

# **Effects of Air Pollution on Health Outcomes in California: Evidence from Electric Vehicles**

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## **ABSTRACT**

This study utilizes publicly available electric vehicle (EV) data from the California Energy Commission to investigate the potential impact of EVs on air quality in California from 2010 to 2021. It also examines how changes in air pollution levels resulting from EV adoption affect respiratory health. First, a fixed-effects panel regression model is employed to analyze the quantitative relationship between air quality and electric vehicle usage. The results indicate that, under the current electricity generation structure, large-scale adoption of electric vehicles could improve air quality. Furthermore, using the ratio of electric vehicles to gasoline-powered vehicles as an instrumental variable, a panel regression with a Poisson control model is applied to assess the correlation between changes in air quality caused by widespread EV adoption and the prevalence of respiratory diseases. The Generalized Method of Moments (GMM) is also used as a robustness check. This study demonstrates that broad implementation of electric vehicles is expected to significantly enhance air quality in California and reduce health risks associated with air pollution.

Keywords: Electric Vehicles, California, Air Pollution, Health Benefits

JEL Codes: C33, C36, I18, Q43, Q53

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## Introduction

This paper explores the relationship between the widespread adoption of electric vehicles and the resulting improvements in air quality, with a particular emphasis on the implications for public health. Our objective is to determine whether there is a statistically significant decline in the incidence rates of diseases strongly associated with air quality, attributable to the reduction of emissions from vehicular traffic. In this chapter, we continue to utilize the data and samples established in the previous analysis while incorporating additional health-related metrics. To investigate the potential health outcomes linked to electric vehicles in California over the past decade, we employ a Poisson control function model in conjunction with an instrumental variable approach. The findings suggest that the improvements in air quality resulting from the adoption of electric vehicles are associated with a significant reduction in the incidence of respiratory diseases. This indicates that, over the long term, electric vehicles not only yield substantial environmental benefits but also promote healthier living conditions for individuals. The following section presents a literature review that examines the health benefits derived from environmental improvements associated with electric vehicles in California and China in recent years.

[Li et al. \(2024\)](#) simulated the changes in air pollutant concentrations and public health under a scenario in which Los Angeles adopts 100% renewable electricity by 2045. The article indicates that, while ensuring a reliable power supply, the city's PM<sub>2.5</sub> concentration is projected to decrease by 8% with the adoption of 100% renewable electricity. Simultaneously, assuming consistent meteorological conditions, the ozone concentration is expected to increase by 5% compared to 2012. These changes could potentially yield up to \$1.4 billion in public health benefits for Los Angeles by 2045. [Hata et al. \(2025\)](#) employed numerical weather prediction techniques to evaluate the alterations in the urban heat island (UHI) phenomenon within the Greater Tokyo Area (GTA) after the integration of BEVs. The results indicated that the introduction of BEVs would lead to a reduction in the peak local temperature in the GTA by 0.25°C. This research implies that the widespread adoption of BEVs has beneficial implications for public health. A substantial body of literature has emerged examining the relationship between electric vehicles and public health, particularly in the context of the COVID-19 pandemic that began in 2020. Considering traffic restrictions and a marked decrease in travel, numerous studies have endeavored to investigate this connection through simulations, modeling, and empirical research methodologies. The subsequent

two articles specifically address the interplay between electric vehicles and health in China in the aftermath of the pandemic. The first article analyzes the effects of COVID-19 on the electric vehicle sector, while the second article evaluates the implications of electric vehicles for public health and air quality. [Wen et al. \(2021\)](#) elucidate the diverse obstacles and prospects linked to the advancement of EVs in China. The authors conduct an analysis of emerging trends and observe a short-term decline in electric vehicle sales attributable to the COVID-19 pandemic. Nevertheless, they argue that this scenario may ultimately catalyze increased demand for electric vehicles in the long term, especially for larger models characterized by superior performance, which are likely to witness even greater demand. [Horton et al. \(2021\)](#) employ a specialized model to simulate the interaction between meteorological conditions and atmospheric chemistry, with the goal of evaluating the potential benefits of adopting electric vehicles during periods of extreme pollution in China. The findings reveal that heavy-duty electric vehicles (HD EVs) and light-duty electric vehicles (LD EVs) each offer distinct environmental and health benefits. Specifically, the widespread implementation of HD EVs is linked to a reduction in nitrogen oxides and fine particulate matter; however, this transition will not lead to a decrease in carbon dioxide emissions unless there is a corresponding increase in zero-emission electricity generation. In contrast, while the extensive adoption of LD EVs consistently results in a reduction of greenhouse gas emissions, it does not significantly improve air quality. Moreover, the economic benefits associated with LD EVs are nearly twice as significant as those related to HD EVs. The study concludes that although moderate public health benefits may be achieved through the adoption of electric vehicles to mitigate severe winter pollution, it emphasizes the need for continued reductions in emissions from electricity production as a more critical priority.

## **Background**

### ***Historical Health Consequences of Air Pollution***

A significant risk factor associated with air pollution is its contribution to the development of various health complications, including respiratory infections, cardiovascular disease, chronic obstructive pulmonary disease, stroke, and lung cancer. Health issues resulting from air pollution may be manifested as respiratory difficulties, asthma, coughing, wheezing, and the exacerbation

of pre-existing respiratory and cardiopulmonary disorders.<sup>1</sup> Air pollution is widely recognized as a major public health risk that poses a persistent threat to human life. This issue has been extensively studied by both medical researchers and economists. The following seven articles illustrate the association between air pollution and mortality rates. The countries involved in the research include China, the United States, Brazil, Colombia, and several other nations worldwide. Yin et al. (2017) conducted an analysis to estimate the correlation between air pollution and mortality rates by examining daily death counts across 38 cities in 27 provinces of China. The research encompasses fatalities from all causes, including both cardiovascular and non-cardiovascular diseases. The results revealed that an increase of 10 micrograms per cubic meter in PM10 concentration on a given day was associated with a 0.44% rise in daily mortality (95% confidence interval: 0.30% to 0.58%). Additionally, the findings indicate that air pollution exerts the most pronounced effect on mortality due to cardiovascular diseases. Deryugina et al. (2019) investigate the correlation between PM2.5 concentrations and mortality rates using healthcare insurance data from the United States. The authors employ variations in local wind direction as an instrumental variable to evaluate air pollution levels and incorporate machine learning techniques to quantify the years of life lost due to pollution exposure. Their results reveal that air pollution exerts the most significant impact on mortality among the elderly population. Aron et al. (2024) provide evidence that individuals diagnosed with COPD, along with various personal risk factors, may exhibit increased susceptibility to the adverse effects of acute outdoor air pollution. This research employs data from 25 metropolitan areas across the United States, spanning the years 2016 to 2019, to investigate the relationship between winter air pollution and mortality rates among COPD patients. The findings suggest that the risk of mortality is projected to increase by a factor of 1.05 (95% CI, 1.02-1.09) for each 10  $\mu\text{g}/\text{m}^3$  rise in winter PM2.5 levels. Luben et al. (2023) present epidemiological evidence from existing literature that highlights the association between short-term exposure to air pollution and infant mortality. Several studies indicate that increased exposure to PM<sub>10</sub>, NO<sub>2</sub>, SO<sub>2</sub>, or CO correlates with elevated rates of infant mortality. Stafoggia et al. (2023) perform a comprehensive analysis of all-cause mortality data from 1995 to 2020, covering 620 cities across 36 countries. This study utilized daily records of air temperature and key air pollutants, specifically PM<sub>10</sub>, PM<sub>2.5</sub>, NO<sub>2</sub>, and O<sub>3</sub>. The results reveal a substantial association between air temperature and the influence of air pollutants on mortality rates, with a

