INSTITUTE
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Faculty of Social Sciences
Charles University

# DECOMPOSITION ANALYSIS OF AIR POLLUTANTS DURING THE TRANSITION AND POST-TRANSITION PERIODS IN THE CZECH REPUBLIC

*Milan Ščasný*
*Beng Wah Ang*
*Lukáš Rečka*

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Institute of Economic Studies,
Faculty of Social Sciences,
Charles University in Prague

[UK FSV – IES]

Opletalova 26
CZ-110 00, Prague
E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Institut ekonomických studií
Fakulta sociálních věd
Univerzita Karlova v Praze

Opletalova 26
110 00 Praha 1

E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz



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# Decomposition Analysis of Air Pollutants During the Transition and Post-Transition Periods in the Czech Republic

Milan Ščasný[a,c]
Beng Wah Ang[b]
Lukáš Rečka[a]

[a]Institute of Economic Studies, Faculty of Social Sciences, Charles University
Opletalova 26, 110 00, Prague, Czech Republic
[b]Department of Industrial Systems Engineering and Management, National University of Singapore, 1 Engineering Drive 2, 117576, Singapore
[c]Charles University, Environment Center, José Martího 2/407, 16200 Praha 6, Czech Republic
Email (corresponding author): milan.scasny@czp.cuni.cz

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**Abstract:**
It is common in index decomposition studies to decompose an aggregate into five or more factors. This applies to energy-related carbon emissions since carbon emission coefficient by fuel type is relatively easy to derive. However, it is extremely demanding to derive the air pollutant emission coefficient by fuel type and by sector. As a result, air pollutant emissions have typically been decomposed into three factors — the scale, the structure and the intensity factor. Using a unique facility-level dataset, this is the first study that decomposes air pollutant emissions into five factors, i.e. by decomposing the emission intensity effect further into the fuel-intensity, the fuel-mix, and the emission-fuel intensity factors. Specifically, we use a 5-factor Logarithmic Mean Divisia Index (LMDI) method to decompose annual changes in the emissions of four types of air quality pollutants (SO2, NOx, CO and particulate matters) stemming from large stationary emission sources in the Czech Republic. Our analysis covers the period 1990 to 2016, during which the Czech economy transited towards a market economy. It also implemented strict environmental regulation to become a full member of the European Union in 2004. The emissions decreased cumulatively by 74% or more in the 1990s, remained at

stable levels during the 2000s and declined again thereafter. We examine how the results differ if one relies on the ‘standard’ 3-factor and the 4-factor decompositions.

**JEL:** P28, Q43, Q53, Q56
**Keywords:** LMDI, 5-factors IDA, air quality pollutants, emission per fuel type, economic transition

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# 1. Introduction

Whether economic growth is pollution reducing or a pollution intensifier has remained under dispute. The IPAT-based literature[1] tends to see population growth (**P)** coupled with growing per capita income (**A**ffluence) as the primary forces driving adverse environmental impacts (**I**), while technology (**T**) is considered to be mostly neutral (Ehrlich and Holdren, 1971; Meadows et al., 1972). However, the IPAT approach has been criticized for its pessimistic perspective on technological progress, a lack of behavioural response to adverse impacts, and the quality of data used in assessments (Carson, 2010). Another stream of literature is based on the Environmental Kuznets Curve (EKC) hypothesis (Grossman and Krueger, 1995). An inverted-U shaped relationship between environmental quality and per capita income is postulated and this has been tested in many studies. See Cavlovic et al. (2000) or Dinda (2004) for a review. However, the study by Grossman and Krueger (1995) highlights the limitations of such analyses. The reduced-form nature of the EKC model limits the policy implications of its results. It is not possible to tell through which channel the level of income per capita affects environmental quality. Neither can the results reveal the extent to which the income factor contributes to changes in environmental quality.

Arising from the shortcomings of the EKC, other statistical techniques have been developed to better understand the mechanisms of changes in energy use (or pollutant emissions). In particular, researchers were looking for ways to quantify the relative impacts of structural shifts in production and changes in sectoral energy intensity on energy consumption. In this regard, decomposition analysis and especially the index decomposition analysis (IDA) has been widely used to understand trends and underlying factors of changes in energy use and emissions (Ang and Zhang, 2000; Ang 2015). Compared to the reduced-form analysis reported in the EKC literature, a decomposition analysis can identify the channels through which environmental quality is affected (Tsurumi and Managi, 2010). 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.

Motivated by the above-mentioned development, we use IDA to examine the driving forces of significant reductions in the key air quality pollutants in Czech Republic, a country that has faced dramatic political, economic and institutional changes over almost three decades. Our analysis targets at its transition from a centrally-planned communist regime towards a market economy during the 1990s, when it was becoming a member of the European Union in the 2000s, and then when it made great effort to comply with EU air quality and climate policy

[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.

goals till 2016. The past changes of the economy and institutions in the Czech Republic serve as a natural and interesting experiment, allowing us to investigate the key driving forces responsible for the at least 81% drop in emissions of air pollutants.

The objectives of this paper are twofold. First, we identify the contribution of five factors affecting the emission level of air pollutants from large stationary sources in the Czech Republic during its transition and post-transition periods. Second, we perform a sensitivity analysis of IDA with respect to the number of factors included and different economy sector breakdown. Specifically, we use the Logarithmic Mean Divisia Index (LMDI) method[2] to decompose changes in the emissions of four air quality pollutants – sulphur dioxide ($SO_2$), carbon monoxide (CO), nitrogen oxides ($NO_x$), and particulate matters (PM). The five factors considered are the activity effect, structure effect, fuel intensity effect, fuel mix effect, and emission-fuel intensity effect. In the IDA literature, it is common to include five or more factors in application areas such as energy use and energy-related $CO_2$ emissions. Due to data availability a 3-factor decomposition has been the norm for air pollutant emissions. To date, there has been no study that decomposed air pollutant emissions using more than three factors and properly measured emission data. Our unique facility-level emission data measured for each facility unit enables us to conduct a more refined decomposition analysis compared to previous studies.

This paper is structured as follows. The next section reviews related literature. Section 3 introduces the methodology and Section 4 describes policy context and the data. Section 5 presents the year-by-year decomposition, starting with 3-factor LMDI, following with 4-factor and 5-factor LMDI, all performed for 1995–2016, and closing with the 5-factor LMDI applied for the period of 1990–2016, focusing on three periods during that the Czech economy transited from centrally-planned system to developed market economy. The final section concludes.

# 2. Literature Review and Background

IDA was first used to study changes in energy consumption industry in the late 1970s and early 1980s. The objective then was to quantify the relative contributions of industry activity structure and activity energy intensity to changes in total energy use in industry. Its application was expanded to other energy consuming sectors, such as transportation, household and electricity generation, and then to energy-related $CO_2$ emissions in all these sectors in the 1980s and 1990s. Thereafter, there have been further extensions to economy-wide energy and emissions analyses as well as areas other than energy and environment. Reviews of these

[2] LMDI has been the most widely used IDA decomposition method. Details about the approach including the general properties and various LMDI models can be found in Ang (2004) and (Ang, 2015).

developments and methodological advancements can be found in Ang and Zhang (2000), Ang (2015) and Ang and Goh (2019).

Specifically, decomposition studies on energy-related $CO_2$ emissions have grown substantially after 1990. This surge is the result of the rising concerns about climate change and global warming. A comprehensive literature survey on the application of IDA to energy-related $CO_2$ emissions can be found in Xu and Ang (2013). The study reviews 80 articles appearing in peer-reviewed journals from 1991 to 2012, summarizes the developments with regard to the IDA approaches used by researchers, and the scope and focus of their studies. It then analyses, consolidates and presents the empirical results reported in the surveyed studies by emission sector, and reveal the relative contributions of key factors contributing to changes in the $CO_2$ emissions.

In comparison, there have been far fewer decomposition studies on air pollutant emissions. It is straightforward to derive the $CO_2$ emission intensity since renewable energy and nuclear do not have any emissions, and $CO_2$ emissions per unit of energy consumption of certain fossil fuel are given by stoichiometry and hence are not time variant (if there is no carbon capture and storage). In contrast, air quality emissions are changing over time depending on end-of-pipe and specific characteristics of fuel (sulphur content, ash, etc.). Ang (2015) points out that air pollutant emissions is a potential area that IDA can be applied. There are a number of such studies in the recent literature and these studies are mainly on China where airborne emissions are investigated. For example, He et al. (2016), Wang et al. (2016) and Yang et al. (2016) focus on $SO_2$ emissions; Chang et al., (2018) investigate $SO_2$ and $NO_x$ emissions; Ding et al. (2017) and Wang et al., (2018) analyse $NO_x$ emissions; and Lyu et al., (2016) and Zhang et al., (2019) deal with PM emissions.

In IDA, the number of factors into which an aggregate is decomposed can vary from a minimum of two to more than ten. To a large extent the number of factors, which is defined in the IDA identity, depends on data availability, the desired level of sophistication, and study objective. In this respect, Ang and Goh (2019) categorise IDA identities in energy-related emission studies into three types, i.e. Type A, Type B and Type C, and the classification is also applicable to air pollution studies. The Kaya identity – IPAT – uses only aggregate variables and is of Type A. Type B allows disaggregation by energy source, while Type C introduces disaggregation by sector, with or without disaggregation by energy source. This implies that structure effect cannot be quantified in Type B, while energy mix is typically quantified in both Type B and Type C. In this study, we use Type C with disaggregation by energy source.

In $CO_2$ and air pollutant studies, Type C decomposition without disaggregation by energy source typically yields a 3-factor or 4-factor IDA. Assume that we wish to decompose changes in the emission level in a country arising from energy use. Let $Q$ denotes the scale effect, $S_i$ is the economic structure effect, $J_i$ and $M_{i,j} = F_{ij}/F_i$ are fuel intensity and fuel-mix factor, respectively, and $I_i$ is emission intensity of energy use, where the subscripts $i$ and $j$ denote sector and energy type, respectively. A 3-factor decomposition is normally represented by $Q \times S_i \times I_i$, while a 4-factor IDA by $Q \times S_i \times J_i \times I_i$. Type C with energy type disaggregation typically yields a 5-factor IDA represented by $Q \times S_i \times J_i \times M_{i,j} \times I_{i,j}$. These 3-factor, 4-factor and 5-factor IDA form the basis of our empirical study.[3] Obviously, in 5-factor IDA, emissions data has to have the same detail and dimension as the last IDA factor, i.e. $E_{i,j}$ which is emissions by sector $i$ and energy type $j$.

Due to data availability on emissions, many IDA studies that decomposed $CO_2$ emissions with 4 factors (Andreoni and Galmarini, 2012), 5 factors (Yi et al., 2016) or 6 factors (De Freitas and Kaneko, 2011; O' Mahony et al., 2012) have been reported. In contrast, there has been only one study that uses more than 3 factors to decompose air pollutant emissions, i.e. Viguier (1999) which used four factors to decompose pollution emission intensities for six European countries. Studies that decompose carbon emissions generally rely on $CO_2$ emission data per unit of energy type which are sector-invariant (Mousavi et al., 2017), and linked to energy balances and allocated to the final consuming sectors in proportion to their final energy consumption (O' Mahony et al., 2012). Without carbon capture and storage technology, it is straightforward to derive fuel-specific carbon emissions based on stoichiometry (emission factors) and relevant oxidation factor. In contrast, due to end-of-pipe-technologies and variable substance content in each fuel, pollutant emissions per unit of fuel varies considerably across facilities. Viguier (1999) computed pollutant emissions using technical parameters of the substance content of given fuels, the fraction of substances removed by pollution abatement, and the fraction of substances retained in ash, respectively.

IDA studies also differ in geographical coverage. Most studies aiming at emissions investigate the former EU-15 countries (Löfgren and Muller, 2010) and Asian countries, mainly China (Lin and Long, 2016; Yi et al., 2016), with some studies focusing on the USA and Canada (Environment Canada, 2014) or selected OECD and IEA countries (see Ang and Zhang, 2000; Goh and Ang, 2019).4 Only a few deal with African countries and Central and Eastern European (CEE) countries, and in this respect our study contributes to filling this gap in the

[3] The number of factors may be easily expanded by adding a population factor. As in the case of the Kaya extension, Type C index-decomposition may be expanded further by adding factors in the middle of the chain, such as share of renewable energy or locally generated electricity. Examples of such studies are O' Mahony et al. (2012) and Mousavi et al. (2017).

