Analyzing variability and decomposing electricity-generation emission factors for three U.S. states

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Abstract

Electricity generation emission factors (EGEF) quantify the relationship between amount of pollutant emitted and amount of electricity generated. Quantifying variability among calculated EGEFs is important when EGEFs are used for decision-making. Variabilities in EGEF due to variability in the amount of coal, natural gas, and petroleum emissions within the fuel mix are quantified for California, Texas, and New York in 2017. The results show a higher coefficient of variation for SO_2 and NO_x compared to CO_2 EGEF. Changes in the EGEF over time are studied using decomposition analysis for California, Texas, and New York from 1990 to 2017. The results show that the main factor in reducing EGEF in California is the improving generation efficiency of power plants; in Texas, it is the increasing the ratio of renewable to non-renewable electricity generation; and in New York, it is the changing mix of fossil fuels that are consumed for electricity generation. The effect of variability of EGEF on environmental impact categories is analyzed. Eutrophication of air, eutrophication of water, and smog formation are subject to high uncertainty because SO_2 and NO_x EGEFs are used to quantify these impacts, whereas global warming potential has less uncertainty because it only uses CO_2 EGEF.

Keywords: variability analysis, electricity generation emission factor, fossil fuel emission factor, decomposition analysis, environmental impact assessment

Nomenclature

AP	Acidification Potential
C	Emissions from electricity generation (kg)
C_{fuel}	Emission by each fossil fuel type (coal, natural gas, or petroleum) (kg)
EF	Emission factor
EGEF	Electricity generation emission factor
Eff	Efficiency
EIA	U.S. Energy Information Administration
EPA	U.S. Environmental Protection Agency
EA	Eutrophication of air
EW	Eutrophication of water
e_{fuel}	Emission factor for each fossil fuel (kg-emissions/MMBtu)
F_{fuel}	Energy input by each fossil fuel type (coal, natural gas, or petroleum) (MMBtu)
FF	Fossil fuel
G	Total electricity generation by state (MWh)

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GWP	Global Warming Potential
HH	Human health
IDA	Index decomposition analysis
LMDI	Logarithmic mean divisia index analysis
m_{fuel}	The electricity generation from each fossil fuel divided by the total electricity generation from all fossil fuels (coal, natural gas, and petroleum)
NG	Natural gas
Pet	Petroleum
PV	Photovoltaics
SA	Smog Air
U.S.	United States
u_{fuel}	The energy input divided by the electricity generation for each fossil fuel (MMBtu/MWh)
Q	Electricity generation by all fossil fuels (coal, natural gas, and petroleum) (MWh)
Q_{fuel}	Electricity generation by each fossil fuel type (coal, natural gas, or petroleum) (MWh)

1. Introduction

Climate change has ramifications on ecosystems, human health, and the energy sector (National Oceanic and Atmospheric Administration, 2019). Human activities and energy consumption, on both global and regional scales, are driving climate change (Stocker et al., 2013). The electricity sector alone contributed to 27.5% of 2017 greenhouse gas emissions in the United States (U.S.), making the sector the country's second-largest source of greenhouse gas emissions (U.S. Environmental Protection Agency (EPA)) and an essential factor in reducing or mitigating climate change. Electricity generation influences ecosystems, human health, and the climate by releasing CO_2, SO_2, and NO_x emissions through fossil fuel–fired generation. Monitoring and measuring the greenhouse gas emissions resulting from electricity generation empowers a country or region to move toward a low-carbon future (Khan, 2019). However, the quantification of greenhouse gas emissions resulting from electricity generation has been associated with a variety of uncertainties and variabilities that may affect such decision-making and carbon management (Li and Huang, 2012). Therefore, defining and quantifying these variabilities and changes in electricity generation–related emissions is also essential. This study aims to define and quantify these factors accordingly.

In this work, we investigate variations between calculated electricity generation emission factor (EGEF) values over time and across U.S. states. Moreover, we quantify the key factors underlying changes in these EGEFs from 1990 to 2017. This work was conducted at the state level, and we have focused on three U.S. states to illustrate a variety of cases. We chose California, Texas, and New York for this analysis because they are three of the country's most populous states. Also, they encompass a wide range of climate conditions and sociopolitical systems, and more electricity sector–related data is publicly available for these three states than for many other U.S. states. Moreover, each of these three states is located in one of the country's three major electrical grid interconnections. California lies within the Western Interconnection; the vast majority of Texas lies within the Electric Reliability Council of Texas (ERCOT); and New York lies within the Eastern Interconnection (U.S. Department of Energy Office of Electricity (2019)). These three states have implemented progressive strategies to increase their renewable electricity generation and reduce their electricity generation carbon footprints (Barbose, 2017).

This work addresses the following key research questions:

1. How do EGEF (that is, the range of expected values for CO_2, SO_2, and NO_x emissions per unit of electricity) vary across in three U.S. states of California, Texas, and New York?
2. How did these EGEFs change from 1990 to 2017, and what underlying factors drove these changes in each of the studied states?

3. Can we reasonably quantify electricity generation's environmental impacts at the state level, given the uncertainty surrounding the data used to calculate these states' emission factors?

In the following subsection, we discuss the research background related to each of these key questions.

1.1. How do EGEFs (that is, the range of expected values for CO_2, SO_2, and NO_x emissions per unit of electricity) vary across in three U.S. states of California, Texas, and New York?

We define the term "emission factor" (EF) according to its use by the U.S. EPA: "An EF is a representative value that attempts to relate the quantity of a pollutant released to the atmosphere with an activity associated with the release of that pollutant" (U.S. EPA). A fossil fuel EF is the quantity of emissions per unit of energy content in a fuel (kg emissions/MMBtu), and this quantity is often provided as a single value; for example, the "EFs for greenhouse gas inventories" document by the EPA provides nationwide averages for coal, natural gas, and petroleum, which are responsible for 66%, 32%, and 1% of total U.S. CO_2 emissions for electricity generation (U.S. Energy Information Administration (EIA), 2019). In reality, a fossil fuel EF's value varies across different regions, sectors, and types of combustion devices (Roy et al., 2009). EF value differences can significantly affect quantifications of CO_2 emissions (Liu et al., 2015). An electricity generation EF (EGEF) calculates the emissions released per unit of electricity generation (kg emissions/MWh generated). The greenhouse gas emissions associated with renewable and nuclear energy used to generate electricity are significantly lower and less variable than the emissions associated with electricity generation using fossil fuels: life-cycle greenhouse gas emissions have been reported at 45 (gCO_2/kWh) for Photovoltaics (PV), 11 (gCO_2/kWh) for wind, 12 (gCO_2/kWh) for nuclear energy, and 1,000 (gCO_2/kWh) for coal (National Renewable Energy Laboratory, 2013). Thus, PV, wind, and nuclear emissions' impact on EGEF were neglected in the present study.

EGEF can be quantified using a weighted sum of the EFs for the individual energy sources in a state's fuel mix, multiplied by their consumption rates. Simply put, the variability of EFs of different energy sources changes the EGEF. Several studies in the literature have investigated the effects of EFs' uncertainty and variability on emissions accounting. Wang et al. (2019) used bootstrap and Monte Carlo simulations to determine methane EF variability for coal, using data from 11,000 power plants in China. They found high variability for methane EFs, which varied widely compared to the average EF values used in the 2006 Intergovernmental Panel on Climate Change (IPCC) "Guidelines for National Greenhouse Gas Inventories." Roy et al. (2009) created equations for estimating coal EFs in India, finding this approach effective in reducing the uncertainty surrounding EFs for this fuel type. This approach yielded estimated EFs that were proposed to be more realistic than national-average EFs in representing coal EFs throughout India.

These studies have analyzed coal EF variability in emissions accounting in India and China. The literature has neglected, however, to analyze EGEFs' variability, based on different energy sources at the U.S. state level, while considering the data's limitations. Therefore, the current study's first objective is to analyze EGEF' variability with the available energy-source EFs at the state level, using our three selected states.

1.2. How did these emission factors change from 1990 to 2017, and what underlying factors drove these changes in each of the studied states?

EGEFs change over the years because of changes in the power generation process. In this work, we consider four major factors involved in those changes (Ang and Su (2016), Goh et al. (2018a), and Goh et al. (2018b)): (1) the fossil fuel share effect (i.e., fossil fuels' share of electricity generation to non–fossil fuels'—hydro-power, biomass, renewables, and nuclear—share of electricity generation), (2) the fossil fuel mix effect (i.e., the mix of fossil fuels consumed for electricity generation), (3) the generation efficiency effect (i.e., power plants' generation efficiency), and (4) the EF effect (i.e., fossil fuel EFs). Understanding how EGEF can be broken down into these four factors can reveal the most effective factors in reducing EGEFs. The results of this analysis may reveal the social, political, or economic changes that have influenced these component factors, which are unique to each region.

Decomposition analysis is a method of breaking the EGEF down into several predefined factors (Ang, 2004). Index decomposition analysis (IDA) is a useful method for performing decomposition analysis and evaluating the main forces driving changes in CO_2 emissions over the years (Xu and Ang (2013) and Zhang et al. (2013)).

Decomposition analysis of EGEFs has enabled a new understanding of the essential factors driving changes in EGEFs over the years. Ang and Su (2016) broke down the CO_2 EGEF in 10 Southeast Asian countries from 1990 to 2013. The results of this decomposition index identified the factor responsible for the largest reductions in several countries' EGEFs: in Myanmar, this factor was an improvement in the country's fossil fuel share effect; in Singapore and Thailand, this factor was changes in the countries' fossil fuel mix effects; and in Vietnam, Brunei, and Malaysia, this factor was an improvement in power plants' generation efficiency effect. Liu et al. (2017) used the IDA method to analyze the forces driving EGEFs at the provincial level in China. They concluded that an improvement to the generation efficiency effect was the most essential factor in reducing China's EGEFs from 2000 to 2014.

Decomposition analysis of CO_2 emissions has also been conducted using electricity generation in the U.S. Jiang and Li (2017) used the LMDI (log mean Divisia index analysis) method to break down CO_2 emissions in the U.S. from 1990 to 2014, concluding that the country's fossil fuel mix effect played the most significant role in reducing electricity CO_2 emissions from 1990 to 2005 (and in the CO_2 emissions predicted between 2005 and 2030). Mohlin et al. (2019) studied changes in CO_2 emissions at the U.S. state level from 1990 to 2015, showing that states' fossil fuel share effect and fossil fuel mix effect were the main factors driving changes in CO_2 emissions.

The studies above demonstrated that the fossil fuel share effect, the fossil fuel mix effect, and the generation efficiency effect tend to account for the largest share of changes in EGEFs (Ang and Su (2016), Malla (2009), and Jiang and Li (2017)), and the most important factors differ between the national and provincial levels (Liu et al. (2017) and Mohlin et al. (2019)). Decomposition analysis of U.S. EGEFs is vital because magnitudes of greenhouse gas emissions resulting from electricity generation vary by location (de Chalendar et al., 2019) since U.S. states may belong to different electrical grid balancing authority areas, may have implemented different renewable energy policies (DSIRE), or may target different energy source mixes over the years while facing different public pressures to act upon these targets.

The current study builds on the work of Mohlin et al. (2019) by examining variability and different possible values for EGEFs, including changes in SO_2 and NO_x EGEF, extending the studied period to 2017, and focusing on three selected states that provide different case studies illustrating this variability. Thus, this study's second objective is to study EGEF changes over the years in California, Texas, and New York at the individual-state level.

1.3. Can we reasonably quantify electricity generation's environmental impacts at the state level, given the uncertainty surrounding the data used to calculate these states' emission factors?

If EGEFs are part of a decision-making process, then any metrics calculated using variations that affect EGEF values will also involve variability that is associated with the calculated metrics. The term "environmental impact," as it is used here, describes the consequence of a plan, policy, or process. It is an example of a method used for decision- and policy-making. Environmental impact quantification is a method of evaluating a system or process's environmental effects through four damage categories: human health, ecosystem quality, climate change, and resources (Jolliet et al., 2003). To quantify electricity generation's environmental impacts, a computational tool can be used first to create a deterministic estimate. The variability associated with EGEF can be used with the analytical tool to quantify a resulting variability in environmental impacts. Traci, an open-source environmental impact assessment tool developed by the U.S. EPA (2012), was used in this study to quantify environmental impacts.

Many studies have quantified electricity generation's environmental impact, but few analyses have incorporated uncertainty and variability into their results. Chen and Corson (2014) used a Monte Carlo simulation to determine the effects of EFs' uncertainty in three environmental impact categories. They concluded that EFs' variability and uncertainty could shift decision outcomes, based on environmental impact assessments. Sonnemann et al. (2003) estimated the effect of site-specific uncertainties and variability in measuring EGEF resulting from a waste incinerator, showing that significant uncertainties are associated with EGEFs because of inventory data uncertainties.

Tools that help decision-making can be improved if their results' uncertainties and variabilities are more transparent (Tenney et al., 2006). We were unable to locate a study investigating the variability of a decision-making tool's results, based on U.S. EGEFs' variability. The lack of such a study may be due to a lack of reliable data on emissions', EFs', and EGEFs' uncertainty and variability. Therefore, the current study's third objective was to quantify how EGEFs' variability affects the environmental impacts, using the limited data available from reliable sources.