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<sup>1</sup> [https://en.wikipedia.org/wiki/Air\\_pollution](https://en.wikipedia.org/wiki/Air_pollution)

particularly marked effect observed during the warmer months. According to Nascimento and Gouveia (2024), Exposure to air pollutants has been linked to a heightened risk of mortality from non-accidental causes, in addition to an increased likelihood of death from cardiovascular and respiratory diseases. Furthermore, individuals residing in areas with lower educational attainment and socioeconomic status face a greater risk of death related to air pollution. Gao et al. (2024) examine the correlation between fine particulate matter associated with wildfires and mortality rates. Their results indicate that exposure to wildfire-related PM<sub>2.5</sub> is linked to an increase of 17.77 deaths per 100,000 individuals (95% CI: 11.12–24.38). Data from the San Joaquin Valley (SVJ) region in 2016, as reported by Zarate-Gonzalez et al. (2024), indicate that the estimated total economic impact of air pollution in this area is approximately \$500 million in emergency room visits and \$220 million in hospitalization expenses. These financial burdens are comprised of four key elements: medical expenditures, productivity losses, school absenteeism, and opportunity costs. The study further emphasizes that a reduction in pollutant concentrations would significantly mitigate the health impacts on SVJ residents, potentially preventing nearly 20,000 emergency room visits and around 20,000 hospitalizations. The financial savings associated with air pollution-related costs are delineated into three primary categories: exceeding \$46 million for PM<sub>2.5</sub>, over \$80 million for nitrogen dioxide (NO<sub>2</sub>), and nearly \$8 million for ozone (O<sub>3</sub>).

Air pollution can also adversely affect mental and psychological health.<sup>2</sup> Chen et al. (2024) investigate a study examining the quantitative relationship between air pollution and mental health disorders. The research utilized data from the China Family Panel Studies, which are conducted between 2014 and 2015, encompassing a sample of 12,615 urban residents. The results indicated a significant positive correlation between levels of air pollution and the prevalence of mental disorders. F. Chen et al. (2023) perform an empirical investigation into the correlation between air pollution and the mental health of the elderly population. This study employs mental health data obtained from the China Health and Nutrition Survey, along with urban-level air pollution metrics. The findings reveal a significant deterioration in the mental health of older adults in reaction to increasing concentrations of air pollutants. Table 1 presents recent literature on the relationship

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<sup>2</sup> <https://www.eea.europa.eu/en/european-zero-pollution-dashboards/indicators/impact-of-air-pollution-on-mental-health-signal-1>

between health and air pollution, primarily covering research articles from China and the United States.

Table 1 Recent Research Has Focused on the Relationship between Health Outcomes and Air Pollution

| <b>Health and air pollution</b> |                                                                                                      |                                |
|---------------------------------|------------------------------------------------------------------------------------------------------|--------------------------------|
| Location                        | Topics                                                                                               | Papers                         |
| World                           | PM2.5 and health burden                                                                              | (Bu et al., 2021)              |
| World                           | PM2.5 and its health effects                                                                         | (Feng et al., 2016)            |
| China                           | Willingness to pay for clean air in China                                                            | (Freeman et al., 2019)         |
| China                           | PM2.5 significantly increases the incidence and mortality of cardiovascular and respiratory diseases | (Pui et al., 2014)             |
| China                           | Health burden and PM2.5                                                                              | (Song et al., 2017)            |
| Czech                           | PM2.5 elevates the incidence of respiratory diseases                                                 | (Šulc et al., 2022)            |
| USA                             | Costs of air pollution                                                                               | (Zarate-Gonzalez et al., 2024) |
| China                           | Air pollution on mental illness                                                                      | (S. Chen et al., 2024)         |
| China                           | Effect of PM2.5 on the mortality of cardiovascular diseases                                          | (Zhu et al., 2024)             |
| USA                             | Health and climate benefits of electric school buses                                                 | (Choma et al., 2024)           |
| USA                             | Air pollution and COVID-19 mortality                                                                 | (X. Wu et al., 2020)           |
| China                           | Particulate air pollution and mortality                                                              | (Yin et al., 2017)             |
| China                           | Air pollution and mental health                                                                      | (F. Chen et al., 2023)         |
| USA                             | The influence of air pollution on mortality rates and healthcare costs.                              | (Deryugina et al., 2019)       |
| USA                             | The relationship between air pollution and low birth weight.                                         | (Gong et al., 2023)            |
| World                           | Air pollution and infant mortality                                                                   | (Luben et al., 2023)           |
| World                           | Joint effect of heat and air pollution on mortality                                                  | (Stafoggia et al., 2023)       |
| Brazil                          | Air pollution and mortality                                                                          | (Nascimento & Gouveia, 2024)   |
| Brazil                          | PM2.5 and cardiovascular mortality                                                                   | (Gao et al., 2024)             |
| Colombia                        | COPD associated with air pollution                                                                   | (Herrera Lopez et al., 2025)   |
| Netherlands                     | COPD prevalence, incidence, and survival                                                             | (Afonso et al., 2011)          |

|     |                                 |                     |
|-----|---------------------------------|---------------------|
| USA | PM2.5 associated with mortality | (Aron et al., 2024) |
|-----|---------------------------------|---------------------|

### ***Potential Health Implications Related to the Implementation of Electric Vehicles***

Some scholarly articles have examined health research pertinent to electric vehicles. In this context, we present a selection of articles that specifically address electric vehicles within the United States, accompanied by analogous studies from various international contexts. [Kazimi \(1997\)](#) conducted an analysis of the total emissions produced by new energy vehicles in the Los Angeles region, examining various pricing scenarios from three decades prior. Utilizing a dynamic microsimulation model, the author assessed the impact of price reductions for alternative fuel vehicles on total emissions. The results indicated that the implementation of compressed natural gas vehicles, methanol vehicles, and electric vehicles resulted in annual health benefits estimated to be between \$20 million and \$120 million, and between \$3.5 million and \$70 million, respectively. [Choma et al. \(2024\)](#) examine the potential impact of electric school buses in the United States on reducing adult mortality rates linked to PM2.5 exposure and mitigating the risk of asthma in children, alongside the associated health benefits. The authors further assess the environmental advantages stemming from a decrease in greenhouse gas emissions. The findings indicate that substituting each diesel school bus with an electric counterpart in the U.S. as of 2017 could result in an overall benefit of \$84,200 per bus. This total benefit is comprised of estimated climate benefits amounting to \$43,800 and health benefits totaling \$40,400 per bus.

The following six articles explore the impact of electric vehicles on public health in the United States. Some articles highlight the positive health outcomes linked to electric vehicles, while others offer a more balanced perspective. A study comprehensively assesses the impact of BEVs adoption. It employs a computable general equilibrium model to evaluate the effects of various scenarios. Three key factors were considered: the levels of subsidies, financial incentives provided to manufacturers, as well as the costs associated with fuel., while also accounting for enhancements in the productivity of battery manufacturing for BEVs. The results show that subsidies significantly influence both GDP and BEVs adoption. Although BEVs adoption contributes to a reduction in tailpipe emissions, non-tailpipe emissions may increase due to enhanced productivity or increased manufacturing activities resulting from subsidies, potentially offsetting the reductions in tailpipe emissions either partially or entirely. Therefore, to achieve the