[4] See Goh and Ang (2019) for a review of applications of IDA based energy efficiency accounting systems.

literature. Viguier (1999) is one of the few studies which analyses emissions in CEE countries. Further, Cherp et al. (2003) analyse the quality of air in Russia over the period 1990-1999, while Bashmakov and Myshak (2014) analyse energy efficiency in Russia. Our paper also follows up a couple of studies previously conducted in the Czech Republic that either applied the 3-factor Laspeyres method (Brůha and Ščasný, 2006), or the 4-factor Divisia index method for much shorter period (Ščasný and Tsuchimoto, 2013), or used a simple econometric EKC model on highly aggregated air emission country-level data (Kreuz et al., 2017).

# 3. Methodology

Following Ang (2005) and Type C IDA identities defined in Ang and Goh (2019), the standard 3-factor IDA identity to decompose emission level of a pollutant attributable to an economic system is as follows[5]:

$$E = \sum_i E_i = \sum_i Q \frac{Q_i}{Q} \frac{E_i}{Q_i} = \sum_i Q S_i I_i, \tag{6}$$

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

$$\Delta E_{tot} = E^T - E^0 = \Delta E_{act} + \Delta E_{str} + \Delta E_{int}. \tag{7}$$

The subscripts $act$, $str$ and $int$ denote the effect associated with the overall activity level (scale), activity structure and sectoral emission intensity, respectively. It is noted again that in this 3-factor decomposition individual fuel type is not considered.

In 4-factor decomposition we have the following IDA identity and equation:

$$E = \sum_i E_i = \sum_i Q \frac{Q_i}{Q} \frac{F_i}{Q_i} \frac{E_i}{F_i} = \sum_i Q S_i J_i I_i, \tag{8}$$

$$\Delta E_{tot} = E^T - E^0 = \Delta E_{act} + \Delta E_{str} + \Delta E_{int} + \Delta E_{em}, \tag{9}$$

where the subscripts $act$ and $str$ respectively denote the activity (scale) effect and structure effect as defined earlier, and $int$ and $em$ respectively denote the fuel intensity effect $J_i$ ($=F_i/Q_i$) and emission-fuel intensity (emission coefficient) effect related to total energy consumption $I_i$

[5] We exclude hereinafter the population factor that is commonly a part of IPAT approach, since population of the Czech Republic did not change significantly during the analysed period.

(=$E_i/F_i$). The sectoral emission intensity effect is disaggregated into two new effects. Again, individual fuel type is not considered.

In 5-factor decomposition, the IDA identity and equation are:

$$E = \sum_{i,j} E_i = \sum_{i,j} Q \frac{Q_i}{Q} \frac{F_i}{Q_i} \frac{F_{i,j}}{F_i} \frac{E_{i,j}}{F_{i,j}} = \sum_{i,j} Q S_i J_i M_{i,j} I_{i,j}, \tag{10}$$

$$\Delta E_{tot} = E^T - E^0 = \Delta E_{act} + \Delta E_{str} + \Delta E_{int} + \Delta E_{mix} + \Delta E_{emf}. \tag{11}$$

where the subscripts $act$, $str$ and $int$ respectively denote the activity (scale) effect, structure effect, fuel intensity effect as in the 4-factor case, and $mix$ and $emf$ respectively denotes the fuel mix effect $M_{i,j}$ (=$F_{i,j}/F_i$) and fuel emission factor effect $I_{i,j}$ (=$E_{i,j}/F_{i,j}$). The subscript $i$ refers to sector as before and $j$ refers to fuel type.

The effects on the right-hand sides of Eq. (7), Eq. (9) and Eq. (11) can be estimated using an appropriate LMDI model.[6] The additive LMDI-I for the 5-factor emission decomposition between year 0 and $T$ are given by:

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

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

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

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

$$\Delta E_{emf} = \sum\nolimits_{i,j} L(E_{i,j}^T, E_{i,j}^0) \ln\left(\frac{I_{i,j}^T}{I_{i,j}^0}\right), \tag{12}$$

where $L\left(E_{i,j}^T, E_{i,j}^0\right) = \frac{E_{i,j}^T - E_{i,j}^0}{lnE_{i,j}^T - lnE_{i,j}^0}$ is logarithmic mean weight, $Q(= \sum_i Q_i)$ is total industrial activity level, $S_i(= \sum_i Q_i/Q)$ and $J_i(= \sum_i F_i/Q_i)$ are, respectively, activity share and fuel

[6] There are eight general LMDI models. Refer to Ang (2015) for further details.

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 $I_{i,j}(=\sum_{i,j} E_{i,j}/F_{i,j})$ is the emission factor of fuel $j$ in sector $i$.[7]

The switch from 3-factor or 4-factor emission decompositions to 5-factor decomposition is a major one in terms of data requirements. Air pollutant emission data by energy source and by sector are required in 5-factor decomposition and the data are very difficult to obtain due to a wide range of possible abatement options implemented and substance content of given fuel. If real data are not available, assumptions could be made as a short cut but the quality of the decomposition results would be compromised. In contrast, without carbon capture and storage, carbon emissions by energy source can be more easily derived by directly using standardly reported coefficients and oxidisation factors. Even then, IDA studies on energy-related carbon emissions have to often rely on carbon emissions that are sector invariant (e.g., Mousavi et al. (2017)) or allocated in proportion to energy use (e.g., O' Mahony et al., 2012).

The data set we use contains information on the volume of each pollutant linked to each fuel used in a process; for instance, how much $SO_2$ is released per tonne of hard coal used in specific facility. This means that the emission coefficients used 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. As such, we are able to adopt the 5-factor decomposition as given by Eqs. (10-12).

# 4. Data

## 4.1. Institutional background

From 1990 to 2006, the Czech economy evolved considerably in terms of scale, structure, and institutions. Our analysis begins in the period of economic and political transformation in the Czech Republic[8] that started after the Velvet Revolution in 1989. After a huge economic downturn due to the Revolution, it took a decade for the economy to recover to 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,

[7] The LMDI model used is Model 1 shown in Table 1 in Ang (2015). The LMDI-I formulae for 3-factor and 4-factor decompositions take the same form as those shown in Eq. (10) except slight differences in the logarithmic mean weight.

[8] The Czech Republic was part of Czechoslovakia until 31 December 1992. Our data represents gross value added, fuel consumption and emissions in the Czech Republic only.

while market services, construction, trade and transport increased their outputs. In the following decade, the Czech economy grew more than 40%, and then by another 13% during 2010-2016.

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 an average of about 16 tonnes of $CO_2$ per capita. Its emission-GDP ratio was six times 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 et al., 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 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.[9] 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 contributed to 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 and Máca, 2009). Consequently, as all large emission sources fulfilled their emission limits by 1999, the emission levels of air quality pollutants decreased only slightly over the next decade. Integrated permits introduced under *Integrated Pollution and Prevention Control* (Directive 96/61/EC) 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 first half of 2000s. The European directive 2001/80/EC on the limitation of emissions of certain pollutants into the air from large combustion plants has initiated adoption of new regulations – Government Order

[9] 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 prostředí (the Czech Environment Inspectorate).

No. 112/2004 Coll. and No. 372/2007 Coll. – that set new emission ceilings for energy sources with 50 MW of thermal input and larger.

The European Directive 2010/75/EC on industrial emissions 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.

## 4.2. Emission and energy data

The emission and energy data used in this study was obtained from the Air Pollution Emission Source Register (*REZZO*).[10] 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 5 MW 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 – *large stationary 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 overall level of Czech emissions. They represent about 80% of total $SO_2$ emissions over almost the entire period. The share of $NO_x$ emissions in R1comb on total NOx emissions decreases across time from 65% in 1990 to approximately 40% in 2016. The share of particulate matters (PM) in R1comb on total PM decreases across time due to a strict abatement introduced in large sources from 60% in 1990 to approximately 5% in 2016. Large combustion sources contribute only small amounts to emissions of CO, from

[10] The REZZO (*Registr emisí a zdrojů znečištění ovzduší*) 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.

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 $NO_x$ and $SO_2$ emissions with increasing trend, its share PM emissions decreases from initial 52% 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, $NO_x$, $SO_2$ and PM in our data set from 1990 to 2016. We can identify three distinct periods with different patterns of emissions development. In the first period, from 1990 to 1999, all emissions dropped rapidly – on average CO, $NO_x$, $SO_2$ 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. The last period, from 2008 to 2016, began by significant reduction in all observed emissions in 2008 (55, 18, 26, and 46 percent reduction in CO, $NO_x$, $SO_2$ and PM emissions, respectively). Then, CO emissions varied, and increased on average by 2% per year, and $NO_x$, $SO_2$ and PM emissions declined again. $SO_2$ 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 $SO_2$ emissions in Section 5.1. 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 1. Emission levels of CO, $NO_x$, $SO_2$ and PM, 1990–2016 for R1comb [Mt]**

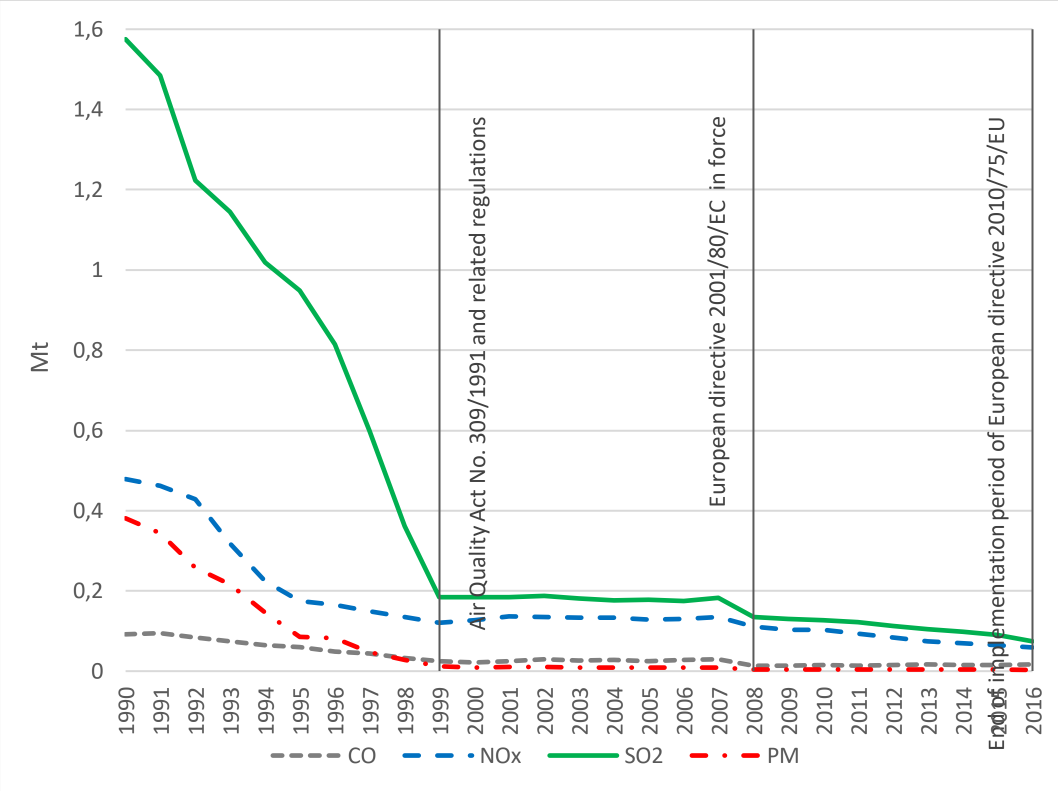
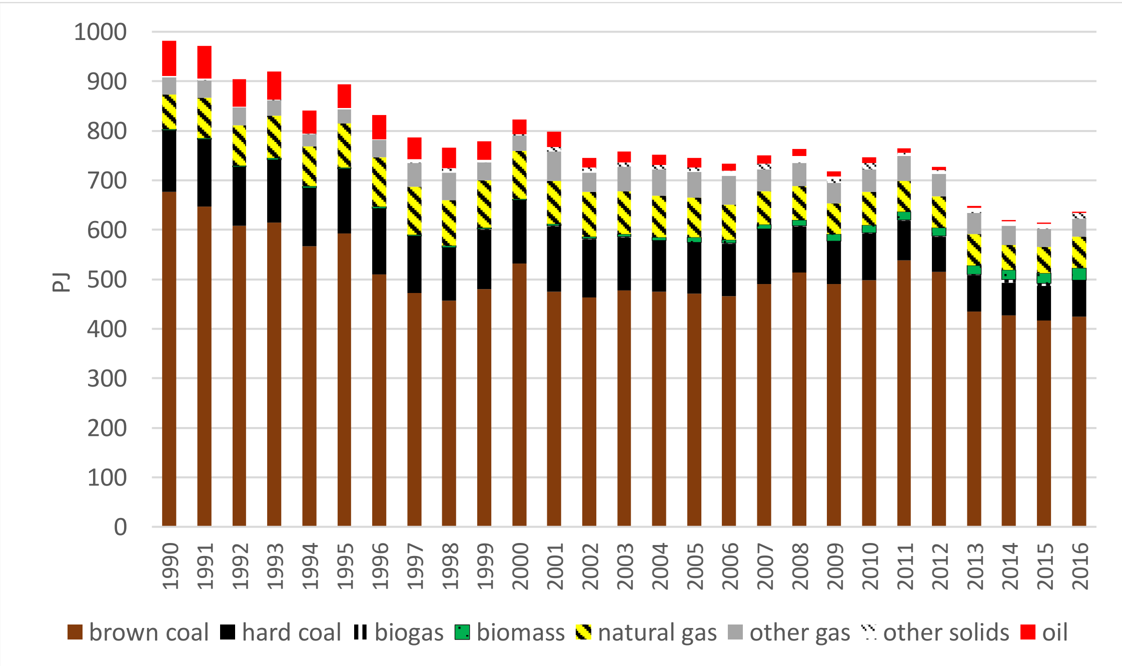