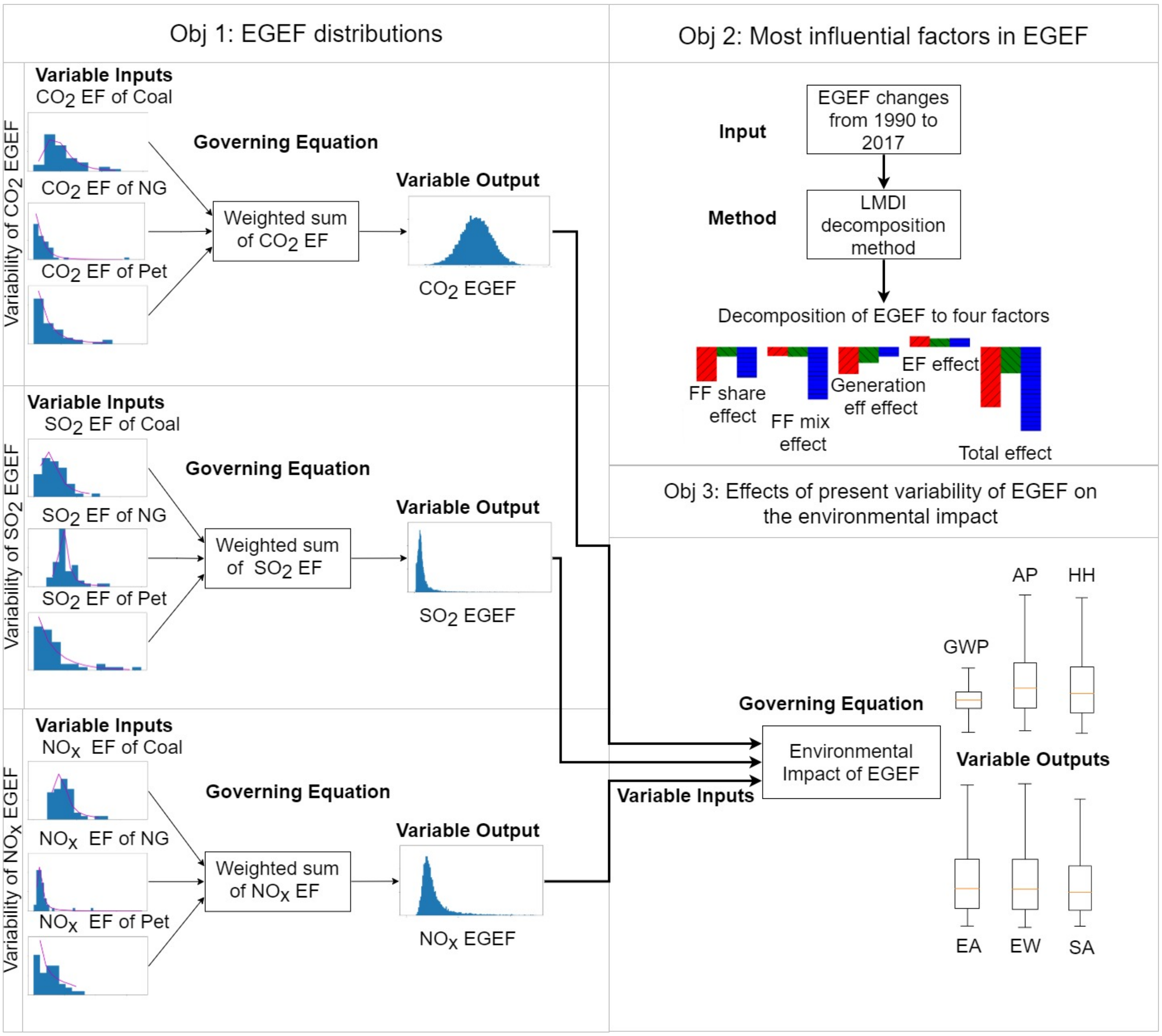

Figure 1: Graphical abstract of this paper's three objectives. EF: emission factor; EGEF: electricity generation emission factor; NG: natural gas; Pet: petroleum; FF: fossil fuel; eff: efficiency; GWP: global warming potential, AP: acidification potential, HH: human health, EA: eutrophication air, EW: eutrophication water, SA: smog air.

Figure 1 depicts this paper's three objectives as a graphical abstract. Fossil fuel EFs are calculated for each of the three emission types (i.e., CO_2, SO_2, and NO_x) considered. EGEFs are broken down to identify the four factors' effects. The impact of EGEF values' variability on the quantification of environmental impacts is described.

Our analysis in this paper presents the following novel contributions:

1. The range and variability of EGEFs for CO_2, SO_2, and NO_x associated with fossil fuel electricity generation in the U.S. are quantified deterministically for all U.S. states. These EGEFs are quantified stochastically, using a Monte Carlo simulation for the three selected states.

2. The CO_2 EGEF is broken down for the three selected states, showing how those EGEFs have changed over time by revealing the main factors that have influenced changes to EGEFs between 1990 and 2017.

3. We quantify the variability of electricity generation's environmental impacts due to variability in EGEFs. However, we caution against relying on any quantification of electricity generation's environmental impacts at the U.S. state level.

2. Methodology

The following three subsections discuss the methods we used to address each of this study's three objectives, respectively.

2.1. Emission factors' distribution for electricity generation

This subsection explains our methodology in determining fossil fuel EFs' variability in the U.S. in 2017 and then using that variability to identify the probability distribution of EGEFs at the state level in 2017. This subsection comprises three parts. First, the data sources and assumptions used to determine the EGEFs are described. Second, the formulations used to calculate EGEFs are presented. Third, the Monte Carlo simulation statistical tool is used to identify the results' variability and probability distribution.

2.1.1. Data sources and assumptions

Three data sources from the "Electricity Detailed State Data from 1990 to 2017" webpage by the U.S. EIA were used to calculate energy-source EGEFs at the state level:

1. Annual data (from 1990 to 2018) for net generation by type of producer (e.g., the total electric power industry, electric generators, electric utilities, combined heat and power, and commercial power) and fuel type (e.g., coal, natural gas, petroleum, hydroelectric conventional, and wind) for 50 U.S. states.

2. Annual data (from 1990 to 2018) for fossil fuel consumption used for electricity generation by producer type (e.g., total electric power industry, electric generators, electric utilities, combined heat and power, and commercial power) and fuel type (e.g., coal, natural gas, petroleum, and other gases) for 50 U.S. states.

3. Annual data (from 1990 to 2017) for the electric power industry's estimated emissions (CO_2, SO_2, and NO_x) for 50 U.S. states.

We made four assumptions in considering the fuels used for electricity generation at the state level:

1. Only emissions associated with fossil fuels' combustion were considered, and emissions from the production, processing, transmission, and storage of energy sources were omitted from our calculations. We made this assumption because of the available electricity generation and emissions data from the EIA "Electricity Detailed State Data from 1990 to 2017" documents' exclusion of other parts of the energy sources life cycle and focus on the production side of energy sources for electricity generation .

2. Emissions associated with renewables (hydro, wind, solar, biomass, and geothermal) and nuclear energy were also excluded from our calculations. Amponsah et al. (2014) reviewed greenhouse gas emissions at different stages of renewable technologies. In most cases (except for two instances using biomass technology), greenhouse gas emissions from power plant operations were less than 20 kgCO_{2eq}/MWh, which is less than greenhouse gas emissions associated with the use of fossil fuels to generate electricity (National Renewable Energy Laboratory, 2013).

3. “Other biomass” and “wood and wood derived fuels” energy sources from the “Electricity Detailed State Data from 1990 to 2017” documents were also excluded from our EGEF calculation. The three selected fossil fuels (i.e., coal, natural gas, and petroleum) are the top-three CO_2 emitters, accounting for 99% of CO_2, 82% of SO_2 emissions, and 82% of NO_x emissions in U.S. electricity generation during 2017. The main energy source excluded from our analysis is “wood and wood derived fuels,” which account for 16% of SO_2 emissions; moreover, “other biomass” and “wood and wood derived fuels” respectively account for 8% and 5% of NO_x emissions. “Other biomass” and “wood and wood derived fuels” were omitted from this study because their consumption data is not available in the “Electricity Detailed State Data from 1990 to 2017” EIA documents.

4. The “other” fuel type was omitted because its heating value is unavailable, and it accounted for only 0.3% of total U.S. electricity generation in 2017, which is a marginal amount (“Electricity Detailed State Data from 1990 to 2017” EIA documents).

2.1.2. Electricity generation emission factor calculation

EF of fossil fuels can be calculated by dividing emissions at the state level for each fuel type by the amount of the consumption of that fuel to generate electricity (kg emissions/MMBtu), using Equation 1 (Intergovernmental Panel on Climate Change, 2006). EGEFs at the state level can be calculated using Equation 2, based on fuel consumption rates and fuel EFs, divided by electricity generation at the state level.

$$\text{Emission Factor}_{fuel} = \text{Emissions} \;/\; \text{Fuel Consumption} \tag{1}$$

$$\text{EGEF} = \frac{\sum_{fuel=1}^{n} \text{Fuel Consumption}_{fuel} \times \text{Emission Factor}_{fuel}}{\text{Electricity Generation}} \tag{2}$$

2.1.3. Statistical analysis

Probabilistic techniques, such as Monte Carlo simulation, can serve as a practical statistical tool in analyzing variability (Environmental Protection Agency, 1997). This study used the five-step Monte Carlo simulation procedure described by Hiraishi et al. (2001) to quantify EGEFs’ variability at the state level.

1. Specify source-category uncertainties; fossil fuel EFs (kg CO_2/MMBtu, kg SO_2/MMBtu, and kg NO_x/MMBtu) for coal, natural gas, and petroleum are variable in the U.S.

2. Set up the necessary information: the quantities of CO_2, SO_2, and NO_x emissions, fossil fuel consumption rates, and electricity generation are available in the “Electricity Detailed State Data from 1990 to 2017” document by the EIA for all 50 U.S. states in 2017. Fossil fuel EFs’ probability density functions were computed using the available continuous distributions in the SciPy Python library (SciPy library, 2019).

3. Select random variables: random CO_2, SO_2, and NO_x EF variables (kg CO_2/MMBtu, SO_2/MMBtu, or NO_x/MMBtu) were generated for coal, natural gas, and petroleum.

4. Estimate EGEFs: EGEFs were calculated for Texas, California, and New York using fossil fuel consumption rates (MMBtu) multiplied by fossil fuel EFs’ random variable (kg CO_2/MMBtu, SO_2/MMBtu, or NO_x/MMBtu), using Equation 2.

5. Iterate and monitor the results: the EGEF value from Step 4 was stored, and then the process was repeated from Step 3.

These five steps were simulated using continuous distributions in the SciPy library in Python, and 10,000 samples from fossil fuel EFs were generated to show EGEFs' variability for the study's three emission types at the state level.

2.2. The most influential elements of electricity generation emission factors

This subsection describes the study's methodology to break EGEFs down into influential factors at the state level from 1990 to 2017.

Two main methods were used for this decomposition analysis: structural decomposition analysis (SDA), which uses input-output models, and IDA, which implements index number theory (Goh et al., 2018b).

IDA has been successfully applied in the literature to evaluate different factors' impacts on energy and changes in emissions over the years (Zhang et al., 2013). In 2004, after 25 years of research on decomposition analysis, researchers had not reached an agreement on the best decomposition method (Ang, 2004). Popular decomposition methods belong to two main groups: (1) methods linked to the Laspeyres index (i.e., the impact of a factor is calculated while all the other factors are constant at their base year) and (2) methods linked to the Divisia index (i.e., a weighted sum of logarithmic growth rates is used) (Ang et al., 1998).

The advantage of the Divisia index approach (i.e., the concept of logarithmic change) over the Laspeyres index approach (i.e., the familiar concept of percentage changes) is the Divisia index symmetric and additive features of relative changes (Ang, 2004). The symmetric feature of the Divisia index means that, in quantifying relative changes between two numbers, the order of the numbers does not affect relative change values. For example, an absolute value of log(1/5) equals log(5/1), but a percentage change between these two numbers gives values of 5 and 0.20 (1/5). The additive feature of the Divisia index means that two relative changes can be summed or subtracted. For example, log(5/1) equals log(5/3) added to log(3/1). But, using the concept of percentage changes, 5 does not equal 1.67 (5/3) added to 3, which gives 4.67.

For cross-country or regional analysis, conventional decomposition methods leave significant residuals, and perfect decomposition methods (e.g., LMDI)—which leave no residuals—have been suggested instead (Zhang and Ang, 2001). Ang (2004) concluded that LMDI is the most "elegant" decomposition method, from a theoretical perspective, for use in regional studies. Therefore, considering its additive and symmetric features and its leaving no residuals, we selected the LMDI method for the current study.

To apply the LMDI method to changes in EGEFs from this study's base year (1990) to its final year (2017) at the state level, Equation 3 was used as the governing equation to be broken down into four factors (Ang and Su, 2016).

$$EGEF = \frac{C}{G} = \sum_{fuel=1}^{3} \frac{Q}{G}\frac{Q_{fuel}}{Q}\frac{F_{fuel}}{Q_{fuel}}\frac{C_{fuel}}{F_{fuel}} \tag{3}$$

- C Emissions from electricity generation (kg)
- G Total electricity generation by state (MWh)
- Q Electricity generation by all fossil fuels (coal, natural gas, and petroleum) (MWh)
- Q_{fuel} Electricity generation by each fossil fuel type (coal, natural gas, or petroleum) (MWh)
- F_{fuel} Energy input by each fossil fuel type (coal, natural gas, or petroleum) (MMBtu)
- C_{fuel} Emission by each fossil fuel type (coal, natural gas, or petroleum) (kg)

Equation 3 can be rewritten as Equation 4 (Ang and Su, 2016).

$$EGEF = \sum_{fuel=1}^{3} p \times m_{fuel} \times u_{fuel} \times e_{fuel} \tag{4}$$

- p The proportion of electricity produced from fossil fuels in the total electricity generation (MWh/MWh)
- m_{fuel} The electricity generation from each fossil fuel divided by the total electricity generation from all fossil fuels (coal, natural gas, and petroleum) (MWh/MWh)
- u_{fuel} The energy input divided by the electricity generation for each fossil fuel generation (MMBtu/MWh)

Characteristic Factor	CO_2	SO_2	NO_x
GWP kg CO_2-eq/kg substance	1	0	0
AP kg SO_2-eq/kg substance	0	1	0.7
HH kg $PM_2.5$-eq/kg substance	0	0.061	0.007
EA kg N-eq/kg substance	0	0	0.044
EW kg N-eq/kg substance	0	0	0.291
SA kg O_3-eq/kg substance	0	0	24.79

Table 1: Characteristic factors of CO_2, SO_2, and NO_x for six impact categories (GWP, AP, HH, EA, EW, and SA) from the U.S. EPA (2012).

e_{fuel} The EGEF of each fossil fuel (kg-emissions/MMBtu)

Next, the total change in EGEFs at the state level from 1990 (the base year) to 2017 was shown as ΔV_{total} (kg emissions/MWh) and broken down into ΔV_p (fossil fuel share effect), ΔV_m (fossil fuel mix effect), ΔV_u (generation efficiency effect), and ΔV_e (EF effect) (kg emissions/MWh) factors in Equation 5.

$$\Delta V_{total} = V^T - V^0 = \Delta V_p + \Delta V_m + \Delta V_u + \Delta V_e \tag{5}$$

Further equations for the LMDI method are available in Appendix (also, see Ang et al. (1998), Ang (2005), Ang et al. (2011), and Ang and Su (2016) for detailed methodology).

2.3. The effects of electricity generation emission factors' present variability on environmental impact quantification

This subsection describes the methodology we used to quantify the effects of EGEFs' variabilities on environmental impact categories during 2017 in California, Texas, and New York, using the five-step Monte Carlo procedure presented earlier under Subsection 2.1.