anticipated reduction in overall emissions, subsidy policies should be integrated with initiatives promoting green manufacturing and renewable energy generation (Z. Chen et al., 2021). A research investigation examines three dimensions of the economic implications associated with electric vehicles: the individual incentives for their adoption, the external benefits they provide, and the most effective policies for promoting their use. The findings suggest that as the electricity grid undergoes a transition from reliance on coal and experiences a rise in the proportion of renewable energy sources, the benefits of reduced pollution attributable to electric vehicles will become more pronounced, particularly in the Midwest region of the United States, where coal remains a significant energy source. Therefore, as the electricity grid becomes increasingly sustainable, it is advisable to enhance subsidies aimed at environmental protection (Rapson & Muehlegger, 2023). A recent study examines the emissions of PM<sub>2.5</sub> and the associated health impacts resulting from a large-scale transition to electric vehicles (EVs) across various states in the United States, as well as in the fifty most populous metropolitan statistical areas (MSAs). The findings suggest that, compared to the current vehicle market framework, the adoption of EVs could lead to a reduction in premature mortality rates by approximately 10%. The study highlights that the electrification of vehicles in the Western and Northeastern regions would provide more substantial health and climate mitigation benefits. Furthermore, if a zero-emission and fully renewable energy grid is established, EVs would be significantly cleaner and more environmentally sustainable than traditional gasoline vehicles. The authors also indicate that vehicle electrification could help alleviate health disparities. They advocate for the widespread implementation of EVs in conjunction with a cleaner energy grid, arguing that vehicle electrification is the most effective strategy for states aiming to improve public health outcomes (Singh et al., 2024). In order to elucidate the numerous advantages associated with electric vehicles, a comprehensive study employs a substantial dataset to quantify these benefits. The findings indicate that the economic returns of electric vehicles, as assessed through cost-benefit analyses, are frequently linked to factors such as human health, air quality, and environmental sustainability (Malmgren, 2016). A recent study investigates the influence of real-world electric vehicle (EV) sales on health impact assessments (HIA) and evaluates the effects of ZEV regulations on childhood asthma. Utilizing data from the United States spanning from 2013 to 2019, the research analyzes the relationship between EV and non-EV vehicle sales and fleets, as well as their impact on the incidence and prevalence of asthma, employing generalized linear mixed models for

analysis. The findings suggest that the sale of new EVs is associated with a decrease in asthma cases; specifically, it is estimated that one case of asthma can be prevented for every 264 new EVs sold (95% CI: 113-401). Furthermore, when EV sales account for 21.4% of the annual market share previously held by non-EV sales, there is significant potential to prevent new cases of childhood asthma attributable to new vehicle sales ([Gujral et al., 2025](#)). Nevertheless, some articles remain skeptical about the current environmental benefits of electric vehicles, including the one mentioned below. A study finds that, regardless of whether the vehicle is fully electric or a plug-in hybrid, whether the household has one car or multiple cars, and regardless of location within or outside of California, the annual mileage of electric vehicles is significantly lower than that of gasoline cars. This discovery indicates that the present environmental advantages of EVs are not as significant as previously expected ([Davis, 2019](#)).

There are five additional articles discussing electric vehicles and their environmental impact in Germany, Italy, India, and other countries, as well as their research on health-related aspects. A study examining electric vehicles in India evaluates their overall influence on the power grid. The analysis employs a model based on battery electric vehicle (BEV) adoption rates of 5% and 15% in New Delhi. The findings indicate that, firstly, the proliferation of BEVs would enhance India's renewable energy capacity. Secondly, it is projected that carbon dioxide emissions from BEVs in India would decrease by approximately 40% compared to conventional vehicles. Lastly, to fully realize the synergistic benefits of electric vehicles, it is essential for the Indian government to align efforts related to the expansion of electric vehicles, the establishment of a national smart grid, and the sustainability of the country's renewable energy resources ([Gopal et al., 2015](#)). A comparative analysis is conducted to evaluate the reduction of carbon dioxide emissions attributable to electric vehicles in Italy and Germany, considering comparable levels of renewable energy integration. The authors noted that achieving a significant reduction in carbon dioxide emissions in Germany would require a substantial increase in renewable energy capacity. Conversely, Italy, despite having a lower capacity for renewable energy, stands to benefit from the electrification of its transportation sector ([Bellocchi et al., 2019](#)). In a chapter titled "Future of Road Transportation," the author explores the various challenges and limitations associated with electric vehicles (EVs) and potential strategies for addressing these issues. The current challenges confronting electric vehicles encompass several key areas: the source of charging energy, which

significantly influences the overall environmental footprint of EVs; restricted driving range; prolonged charging times; concerns regarding battery recycling and environmental contamination; inadequate charging infrastructure; the risk of grid overload; and the high costs associated with the purchase and maintenance of electric vehicles ([Kantumuchu, 2023](#)). This research endeavor seeks to assess the empirical correlation between the utilization of BEVs and HEVs and their effects on public health. A thorough literature review was conducted across six prominent databases, resulting in the identification of 897 peer-reviewed articles published over a 35-year period, from 1990 to 2024. The findings reveal that 52 articles satisfy the inclusion criteria, with 94% of these focusing on the transition to electric vehicles. Among the selected studies, 41 specifically examine premature mortality and monetized health outcomes, with only one being an observational study; the remainder are empirical in nature. Significantly, 98% of the studies indicate a beneficial impact of electric or hybrid electric vehicles on health ([Pennington et al., 2024](#)). A recent study analyzed 38 scholarly articles concerning electric vehicles, which include BEVs, PHEVs, and HEVs, published from 1990 to 2023. Employing meta-regression techniques, the research evaluates the impact of various determinants on the adoption of electric vehicles. The results highlight four primary factors that exert a global influence: user perception, user characteristics, environmental awareness, and barriers to adoption. Furthermore, it is observed that European nations exhibit the most pronounced spatial effects. In light of the substantial greenhouse gas emissions produced by China and India, the authors advocate for the large-scale adoption of electric vehicles in these countries, along with an increase in the share of renewable energy in regions that promote electric vehicle utilization ([Y. Wang & Witlox, 2025](#)). Table 2 presents an overview of recent studies examining the association between electric vehicles and health outcomes, alongside their influence on air quality, with a particular focus on research conducted within the United States. The prevailing agreement among scholars indicates that electric vehicles contribute positively to public health. For example, EVs play a beneficial role in the environment ([Kazimi, 1997](#); [He et al., 2019](#); [Wen et al., 2021](#); [Horton et al., 2021](#); [Singh et al., 2024](#)). EVs may have negative consequences that undermine their environmental benefits ([Davis, 2019](#); [Y. Li et al., 2024](#); [Z. Chen et al., 2021](#)).

Table 2 Recent Studies Have Examined the Relationship between Health Outcomes and Air Pollution in the Context of Electric Vehicles

| Health, air pollution and electric vehicles |
|---------------------------------------------|
|---------------------------------------------|

| Location                | Yes or no | Topics                                                                           | Papers                       |
|-------------------------|-----------|----------------------------------------------------------------------------------|------------------------------|
| China                   | No        | Health impact and environmental equity                                           | (Ji et al., 2012)            |
| Taiwan                  | Yes       | Health benefits                                                                  | (Lin et al., 2020)           |
| India                   | Yes       | Air, health benefits and equity                                                  | (Peshin et al., 2024)        |
| California              | Yes       | EVs and impact on health                                                         | (Limoochi & Rodriguez, 2024) |
| Japan                   | Yes       | EVs, temperature and health                                                      | (Hata et al., 2025)          |
| California              | Neutral   | Air quality and public health co-benefits of 100% renewable electricity adoption | (Y. Li et al., 2024)         |
| California              | Yes       | Environmental Impact                                                             | (Kazimi, 1997)               |
| China, USA, and Germany | Yes       | Economic and Climate Benefits                                                    | (He et al, 2019)             |
| China                   | Yes       | Impacts of COVID-19 on the electric vehicle industry                             | (Wen et al., 2021)           |
| China                   | Yes       | EVs impact public health and air pollution                                       | (Horton et al., 2021)        |
| USA                     | Yes       | EVs and mortality risks of PM2.5 emissions                                       | (Singh et al., 2024)         |
| USA                     | Yes       | Societal benefits of EVs                                                         | (Malmgren, 2016)             |
| USA                     | Yes       | Impact of EVs sales on childhood asthma                                          | (Gujral et al., 2025)        |
| USA                     | Neutral   | Environmental and economic impact of EVs                                         | (Z. Chen et al., 2021)       |
| USA                     | Yes       | Economics of EVs                                                                 | (Rapson & Muehlegger, 2023)  |
| USA                     | Neutral   | Electric vehicles offer limited environmental benefits.                          | (Davis, 2019)                |
| World                   | Yes       | EVs and health                                                                   | (Pennington et al., 2024)    |
| Germany and Italy       | Yes       | role of EVs towards low-carbon energy systems                                    | (Bellocchi et al., 2019)     |
| India                   | Yes       | BEVs can reduce greenhouse gas emissions and make renewable energy cheaper       | (Gopal et al., 2015)         |
| World                   | Yes       | Challenges and limitations of EVs                                                | (Kantumuchu, 2023)           |

|       |     |                                                                                                        |                          |
|-------|-----|--------------------------------------------------------------------------------------------------------|--------------------------|
| World | Yes | Global trends in EVs adoption and the impact of environmental awareness, user attributes, and barriers | (Y. Wang & Witlox, 2025) |
|-------|-----|--------------------------------------------------------------------------------------------------------|--------------------------|

