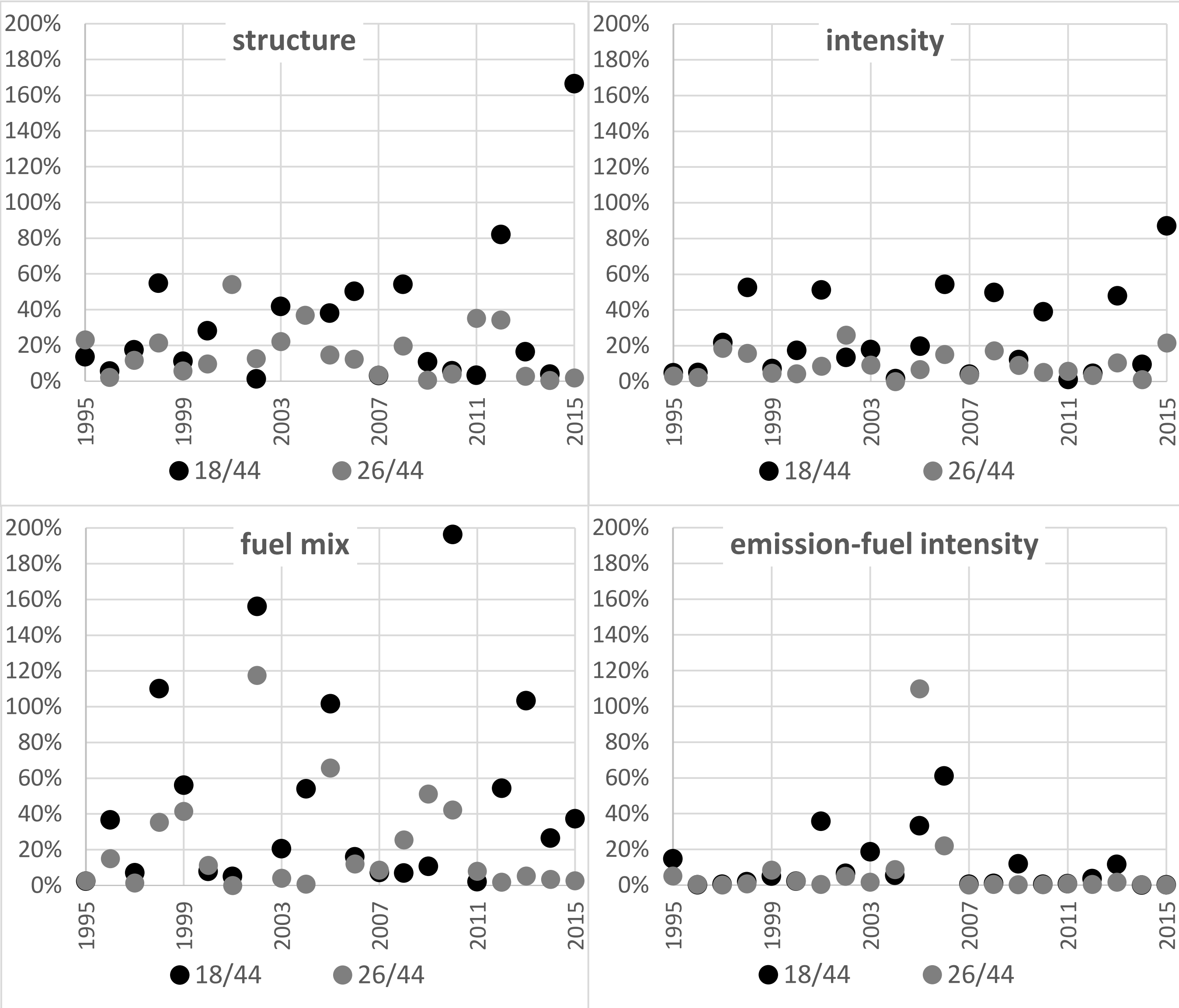
The availability of data can often affect the number of sectors included in the decomposition, either in the sense that only some sectors are included or that the sectors are aggregated to some degree. Although, as Rørmose & Olsen (2003) and (Seibe, 2003) find, the more aggregated input data for the decomposition analysis is, the more information is lost. We focus on the role of sectoral aggregation of results of LMDI decomposition here.