Environmental impact quantification anticipates a system or process's environmental effects through four damage categories: human health, ecosystem quality, climate change, and resources (Jolliet et al., 2003). Midpoint categories can be used to connect emission inventory data to damage categories. Six midpoint categories were used in the current study: global warming potential (GWP), acidification potential (AP), human health (HH), eutrophication air (EA), eutrophication water (EW), and smog air (SA). These midpoint categories were chosen because they connect CO_2, SO_2, and NO_X—the available emissions data in this study—to the damage categories. GWP affects climate change. AP, EA, EW, and SA affect ecosystem quality. Finally, HH and SA affect human health (Jolliet et al., 2003).

Traci, an open-source environmental impact assessment tool developed by the EPA, was used in this study to determine the environmental impacts of electricity generation at the state level by providing the characteristic factors shown in Table 2.3. Traci was selected for this study as a free, U.S.–based tool developed by the EPA, a reliable source for environmental studies. A Monte Carlo simulation was used to calculate the variability of electricity generation's environmental impacts, following the five-step procedure described in Subsection 2.1.

1. Specify source category uncertainties: EGEFs are variable (kg CO_2/MWh, kg SO_2/MWh, and kg NO_x/MWh) in California, Texas, and New York, based on the results of the first objective identified in Subsection 3.1.

2. Set up the necessary information: characteristic factors of CO_2, SO_2, and NO_x for six impact categories (GWP, AP, HH, EA, EW, and SA) were obtained from the Traci, which are shown in Table 2.3. EGEFs' probability density functions can be calculated using the Subsection 2.1 method and are shown in Table 5 in Appendix.

3. Select random variables: random variables for CO_2, SO_2, and NO_x EGEF (kg CO_2/MWh, SO_2/MWh, or NO_x/MWh) were determined for California, Texas, and New York.

4. Estimate the environmental impact: GWP, AP, HH, EA, EW, and SA were calculated for California, Texas, and New York using the Traci characteristic factors in Table 2.3, multiplied by CO_2, SO_2, and NO_x EGEF random variables from Step 3.

5. Iterate and monitor the results: The environmental impact categories' values from Step 4 were stored, and then the process was repeated from Step 3 to show the variability of EGEFs' environmental impacts in California, Texas, and New York during 2017.

3. Results and Discussion

The results obtained by addressing each of this study's three objectives are discussed in the three subsections below.

3.1. Emission factors' distribution for electricity generation

This subsection first reveals the CO_2, SO_2, and NO_x EF distributions of coal, natural gas, and petroleum in the U.S. during 2017. Next, the variability of CO_2, SO_2, and NO_x EGEFs are presented for California, Texas, and New York in 2017.

The EF units for fossil fuels are compatible with the units in the "EFs for greenhouse gas inventories" document by the EPA, kg of emissions per MMBtu of fossil fuel consumption.

The probability distribution of CO_2 EFs for coal, natural gas, and petroleum are shown in Figures 2, 3, and 4. The median of CO_2 EF using coal was 95.38 kg-CO_2/MMBtu (0.32 kg-CO_2/kWh), while the corresponding median for natural gas was 56.38 kg-CO_2/MMBtu (0.19 kg-CO_2/kWh), and the corresponding median for petroleum was 73.92 kg-CO_2/MMBtu (0.25 kg-CO_2/kWh). The average results for coal, natural gas, and petroleum EF were 95.52, 53.06, and 73 kg-CO_2/MMBtu (0.33, 0.18, and 0.25 kg-CO_2/kWh), respectively, in the "EFs for greenhouse gas inventories" document by the EPA. A coefficient of variation (i.e., the data's standard deviation, divided by the data's mean) can be used to compare uncertainty across data sets when means differ. The coefficients of variation for CO_2 EF using coal, natural gas, and petroleum were 10.43%, 4.65%, and 11.06%, respectively.

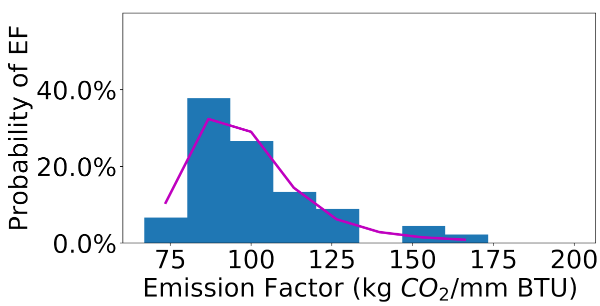

Figure 2: Probability distribution of CO_2 EFs for coal in the 50 U.S. states during 2017.

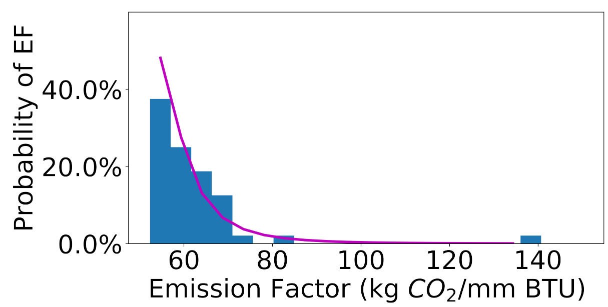

Figure 3: Probability distribution of CO_2 EFs for natural gas in the 50 U.S. states during 2017.

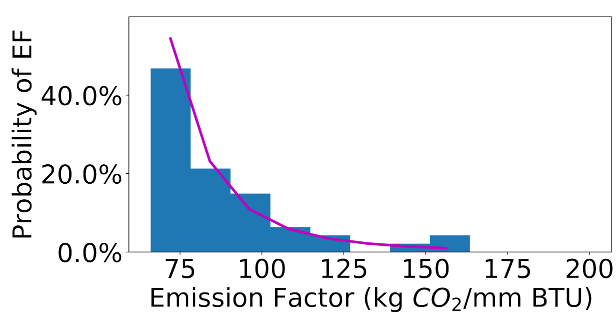

Figure 4: Probability distribution of CO_2 EFs for petroleum in the 50 U.S. states during 2017.

The probability distribution of SO_2 EFs for coal, natural gas, and petroleum are shown in Figures 5, 6, and 7. The median of SO_2 EF using coal was 0.08 kg-SO_2/MMBtu (0.27 g-SO_2/kWh), while the corresponding median for natural gas was 0.0 kg-SO_2/MMBtu (0.0 g-SO_2/kWh), and the corresponding median for petroleum was 0.11 kg-SO_2/MMBtu (0.37 g-SO_2/kWh). The coefficient of variation for SO_2 EFs using coal, natural gas, and petroleum were 61.56%, 36.25%, and 109.08%, respectively.

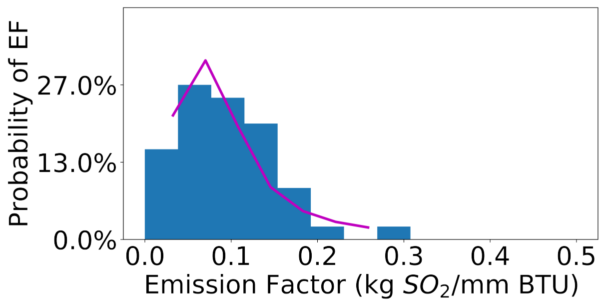

Figure 5: Probability distribution of SO_2 EFs for coal in the 50 U.S. states during 2017.

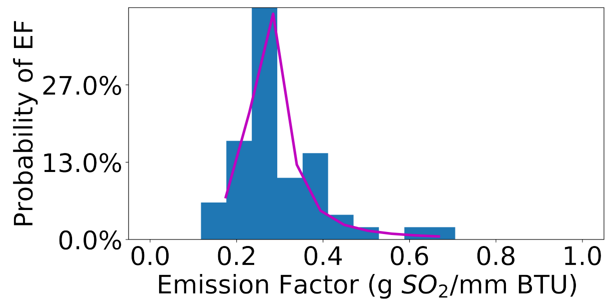

Figure 6: Probability distribution of SO_2 EFs for natural gas in the 50 U.S. states during 2017.

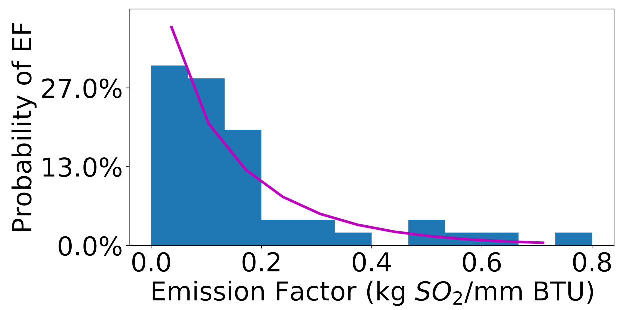

Figure 7: Probability distribution of SO_2 EFs for petroleum in the 50 U.S. states during 2017.

The probability distribution of NO_x EFs for coal, natural gas, and petroleum are shown in Figures 8, 9, and 10. The median of NO_x EFs using coal was 0.07 kg-NO_x/MMBtu (0.24 g-NO_x/kWh), while the corresponding median for natural gas was 0.03 kg-NO_x/MMBtu (0.10 g-NO_x/kWh), and the corresponding median for petroleum was 0.10 kg-NO_x/MMBtu (0.34 g-NO_x/kWh). The coefficient of variation for NO_x EFs using coal, natural gas, and petroleum were 38.12%, 155.71%, and 66.42%, respectively.

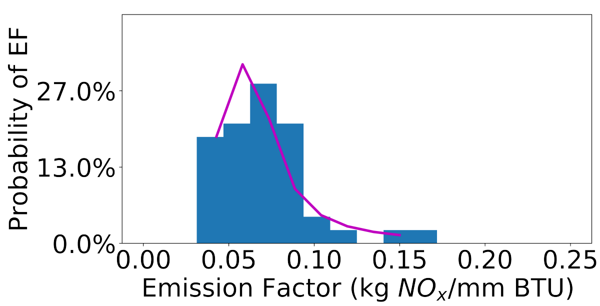

Figure 8: Probability distribution of NO_x EFs for coal in the 50 U.S. states during 2017.

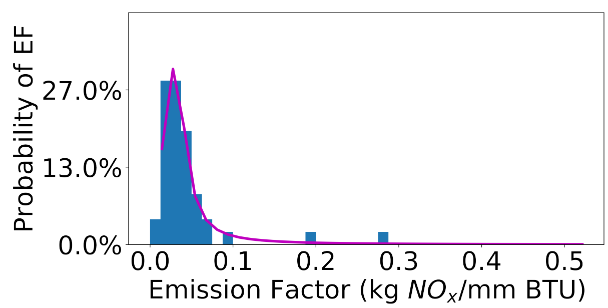

Figure 9: Probability distribution of NO_x EFs for natural gas in the 50 U.S. states during 2017.

The probability density functions of nine EF types are depicted in Figures 2–10, which are shown in Table 5 in Appendix. In Step 3 of this study's Monte Carlo method, random variables from probability density functions (Figures 2–4) were generated and combined, based on each state's share of coal, natural gas, and petroleum (i.e., energy mix). In Step 4 of this study's Monte Carlo method, 10,000 samples were generated to calculate the CO_2, SO_2, and NO_x EGEFs. The probability distribution of EGEFs using CO_2, SO_2, and NO_x of the study's 10,000 samples are shown in Figures 11, 12, and 13 for Texas.

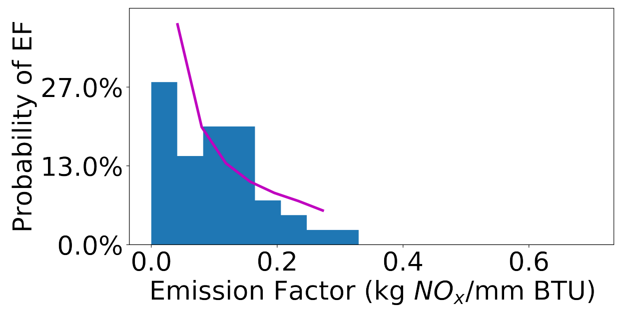

Figure 10: Probability distribution of NO_x EFs for petroleum in the 50 U.S. states during 2017.

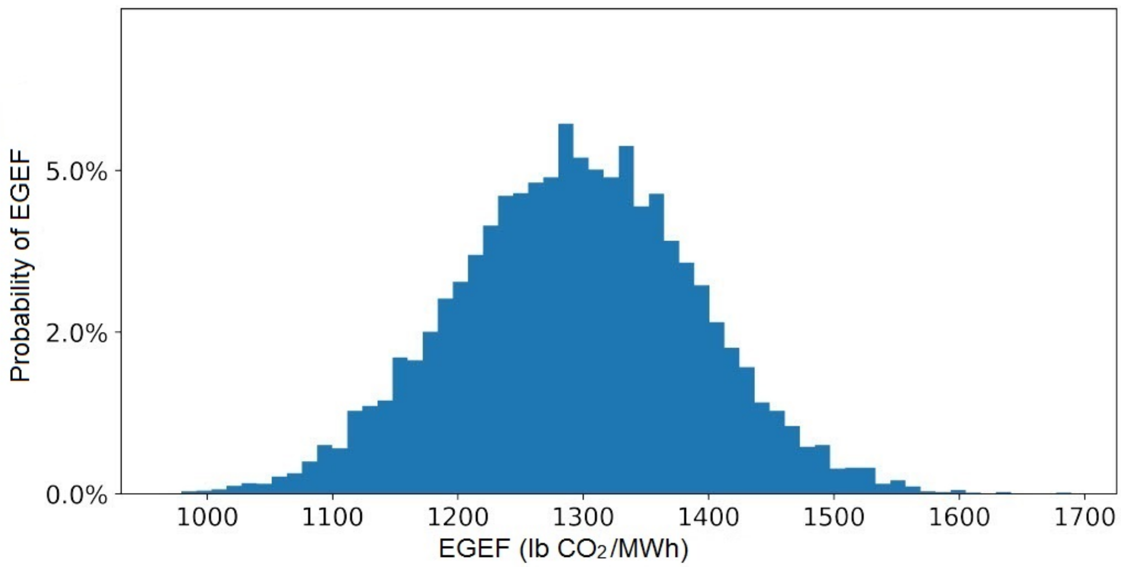

Figure 11: CO_2 EGEF distribution in Texas during 2017, using sources' (i.e., coal, natural gas, and petroleum) EF distributions

The CO_2, SO_2, and NO_x EGEFs in Texas were, respectively, 1,166 lb CO_2/MWh, 1.3 lb SO_2/MWh, and 0.8 lb NO_x/MWh in 2017, as per the "State Electricity Profiles in 2017" EIA document. The median values—using Figures 11, 12, and 13—were, respectively, 1,293.25 lb CO_2/MWh, 0.83 lb SO_2/MWh, and 0.9 lb NO_x/MWh, reflecting 10.9%, 36%, and 12.5% respective differences between the median values in this study and the data in the "Electricity Detailed State Data from 1990 to 2017" EIA document. The coefficient of variation (i.e., the data's standard deviation, divided by the data's mean) for CO_2, SO_2, and NO_x EGEFs in Texas were 7%, 697%, and 1061%, respectively.