**Figure 2. Fuel consumption, 1990–2016 for R1comb (PJ)**



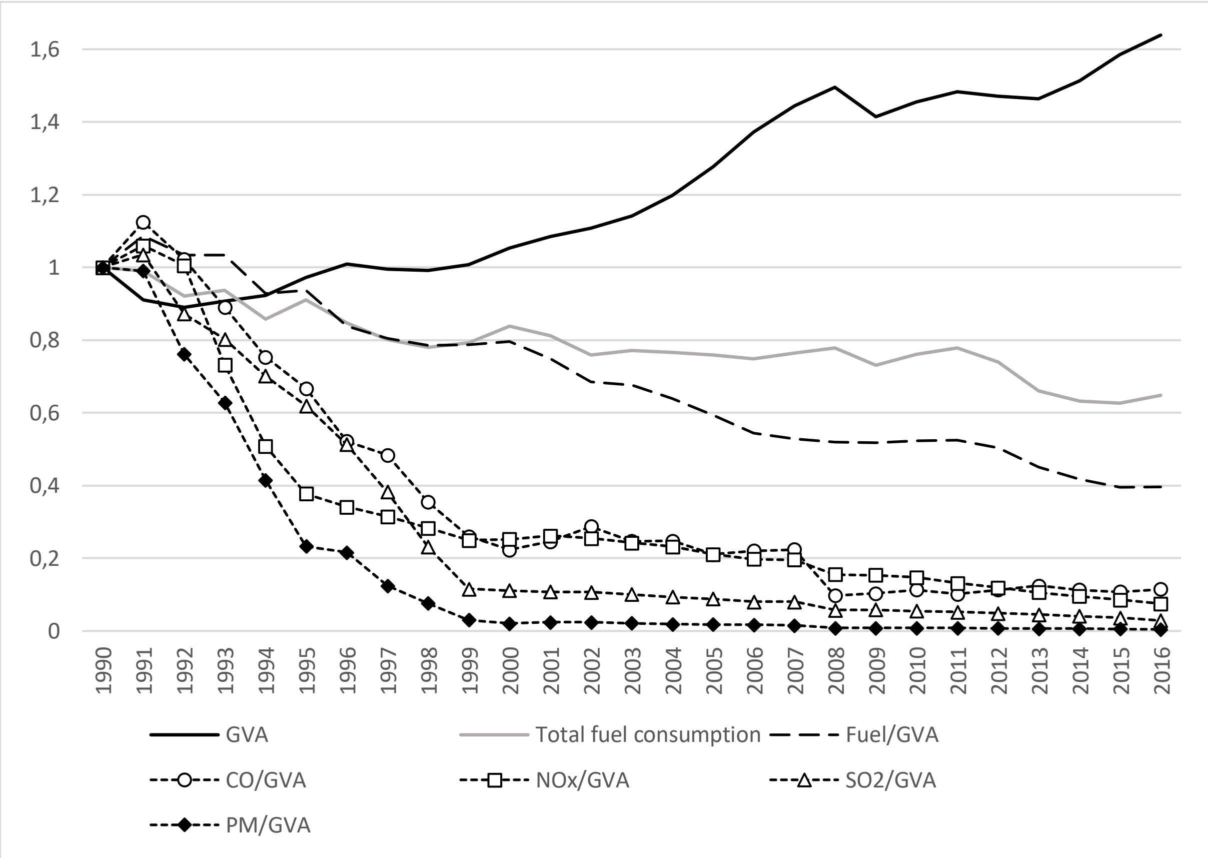

Note: Biogas use has started to be reported since 1997. In 2016, use of biogas, biomass and other solid fuels was 21-, 10- and 6-times larger than in 1990 or 1997, respectively.

## 4.3. 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 Statistical Classification of Economic Activities in the European Community (NACE) changed in 2008. As a result, SUT are not consistent 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 until 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. We apply the LMDI decomposition to both datasets. Figure 3 depicts the relative development of Czech GVA from 1990 to 2016. During this period, the GVA in constant prices of 1995 has increased by almost 64%. Sectoral aggregation and shares of economic sectors on total GVA are provided in the online Supplementary Information material.

**Figure 3. Relative development of gross value added (GVA), total fuel consumption, fuel intensity and emissions per GVA, 1990–2016 (1990 level = 1.0)**



# 5. Results

## 5.1. 3-factor IDA: a golden standard

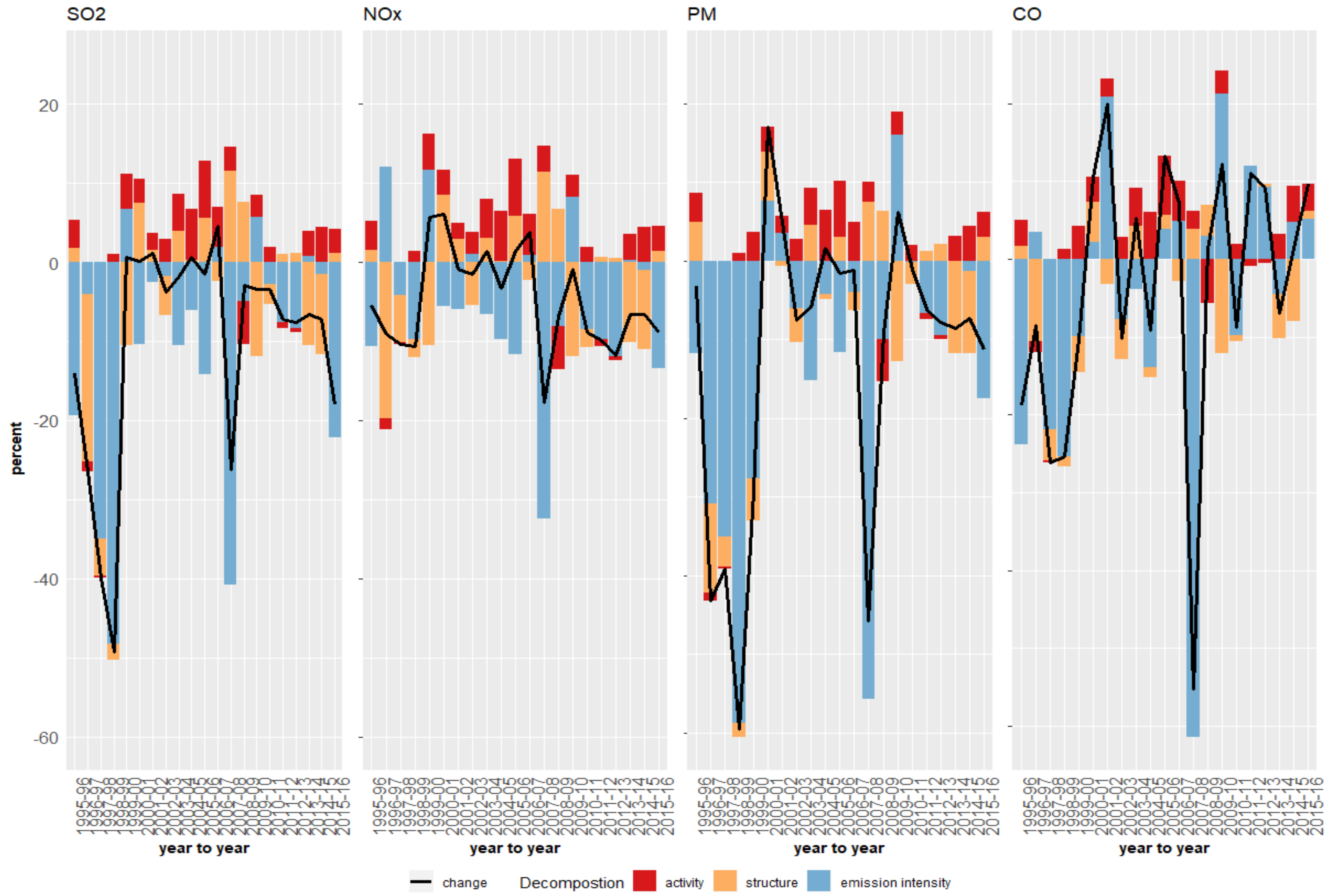
Due to limited data availability, so far the 3-factor IDA has been a golden standard to decompose air quality emissions. Our study contributes to this literature – that is still quite scarce – by decomposing changes in emissions of four pollutants (SO2, NOx, PM, and CO) into the three factors. These results for the period of 1995–2016 are presented in Figure 4. Since emissions of three out of four analysed pollutants have followed a decreasing trend during the whole analysed period, annual changes are negative for almost each year (solid black line in Figure 4). Annual changes in emissions of CO went upside down from 2000.

As the Czech economy has a growing trend, the activity effect (red bars in Figure 4) is positive in most of the years for all four pollutants. Thus, the activity pushes the emissions to grow most of the period, with magnitude given by annual GDP growth. Other changes remain due to changes in the economic structure and emission intensity.

Regarding the former, economic structure (orange bars in Figure 4) affected emissions in both directions. There is a common pattern of the structure effect in $SO_2$ and $NO_x$ affecting their emission positively between 1995 and 1996, in most years between 2000–2013, and then again at the end of the period. Changes in economic structure led to large increases in emissions especially during 2007–2009, i.e. during global economic recession. The structure effect is reducing emissions particularly during the period 1997-2000 and, in most cases, it even largely exceeds the activity effect. During this period, economic production declines particularly in agriculture, power, transport and mining and quarrying sector, which all belonged to relatively emission-intensive sectors.

The emission intensity results in the strongest effect in the case of all four pollutants during nearly the entire period. The emission intensity effect also contributed most to emission reductions, with median in absolute values at 7, 8, 10, and 9 percent and absolute peaks at is -48, -32, -59 and -61 percent for $SO_2$, $NO_x$, PM, and CO, respectively. For instance, in terms of $SO_2$ emission, the emissions intensity effect is the main driver of emissions reduction (in sum and in 14 cases of 21), followed by the structure effect, whilst the activity effect is positive in 17 of 21 cases (see also Figure 4). Since the emission intensity effect aggregates three drivers of emission change, i.e. it captures abatements through end-of-pipe technology (fuel emission factor), fuel switch (fuel mix effect) and technological and/or product changes that can affect the fuel intensity, we cannot identify the main driver of emission changes based on the 3-factor IDA. Which of these factors are activated more and when remain to answer for following sub-sections.