## Data and Variables

The data utilized in this study is derived from publicly accessible information provided by relevant agencies of the United States federal government and the state government of California. It is important to note that there are instances of missing data for specific years. The dataset covers a time frame from 2010 to 2021 and includes 58 counties within California, excluding Los Angeles County, resulting in a total sample size of 684. All data employed in this research is publicly available. For a comprehensive description of the dataset, please consult Table 3. For an extensive statistical analysis, refer to Table 4.

### *Health Impact Data*

In this study, we utilize two types of health impact data. The first type is the annual number of emergency department visits for COPD among individuals aged 25 years and older in each county from 2010 to 2021. The second type is the crude rate of emergency department visits for asthma per 10,000 population at the county level over the same 12-year period. Both data are sourced from CDC. Table 3 presents a description of both datasets, while Table 4 provides summary statistics.

Table 3 Description of Variables

| Variable   | Description                                                                                                                                  | Source                                     |
|------------|----------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------|
| COPDVISITS | The annual number of emergency department visits for chronic obstructive pulmonary disease (COPD) among individuals aged 25 years and older. | Centers for Disease Control and Prevention |
| ASTHMA     | The crude rate of emergency department visits for asthma per 10,000 population.                                                              | Centers for Disease Control and Prevention |

The following two articles explore the relationships between COPD and age, as well as the correlation between COPD and air quality. One article is from the Netherlands, while the other originates from Colombia. [Afonso et al. \(2011\)](#) conduct a study examining the prevalence, incidence, and lifetime risk of COPD within the general population. The researchers analyze data from individuals aged 40 and older, sourced from the Dutch Integrated Primary Care Information (IPCI) database, employing a two-step validation algorithm to identify cases of COPD. Their findings reveal a significant increase in the incidence of COPD with advancing age, with a notably higher incidence observed in males compared to females. [Herrera Lopez et al. \(2025\)](#) present evidence suggesting that the incidence of exacerbations in COPD among patients residing in Bogotá is significantly correlated with prolonged exposure to elevated concentrations of nitrogen dioxide (NO<sub>2</sub>).

Table 3 Summary Statistics

| Variable                      | Definition                                                                         | Mean     | Standard<br>Deviation | Minimum  | Maximum |
|-------------------------------|------------------------------------------------------------------------------------|----------|-----------------------|----------|---------|
| <b>Dependent Variables</b>    |                                                                                    |          |                       |          |         |
| COPDVISITS10K                 | Annual number of emergency department visits for COPD per 10,000 population        | 48.042   | 27.146                | 0        | 163.254 |
| lnCOPDVISITS10K               | Log of annual number of emergency department visits for COPD per 10,000 population | 3.706    | .726                  | 0        | 5.101   |
| ASTHMA10K                     | Crude rate of emergency department visits for asthma per 10,000 population         | 47.693   | 11.653                | 15.8     | 79.5    |
| lnASTHMA10K                   | Log of crude rate of emergency department visits for asthma per 10,000 population  | 3.831    | .272                  | 2.76     | 4.376   |
| <b>Instrumental Variables</b> |                                                                                    |          |                       |          |         |
| RATEV_GAS                     | Ratio between number of EVs and number of gasoline vehicles                        | .006     | .01                   | 0        | .064    |
| TEMP                          | Average temperature in summer                                                      | 71.907   | 6.494                 | 56.267   | 93.6    |
| TEMPSQUARED                   | Square of temperature                                                              | 5212.704 | 960.27                | 3165.938 | 8760.96 |

|                          |                                                                |         |          |        |           |
|--------------------------|----------------------------------------------------------------|---------|----------|--------|-----------|
| MANUFACTURING            | Percentage by employment                                       | 2.315   | 1.731    | 0      | 9.95      |
| WILDFIRENO               | Number of Fires                                                | 55.067  | 55.398   | 0      | 262       |
| PRECIPITATION            | Annual precipitation                                           | 26.493  | 18.541   | 2.06   | 102.62    |
| <b>Control Variables</b> |                                                                |         |          |        |           |
| ln POPULATION            | Log of population                                              | 11.975  | 1.755    | 6.954  | 15.021    |
| POPDENSITY               | Population per square mile                                     | 654.189 | 2425.181 | 1.417  | 18756.362 |
| ln INCOME                | Log of per capita annual personal income                       | 10.763  | .335     | 10.173 | 12.008    |
| FARM                     | Percentage by employment                                       | 2.311   | 2.918    | 0      | 14.53     |
| SERVICE                  | Percentage by employment                                       | 30.376  | 65.848   | 6.18   | 594.44    |
| COVID                    | Dummy variable Covid =1 from 2020-2021)                        | .167    | .373     | 0      | 1         |
| AGE65                    | Percentage of individuals aged 65 and older                    | 16.66   | 5.302    | 7.9    | 31        |
| RACENONWHITE             | Proportion of individuals identified as belonging to non-white | 18.555  | 10.517   | 4.2    | 52.3      |
| UNEMPLOYMENT RATE        | Unemployment rate                                              | 9.453   | 3.34     | 2.4    | 18.4      |
| HOMEOWNERSHIP            | Annual homeownership                                           | 61.865  | 7.805    | 42.58  | 85.69     |
| Observation              | 684                                                            |         |          |        |           |

### ***Dependent Variables***

The dependent variables in this Poisson control function model comprise two health-related indicators: the annual incidence of emergency department visits for COPD per 10,000 individuals and the crude rate of emergency department visits for asthma per 10,000 individuals. As shown in Table 4, the mean annual number of COPD visits is 48, with a variation ranging from 0 to 163. Similarly, the mean annual number of asthma visits is also 48, with a range from 16 to 80. Figure 1 illustrates the geographic distribution of asthma emergency room visits per 10,000 individuals across California counties in 2010. In contrast, Figure 2 presents the geographic distribution of asthma emergency room visits per 10,000 individuals in California counties for the year 2021. A comparison of the two figures reveals a noticeable decline in the number of asthma emergency room visits in 2021 compared to the figures from 2010.

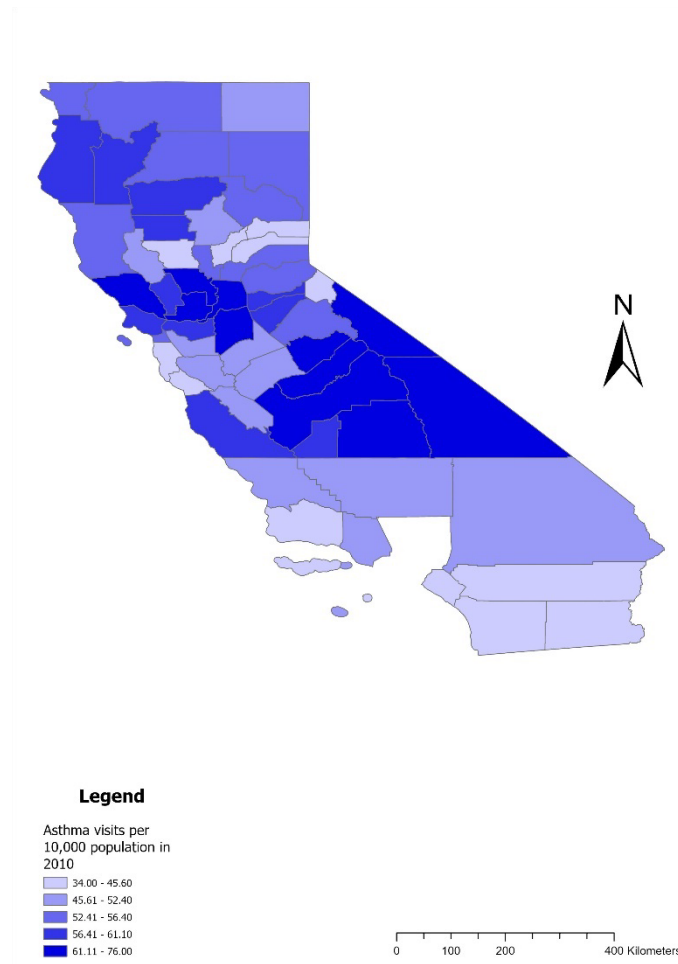


Figure 1 Distribution of asthma visits per 10,000 population by county in California in 2010