Figures A.1, A.2, and A.3 in Appendix show the distributions of CO_2, SO_2, and NO_x EGEFs in California.

The CO_2, SO_2, and NO_x EGEFs in California were, respectively, 474 lb CO_2/MWh, 0.0 lb SO_2/MWh, and 0.7 lb NO_x/MWh in 2017, as per the "State Electricity Profiles in 2017" EIA document. The median values—using Figures A.1, A.2, and A.3—were, respectively, 400.76 lb CO_2/MWh, 0.0 lb SO_2/MWh, and 0.25 lb NO_x/MWh, reflecting 15.4%, 0%, and 95% respective differences between the median values in this study and the data in the "Electricity Detailed State Data from 1990 to 2017" EIA document. The coefficient of variation for CO_2, SO_2, and NO_x EGEFs in California were 4.8%, 504%, and 1444%, respectively.

Figures A.4, A.5, and A.6 in Appendix show the distribution of CO_2, SO_2, and NO_x EGEFs in New York.

The CO_2, SO_2, and NO_x EGEFs in New York were, respectively, 439 lb CO_2/MWh, 0.3 lb SO_2/MWh, and 0.5 lb NO_x/MWh in 2017, as per the "State Electricity Profiles in 2017" EIA document. The median values—using Figures A.4, A.5, and A.6—were, respectively, 389.29 lb CO_2/MWh, 0.03 lb SO_2/MWh, and 0.25 lb NO_x/MWh, reflecting 11.3%, 90%, and 50% differences between the median values in this study

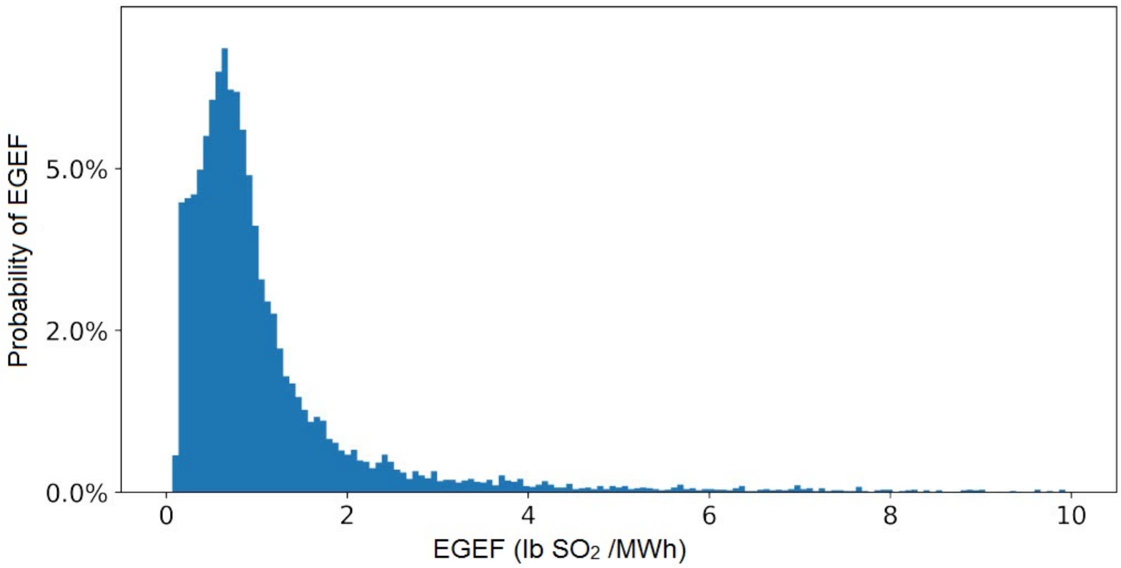

Figure 12: SO_2 EGEF distribution in Texas during 2017, using sources' (i.e., coal, natural gas, and petroleum) EF distributions

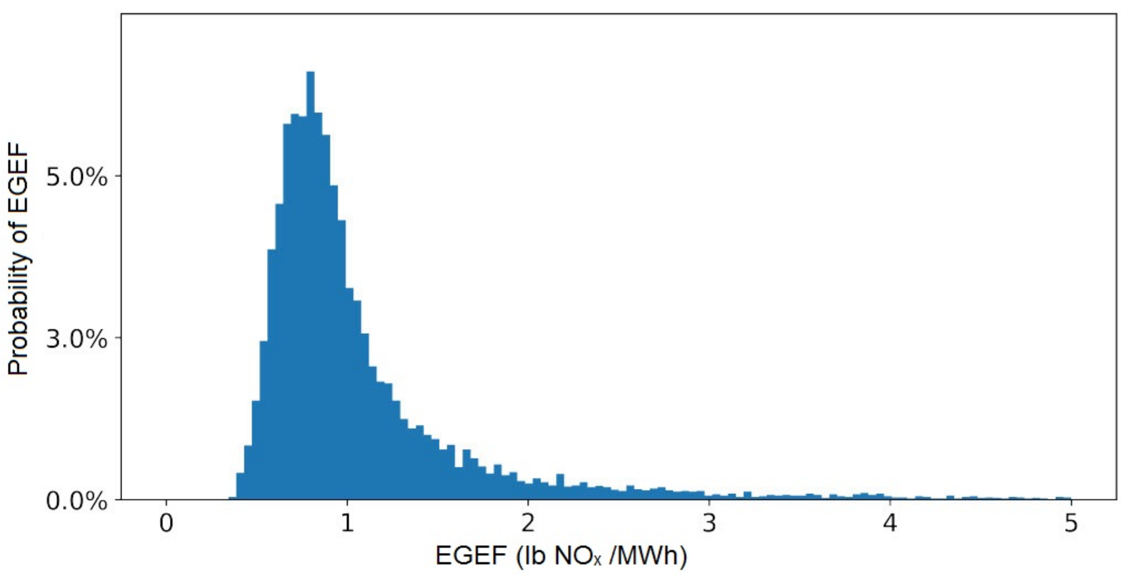

Figure 13: NO_x EGEF distribution in Texas during 2017, using sources' (i.e., coal, natural gas, and petroleum) EF distributions

and the data in the "Electricity Detailed State Data from 1990 to 2017" EIA document. The coefficient of variation for CO_2, SO_2, and NO_x EGEFs in New York were 4.6%, 432%, and 1,393%, respectively.

Two conclusions can be drawn from a comparison of this study's results for the three states examined:

1. For the three states, SO_2 and NO_x EGEFs showed significant variability compared to CO_2 EGEFs.
2. EGEFs for states with higher shares of coal, natural gas, and petroleum were estimated to differ less from the EIA document values. The shares of emissions in Texas, California, and New York were as follows:
   (a) In Texas, 99% of CO_2, 94% of SO_2, and 94% of NO_x emissions for electricity generation resulted from coal, natural gas, and petroleum consumption, respectively, which resulted in the lowest difference between this study's calculated values and the EIA document values.
   (b) In California, coal, natural gas, and petroleum accounted for 95% of CO_2 emissions, 45% of SO_2 emissions, and 73% of NO_x emissions, respectively, for electricity generation. Including other energy sources (i.e., "wood and wood derived fuels," "other biomass," and "other") would improve estimations of SO_2 and NO_x EGEFs in California.
   (c) In New York, coal, natural gas, and petroleum were responsible for 97% of CO_2 emissions, 71% of SO_2, and 63% of NO_x emissions for electricity generation, respectively. Including other energy sources (i.e., "wood and wood derived fuels," "other biomass," and "other") would improve estimations of SO_2 and NO_x EGEFs in New York.

3.2. The most influential elements of electricity generation emission factors

This subsection breaks down four influential elements (the fossil fuel share effect, the fossil fuel mix effect, the generation efficiency effect, and the EF effect) of EGEFs to show how these four elements changed EGEFs at the state level from 1990 to 2017.

The LMDI method was performed for the study's three examined states: Texas, California, and New York. The results of this process for the fossil fuel share effect, the fossil fuel mix effect, the generation efficiency effect, the EF effect, and the sum of all four effects (i.e., the total) are shown in Figure 14.

Figure 14 shows that total EGEFs have decreased in all three examined states from 1990 to 2017. The highest reduction occurred in New York, and the lowest reduction occurred in California.

The fossil fuel share effect was responsible for 42%, 36%, and 37% of the EGEF changes from 1990 to 2017 in Texas, California, and New York, respectively. This finding shows that fossil fuels' share of electricity generation in the three states has decreased, substituted by renewables, nuclear energy, and biomass. From 1990 to 2017, coal, natural gas, and petroleum's shares of electricity generation changed from 92% to 75% in Texas, from 50% to 43% in California, and from 61% to 38% in New York.

The fossil fuel mix effect was responsible for 15%, 36%, and 63% of the EGEF changes in Texas, California, and New York, respectively, from 1990 to 2017. This change in electricity EGEFs reveals that the three states' fuel mixes changed to environmentally friendly fossil fuels by decreasing the shares of coal and petroleum and increasing the shares of natural gas from 1990 to 2017. Coal and petroleum's shares of electricity generation reduced by 13% and 1%, respectively, in Texas, 2% and 3% in California, and 18% and 25% in New York. Natural gas shares increased by 2% in California and 20% in New York.

The generation efficiency effect was responsible for 45%, 60%, and 19% of the EGEF changes in Texas, California, and New York, respectively, from 1990 to 2017. This change means that more electricity was generated from one unit of fossil fuel over the years because of improved efficiency for power plants or generators. The definition of "generation efficiency" is compatible with the heat rate of fossil fuels (i.e., the energy input to a system, divided by electricity generation).The heat rate values of coal, natural gas, and petroleum have improved over the years in the U.S. (U.S. Energy Information Administration, 2019b). Changes to the generation efficiency effect with heat rate values are shown in Figures A.9, A.10, and A.11 in Appendix for California, Texas, and New York.

The EF effect increased in the three studied states, which shows that more emissions were produced from one unit of fossil fuel over the years. This increase in the EF effect might have resulted from these states' using more exact metrics.

The "Annual energy outlook 2019: with projections to 2040" EIA document described several elements that have influenced EGEFs. Three of these elements that can be quantified over the years were selected

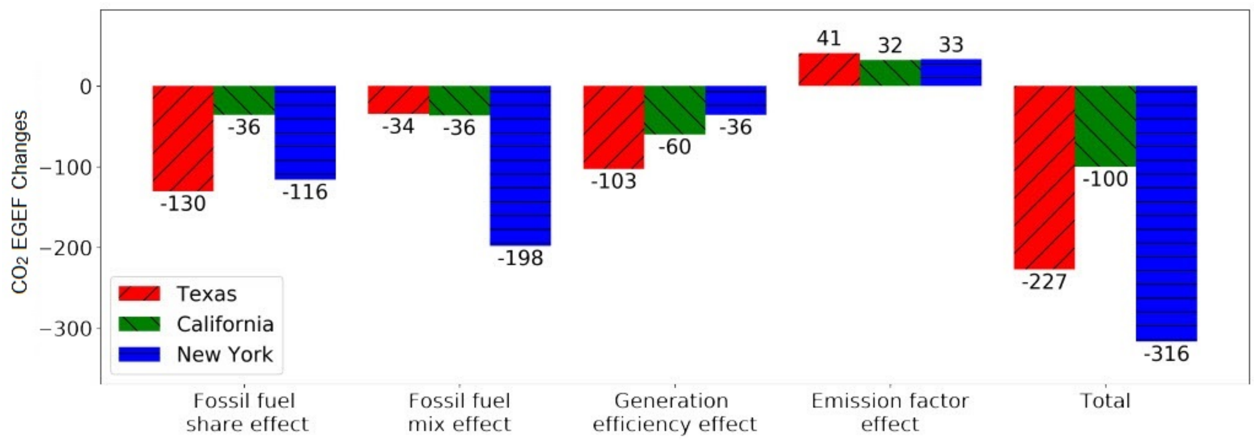

Figure 14: A comparison of Texas, California, and New York's respective changes in CO_2 EGEFs from 1990 to 2017 (lb CO_2)/MWh

for observation in this study: natural gas prices, levelized costs of solar and wind energy, and old power plants' retirement capacity. Other elements can also change EGEFs but were not considered in this study. The selected three factors are part of a system, interconnecting with one another. The following connections show, to some extent, how these three elements might affect EGEFs over the years, though they share no simple cause-and-effect relationship.

Natural gas prices alter the fossil fuel mix effect by decreasing coal-fired power generation's competitiveness (the "Annual energy outlook 2019: with projections to 2040" EIA document). Therefore, it is expected to see lower EGEFs of fossil fuel mix effect with lower natural gas prices. Figures A.18, A.19, and A.20 in Appendix show the CO_2 EGEFs of the fossil fuel mix effect and natural gas prices in California, Texas, and New York from 1990 to 2017.

Levelized costs of electricity of solar and wind power decreased, based on a Lazard report, from 2009 to 2017. Such policies and renewables' LCOE helped EGEFs for the fossil fuel share effect decrease over the years at the state level. Figures A.12, A.13, and A.14 in Appendix show the renewable LCOE and fossil fuel share effects in California, Texas, and New York from 1990 to 2017.

The retirement of older and less-efficient power plants effectively reduced EGEFs at the state level over the years (U.S. EIA, 2019). Figures A.15, A.16, and A.17 in Appendix show the capacity for coal-, natural gas–, and petroleum-based power plants' retirement during each studied year in California, Texas, and New York, respectively.

3.3. The effects of electricity generation emission factors' present variability on environmental impact quantification

This subsection discusses the variabilities of six environmental impact categories—global warming potential (GWP), acidification potential (AP), human health (HH), eutrophication air (EA), eutrophication water (EW), and smog air (SA)—based on variability in EGEFs in California, Texas, and New York in 2017.

Figures 15–20 show the minimum, maximum, lower quarter, upper quarter, interquartile range, and median of the environmental impacts of electricity generation in Texas, California, and New York in 2017 because of EGEFs' variability in the U.S.

The results' SO_2 and NO_x characteristics for GWP, which are shown in Table 2.3, stood at zero. Thus, CO_2 EGEFs drove GWP in this study. The median value of Texas's GWP, shown in Figure 15, exceeded California and New York's corresponding values, and this finding is compatible with the higher CO_2 EGEFs noted in the "EFs for greenhouse gas inventories" EPA document. As we have shown, a coefficient of variation (i.e., the data's standard deviation divided by the data's mean) can be used to compare data sets' uncertainty when means differ. This study's coefficients of variation for GWP were 4.8%, 7.4%, and 4.5 % for California, Texas, and New York, respectively. These values equal the coefficient of variation for CO_2 EGEFs in Subsection 3.1 since they represent the same data's coefficient of variation.