**Figure 4. 3-factor decomposition of air pollutants from 1995 to 2016**



## 5.2. From 3-factor to 4-factor IDA

In the 3-factor IDA, we find that the emission intensity effect is the key factor responsible for significant reduction in air quality emissions in the Czech Republic during 1995–2016. Still, which specific factor was more activated remains undiscovered. Among the three possible abatement channels grouped into the emission intensity factor, the 4-factor decomposition allows to distinguish two underlying drivers of change in emissions that are captured together in the emission intensity factor, and these two are, *the fuel intensity effect* that measures energy input per unit of economic output (i.e. $F_i/Q_i$) and *the emission-fuel intensity effect* indicating emissions generated per unit of aggregate fuel (i.e. $E_i/F_i$, note that ($F_i/Q_i$ x $E_i/F_i = E_i/Q_i$)).

Looking at the aggregate, fuel intensity is continuously declining during 1995–2016, as shown in Figure 3, fuel intensity by sector may, however, go either direction. Thanks to the decomposition, we find the fuel intensity effect (light blue bars in Figure 5, Panel B) is negative especially during the whole period 2000–2013, except two years of global economic recession in 2010 and 2011 (for $SO_2$). During this it was the fuel intensity, rather than end-of-pipe abatement that was responsible for not increasing SO2 emission overall when economy was growing.

Emission intensity of fuel aggregate (dark blue bars in Figure 5, Panel B) is reducing emissions mainly during 1995-2000 when strict emission standard was required by the Air Quality Law implemented in 1991 and then during 2014-2016 when new air quality requirement started to be enforced and this holds for all four concerned pollutants. Huge abatement activity of firms especially during the 1990's involved large investment, as documented in (Ščasný and Tsuchimoto, 2013).

Effect of each of these two factors is in detail reported in Table 1, while Figure 5 displays how the results between 3-factor and 4-factor IDA differ. Only thanks to the 4-factor IDA we are able to recognise that almost all of the negative effect attributable to the emission intensity during 1997-1999 (as observed in the 3-F IDA) is due to the emission-fuel intensity (e.g. due to end-of-pipe abatement), while large negative effect attributable to the emission intensity during 2003-2006 is rather due to the fuel-intensity effect. We note here that the emission-fuel intensity still captures the effect of both fuel emission factor related to each individual fuel and possible switches in fuel mix, which we can analyse in next sub-section.

## 5.3. From 3-factor to 5-factor IDA

The 5-factor decomposition goes even one step further than the 4-factor IDA by decomposing *the emission-fuel intensity* when fuel represents fuel in its aggregate (i.e. the fourth factor in the 4-factor IDA) into *the fuel mix effect* and *the fuel emission factor effect* when fuel now represents specific fuel type (i.e. the fourth and the fifth factor in the 5-F IDA). Specifically, *the fuel mix effect* (deep dark blue bars in Figure 5, Panel C) captures the effect of switching fuel type on emissions (e.g., switch from coal to gas), while *the fuel emission factor effect* (dark blue bars in Figure 5, Panel C) captures changes in the quality of given fuel type (e.g. shift from brown coal with high content sulphur to brown coal with low content of sulphur) and/or changes in end-of-pipe abatement technology.

For sake of clarity, we demonstrate added value of the 5- factor IDA compared to the 4-factor, and 3-factor IDA, respectively, on $SO_2$ emissions, as emissions of this pollutant dropped most of all analysed pollutants.

Panels A–C in Figure 5 compare the results of 3-factor, 4-factor, and 5-factor, respectively, for the year-by-year decomposition of SO2 emissions from 1995 to 2016 (with economy disaggregated into 44 sectors). Changes in emissions levels are displayed in relative terms, in percentages. Comparing Panels A and B reveals graphically how the emission intensity effect is composed from the fuel intensity and emission-fuel intensity, whether the two effects contribute by the same direction or there are rather acting in opposite way. For example, the emission intensity contributed to reduction in SO2 emissions annually by -4.0% in 1997 (see Panel A). From Panel B, we can see that those -4.0% can be disentangle into i] positive, emission-increasing, effect of changing fuel intensity, that is +17.8 % plus ii] negative, emission-reducing, effect of emission-fuel intensity that amounts -21.8 %, yielding just the sum we can get from the 3-factor IDA (-4.0 %). In another words, the 3-factor IDA identifies the effects of overall economic activity and economic structure, but it does not explain why emissions changed within the sectors. The 5-factor IDA goes in more depth: the -4.0 % effect of changing emission intensity is decomposed into i] emission-increasing effect of energy intensity (+17.8 %) plus ii] emission-reducing effect of fuel mix (-0.9 %) plus iii] emission-reducing effect of fuel emission intensity (-20.9 %), see Panel C.

Table 1 displays the decomposition of the emission intensity effect from 3-factor IDA (column 1), energy intensity effect and emission-fuel intensity effect of 4-factor IDA (columns 2 and 3), energy intensity, fuel mix and fuel emission factor effects in 5-factor IDA (columns 4–6). While the emission intensity in 3-factor IDA is negative in 17 of out 21 years, the fuel intensity is negative only in 11 cases with significantly lower magnitude in most cases, both in 4- and 5- factor IDA. The fuel mix effect in 5-factor IDA brings additional information by capturing the changes in emissions caused by fuel switches. As a result, we can distinguish the effect of changing fuel type from the change in fuel emission factor (we remind that is fuel type specific). The last column in Panels A–C in Figure 5 compare the results of 3-factor, 4-factor, and 5-factor, respectively, for the year-by-year decomposition of SO2 emissions from 1995 to 2016 (with economy disaggregated into 44 sectors). Changes in emissions levels are displayed in relative terms, in percentages. Comparing Panels A and B reveals graphically how the emission intensity effect is composed from the fuel intensity and emission-fuel intensity, whether the two effects contribute by the same direction or there are rather acting in opposite way. For example, the emission intensity contributed to reduction in SO2 emissions annually by -4.0% in 1997 (see Panel A). From Panel B, we can see that those -4.0% can be disentangle into i] positive, emission-increasing, effect of changing fuel intensity, that is +17.8 % plus ii] negative, emission-reducing, effect of emission-fuel intensity that amounts -21.8 %, yielding just the sum we can get from the 3-factor IDA (-4.0 %). In another words, the 3-factor IDA identifies the effects of overall economic activity and economic structure, but it does not explain why emissions changed within the sectors. The 5-factor IDA goes in more depth: the -4.0 % effect of changing emission intensity is decomposed into i] emission-increasing effect of energy intensity (+17.8 %) plus ii] emission-reducing effect of fuel mix (-0.9 %) plus iii] emission-reducing effect of fuel emission intensity (-20.9 %), see Panel C.

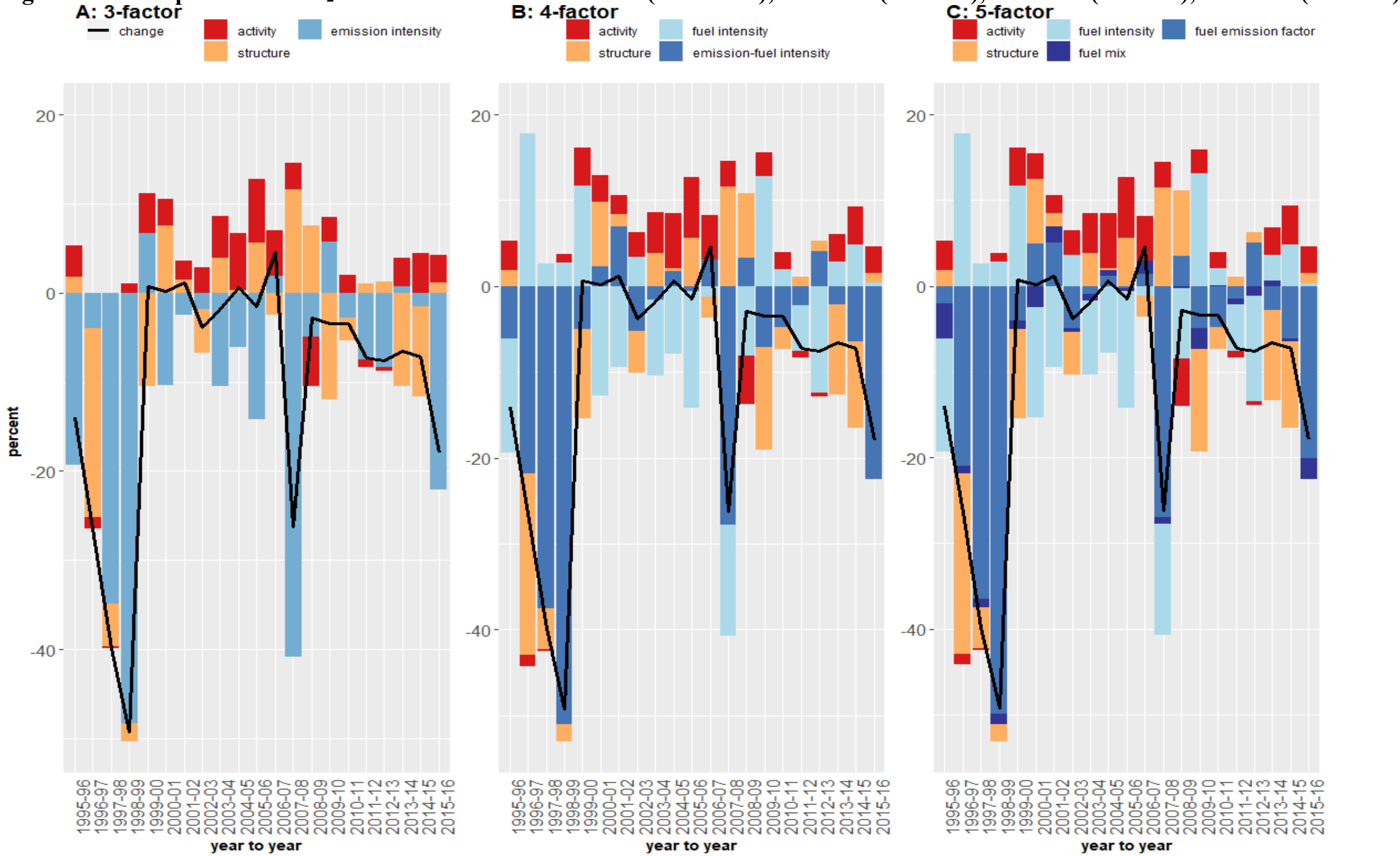
Table 1 shows a proportion of emission fuel intensity effect from 4F IDA (say -6.1 % in 1996/1995) is attributable to fuel emission factor in 5F IDA, that is 34 % of 6.1 % annual change that gives -2.1 % in 1996/1995. Contribution of fuel mix factor is then 100 % minus contribution of the fuel emission factor, for the 1996/1995 case, it is 64 % of -6.1 % that gives -4.0 % due to fuel mix effect. There are several cases when the fuel mix goes opposite direction than the fuel emission factor in 5F IDA and as the emission-fuel intensity effect in 4F IDA; see, for instance, annual changes for 2001/2000 when the emission-fuel intensity effect is +2.4 %, while the fuel mix and the fuel emission factor are -2.5 %, and +5.0 %, respectively. Such opposite effect can be only discovered thanks to the 5-factor IDA.

Panels A–C in Figure 5 compare the results of 3-factor, 4-factor, and 5-factor, respectively, for the year-by-year decomposition of SO2 emissions from 1995 to 2016 (with economy disaggregated into 44 sectors). Changes in emissions levels are displayed in relative terms, in percentages. Comparing Panels A and B reveals graphically how the emission intensity effect is composed from the fuel intensity and emission-fuel intensity, whether the two effects contribute by the same direction or there are rather acting in opposite way. For example, the emission intensity contributed to reduction in SO2 emissions annually by -4.0% in 1997 (see Panel A). From Panel B, we can see that those -4.0% can be disentangle into i] positive, emission-increasing, effect of changing fuel intensity, that is +17.8 % plus ii] negative, emission-reducing, effect of emission-fuel intensity that amounts -21.8 %, yielding just the sum we can get from the 3-factor IDA (-4.0 %). In another words, the 3-factor IDA identifies the effects of overall economic activity and economic structure, but it does not explain why emissions changed within the sectors. The 5-factor IDA goes in more depth: the -4.0 % effect of changing emission intensity is decomposed into i] emission-increasing effect of energy intensity (+17.8 %) plus ii] emission-reducing effect of fuel mix (-0.9 %) plus iii] emission-reducing effect of fuel emission intensity (-20.9 %), see Panel C.