Since we need to have consistent dataset at least from 1995, we aggregate the economic sectors to 44 and to 26 sectors, in order to have a consistent dataset from 1990 to 2016. We created a third aggregation of 18 sectors to test the impact of aggregation on values of factors in LMDI decomposition. The 44 sector aggregation is our reference as the most detailed LMDI decomposition we are able to perform with a consistent dataset.

Figure 14 depicts the relative difference in the values of intensity, structure, fuel mix and emission effects with respect to the values of effects based on LMDI with 44 sector aggregation. The differences in activity effects across the three sectoral aggregation are negligible (up to 0.9 %), as shown in Table 3. The bias from the 44 sector aggregation is significantly lower in the case of 26 sectors than in the case of just 18.

On average, the structure, intensity, fuel mix and emission-fuel intensity effects are biased by 15.7, 9.1, 21.7 and 8.1 percent, respectively, in the 26 sector aggregation from the 44 sector aggregation in the period from 1995 to 2016. The median bias is much lover: 12.3, 6.7, 8.6 and 0.8 percent, respectively. The median of absolute values of effects in LMDI with 44 sectors are 80, 94, 14 and 101 percent for the structure, intensity, fuel mix and emissions factor effects, respectively. We see that the bias is relatively low by the most important effect – the emissions factor effect (0.8 % on median).

Figure 14 Relative difference in effect value using LMDI with 18 and 26 sectors relative to the effect value based on LMDI with 44 sectors



Note: Absolute value of percentage difference relative to the factor value derived from the LMDI with 44 economic sectors. There are three cases with very large value of difference, always when comparing the LMDI with 18 sectors and 44 sectors; to display these large values using the same scale we divide the value of percentage difference by ten and display them by rhombus (the large difference are reported for the intensity factor in 2015 [870 %], for the fuel mix factor [1964 %] and for the emission intensity factor [332 %]).

Table 3. Sumary statistics of relative divefences in efect value using LMDI with 18 and 26 sectors relative to the factor value based on LMDI with 44 sectors

		activity	structure	intensity	fuel mix	emission-fuel
min.	18/44	0.0%	1.2%	1.1%	2.0%	0.1%
max.	18/44	0.9%	205.0%	870.6%	1964.2%	331.8%
mean	18/44	0.2%	48.4%	62.2%	132.7%	24.5%
median	18/44	0.2%	17.6%	17.4%	26.5%	3.6%
min.	26/44	0.0%	0.4%	0.0%	0.0%	0.1%
max.	26/44	0.5%	54.1%	26.0%	117.6%	109.8%
mean	26/44	0.1%	15.7%	9.1%	21.7%	8.1%
median	26/44	0.0%	12.3%	6.7%	8.6%	0.8%

1.5. Conclusions

This study applies Logarithmic Mean Divisia Index decomposition to examine the factors that were active in changing the emissions level of four air pollutants from large stationary sources – SO_2, NOx, CO and particulate matters – during the transition and post-transition periods of the Czech economy, from 1990 to 2016. We perform 5-factor LMDI decomposition, in which the standard third factor – emission intensity – is further decomposed to fuel intensity, fuel mix and emission-fuel intensity effects.

Our time span overlaps two versions of the Statistical Classification of Economic Activities in the European Community (NACE) – revision 1 and revision 2. Due to changing NACE nomenclature in the REZZO fuel and emission database and the simplified structure of GVA for the 1990-1994 period, we create two consistent, but aggregated datasets. The first is aggregated to 26 sectors for the entire 1990-2016 period, and the second is aggregated to 44 sectors for 1995-2016.