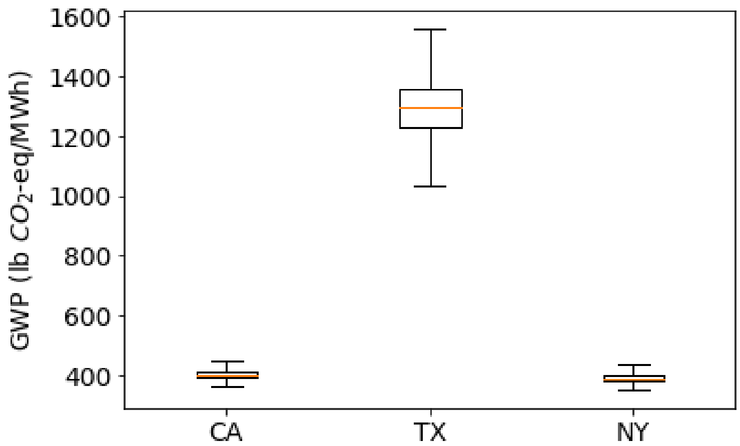

Figure 15: A statistical visualization of GWP (kg CO_2-eq/MWh) showing the minimum, maximum, lower quarter, upper quarter, interquartile range, and median of the three studied states (i.e., California, Texas, and New York) in 2017.

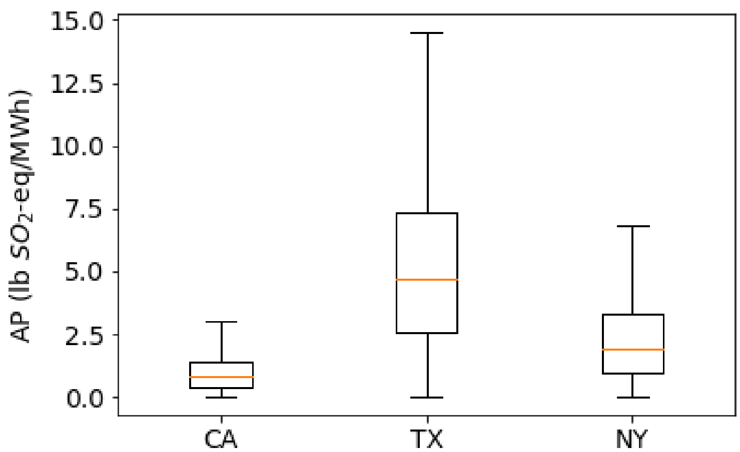

Figure 16: A statistical visualization of AP (kg SO_2-eq/MWh) showing the minimum, maximum, lower quarter, upper quarter, interquartile range, and median of the three studied states (i.e., California, Texas, and New York) in 2017.

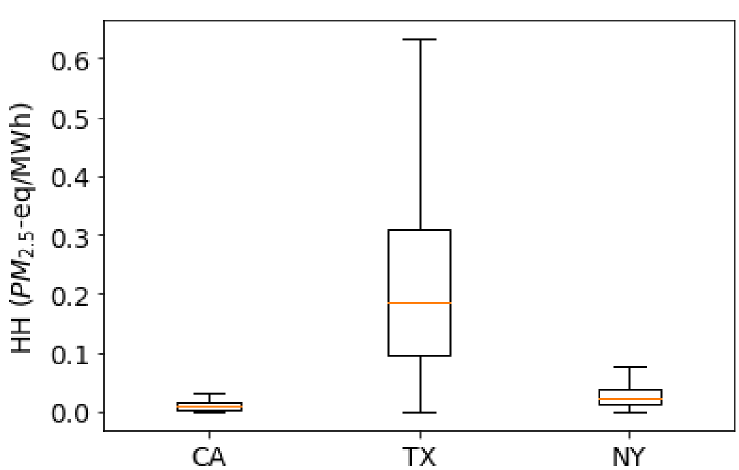

Figure 17: A statistical visualization of HH (PM2.5-eq/MWh) showing the minimum, maximum, lower quarter, upper quarter, interquartile range, and median of the three studied states (i.e., California, Texas, and New York) in 2017.

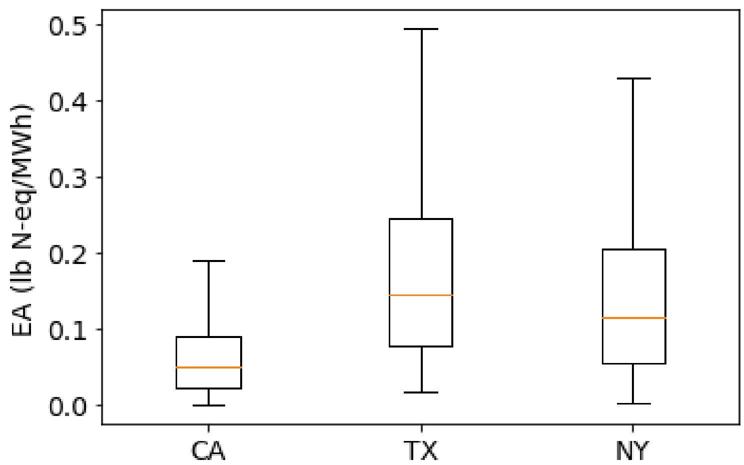

Figure 18: A statistical visualization of EA (kg N-eq/MWh) showing the minimum, maximum, lower quarter, upper quarter, interquartile range, and median of the three studied states (i.e., California, Texas, and New York) in 2017.

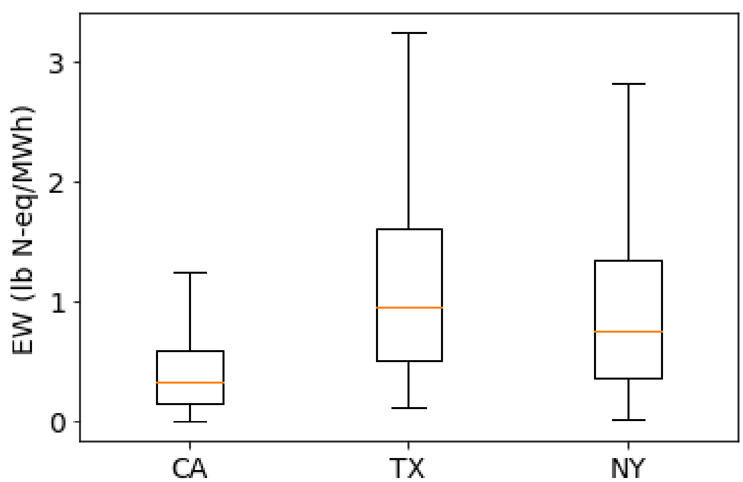

Figure 19: A statistical visualization of EW (kg N-eq/GWh) showing the minimum, maximum, lower quarter, upper quarter, interquartile range, and median of the three studied states (i.e., California, Texas, New York) in 2017.

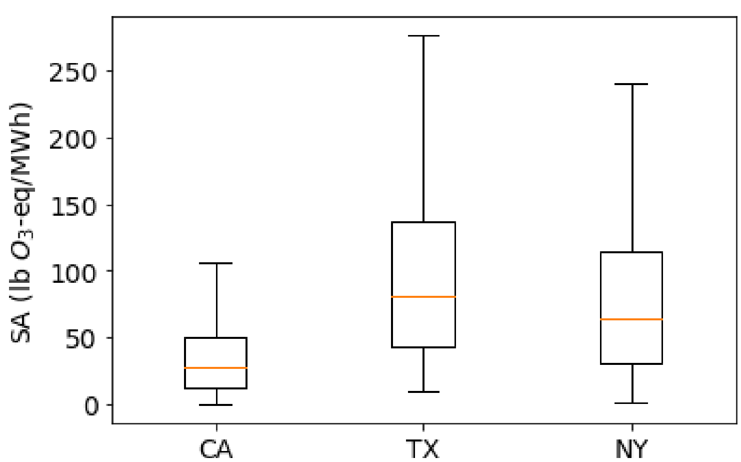

Figure 20: A statistical visualization of SA (kg O_3-eq/MWh) showing the minimum, maximum, lower quarter, upper quarter, interquartile range, and median of the three studied states (i.e., California, Texas, and New York) in 2017.

Acidification potential, shown in Figure 16, was calculated based on SO_2 emissions (with a characteristic factor of 1 [kg SO_2-eq/kg substance]) and NO_x emissions (with a characteristic factor of 0.7 [kg SO_2-eq/kg substance]). The coefficients of variation for AP were 86%, 64%, and 77% for California, Texas, and New York, respectively.

Human health's impact, shown in Figure 17, was calculated based on SO_2 emissions (with a characteristic factor of 0.061 [$PM_{2.5}$-eq/kg substance]) and NO_x emissions (with a characteristic factor of 0.007 [$PM_{2.5}$-eq/kg substance]). The coefficients of variation for HH were 85%, 72%, and 67% for California, Texas, and New York, respectively.

The eutrophication of air, water, and smog formation—shown in Figures 18, 19, and 20—were calculated based on NO_x EGEFs, with characteristic factors of 0.044 kg N-eq/kg substance for coal, 0.291 kg N-eq/kg substance for natural gas, and 24.793 kg O_3-eq/kg substance for petroleum, which resulted in a low natural-gas environmental impact quantification. The coefficients of variabilities for each fossil fuel were constant across the three categories because of the constant variability of NO_x EGEF for each source, which equaled 86%, 76%, and 80% for California, Texas, and New York, respectively. California's lower coefficient of variabilities compared to Texas and New York is compatible with California's lower coefficient of NO_x EGEF compared to Texas and New York.

GWP, which represents CO_2 EGEFs' variability, had the lowest coefficient variability among the environmental categories we assessed. The coefficients of variability for EA, EW, and SA were constant, as NO_x EGEFs' variability remained the same for each fossil fuel. Also, EA, EW, and SA had the highest coefficient variability among the environmental categories examined.These results show that higher variabilities are associated with environmental impacts that use SO_2 and NO_x EGEFs.

4. Limitations and future work

This work involved the following limitations:

- We assumed the three fossil fuel types—coal, natural gas, and petroleum—were used identically in different states. This assumption was incorrect; different sub-types of coal, natural gas, and petroleum are used for electricity generation. Also, fossil fuels' characteristics differ, depending on the fuels' region of extraction, as data for the 50 U.S. states, categorized into these three main fossil fuel types, in the EIA's "Electricity Detailed State Data from 1990 to 2017" document reveal.

- Moreover, we neglected "wood and wood derived fuels," "other biomass," and "other" in quantifying EGEFs in this study since their consumption rate data were unavailable in the "Electricity Detailed State Data from 1990 to 2017" EIA document. However, "Electricity Detailed State Data from 1990 to 2017" EIA document on electricity emissions stated "wood and wood derived fuels" is responsible for 16% of SO_2 emissions and 5% NO_x emissions from electricity generation in the U.S. Also, "other biomass" is responsible for 8% of NO_x emissions from electricity generation in the country.

- The characteristic factors of quantifying environmental impacts, shown in Table 2.3, are also site-specific, depending on a region of study. In this study, an average number for the three U.S. states that we considered was obtained since data on site-specific characteristics were unavailable in the U.S., to the best of our knowledge.

- CO_2 emission, electricity generation, and energy source consumption data were available for approximately 6,000 power plants throughout the U.S., which enabled a calculation of CO_2 EGEFs. EGEFs are more concentrated and show less variability when the data derives from power plants, instead of states. However, a limitation of using data from power plants is that SO_x and NO_x emissions are unavailable in the data sets within the "Electricity emissions by plant and by region" EIA document, and only CO_2 EGEFs could be calculated. This problem limited our estimation of SO_x and NO_x EGEFs, as well as our calculations of the variability in environmental impacts from different categories involving SO_x and NO_x EGEFs.

The potential topics for future work following up on the current study are as follows.

- A consumption based method of accounting electricity generation emissions should be considered in future work since the current study focused on the production side. A consumption based accounting system considers the emissions from outside the system boundary (Ghaemi and Smith, 2020) and considers how changes in demand affect EGEFs. It also includes upstream (i.e., fossil fuel extraction, refinery, material manufacturing, and construction) and downstream (i.e., marketing, transmission, and distribution) emissions from electricity generation .

- In the current study, variability in environmental impacts and electricity generation were limited to variability in EGEFs from fossil fuels. Measurement uncertainties regarding fossil fuel consumption, emissions, and electricity generation reveal more information on variability in environmental impacts and electricity generation.

- Four factors were broken down from the current study's governing equation of electricity generation, using the LMDI method. Other factors could be broken down from the governing equation using the LMDI method, such as sector-specific factors, to reveal more information about how EGEFs have changed in California, Texas, and New York.

5. Conclusions

As we have shown, variability in fossil fuel emission factors (EF) in the 50 U.S. states has caused variations in the quantities of electricity generation emission factors (EGEF) at the state level. Knowing the range of expected values for EGEFs enables an understanding of the decision risks associated with fossil fuel EFs. The relative ranges (i.e., the ratios of the ranges and the means of the data set) for CO_2 EGEFs were 43%, 59%, and 42% in California, Texas, and New York, respectively, during 2017. The coefficients of variation or relative standard deviations (i.e., the ratio of standard deviation and the mean of the data set) were 4.7%, 7.4%, and 4.5% for CO_2 EGEFs in California, Texas, and New York, respectively, in 2017. These variabilities in EGEFs have shown that using site-specific fossil fuel EFs is necessary when making important decisions using EGEFs.

Moreover, this study by using the background data from Energy Information Administration (EIA) has shown that EGEFs changed from 1990 to 2017 in the U.S. Four elements that affect these EGEF changes can be broken down from the governing equation (Equation 3) for electricity generation: (1) the fossil fuel share effect (i.e., the share of fossil fuel to non–fossil fuel [hydro-power, biomass, renewables, and nuclear energy] in electricity generation), (2) the fossil fuel mix effect (i.e., the mix of fossil fuels consumed for electricity generation), (3) the generation efficiency effect (i.e., power plants' generation efficiency), and (4) the EF effect (i.e., the EFs of energy sources). California, Texas, and New York reduced their EGEFs from 1990 to 2017 by 100, 227, and 316 lbCO_2/MWh, respectively. The most effective element of this reduction in New York was the fossil fuel mix effect, which reduced the state's EGEFs by 198 lbCO_2/MWh. In California, the generation efficiency effect decreased the state's EGEFs by 60 lbCO_2/MWh. In Texas, the EGEF has been mitigated by 130 lbCO_2/MWh because of changes in the fossil fuel share effect. These results indicate that state-specific laws and regulations should be enacted to effectively mitigate EGEFs since each state's potential to reduce electricity generations emissions differs.