**Table 1 Decomposition of emission intensity for $SO_2$ from 3-factor IDA into 2 factors in 4- and 3 factors in 5/factor IDA, annual changes in percent**

| | 3-factor | 4-factor | | 5-factor | | | Fuel emission factor (5F) / Emission fuel intensity (4F) |
|---|---|---|---|---|---|---|---|
| Year to year | Emission intensity | Fuel intensity | Emission-fuel intensity | Fuel intensity | Fuel mix | Fuel emission factor | |
| 1995-96 | -19.3 | -13.3 | -6.1 | -13.2 | -4.0 | -2.1 | 0.34 |
| 1996-97 | -4.0 | 17.8 | -21.8 | 17.8 | -0.9 | -20.9 | 0.96 |
| 1997-98 | -34.9 | 2.6 | -37.5 | 2.6 | -1.1 | -36.5 | 0.97 |
| 1998-99 | -48.3 | 2.7 | -51.0 | 2.8 | -1.2 | -49.9 | 0.98 |
| 1999-00 | 6.7 | 11.7 | -5.0 | 11.7 | -0.9 | -4.1 | 0.82 |
| 2000-01 | -10.4 | -12.7 | 2.4 | -12.8 | -2.5 | 5.0 | 2.08 |
| 2001-02 | -2.5 | -9.4 | 6.9 | -9.5 | 2.0 | 5.0 | 0.72 |
| 2002-03 | -1.8 | 3.4 | -5.2 | 3.6 | -0.5 | -4.9 | 0.94 |
| 2003-04 | -10.5 | -8.9 | -1.6 | -8.6 | -0.8 | -1.0 | 0.63 |
| 2004-05 | -6.0 | -7.8 | 1.8 | -7.8 | 0.6 | 1.2 | 0.67 |
| 2005-06 | -14.2 | -13.7 | -0.6 | -13.6 | -0.3 | -0.3 | 0.50 |
| 2006-07 | 1.9 | -1.2 | 3.1 | -1.1 | 1.5 | 1.4 | 0.45 |
| 2007-08 | -40.8 | -13.0 | -27.8 | -13.0 | -0.7 | -27.0 | 0.97 |
| 2008-09 | -4.9 | -8.1 | 3.3 | -8.1 | -0.3 | 3.6 | 1.09 |
| 2009-10 | 5.8 | 12.8 | -7.1 | 13.1 | -2.5 | -4.9 | 0.69 |
| 2010-11 | -2.8 | 2.0 | -4.8 | 2.0 | 0.0 | -4.8 | 1.00 |
| 2011-12 | -7.5 | -5.3 | -2.3 | -5.4 | -0.7 | -1.5 | 0.65 |
| 2012-13 | -8.3 | -12.4 | 4.0 | -12.3 | -1.1 | 5.1 | 1.28 |
| 2013-14 | 0.7 | 2.9 | -2.2 | 2.9 | 0.6 | -2.8 | 1.27 |
| 2014-15 | -1.5 | 4.9 | -6.4 | 4.9 | -0.3 | -6.1 | 0.95 |
| 2015-16 | -22.1 | 0.4 | -22.5 | 0.3 | -2.4 | -20.1 | 0.89 |

Figure 5. Decomposition of $SO_2$ emissions from 1995 to 2016 (44 sectors), 3 factors (Panel A), 4 factors (Panel B), 5 factors (Panel C)



We note that adding fuel specific dimension in the 5-factor decomposition– affects not only the last factor that is decomposed (i.e. the emission-fuel intensity in 4-F IDA), but it may also affect the other factors since $\sum_{i,j} L(E_{i,j}^{T}, E_{i,j}^{0}) \ln\left(\frac{Q^T}{Q^0}\right)$ does not equal to $\sum_{i} L(E_{i}^{T}, E_{i}^{0}) \ln\left(\frac{Q^T}{Q^0}\right)$. Table 2 inspects this effect in detail by comparing the activity, structure and intensity effects in 5-factor LMDI and 3-factor and 4-factor LMDI. As we can see, extending the number of LMDI's factors to five decreases magnitude of the activity effect for each year as well as of the structure effect for the most of the years. Effect of the fuel intensity is much larger than in the case of the activity and the scale factor suggesting that LMDI with more factors yields more valid result in particular for the fuel intensity.

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

| Factors compared: | 5F/3F | | 5F/4F | | |
|---|---|---|---|---|---|
| Effect | Activity | Structure | Activity | Structure | Fuel 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% |

## 5.4. 5-factor LMDI of air quality emissions for 1990–2016

This section summarizes the results of the 5-factor LMDI decomposition of $SO_2$, $NO_x$, PM and CO emissions performed for each year for much longer period, covering 1990–2016. Due to the data availability, this decomposition is performed when fuel aggregate is again differentiated into 8 different fuel types, but with the economy breakdown by 26 (instead of 44) economic sectors. It implies our analysis relies on 208 different fuel emission factors in 5-factor LMDI and 26 emission-fuel intensities in 4-factor LMDI that are specific for each year. Results of 5-factor LMDI, with the economy breakdown by 44 from 1995 to 2016, are provided in Figures B.1–4 in the Appendix B.

Table 3 provides the results for the three periods (1990-1999, 1999-2007 and 2007-2016) aggregated from the results derived from the year-by-year decompositions.[11] From the left to the right, we report the total change that occurred before the end and the beginning of each particular period in kilotons (kt) as well as in percentage. For instance, emissions of $SO_2$ decreased by 1,391 kt between 1990 and 1999, or by 88%. In the following period, $SO_2$ emissions remained almost the same and in the next period, these emissions decreased further by about 108 kt, or 59% compared to 2007 level (with the largest drop of 47 kt in 2007). The remaining five columns display overall whether and how many times a given factor contributed positively (increasing emissions) or negatively (decreasing emissions). Again, in the case of $SO_2$ emissions and for the first period with 9 year-by-year changes, there were by one more positive effects than negative ones of the activity factor (therefore we report +1 in Table 3). For the same period and the same pollutant, changes in fuel mix affected emissions seven times more negatively than positively, while fuel emission factor was constantly reducing emissions (i.e. the effect of this factor was always – nine times – negative).

Table 3 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 fuel emission factor was dominant in reducing emissions of all four pollutants, followed by the fuel-intensity effect and the fuel-mix effect. In contrast, the activity and the structure effects had positive impacts on emissions growth.

[11] As Löfgren and 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". 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.)*. We therefore present such results only in the Table A.1. and Table A.2. in Appendix A.

**Table 3 Cumulative emissions change by period and indication of LMDI effects impacts**

| Pollutant | Period | Change (kt) | Change (%) | Activity | Structure | Fuel intensity | Fuel mix | Fuel emission factor |
|---|---|---|---|---|---|---|---|---|
| CO | 1990-99 | -68.2 | -74% | 1 | -3 | -5 | -5 | -5 |
| | 1999-07 | 5.7 | 23% | 8 | -2 | -6 | 0 | 0 |
| | 2007-16 | -12.6 | -42% | 3 | 1 | -3 | 3 | 1 |
| $NO_x$ | 1990-99 | -358.5 | -75% | 1 | -1 | 1 | -3 | -7 |
| | 1999-07 | 15.0 | 12% | 8 | 2 | -4 | 0 | 2 |
| | 2007-16 | -76.1 | -56% | 2 | 0 | 0 | -2 | -8 |
| PM | 1990-99 | -369.3 | -97% | 1 | 1 | -1 | -9 | -7 |
| | 1999-07 | -3.0 | -26% | 8 | 0 | -4 | -2 | 0 |
| | 2007-16 | -5.7 | -66% | 3 | 1 | -1 | -1 | -9 |
| $SO_2$ | 1990-99 | -1391.4 | -88% | 1 | -1 | 1 | -7 | -9 |
| | 1999-07 | -1.0 | -1% | 8 | 2 | -4 | 0 | 0 |
| | 2007-16 | -108.3 | -59% | 3 | 1 | 1 | -5 | -5 |

Note: The last five columns indicate how many times a given decomposition factor was either positive (increasing emissions) or negative (reducing emissions) during the given period. 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 nine effects for 2007-2016.

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 from large stationary sources during the early years of economic transformation (1990-1992). Fuel intensity and activity worked in opposite directions in the first years after the 1989 Revolution, reducing emissions by relatively large amounts and percentages. Fuel emission factor 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 became at least as important as the fuel emission factor.

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 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 fuel emission factor was both positive and negative during this period, as shown in Figures Figure 6–9. It reduced emissions of PM, its effect was almost neutral for $SO_2$, and it increased emissions of $NO_x$ and CO. Over the second period, CO and $NO_x$ emissions increased by 23 and 12 percent, while emissions of PM and $SO_2$ decreased by 26 and 1 percent, respectively.

In the last period, from 2007 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 fuel emission factor is the most important factor in reductions of $SO_2$, $NO_x$ and PM emissions. All emissions decreased significantly in 2008 when fuel emission-factor decreased due to the European directive 2001/80/EC and related Czech regulation. Then, $SO_2$, $NO_x$ and PM emissions followed a decreasing trend in this period. Emissions of CO rose and fell after 2008, but overall CO emissions rose, following the trend between 1999 and 2007. In this case, while the activity, fuel-intensity and fuel emission 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 over the whole 1990–2019 are displayed in detail in Figures 6–9 (in tonnes on the left panels and in percentage points on the right panels). Although the patterns of emission reductions and their drivers vary across the four pollutants analysed, overall, the fuel intensity and the fuel emission factor are responsible for the largest portion of emissions reductions of each pollutant during nearly the entire period. $SO_2$, $NO_x$ 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. We note that CO emissions were in 1990at the lowest, and much lower, initial level, compared to the starting levels of other three pollutants (see Figure 1), so interpretation of the relative changes in the case should consider this fact. While decline in CO emissions was relatively low in magnitude compared to other pollutants, most of their reductions were realised mostly before 2000 and then in 2008, and primarily due to the fuel emission factor that act as emission-saving measure.