Following Löfgren & Muller (2010), we consider annual changes rather than decomposition on longer time intervals to avoid biased results. However, we can identify three sub periods in our time span with common trends and similar patterns for SO_2, NOx and particulate matters; 1990-1999, 1999-2007 and 2008-2016. CO emissions developed differently than those of the other pollutants. The largest drop in emissions of all four pollutants occurred in the period from 1990 to 1999, when the emissions decreased cumulatively by at least 74 %. In this period, firms faced a newly competitive environment and new command-and-control regulations. As a result, a negative fuel emissions factor effect was the key driver of emissions reductions. However, the fuel intensity effect contributed most to reduction of SO_2, NOx and PM emissions in the first 3 years after the Velvet Revolution, when the Czech and Slovak economies uncoupled. In 1999, all large stationary emission sources were required to comply with emission limits introduced in 1991. Therefore, it was mainly market mechanisms that affected development of SO_2, NOx and PM emissions. Economic growth reflected by a strong positive activity effect pushed emissions upwards, though reductions driven by fuel intensity held emissions down. Since 2008, the magnitude of activity, structure, intensity and emissions factor effects moved closer. In the last two years of our time span, 2015 and 2016, the emissions factor effect became important again, as large stationary emission sources were required to comply with strict new emissions limits based on the directive on industrial emissions. The fuel mix effect reaches absolute values higher than 6 % only in relation to CO emissions (up to 15 % in 2005-2006 and 2006-2007).

To identify differences in 3-, 4- and 5-factor LMDI decomposition, we perform a sensitivity analysis for SO2 emissions with our most detailed dataset of 44 sectors during 1995-2016. The differences in the emission intensity in 3-factor LMDI and emission coefficient effects related to total energy consumption in 4-factor LMDI, which are decomposed into more detailed effects by 4- and 5- factor LMDI, are as expected. We want to highlight that adding a fuel specific dimension – in the 5-factor decomposition –affects not only the last factor that is decomposed, but decreases all other LMDI effects in most cases. In our case, the activity effect is reduced by up to 1.3 %, the structure effect by up to 3.1 % and the fuel intensity in the 4-factor decomposition is reduced by up to 18.4 %. Nevertheless, the means of absolute values of the differences are significantly lower: 0.4, 0.8 and 2.4 percent for the activity, structure and fuel intensify effect, respectively.

Since we have two datasets with different sector breakdowns of the economy, we perform a sensitivity analysis of 5-factor LMDI decomposition of SO2 emission with respect to levels of sector breakdown. We also add a third sectoral breakdown of 18 sectors to our two datasets with 44 and 26 sectors. We summarise our result so that, the more aggregated the economic sectors are, the larger the bias is. The differences breakdowns for 44 sectors are at least 3 times lower with 26 sectors than with 18. The differences in the activity effects are negligible. On the other hand, we find the highest relative differences driven by the fuel mix effect, which may be related to the low magnitude of this effect. The relative differences in absolute values of LMDI effects between the breakdown to 44 and 26 sectors, which we use for our decomposition from 1990 to 2016, are on average 0.1, 15.7, 9.1, 21.7 and 8.1 percent for the activity, structure, intensity, fuel mix and emission-fuel intensity effects, respectively. Our results support applying as detailed a sector disaggregation as possible in decomposition analysis.

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Appendix

Table 4 Aggregation of sectors

Sec (18)	Simple NACE rev.2	**Simple_Str (26)**	**NACE2 agregation (44)**	NACE rev.2	Description - NACE rev.2 (adjusted)
A	A	A	A	01	Agriculture
A	A	A	A	02	Forestry and logging
A	A	A	A	03	Fishing and aquaculture
B	B	B	05	05	Mining of coal and lignite
B	B	B	06	06	Extraction of crude petroleum and natural gas
B	B	B	07	07	Mining of metal ores
B	B	B	08	08	Other mining and quarrying
B	B	B	09	09	Mining support service activities
C,J,K	CA	CA	10	10	Food products
C,J,K	CA	CA	11	11	Beverages
C,J,K	CA	CA	12	12	Tobacco products
C,J,K	CB	CB	13	13	Textiles
C,J,K	CB	CB	14	14	Wearing apparel
C,J,K	CB	CB	15	15	Leather and related products
C,J,K	CC	CC,JK	16	16	Wood and of products of wood , except furnitur
C,J,K	CC	CC,JK	17	17	Paper and paper products
C,J,K	CC	CC,JK	18,J,K	18	Printing and reproduction of recorded media
C,J,K	CD	CD	19	19	Coke and refined petroleum products
C,J,K	CE	CE	20	20	Chemicals and chemical products
C,J,K	CF	CF	21	21	Pharmaceutical products and preparations
C,J,K	CG	CG	22	22	Rubber and plastic products
C,J,K	CG	CG	23	23	Non-metallic mineral products
C,J,K	CH	CH-CM	24	24	Basic metals
C,J,K	CH	CH-CM	25, 28-30, 33	25	Fabricated metal products, except machinery
C,J,K	CI	CH-CM	26-27,32	26	Computer, electronic and optical products
C,J,K	CJ	CH-CM	26-27,32	27	Electrical equipment
C,J,K	CK	CH-CM	25, 28-30, 33	28	Machinery and equipment n.e.c.
C,J,K	CL	CH-CM	25, 28-30, 33	29	Motor vehicles, trailers and semi-trailers
C,J,K	CL	CH-CM	25, 28-30, 33	30	Other transport equipment
C,J,K	CM	CH-CM	31	31	Furniture
C,J,K	CM	CH-CM	26-27,32	32	Other manufacturing
C,J,K	CM	CH-CM	25, 28-30, 33	33	Repair and installation of machinery
D	D	D	35	35	Electricity, heat and gas
E	E	E	36	36	Water collection, treatment and supply
E	E	E	37-39	37	Sewerage
E	E	E	37-39	38	Waste collection, treatment; materials recovery
E	E	E	37-39	39	Remediation activities
F	F	F	F	41	Construction of buildings
F	F	F	F	42	Civil engineering