Variability and uncertainty in EGEFs affect the decision-making tools' results. One such decision-making tool used in the emissions reduction field is environmental impact assessments. EGEFs are used to calculate electricity generation's environmental impact, which shows the variability in environmental impact results. In this study, global warming potential showed the lowest variability among such results, with relative standard deviations of 4.8%, 7.4%, and 4.5% in California, Texas, and New York, respectively, in 2017. Eutrophication of air, water, and smog formation (based on NO_x emissions) showed the highest variability because of EGEFs' variability. The standard deviations were 4.5, 3.0, and 4.5 times greater, respectively, than the mean values for eutrophication of air, water, and smog formation in California, Texas, and New York in 2017. Therefore, calculated environmental impacts will vary significantly when considering SO_2 or NO_x EGEFs compared with considering CO_2 EGEFs. As a result, decision-makings that use eutrophication of air, water, and smog formation categories are unreasonable due to dealing with relatively high uncertainty compared to decision-makings that use global warming potential.

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Data Availability

Three data sources from the "Electricity Detailed State Data from 1990 to 2017" webpage by the U.S. Energy Information Administration were used to calculate electricity generation emission factors at the U.S. state level from 1990 to 2017 in this paper:

1. The annual data for net electricity generation (Net Generation by State by Type of Producer by Energy Source (EIA-906, EIA-920, and EIA-923) excel file)

2. The annual data for fossil fuel consumption used for electricity generation (Fossil Fuel Consumption for Electricity Generation by Year, Industry Type and State (EIA-906, EIA-920, and EIA-923) excel file)

3. The annual data for the electric power industry's estimated emissions (CO_2, SO_2, and NO_x) (U.S. Electric Power Industry Estimated Emissions by State (EIA-767, EIA-906, EIA-920, and EIA-923) excel file)

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Appendix

ΔV_{total} shows the total impact of changes in EGEFs in each state from 1990 (the base year) to 2017. ΔV_p, ΔV_m, ΔV_u, and ΔV_e also relate to the impact of changes in p, m_{fuel}, u_{fuel}, e_{fuel}.

$$\Delta V_{total} = V^T - V^0 = \Delta V_p + \Delta V_m + \Delta V_u + \Delta V_e \tag{A.1}$$

Following the implementation of the LMDI method from Ang and Su (2016), ΔV_p, ΔV_m, $\Delta\ V_u$, and ΔV_e can be calculated using Equations A.2, A.3, A.4, and A.5, respectively.

$$\Delta V_p = \sum_{fuel=1}^{3} \frac{w^T{}_{fuel} - w^0{}_{fuel}}{\ln \frac{w^T{}_{fuel}}{w^0{}_{fuel}}} \ln \frac{p_j^T}{p_j^0} \tag{A.2}$$

$$\Delta V_m = \sum_{fuel=1}^{3} \frac{w^T{}_{fuel} - w^0{}_{state,fuel}}{\ln \frac{w^T{}_{fuel}}{w^0{}_{fuel}}} \ln \frac{m_j^T}{m_j^0} \tag{A.3}$$

$$\Delta V_u = \sum_{fuel=1}^{3} \frac{w^T{}_{fuel} - w^0{}_{fuel}}{\ln \frac{w^T{}_{fuel}}{w^0{}_{fuel}}} \ln \frac{u_j^T}{u_j^0} \tag{A.4}$$

$$\Delta V_e = \sum_{fuel=1}^{3} \frac{w^T{}_{fuel} - w^0{}_{fuel}}{\ln \frac{w^T{}_{fuel}}{w^0{}_{fuel}}} \ln \frac{e_j^T}{e_j^0} \tag{A.5}$$

where $w^T{}_{fuel}$ and $w^0{}_{fuel}$ in Equation A.6 were used.

$$w^T{}_{fuel} = \frac{C_{fuel}^T}{G^T} \qquad w^0{}_{fuel} = \frac{C_{fuel}^0}{G^0} \tag{A.6}$$

Type	CO_2	SO_2	NO_x
Coal EF in the U.S.	Levy Stable	Folded Cauchy	Folded Cauchy
Natural Gas EF in the U.S.	Power Log-Normal	Cauchy	Folded Cauchy
Petroleum EF in the U.S.	Johnson SU	Pearson Type III	Johnson SB
EGEF in California	Generalized Extreme	Logarithm of the Gamma	Generalized Half-Logistic
EGEF in Texas	Tukey Lambda	Hyperbolic Secant	Logarithm of the Gamma
EGEF in New York	Generalized Extreme	Pearson Type III	Generalized Half-Logistic

Table A.1: EGEF and fossil fuel EFs' distribution types for CO_2, SO_2, and NO_x

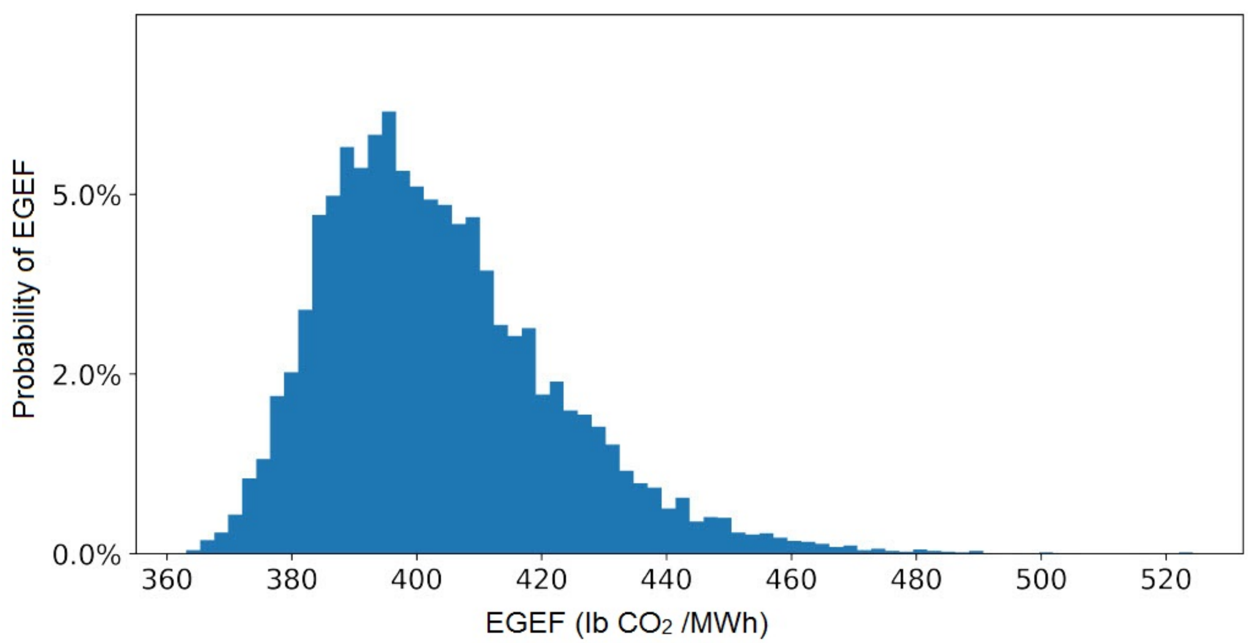

Figure A.1: CO_2 EGEF distribution in California during 2017, using sources' (i.e., coal, natural gas, and petroleum) EF distributions

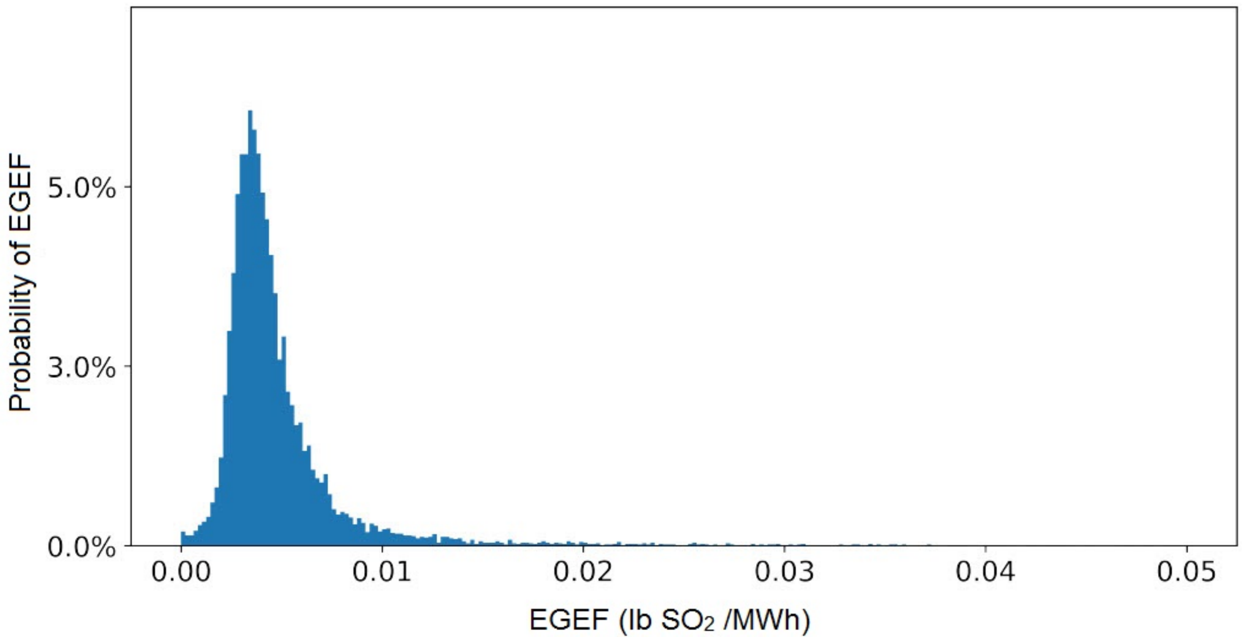

Figure A.2: SO_2 EGEF distribution in California during 2017, using sources' (i.e., coal, natural gas, and petroleum) EF distributions

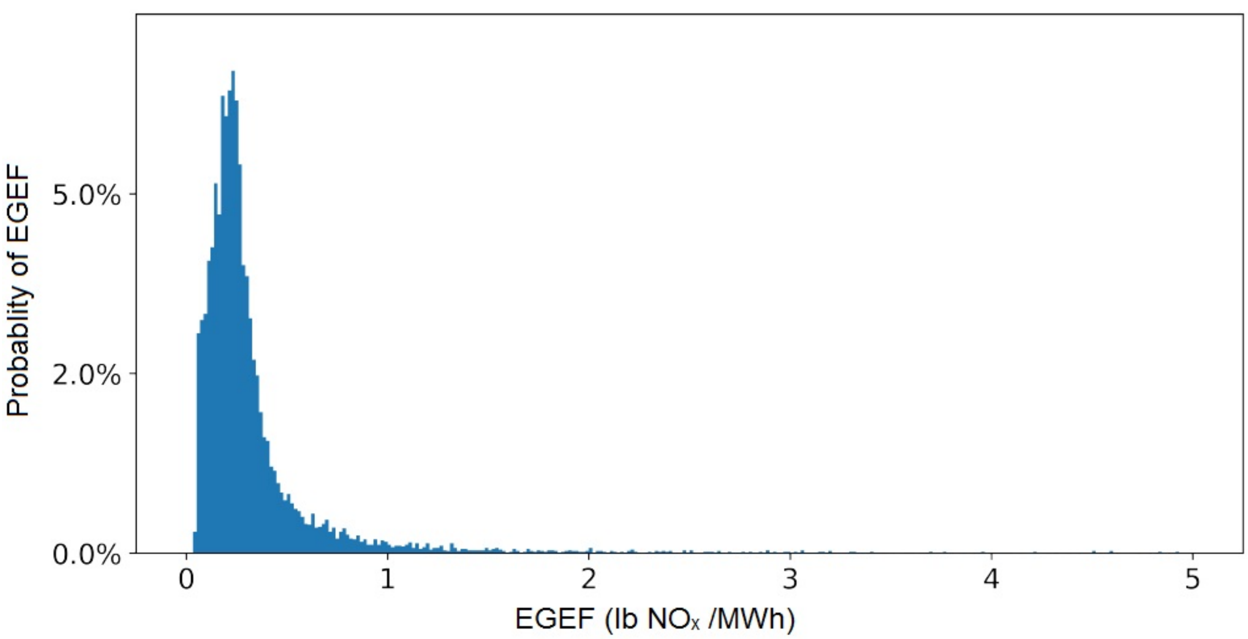

Figure A.3: NO_x EGEF distribution in California during 2017, using sources' (i.e., coal, natural gas, and petroleum) EF distributions

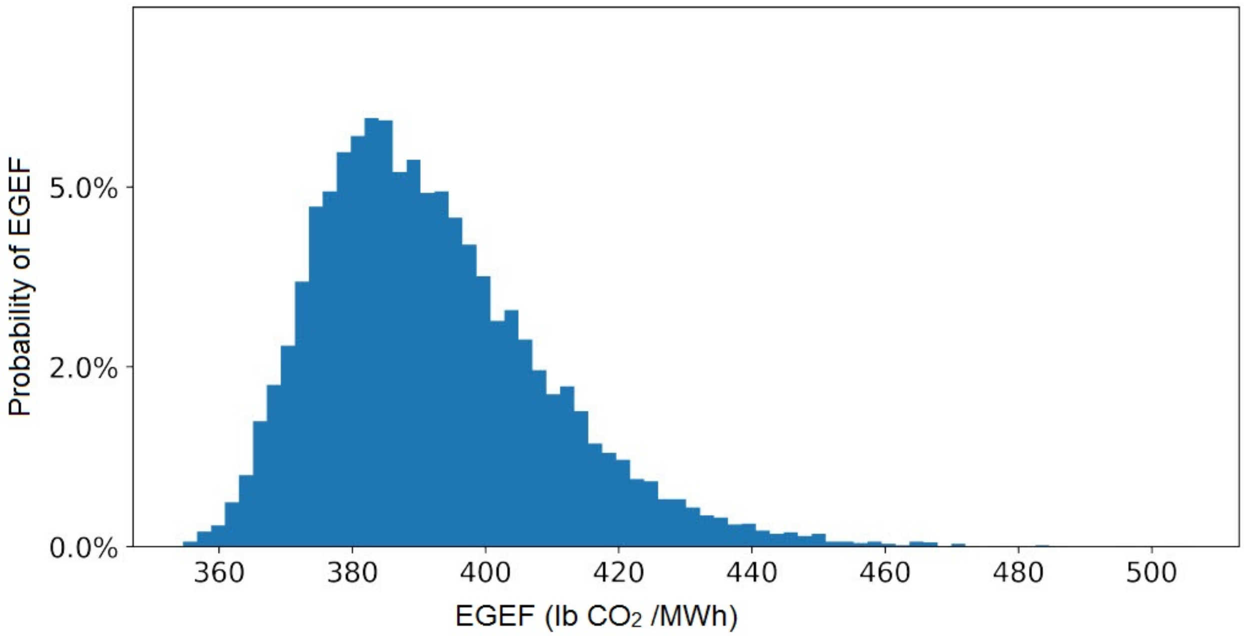

Figure A.4: CO_2 EGEF distribution in New York during 2017, using sources' (i.e., coal, natural gas, and petroleum) EF distributions