**Figure 6. 5-factor decomposition of SO2 emissions from 1990 to 2016**

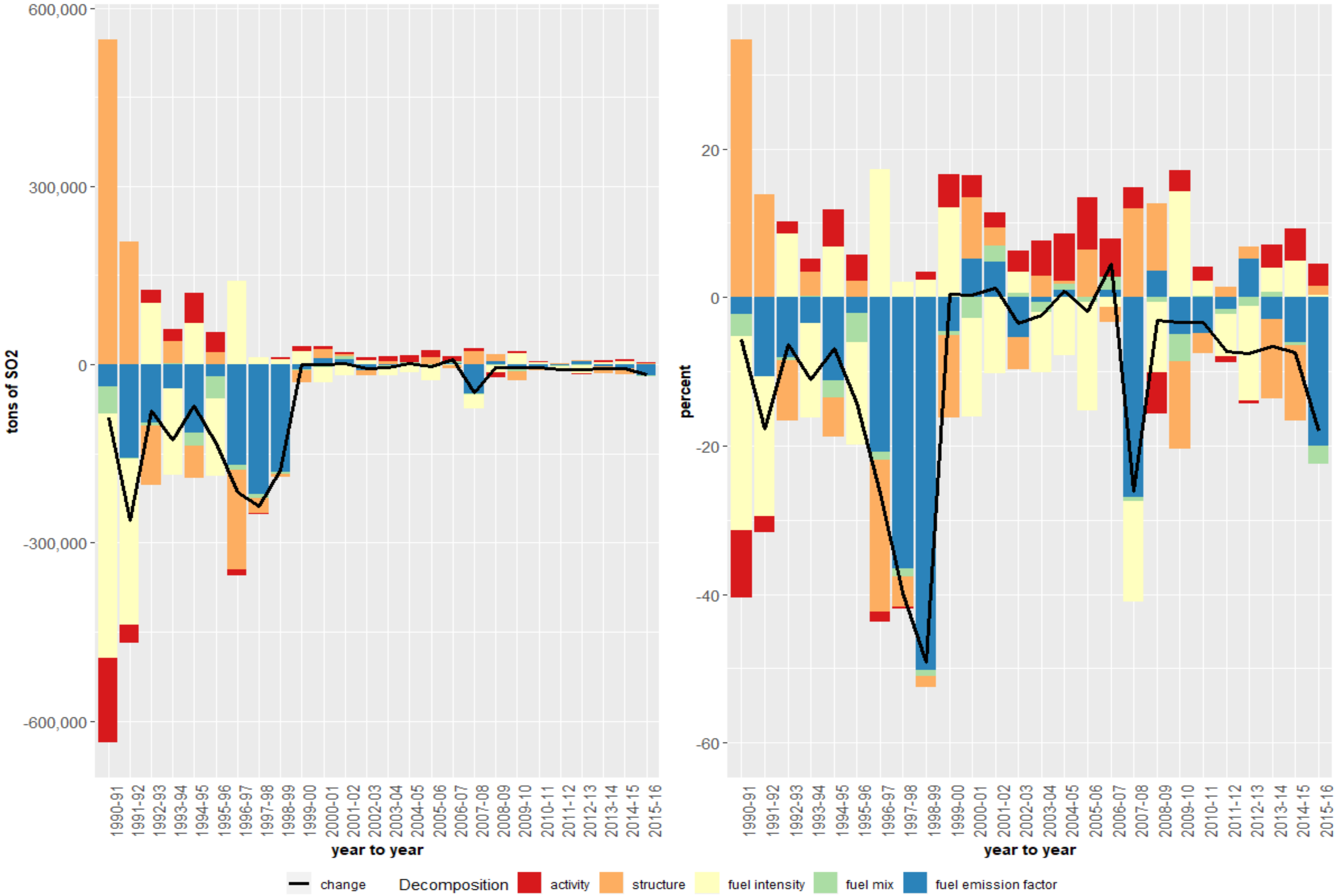


**Figure 7. 5-factor decomposition of NOx emissions from 1990 to 2016**

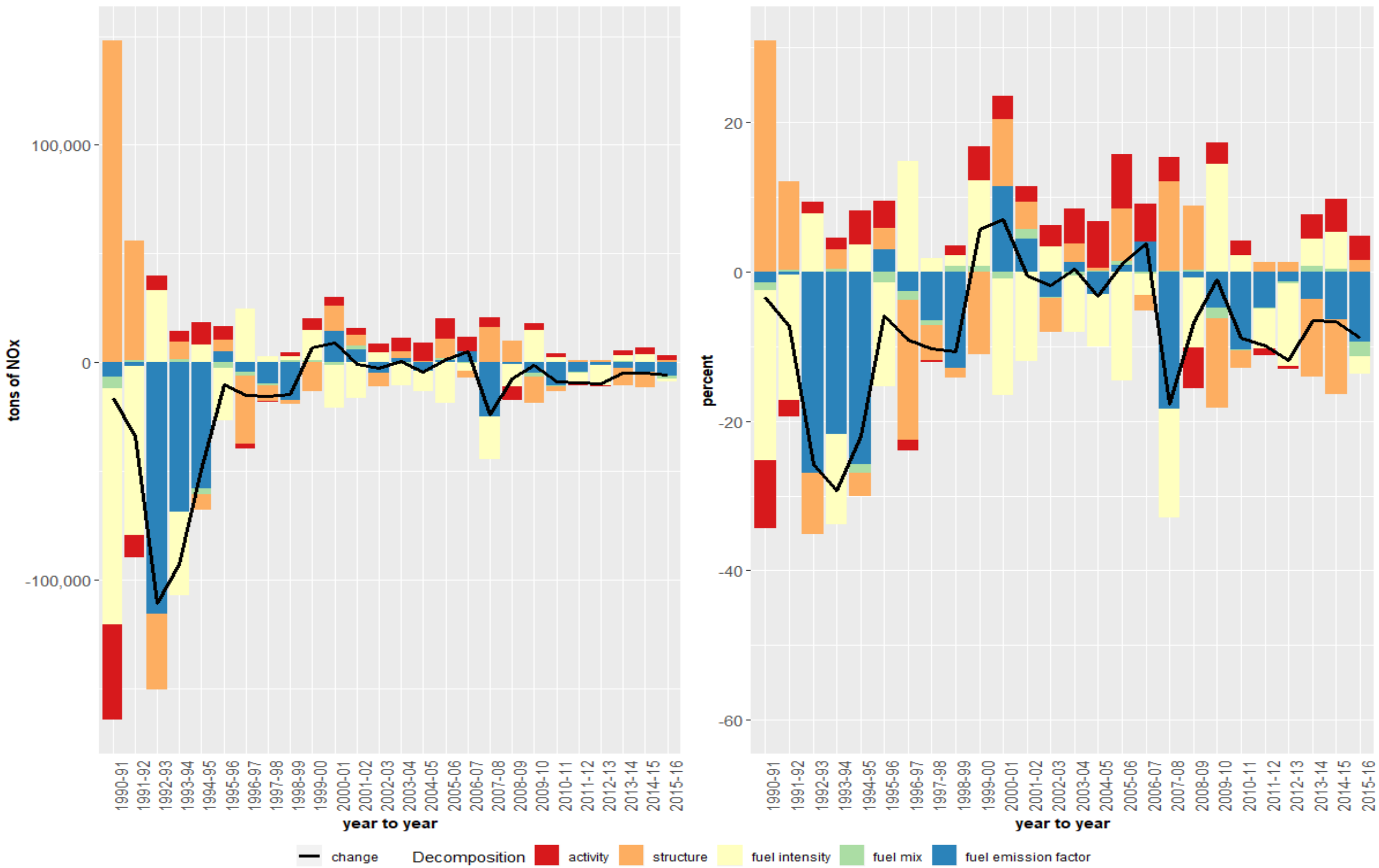


**Figure 8. 5-factor decomposition of PM emissions from 1990 to 2016**

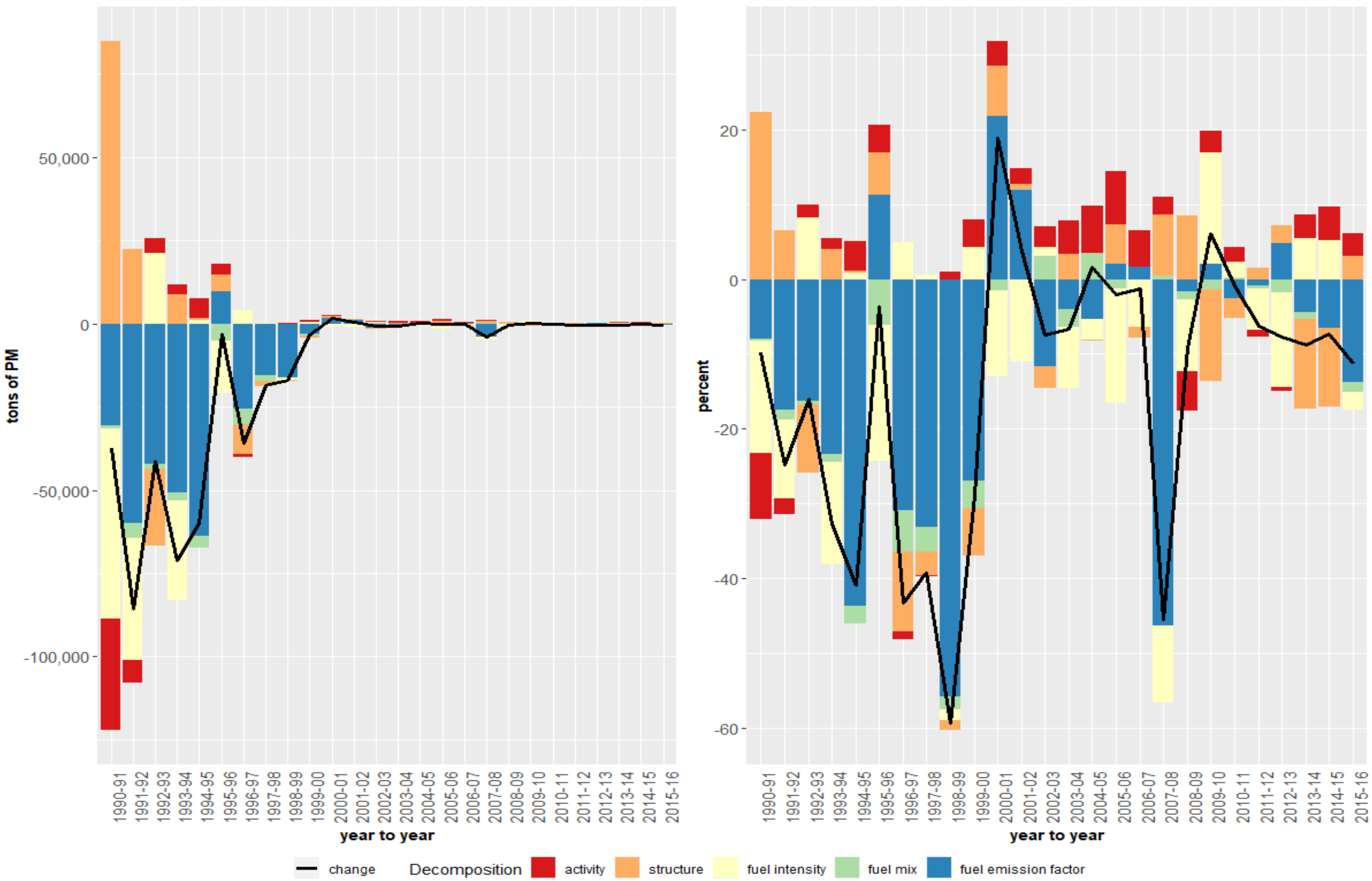
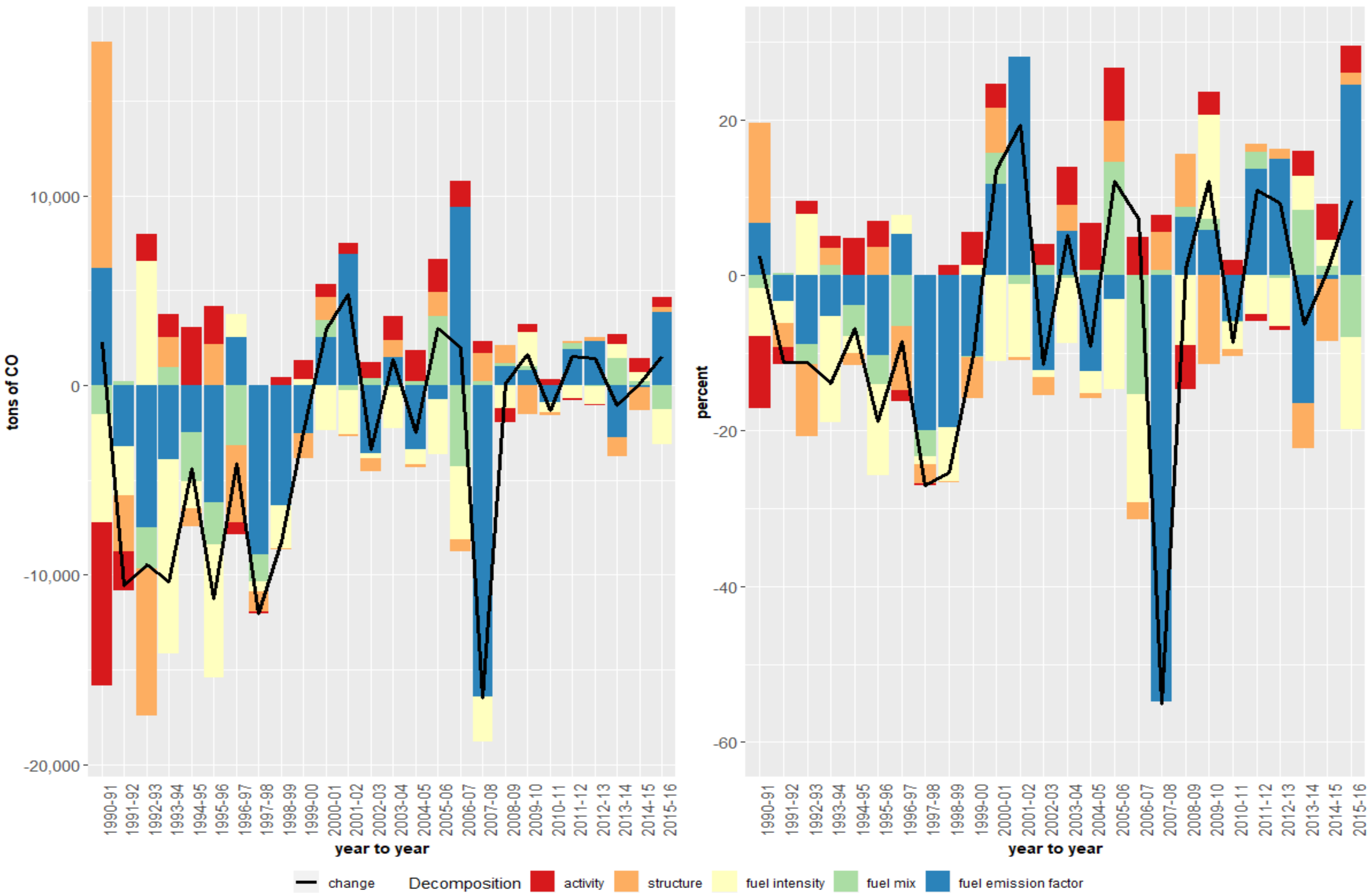