The figure above illustrates the geographic distribution of asthma emergency room visits per 10,000 individuals across California counties in 2010. It indicates that the number of visits in Central California exceeds that in Southern California.



Figure 2 Distribution of asthma visits per 10,000 population by county in California in 2021

Figure 2 illustrates the geographic distribution of asthma emergency room visits per 10,000 individuals across California counties for the year 2021. A comparison with Figure 3.1 indicates a significant decline in the number of visits in all counties. The overall trend from 2010 to 2021 shows a substantial decrease in asthma incidents in California. This phenomenon may be attributed to varied factors. Furthermore, the current adoption rate of electric vehicles remains relatively low, which may have some short-term impacts.

### ***Explanatory Variables***

The explanatory variables in this model consist of three indicators related to air quality: the median Air Quality Index, the maximum annual mean concentration of particulate matter, and the number of days on which ozone levels exceed established air quality standards. According to Table 3, The

annual average median AQI by county is 47, with a range from 9 to 102. The annual average PM<sub>2.5</sub> level by county is 9.91  $\mu\text{g}/\text{m}^3$ , with a range from 3  $\mu\text{g}/\text{m}^3$  to 39.10  $\mu\text{g}/\text{m}^3$ , is greater than the EPA's primary annual standard for PM<sub>2.5</sub> (9.0  $\mu\text{g}/\text{m}^3$ ). The annual average number of days on which ozone levels exceed air quality standards is 18, ranging from 0 to 154.

### ***Instrumental Variables***

There are six instrumental variables as follows: the proportion of electric vehicles to internal combustion engine vehicles; the average summer temperature; the square of the average summer temperature; the percentage of annual employment in the manufacturing industry; the annual number of wildfires; and the average annual precipitation. According to Table 4, the mean county-level of annual EVs per 10,000 population to the annual holdings of gasoline vehicles per 10,000 population is 0.006, with a range from 0 to 0.064. Similarly, the annual summer temperature has a mean of 71.91°F, with a range from 56.27°F to 93.60°F. The average annual percentage of statistics in the manufacturing industry by county is 2.32%, ranging from 0% to 9.95%. The average annual number of wildfires is 55, with a range from 0 to 262. The mean annual precipitation by county is 26.49 inches, with a range from 2.06 to 102.62 inches. The rationale for selecting these variables as instrumental variables will be discussed in the following sections.

### **Poisson Control Function Model and Hypotheses**

In this research, the two dependent variables under investigation are the annual emergency department visits for chronic obstructive pulmonary disease among individuals aged 25 and older, and the crude rate of emergency department visits for asthma per 10,000 population. Both variables are classified as count data. It is posited that these counts follow a Poisson distribution, with the logarithm of the expected counts being a linear function of the predictor variables. Consequently, Poisson regression is employed for this analysis. The Poisson control function (CF) model integrates Poisson regression with control function methodology to address endogeneity concerns within the model. This approach is particularly beneficial when certain predictor variables in the Poisson regression are correlated with the error term, as neglecting to account for this correlation can result in biased estimates. The control function method is a strategy designed to mitigate endogeneity issues in regression models. Endogeneity arises when predictor variables are

correlated with the model's error term, leading to biased coefficient estimates. The control function method involves estimating a "first-stage" model for the endogenous variable and subsequently incorporating the residuals from this model as a control function in the primary "second stage" model (i.e., Poisson regression). By integrating the control function into the main model, the correlation between the endogenous variable and the error term is reduced, thereby minimizing estimation bias. In the context of the Poisson control function model, the control function (the residuals from the first-stage model) is included as a predictor variable within the Poisson regression framework. This methodology allows researchers to estimate the causal effects of predictor variables on count outcomes while effectively addressing endogeneity. The primary advantage of the Poisson control function model is its ability to estimate causal effects in the presence of endogeneity. This model offers a robust framework for analyzing count data that may be affected by endogeneity issues, thereby broadening the applicability of Poisson regression in more complex scenarios. In conclusion, the Poisson control function model serves as a valuable tool for analyzing count data when endogeneity is a concern, facilitating the attainment of more reliable estimates regarding the relationships between variables.

The following two articles focus on econometric theory and employ control function models. Each article outlines the necessary conditions and principles for applying this methodology, with a particular emphasis on its effectiveness in addressing endogeneity concerns. [Lee \(2007\)](#) investigates a linear triangular simultaneous equation model that incorporates conditional quantile restrictions. The author employs the control function approach to address the issue of endogeneity and introduces a straightforward two-step estimation procedure. In the first step, the residuals obtained from estimating the reduced-form equation for the endogenous explanatory variables are calculated. These residuals are then included as an additional explanatory variable in a non-parametric format within the primary equation during the second step of the estimation process. The analysis assumes that the explanatory variables are observable, and no constraints are imposed on the relationship between the residuals and the disturbance terms in the equations. Ultimately, the paper's significant contributions lie in establishing the regularity conditions necessary for the consistency and asymptotic normality of the two-step estimator. [Wooldridge \(2015\)](#) elucidates the application of the control function method to address the challenges posed by endogenous explanatory variables (EEVs) in both linear and nonlinear models.

A critical prerequisite for the CF method to yield valid interpretations is the acknowledgment that the "insertion" method is associated with inconsistent parameter estimates and partial effect estimates.

Based on existing literature and logical reasoning, the model is predicated on the following two hypotheses:

**Hypothesis One:** There is a positive correlation between elevated levels of air pollution and an increase in medical visits related to COPD.

**Hypothesis Two:** A greater prevalence of electric vehicles is linked to a reduction in the incidence of visits associated with respiratory diseases.

### Estimation Strategy

This model is based on the findings from the previous chapter and employs a Poisson control function model combined with an instrumental variable approach to obtain regression coefficients to minimize bias as much as possible. First, we will use the fixed effects panel regression from Chapter Two as the first stage. The independent variables are divided into two main categories: instrumental variables and control variables. After obtaining the residuals of the outcome variable from the first stage, we will include both the outcome variable and its residuals into the second stage of the Poisson regression to obtain the Poisson regression coefficients using instrumental variables. Please refer to Equations (1) and (2) for the two-stage regression methodology.