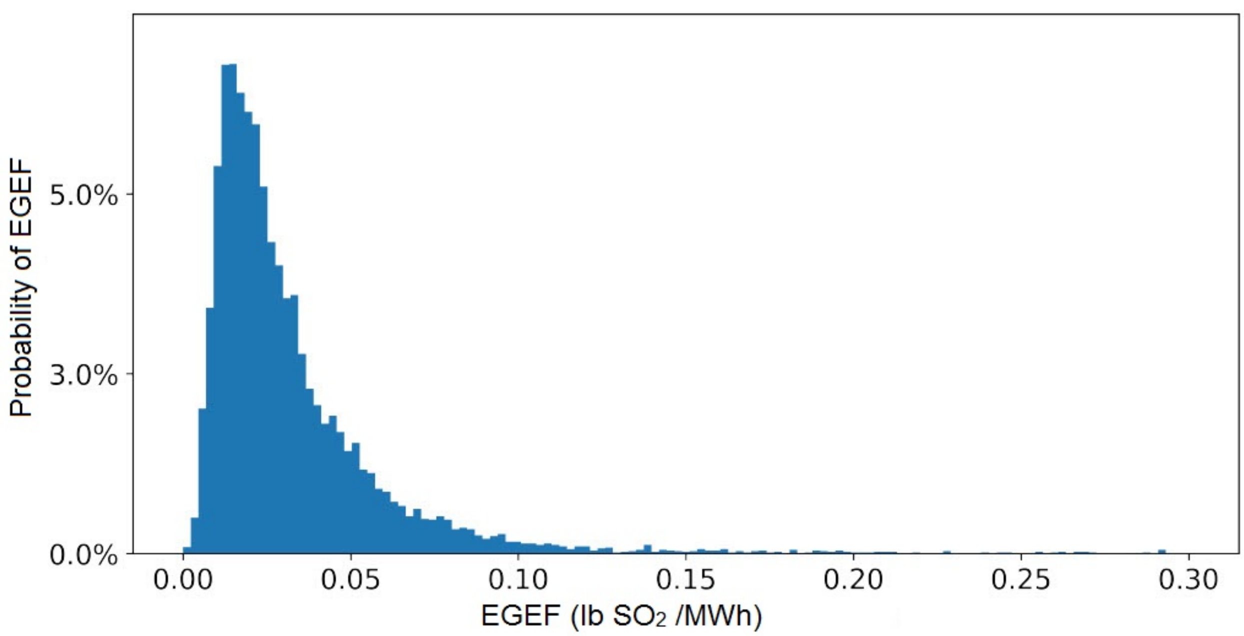

Figure A.5: SO_2 EGEF distribution in New York during 2017, using sources' (i.e., coal, natural gas, and petroleum) EF distributions

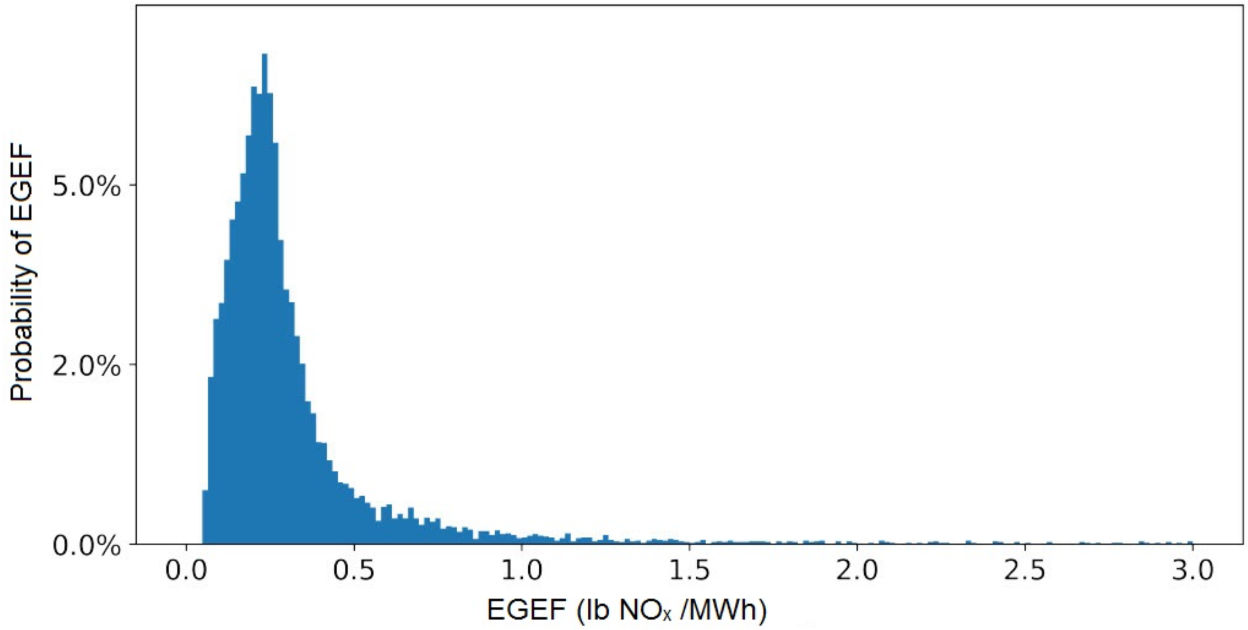

Figure A.6: NO_x EGEF distribution in New York during 2017, using sources' (i.e., coal, natural gas, and petroleum) EF distributions

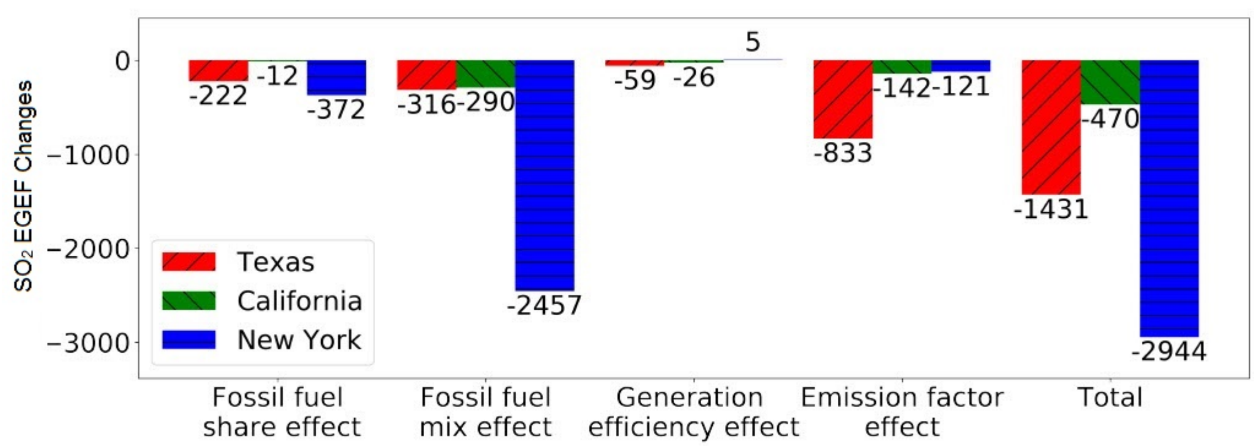

Figure A.7: A comparison of Texas, California, and New York's changes in SO_2 EGEFs from 1990 to 2017 (10^{-3}-lb SO_2)/MWh.

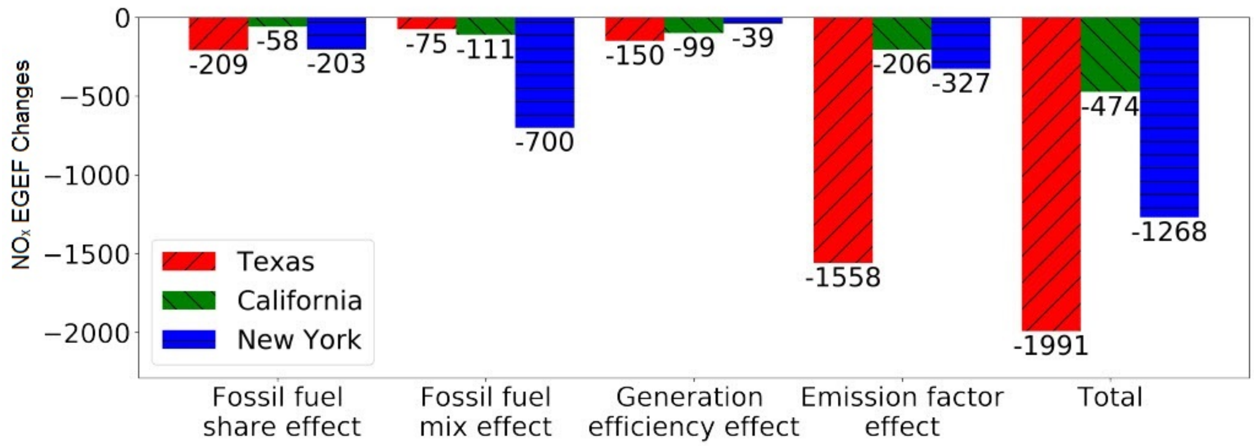

Figure A.8: A comparison of Texas, California, and New York's changes in NO_x EGEFs from 1990 to 2017 (10^{-3}-lbNO_x/MWh.

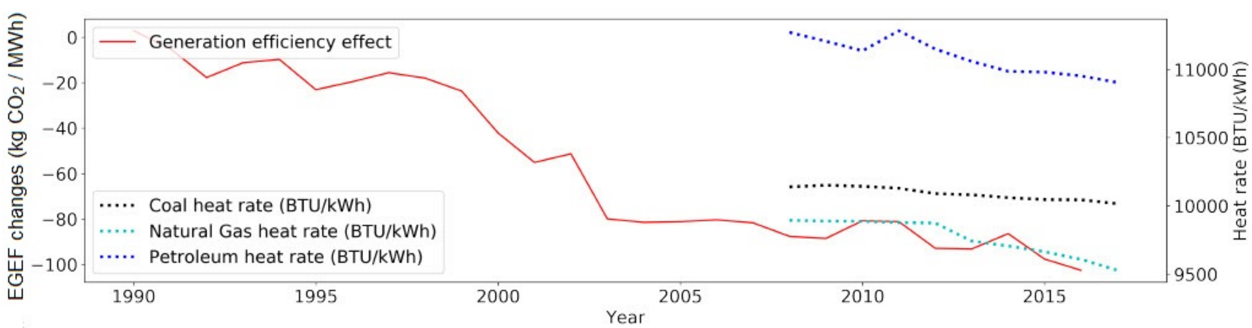

Figure A.9: A comparison of the generation efficiency effect and coal, natural gas, and petroleum heat rates (Btu/kWh) in California.

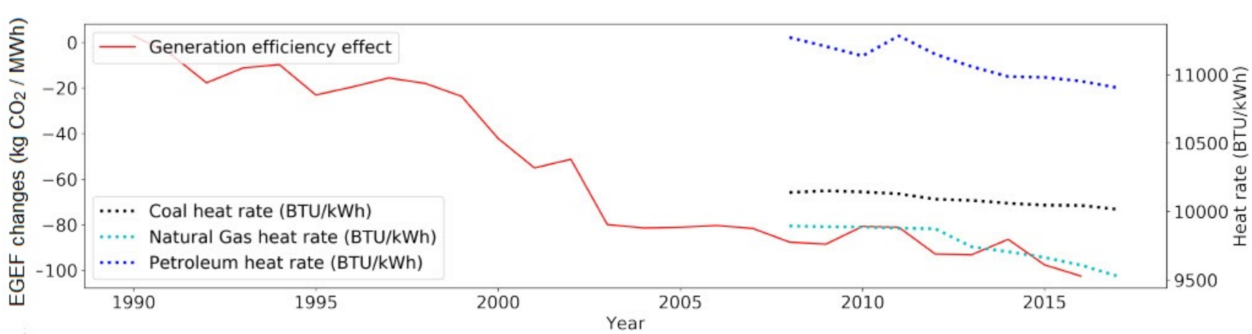

Figure A.10: A comparison of the generation efficiency effect and coal, natural gas, and petroleum heat rates (Btu/kWh) in Texas.

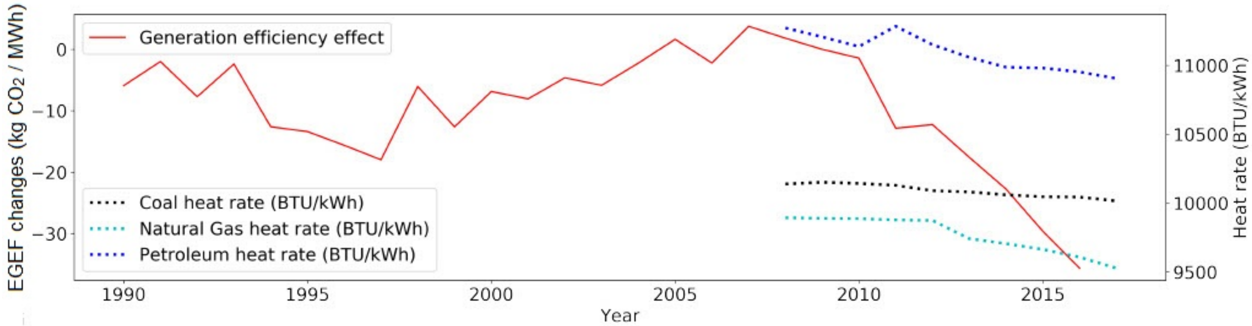

Figure A.11: A comparison of the generation efficiency effect and coal, natural gas, and petroleum heat rates (Btu/kWh) in New York.