**Figure 9. 5-factor decomposition of CO emissions from 1990 to 2016**



# 6. Conclusions

This study applies LMDI decomposition to identify factors that were responsible for changing the emissions level of four air pollutants from large stationary emission sources during the transition and post-transition periods of the Czech economy from 1990 to 2016. We perform 5-factor decomposition, in which the standard third, emission intensity, factor in a 3-factor decomposition is further decomposed to fuel intensity, fuel mix and fuel emission factor effects. These three factors indicate the effects of the environmentally friendliness of economic activity with distinguishing further through which channel the emissions were changed: product or technological changes that affected the fuel intensity of production, fuel switch and end-of-pipe technology, respectively. Although 5 or more factor IDA is a standard in studies decomposing carbon emissions or energy use, more than 3-factor IDA is new for decomposition of emissions of air pollutants.

The study time span overlaps two versions of the 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 to 44 sectors for 1995-2016.

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 $SO_2$, $NO_x$ and particulate matters, i.e. 1990-1999, 1999-2007 and 2007-2016. 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%.

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 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. After satisfying the emission limits requirements by 1999, fuel intensity in the large emission sources was considerably decreased. Reduced fuel intensity was in fact the main driver that helped to keep their emissions on steady level between 1999 and 2007, despite the strong economic growth during that period. In 2008, regulations related to the European directive 2001/80/EC enforced further significant reduction in all emissions in this study that was realized mainly through emission-fuel intensity factor. Since 2008, activity, structure, intensity and emission-fuel intensity effects have affected emission volumes by similar magnitude. The emission-fuel intensity effect became important factor again in 2015–2016, since the large stationary emission sources had to comply with new strict emission limits required by the EC 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 $SO_2$ emissions with our most detailed dataset of 44 sectors during 1995-2016. The sensitivity analysis demonstrates the additional information of 4- and 5-factor LMDI decomposition compared to 3-factor LMDI decomposition, where the emission intensity effect does not distinguish though witch channel the emissions are changed within the sectors. 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 also 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.

The strength of 3-factor decomposition is that it summarizes the relative contributions of the three broad, “macro-level” effects as defined in the IDA identity. However, since the emission intensity effect gives the aggregate of three drivers of emission change, i.e. it captures abatements through end-of-pipe technology (fuel emission factor), fuel switch (fuel mix effect) and technological and/or product changes that can affect the fuel intensity, we cannot identify the main driver of emission changes based on the results of 3-factor decomposition. Without further decomposition of the emission effect, it is not possible to link the results to the “micro-level” emission abatement measures that have been implemented. Since the emission intensity effect has been found to be the main contributor to decreases in emissions for the four pollutants in the Czech Republic, the results from the standard 3-factor decomposition analysis are useful but not adequate.

Thanks to 4-factor decomposition, we are able to recognise that almost all of the negative effect attributable to the *emission intensity* (as observed in the 3-F decomposition) is due to the *emission-fuel intensity* during one period (1997-1999), while it is rather due to *fuel-intensity effect* during another period (2003-2006). The fuel mix effect in the 5-factor IDA brings additional information by capturing the changes in emissions caused by fuel switches. As a result, we can distinguish the effect of changing fuel type from the change in fuel emission factor which is fuel-type specific.

In summary, the extension from the standard 3-factor to 4-factor or 5-factor decomposition provides additional insight as to the relative contribution of several fuel-related drivers to changes in pollutant emissions. The decomposition results can be meaningfully linked to policy measures that have been taken whereby the effectiveness or level of success of such measures can be assessed. The golden standard of a 3-factor IDA as has been widely used in the literature can only provide partial information of the underlying drivers and may not be able to fully answer questions that are of interest to policymakers. On the other hand the adoption of the comprehensive 5-factor decomposition requires highly disaggregate fuel consumption and emission related data. The main challenge clearly arises from the availability of such disaggregate data and its quality.

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Appendix A.

**Table A.1. 5-factor decompostion for selected periods – first and last years**

| Pollutant | Period | Change (kt) | Change | Activity | Structure | Fuel intensity | Fuel mix | Fuel Emis. factor |
|---|---|---|---|---|---|---|---|---|
| CO | 1990-99 | -68.2 | -74% | 0.4% | 1.8% | -27.4% | -15.0% | -33.6% |
| | 1999-07 | 5.7 | 23% | 36.9% | 4.4% | -61.8% | 4.2% | 39.7% |
| | 2008-16 | 3.9 | 29% | 9.9% | -18.4% | -12.3% | 4.6% | 45.6% |
| NOx | 1990-99 | -358.5 | -75% | 0.4% | 6.2% | -18.9% | -4.0% | -58.5% |
| | 1999-07 | 15.0 | 12% | 37.5% | 4.9% | -48.8% | 0.0% | 18.9% |
| | 2008-16 | -52.2 | -47% | 6.6% | -15.3% | -3.6% | -2.5% | -32.2% |
| PM | 1990-99 | -369.3 | -97% | 0.2% | 1.8% | -11.1% | -8.3% | -79.6% |
| | 1999-07 | -3.0 | -26% | 29.3% | 3.1% | -42.8% | 1.6% | -16.8% |
| | 2008-16 | -1.8 | -38% | 7.0% | -15.7% | -3.7% | -5.2% | -20.3% |
| SO2 | 1990-99 | -1391.4 | -88% | 0.3% | 5.2% | -14.1% | -6.5% | -73.3% |
| | 1999-07 | -1.0 | -1% | 34.7% | 3.0% | -40.5% | 1.2% | 0.9% |
| | 2008-16 | -60.6 | -45% | 6.7% | -15.7% | -3.4% | -6.8% | -25.8% |

Note: The change from 2007 to 2008 is not included in the cumulative decomposition due to the data inconsistency between years 2007 and 2008, described in section 4.1.

**Table A.2. 5-factor decompostion for selected periods – sums over years in periods**

| Pollutant | Period | Change (kt) | Change | Activity | Structure | Fuel intensity | Fuel mix | Fuel Emis. factor |
|---|---|---|---|---|---|---|---|---|
| CO | 1990-99 | -68.2 | -74% | -3.6% | -1.2% | -23.7% | -13.0% | -32.3% |
| | 1999-07 | 5.7 | 23% | 39.9% | 8.4% | -69.2% | 2.3% | -26.1% |
| | 2007-16 | -12.6 | -42% | 16.4% | -7.2% | -34.3% | 8.5% | -76.7% |
| NOx | 1990-99 | -358.5 | -75% | -5.6% | 28.2% | -37.4% | -2.1% | -57.9% |
| | 1999-07 | 15.0 | 12% | 39.0% | 6.0% | -49.8% | 0.9% | 16.5% |
| | 2007-16 | -76.1 | -56% | 8.5% | -0.4% | -20.4% | -1.9% | -54.2% |
| PM | 1990-99 | -369.3 | -97% | -6.5% | 22.9% | -29.6% | -6.4% | -77.3% |
| | 1999-07 | -3.0 | -26% | 27.9% | 2.1% | -37.2% | -2.2% | -16.1% |
| | 2007-16 | -5.7 | -66% | 10.7% | -2.7% | -22.8% | -4.7% | -101.9% |
| So2 | 1990-99 | -1391.4 | -88% | -3.6% | 29.3% | -40.1% | -8.2% | -65.8% |
| | 1999-07 | -1.0 | -1% | 35.1% | 2.6% | -39.3% | -0.3% | 1.4% |
| | 2007-16 | -108.3 | -59% | 9.6% | -1.0% | -21.6% | -7.9% | -59.3% |