$$\begin{aligned}
 PM25_{it} = & \beta_0 + \beta_1 RATEV\_GAS + \beta_2 TEMP + \beta_3 TEMPSQUARED + \beta_4 MANUFACTURING + \\
 & \beta_5 WILDFIRESNO + \beta_6 PRECIPITATION + \beta_7 \ln POPULATION + \beta_8 POPDENSITY + \\
 & \beta_9 \ln INCOME + \beta_{10} FARM + \beta_{11} SERVICE + \beta_{12} COVID + \beta_{13} AGE65 + \\
 & \beta_{14} RACENONWHITE + \beta_{15} UNEMPLOYMENTRATE + \beta_{16} HOMEOWNERSHIP + \\
 & \mu_t + u_i + e_{it}
 \end{aligned}
 \tag{1}$$

$$\begin{aligned}
& \text{Log}(\text{COPDVISITS10K}_{it}) \\
&= \gamma_0 + \gamma_1 \text{PM25} + \gamma_2 \text{PM25}_{\text{Residuals}} + \gamma_3 \ln \text{POPULATION} + \gamma_4 \text{POPDENSITY} \\
&+ \gamma_5 \ln \text{INCOME} + \gamma_6 \text{FARM} + \gamma_7 \text{SERVICE} + \gamma_8 \text{COVID} + \gamma_9 \text{AGE65} \\
&+ \gamma_{10} \text{RACENONWHITE} + \gamma_{11} \text{UNEMPLOYMENTRATE} \\
&+ \gamma_{12} \text{HOMEOWNERSHIP} + \varepsilon_{it}
\end{aligned} \tag{2}$$

In equation (1), the dependent variables may denote one of three air pollutants: the median air quality index (MEDIANAQI), the maximum annual mean concentration of particulate matter (PM25), and the frequency of days on which ozone levels surpass established air quality standards (O3). The instrumental variables employed in this analysis include six factors: the proportion of EVs in relation to gasoline-powered vehicles (RATEV\_GAS), the average summer temperature (TEMP), the square of the average summer temperature (TEMPSQUARED), the percentage of annual employment within the manufacturing sector (MANUFACTURING), the annual count of wildfires (WILDFIRESNO), and the average annual precipitation (PRECIPITATION). Furthermore, the model incorporates ten control variables: the natural logarithm of annual population by county (lnPOPULATION), annual population density by county (POPDENSITY), the natural logarithm of per capita annual personal income by county (lnINCOME), the percentage of annual employment in the agricultural sector (FARM), the percentage of annual employment in the service sector (SERVICE), a binary variable indicating the COVID-19 pandemic (COVID = 1 for the years 2020-2021), the annual percentage of individuals aged 65 and older (AGE65), the proportion of individuals identified as non-white by county (RACENONWHITE), the annual unemployment rate by county (UNEMPLOYMENTRATE), and the annual homeownership rate (HOMEOWNERSHIP). Additionally, the model accounts for time fixed effects and county fixed effects, along with error terms.

In equation (2), the dependent variables are restricted to two specific health outcomes: COPDVISITS10K and ASTHMA10K. The primary parameter of interest is the coefficient  $\gamma_1$  that clarifies the association between health outcomes and air pollutants. A negative coefficient implies that higher levels of air pollution are advantageous for health, while a positive coefficient suggests that air pollution may result in significant health detriment. Since equation (1) already includes a

time variable, and adding a time variable to equation (2) produces the same regression results as the current equation (2), there is no time variable included in equation (2) here.

## **Empirical Results**

This section is divided into six subsections. The results section presents six groups of Poisson regression outcomes, along with comparisons of three sets of regression coefficients. It also includes Poisson regression results without IVs and the Generalized Method of Moments (GMM) results. Each table or figure illustrates results derived from four distinct sets of control variables. Additionally, the section includes model diagnostics, endogeneity assessments, model selection, robustness check and bootstrapping methods.

### ***Model Diagnostics***

As illustrated in Figure 3, there appears to be a correlation between the annual number of emergency department visits for COPD and the median air quality index. This relationship is represented by the fitted lines across various counties in California from 2010 to 2021. The left fitted line includes data from 58 counties, while the right fitted line includes data from 57 counties, excluding Los Angeles County. By comparing the two figures, we observe that the slope of the line in the right image is steeper. This suggests that it is reasonable to exclude the data from Los Angeles County. Furthermore, both figures indicate that an increase in the median air quality index is associated with an increase in the annual number of emergency department visits for COPD, suggesting that deteriorating air quality has the potential to cause health damage.

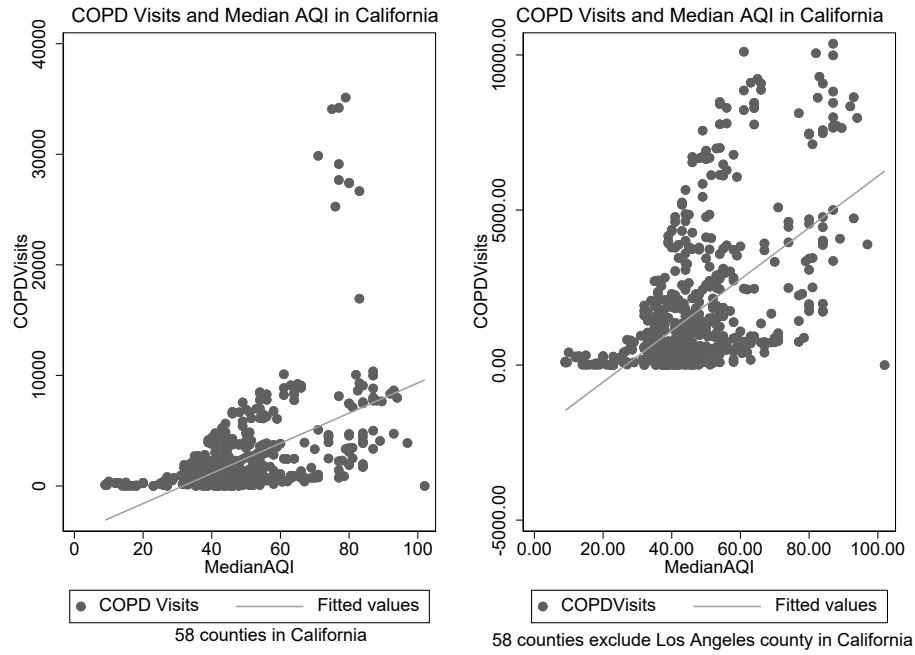


Figure 3 Line fitness between annual number of emergency department visits for COPD and median AQI by county in California from 2010 to 2021

### ***Endogeneity***

It is always hard to find a legitimate instrument variable. However, it is still worth doing the endogeneity test for a potential IV. In this model, the IV regression approach uses six instrumental variable correlated with the endogenous predictor variable (air pollutants) but not with the health outcome variables. Unfortunately, there is no formal panel data test for exclusion restrictions. From Table 5, Table 6, and Table 7, we observe that among the six instrumental variables, the ratio of electric vehicles to gasoline vehicles is significant, as is the employment rate in the manufacturing sector. Furthermore, the F-test values in the first stage are approximately 5, and the regression results from this stage are satisfactory. At the same time, the highly significant residuals in the Poisson regression indicate that there is exclusivity between the instrumental variables in the first stage and the outcome variable in the second stage. Consequently, we select these six instrumental variables because they potentially satisfy both the relevance and exclusivity criteria.

## Results

From Table 5, we can see the quantitative relationship between annual emergency room visits for two types of respiratory diseases and three indicators of air quality. Using three different methods, we obtained different regression coefficients and varying levels of statistical significance. For specific information, please refer to the following introduction. The results presented in Table 6, which does not employ instrumental variables, indicate that the regression coefficients for COPD and median air quality are positive but not statistically significant. The results presented in Table 7, which employ instrumental variables, indicate that the regression coefficients for COPD and median air quality are both positive and highly significant. The fourth group outperforms the others, as it has the lowest AIC value. Table 8 presents the results from GMM, where the regression coefficients are also positive. Although it is not as significant as the results obtained using instrumental variables, it supports the findings presented in Table 7.