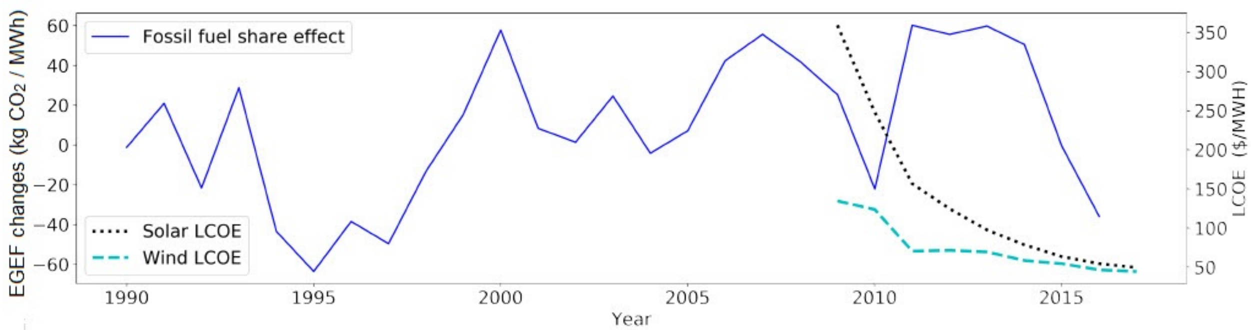

Figure A.12: A comparison of the fossil share effect and LCOE in California.

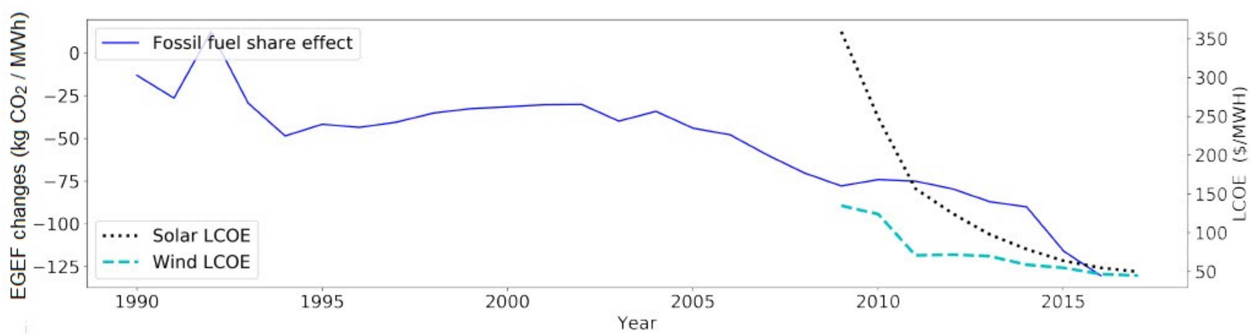

Figure A.13: A comparison of the fossil share effect and LCOE in Texas.

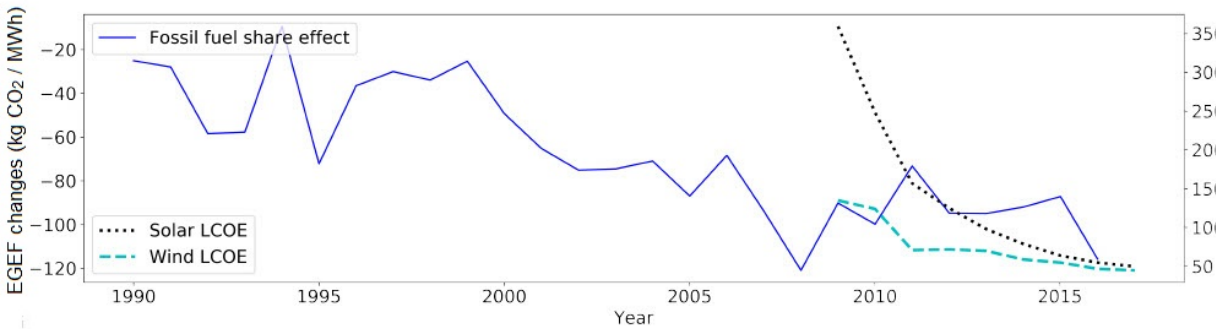

Figure A.14: A comparison of the fossil share effect and LCOE in New York.

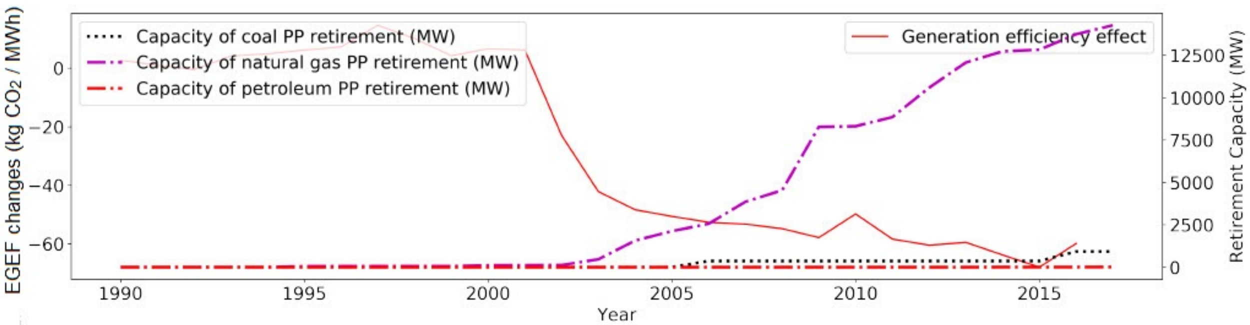

Figure A.15: A comparison of the generation efficiency effect and the capacities for coal, natural gas, and petroleum power plants' retirement (MW) in California.

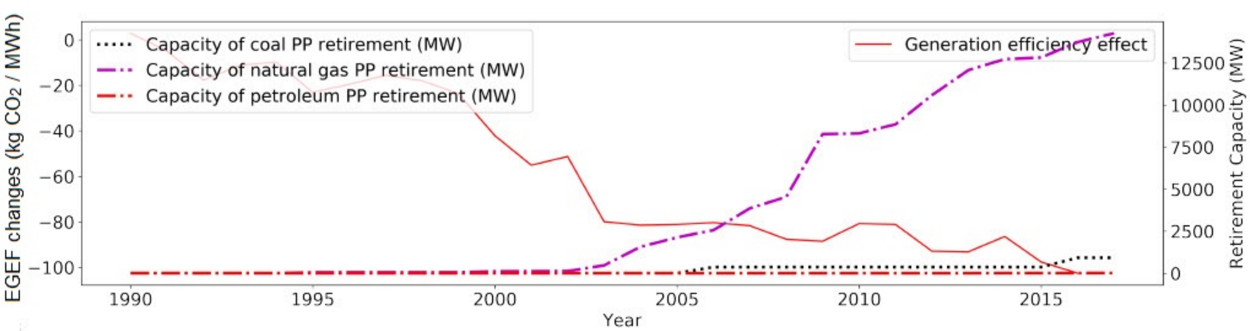

Figure A.16: A comparison of the generation efficiency effect and the capacities for coal, natural gas, and petroleum power plants' retirement (MW) in Texas.

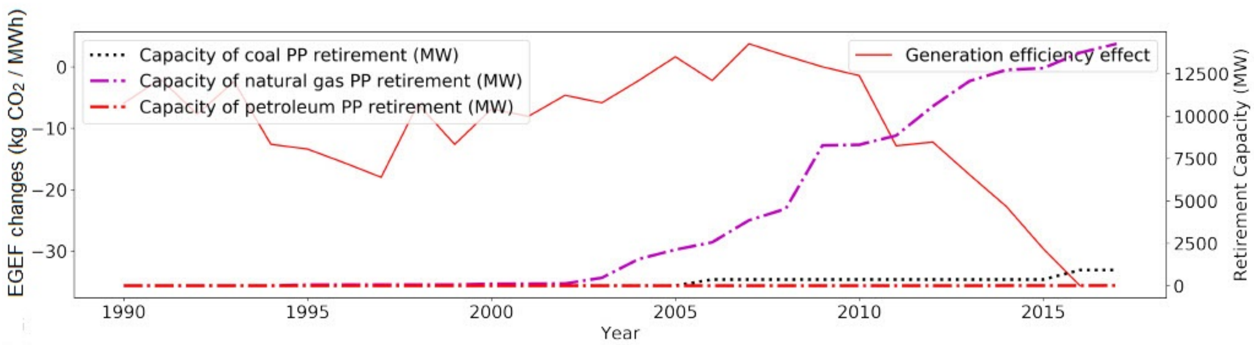

Figure A.17: A comparison of the generation efficiency effect and the capacities for coal, natural gas, and petroleum power plants' retirement (MW) in New York.

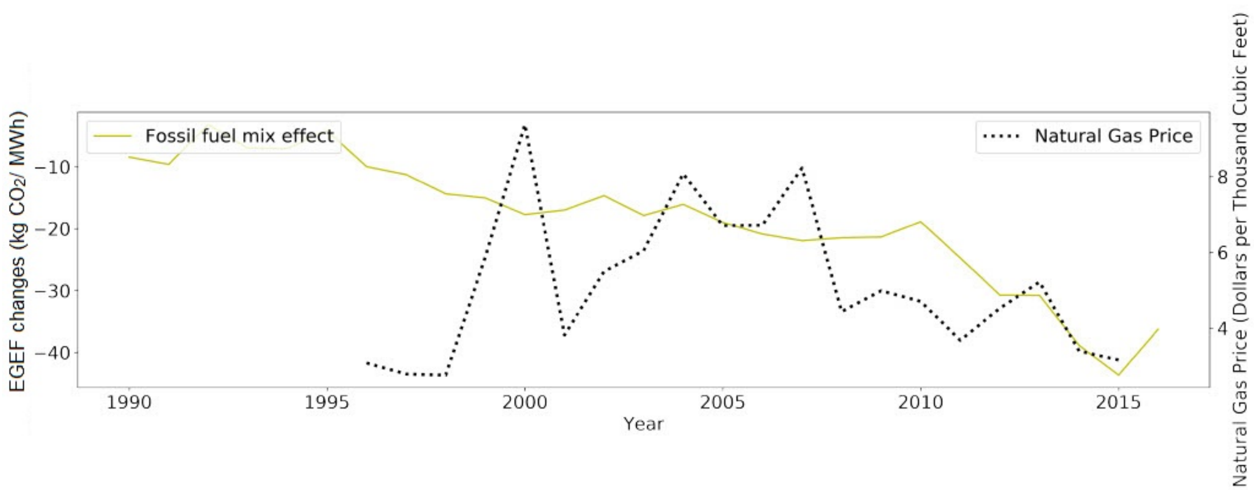

Figure A.18: A comparison of the fossil fuel mix effect and natural gas prices in California.

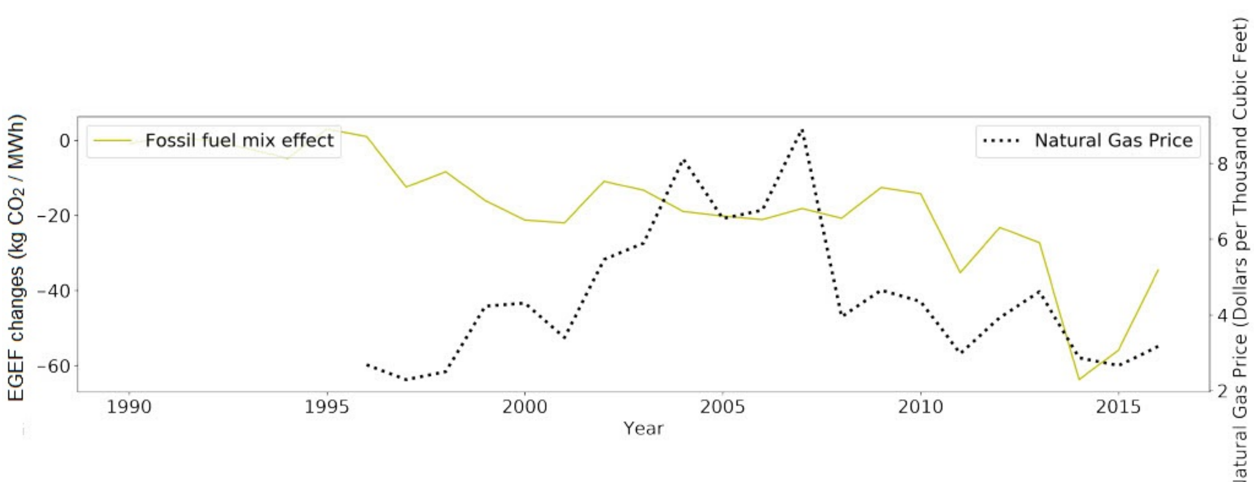

Figure A.19: A comparison of the fossil fuel mix effect and natural gas prices in Texas.

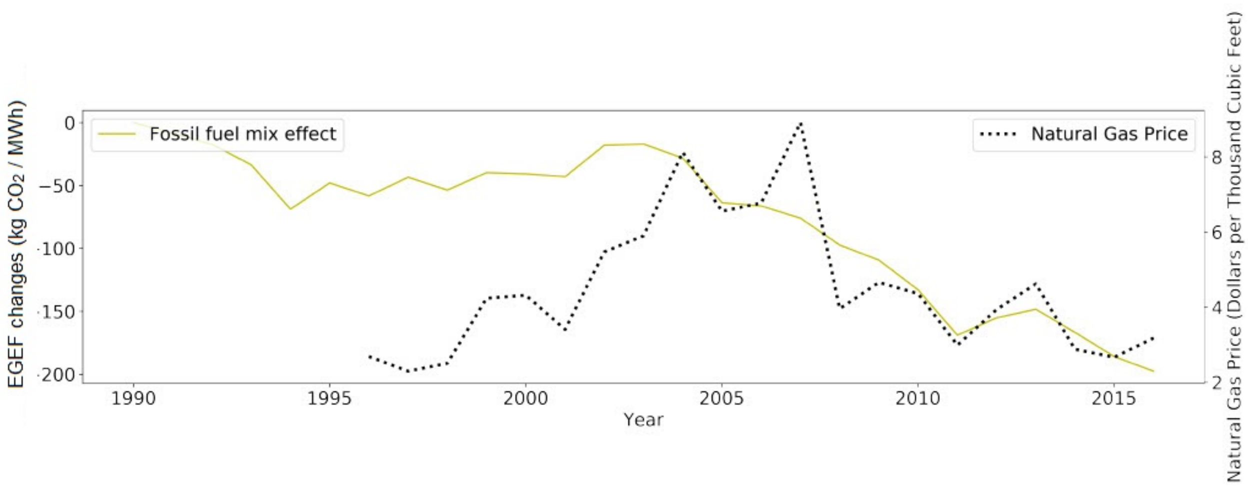

Figure A.20: A comparison of the fossil fuel mix effect and natural gas prices in New York.