# Appendix B. – Five-factor decomposition for 44 sector aggregation from 1995 to 2016

**Figure B.1. 5-factor decomposition of SO2 emissions from 1995 to 2016 (44 sectors)**

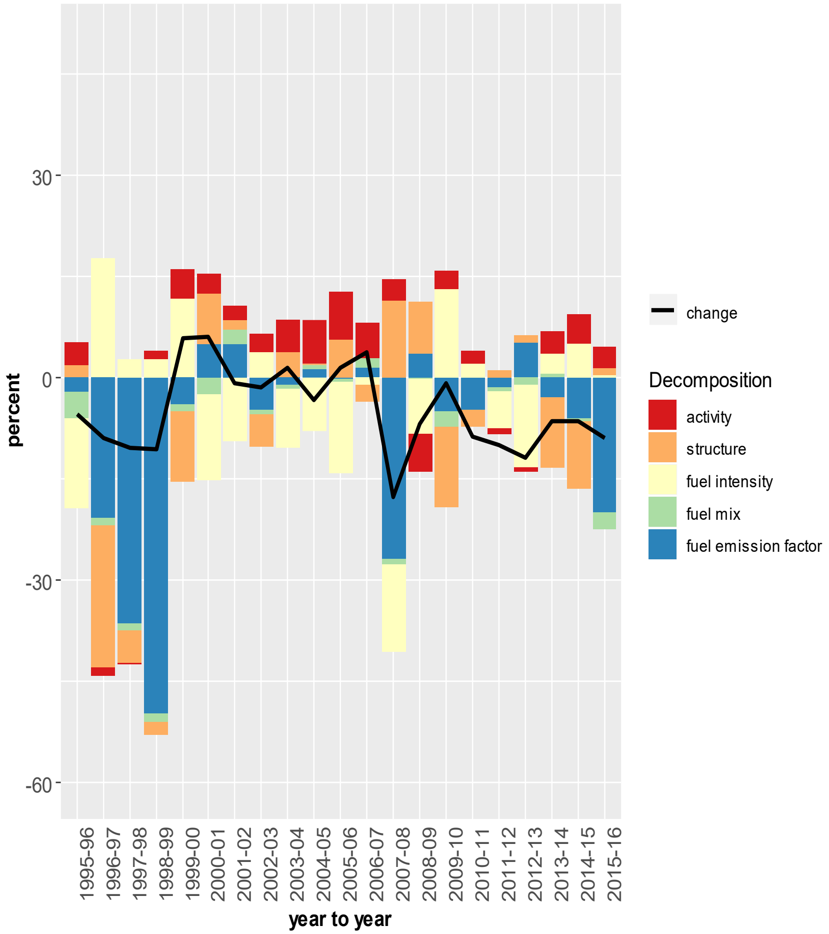



**Figure B.2. 5-factor decomposition of NOx emissions from 1995 to 2016 (44 sectors)**

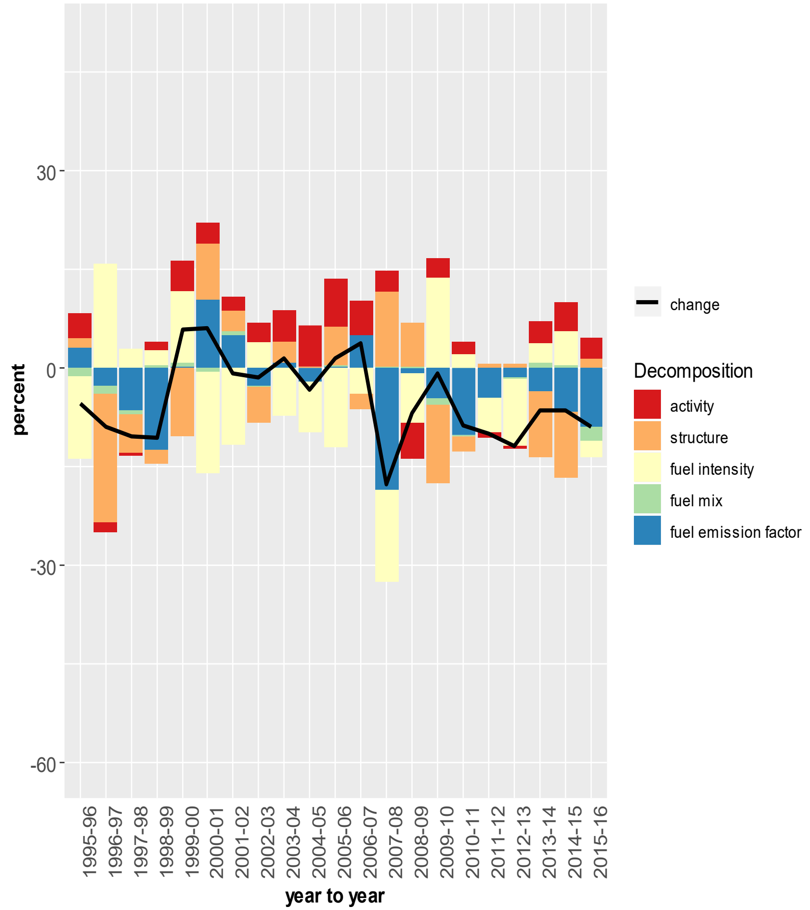


**Figure B.3. 5-factor decomposition of CO emissions from 1995 to 2016 (44 sectors)**

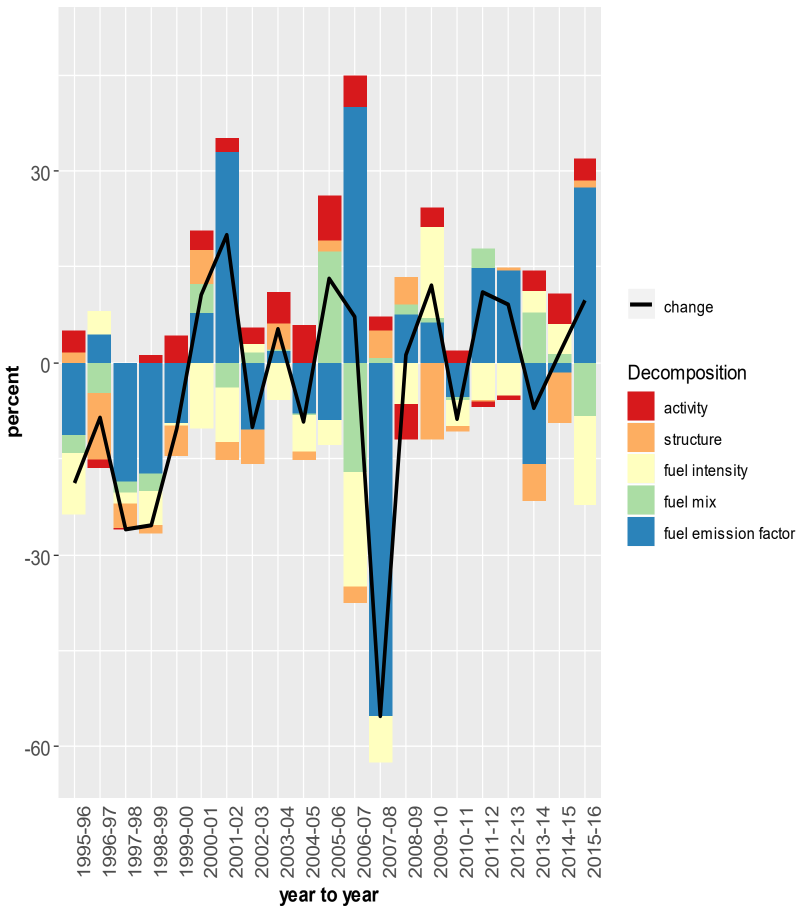
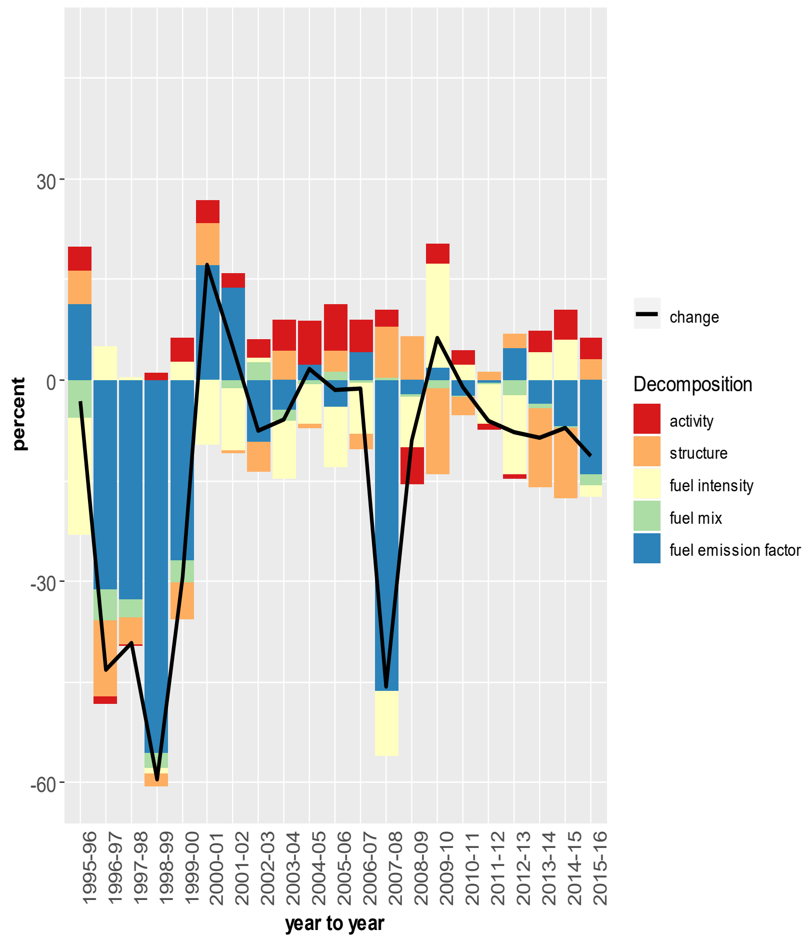



**Figure B.4. 5-factor decomposition of PM emissions from 1995 to 2016 (44 sectors)**



# Appendix C.

***Effect of sectoral aggregation***

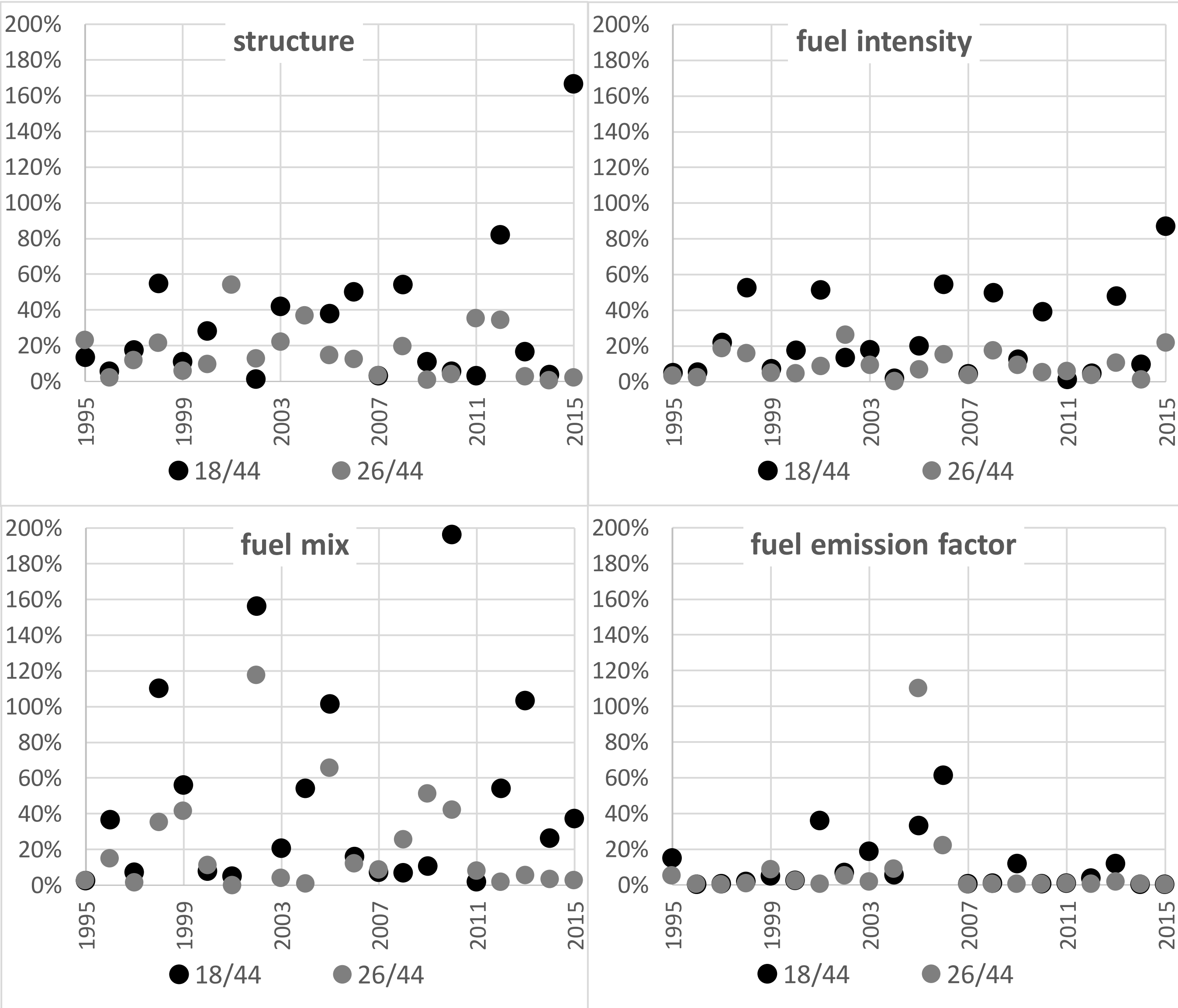
The availability of data can often affect the number of sectors included in the decomposition, either in the sense that only some sectors are included or that the sectors are aggregated to some degree. Although, as Rørmose & Olsen (2003) and (Seibe, 2003) find, the more aggregated input data for the 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 C.10 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 C.1. 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 C.10. 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 C.1. Sumary statistics of relative differennces in effect value using LMDI with 18 and 26 sectors relative to the factor value based on LMDI with 44 sectors (1995-2016)**

| | | Activity | Structure | Fuel intensity | Fuel mix | Fuel Emis. factor |
|---|---|---|---|---|---|---|
| *18 vs. 44 sectors* | min | 0.0% | 1.2% | 1.1% | 2.0% | 0.1% |
| | max | 0.9% | 205.0% | 870.6% | 1964.2% | 331.8% |
| | mean | 0.2% | 48.4% | 62.2% | 132.7% | 24.5% |
| | median | 0.2% | 17.6% | 17.4% | 26.5% | 3.6% |
| *26 vs. 44 sectors* | min. | 0.0% | 0.4% | 0.0% | 0.0% | 0.1% |
| | max | 0.5% | 54.1% | 26.0% | 117.6% | 109.8% |
| | mean | 0.1% | 15.7% | 9.1% | 21.7% | 8.1% |
| | median | 0.0% | 12.3% | 6.7% | 8.6% | 0.8% |

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Univerzita Karlova v Praze, Fakulta sociálních věd
Institut ekonomických studií [UK FSV – IES] Praha 1, Opletalova 26
E-mail : ies@fsv.cuni.cz http://ies.fsv.cuni.cz