Table 4 Regression Results for Health Outcomes and Air Pollutants

| Results | COPD   |      |      | ASTHMA |      |      |
|---------|--------|------|------|--------|------|------|
| AQI     | NO IVs | IVs  | GMM  | NO IVs | IVs  | GMM  |
|         | +      | **** | +    | +      | **** | -    |
| PM25    | NO IVs | IVs  | GMM  | NO IVs | IVs  | GMM  |
|         | ****   | **** | **** | ****   | **** | **** |
| O3      | NO IVs | IVs  | GMM  | NO IVs | IVs  | GMM  |
|         | ***    | **** | +    | -      | **** | **** |

Table 5 Poisson Model without IVs between COPD and AQI

|           | (1)           | (2)           | (3)           | (4)           |
|-----------|---------------|---------------|---------------|---------------|
| VARIABLES | COPDVisits10k | COPDVisits10k | COPDVisits10k | COPDVisits10k |

|                                       |            |             |                                |            |
|---------------------------------------|------------|-------------|--------------------------------|------------|
| MedianAQI                             | 0.00124    | 0.00264     | 0.00251                        | 0.00237    |
|                                       | -0.00156   | -0.00182    | -0.0018                        | -0.00155   |
| lnPopulation                          | -0.571     | -0.919**    | -0.860**                       | -1.105**   |
|                                       | -0.476     | -0.422      | -0.421                         | -0.443     |
| Popdensity                            | 9.31e-05** | -0.000106** | -8.80E-05                      | -7.47E-05  |
|                                       | -4.41E-05  | -5.38E-05   | -5.48E-05                      | -5.32E-05  |
| COVID                                 | -0.284***  | -0.397***   | -0.380***                      | -0.351***  |
|                                       | -0.0234    | -0.0314     | -0.0317                        | -0.0334    |
| Age65                                 | 0.0249***  | -0.00557    | -0.00415                       | -0.00514   |
|                                       | -0.00882   | -0.00821    | -0.00792                       | -0.00825   |
| RaceNonWhite                          | -0.0122    | -0.0680***  | -0.0653***                     | -0.0697*** |
|                                       | -0.0127    | -0.0196     | -0.0214                        | -0.0219    |
| UnemploymentRate                      |            | 0.00367     | 0.00423                        | 0.000649   |
|                                       |            | -0.00608    | -0.00584                       | -0.00594   |
| lnIncome                              |            | 1.006***    | 0.920***                       | 0.904***   |
|                                       |            | -0.218      | -0.218                         | -0.213     |
| Farm                                  |            |             | 0.0496                         | 0.039      |
|                                       |            |             | -0.0462                        | -0.0425    |
| Service                               |            |             | 0.000820*                      | 0.00058    |
|                                       |            |             | -0.000487                      | -0.000474  |
| Homeownership                         |            |             |                                | -0.00995** |
|                                       |            |             |                                | -0.0047    |
| Observations                          | 672        | 672         | 672                            | 672        |
| Number of county                      | 56         | 56          | 56                             | 56         |
| AIC                                   | 4305.5     | 4251.0      | 4248.4                         | 4239.4     |
| BIC                                   | 4332.6     | 4287.1      | 4293.5                         | 4289.1     |
| Robust standard errors in parentheses |            |             | *** p<0.01, ** p<0.05, * p<0.1 |            |

Table 6 Poisson Model with IVs between COPD and AQI

|                 | (1)           | (2)           | (3)           | (4)           |
|-----------------|---------------|---------------|---------------|---------------|
| VARIABLES       | COPDVisits10k | COPDVisits10k | COPDVisits10k | COPDVisits10k |
| MedianAQI       | 0.0121***     | 0.0200***     | 0.0191***     | 0.0183***     |
|                 | -0.00357      | -0.00349      | -0.00342      | -0.00319      |
| MedianAQI_resid | -0.0130***    | -0.0200***    | -0.0191***    | -0.0184***    |
|                 | -0.00428      | -0.00406      | -0.004        | -0.0037       |

|                                       |            |             |                                |            |
|---------------------------------------|------------|-------------|--------------------------------|------------|
| lnPopulation                          | -0.339     | -0.728*     | -0.697                         | -0.945**   |
|                                       | -0.483     | -0.426      | -0.425                         | -0.445     |
| Popdensity                            | 9.22e-05** | -0.000123** | -0.000109**                    | -9.45e-05* |
|                                       | -4.41E-05  | -5.40E-05   | -5.43E-05                      | -5.25E-05  |
| COVID                                 | -0.297***  | -0.436***   | -0.422***                      | -0.392***  |
|                                       | -0.0245    | -0.0337     | -0.0333                        | -0.0335    |
| Age65                                 | 0.0238***  | -0.0157*    | -0.0143*                       | -0.0148*   |
|                                       | -0.00904   | -0.00815    | -0.00766                       | -0.00804   |
| RaceNonWhite                          | -0.00701   | -0.0744***  | -0.0718***                     | -0.0757*** |
|                                       | -0.0126    | -0.0183     | -0.0198                        | -0.0205    |
| UnemploymentRate                      |            | -0.00284    | -0.00219                       | -0.00544   |
|                                       |            | -0.00578    | -0.00557                       | -0.00579   |
| lnIncome                              |            | 1.157***    | 1.088***                       | 1.065***   |
|                                       |            | -0.211      | -0.207                         | -0.204     |
| Farm                                  |            |             | 0.0374                         | 0.0277     |
|                                       |            |             | -0.044                         | -0.041     |
| Service                               |            |             | 0.000438                       | 0.000219   |
|                                       |            |             | -0.000487                      | -0.000479  |
| Homeownership                         |            |             |                                | -0.00970** |
|                                       |            |             |                                | -0.00454   |
| Observations                          | 672        | 672         | 672                            | 672        |
| Number of county                      | 56         | 56          | 56                             | 56         |
| AIC                                   | 4291.8     | 4221.5      | 4222.1                         | 4215.2     |
| BIC                                   | 4323.3     | 4262.1      | 4271.7                         | 4269.3     |
| Robust standard errors in parentheses |            |             | *** p<0.01, ** p<0.05, * p<0.1 |            |

Figure 4 presents four distinct sets of regression coefficients derived from Table 7. Each of these sets exhibits positive coefficients, with values ranging from 0.01 to 0.02. Notably, the fourth set with the most control variables is characterized by the lowest AIC value.