F	F	F	F	43	Specialised construction activities
G	G	G	G	45	Wholesale and retail trade
G	G	G	G	46	Wholesale trade, except of motor vehicles and motorcycles
G	G	G	G	47	Retail trade, except of motor vehicles and motorcycles
H	H	H	H	49	Land transport and transport via pipelines
H	H	H	H	50	Water transport
H	H	H	H	51	Air transport
H	H	H	H	52	Warehousing and support activities for transportation
H	H	H	H	53	Postal and courier activities
I,L	I	I,L	I,68	55	Accommodation
I,L	I	I,L	I,68	56	Food and beverage service activities
C,J,K	JA	CC,JK	18,J,K	58	Publishing activities
C,J,K	JA	CC,JK	18,J,K	59	Motion picture, video and television programm production, sound recording and music publishi activities
C,J,K	JA	CC,JK	18,J,K	60	Programming and broadcasting activities
C,J,K	JB	CC,JK	18,J,K	61	Telecommunications
C,J,K	JC	CC,JK	18,J,K	62	Computer programming, consultancy and relate activities
C,J,K	JC	CC,JK	18,J,K	63	Information service activities
C,J,K	K	CC,JK	18,J,K	64	Financial service activities, except insurance anc pension funding
C,J,K	K	CC,JK	18,J,K	65	Insurance, reinsurance and pension funding, exc compulsory social security
C,J,K	K	CC,JK	18,J,K	66	Activities auxiliary to financial services and insurance activities
I,L	L	IL	I,68	68	Real estate activities
M	MA	M	M	69	Legal and accounting activities
M	MA	M	M	70	Activities of head offices; management consulta activities
M	MA	M	M	71	Architectural and engineering activities; technic testing and analysis
M	MB	M	M	72	Scientific research and development
M	MC	M	M	73	Advertising and market research
M	MC	M	M	74	Other professional, scientific and technical activities
M	MC	M	M	75	Veterinary activities
N	N	N	77,81,82	77	Rental and leasing activities
N	N	N	78	78	Employment activities
N	N	N	79	79	Travel agency, tour operator and other reservat service and related activities
N	N	N	80	80	Security and investigation activities
N	N	N	77,81,82	81	Services to buildings and landscape activities
N	N	N	77,81,82	82	Office administrative, office support and other business support activities

O	O	O	84		84	Public administration and defence; compulsory social security
P	P	P	85		85	Education
Q	QA	Q	Q		86	Human health activities
Q	QB	Q	Q		87	Residential care activities
Q	QB	Q	Q		88	Social work activities without accommodation
R	R	R	R		90	Creative, arts and entertainment activities
R	R	R	R		91	Libraries, archives, museums and other culture
R	R	R	R		92	Gambling and betting activities
R	R	R	R		93	Sports and recreation activities and amusement
S	S	S	94,96		94	Activities of membership organisations
S	S	S	95		95	Repair of computers and household goods
S	S	S	94,96		96	Other personal service activities
T	T	T	T		97	Activities of households as employers
T	T	T	T		98	Undifferentiated goods-
U	U	U		99	99	Activities of extraterritorial organisations