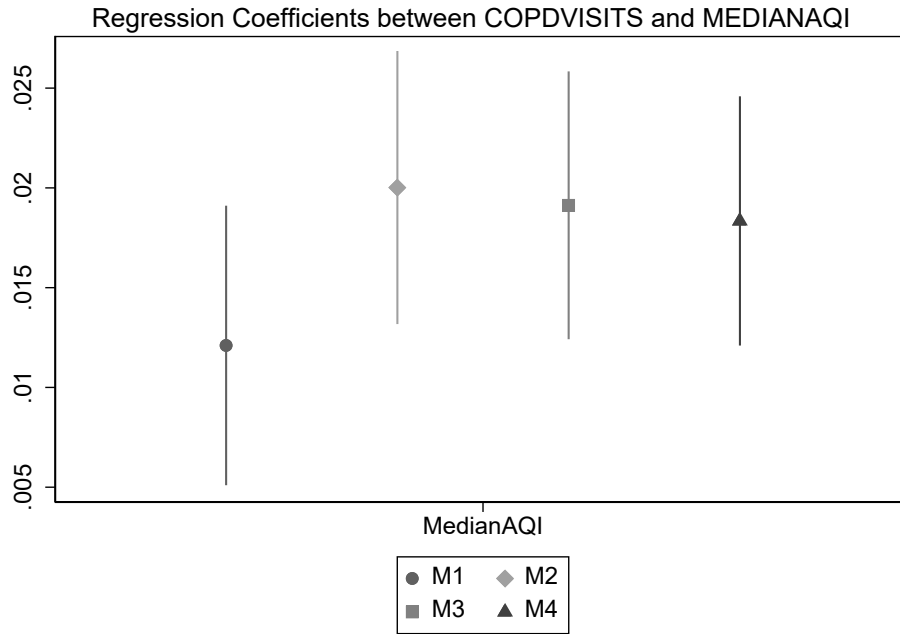


Figure 4 Regression coefficients between COPDVISITS and MEDIANAQI

Table 7 GMM Model with IVs between COPD and AQI

|                  | (1)             | (2)             | (3)             | (4)             |
|------------------|-----------------|-----------------|-----------------|-----------------|
| VARIABLES        | lnCOPDVisits10k | lnCOPDVisits10k | lnCOPDVisits10k | lnCOPDVisits10k |
| Median AQI       | 0.00425         | 0.0161**        | 0.0132*         | 0.0127*         |
|                  | -0.00634        | -0.00747        | -0.00743        | -0.0074         |
| lnPopulation     | -0.341          | -0.43           | -0.443          | -0.549          |
|                  | -0.336          | -0.344          | -0.334          | -0.353          |
| Popdensity       | 7.41E-05        | -7.29E-05       | -5.17E-05       | -4.73E-05       |
|                  | -0.000102       | -0.000112       | -0.00011        | -0.000109       |
| COVID            | -0.309***       | -0.410***       | -0.388***       | -0.377***       |
|                  | -0.0243         | -0.0351         | -0.036          | -0.0375         |
| Age65            | 0.0265***       | -0.000724       | 0.00149         | 0.00148         |
|                  | -0.00579        | -0.0092         | -0.00907        | -0.00903        |
| RaceNonWhite     | -0.0163         | -0.0506***      | -0.0443***      | -0.0446***      |
|                  | -0.0119         | -0.0148         | -0.0149         | -0.0148         |
| UnemploymentRate |                 | -0.00233        | -0.000507       | -0.00147        |
|                  |                 | -0.00525        | -0.00521        | -0.00531        |

|                                |        |          |                                |          |
|--------------------------------|--------|----------|--------------------------------|----------|
| lnIncome                       |        | 0.728*** | 0.626***                       | 0.615*** |
|                                |        | -0.168   | -0.171                         | -0.171   |
| Farm                           |        |          | 0.0549**                       | 0.0512*  |
|                                |        |          | -0.0279                        | -0.0281  |
| Service                        |        |          | 0.000211                       | 0.000144 |
|                                |        |          | -0.00107                       | -0.00107 |
| Homeownership                  |        |          |                                | -0.00348 |
|                                |        |          |                                | -0.00391 |
| Observations                   | 684    | 684      | 684                            | 684      |
| Number of county               | 57     | 57       | 57                             | 57       |
| AIC                            | -410.5 | -337.3   | -371.1                         | -374.4   |
| BIC                            | -383.4 | -301.1   | -325.9                         | -324.6   |
| Standard errors in parentheses |        |          | *** p<0.01, ** p<0.05, * p<0.1 |          |

The findings presented in Table 9 indicate that, in the absence of instrumental variables, the regression coefficients for asthma visits in relation to median air quality are positive yet statistically insignificant. Conversely, the results displayed in Table 10, which incorporate instrumental variables, reveal that the regression coefficients for asthma visits and median air quality are both positive and statistically significant. The second model is favored over the alternatives due to its lowest AIC value. Additionally, Table 11 outlines GMM results, which demonstrate a negative and statistically insignificant regression coefficient, thereby contradicting the outcomes observed in the previous two methodologies.

Table 8 Poisson Model without IVs between ASTHMA and AQI

| VARIABLES    | (1)          | (2)          | (3)          | (4)          |
|--------------|--------------|--------------|--------------|--------------|
|              | Asthma10k    | Asthma10k    | Asthma10k    | Asthma10k    |
| Median AQI   | 0.00177      | 0.000907     | 0.000862     | 0.000873     |
|              | -0.00111     | -0.000907    | -0.000896    | -0.000942    |
| lnPopulation | -0.327*      | -0.105       | -0.0934      | 0.00321      |
|              | -0.187       | -0.177       | -0.175       | -0.174       |
| Popdensity   | -0.000154*** | -0.000195*** | -0.000198*** | -0.000202*** |
|              | -2.22E-05    | -2.48E-05    | -2.42E-05    | -2.46E-05    |
| COVID        | -0.227***    | -0.229***    | -0.226***    | -0.235***    |
|              | -0.00785     | -0.00948     | -0.0106      | -0.0142      |

|                                       |            |            |                                |             |
|---------------------------------------|------------|------------|--------------------------------|-------------|
| Age65                                 | -0.0239*** | -0.0194*** | -0.0189***                     | -0.0185***  |
|                                       | -0.00287   | -0.00412   | -0.0041                        | -0.00418    |
| RaceNonWhite                          | -0.00434   | -0.00368   | -0.00569                       | -0.00539    |
|                                       | -0.00621   | -0.00747   | -0.00819                       | -0.00801    |
| UnemploymentRate                      |            | 0.0170***  | 0.0172***                      | 0.0183***   |
|                                       |            | -0.00242   | -0.00246                       | -0.00277    |
| lnIncome                              |            | 0.125*     | 0.119                          | 0.125       |
|                                       |            | -0.0715    | -0.0806                        | -0.0851     |
| Farm                                  |            |            | 0.00141                        | 0.00485     |
|                                       |            |            | -0.0163                        | -0.0161     |
| Service                               |            |            | 0.000844***                    | 0.000919*** |
|                                       |            |            | -0.00024                       | -0.000261   |
| Homeownership                         |            |            |                                | 0.00307     |
|                                       |            |            |                                | -0.00203    |
| Observations                          | 684        | 684        | 684                            | 684         |
| Number of county                      | 57         | 57         | 57                             | 57          |
| AIC                                   | 3958.4     | 3935.1     | 3937.9                         | 3938.9      |
| BIC                                   | 3985.6     | 3971.3     | 3983.2                         | 3988.7      |
| Robust standard errors in parentheses |            |            | *** p<0.01, ** p<0.05, * p<0.1 |             |

Table 9 Poisson Model with IVs between ASTHMA and AQI

|              | (1)          | (2)          | (3)          | (4)          |
|--------------|--------------|--------------|--------------|--------------|
| VARIABLES    | Asthma10k    | Asthma10k    | Asthma10k    | Asthma10k    |
| MedianAQI    | 0.0149***    | 0.0114***    | 0.0113***    | 0.0114***    |
|              | -0.00106     | -0.00124     | -0.00124     | -0.00126     |
| lnPopulation | -0.0181      | 0.0116       | 0.0177       | 0.125        |
|              | -0.169       | -0.185       | -0.183       | -0.175       |
| Popdensity   | -0.000153*** | -0.000208*** | -0.000212*** | -0.000216*** |
|              | -1.75E-05    | -2.27E-05    | -2.17E-05    | -2.18E-05    |
| COVID        | -0.237***    | -0.252***    | -0.251***    | -0.261***    |
|              | -0.00677     | -0.00909     | -0.00967     | -0.0129      |
| Age65        | -0.0252***   | -0.0261***   | -0.0257***   | -0.0254***   |
|              | -0.00255     | -0.00358     | -0.00356     | -0.00362     |
| RaceNonWhite | -0.00213     | -0.00804     | -0.0101      | -0.00986     |
|              | -0.00463     | -0.00661     | -0.00724     | -0.0071      |

|                                |        |           |                                |            |
|--------------------------------|--------|-----------|--------------------------------|------------|
| UnemploymentRate               |        | 0.0126*** | 0.0128***                      | 0.0139***  |
|                                |        | -0.00253  | -0.00259                       | -0.00292   |
| lnIncome                       |        | 0.219***  | 0.223***                       | 0.229***   |
|                                |        | -0.0648   | -0.07                          | -0.0736    |
| Farm                           |        |           | -0.00455                       | -0.000875  |
|                                |        |           | -0.0146                        | -0.0146    |
| Service                        |        |           | 0.000592**                     | 0.000673** |
|                                |        |           | -0.000243                      | -0.000264  |
| Homeownership                  |        |           |                                | 0.00334*   |
|                                |        |           |                                | -0.00203   |
| Observations                   | 684    | 684       | 684                            | 684        |
| Number of county               | 57     | 57        | 57                             | 57         |
| AIC                            | 3935.3 | 3924.9    | 3928.0                         | 3928.8     |
| BIC                            | 3967.0 | 3965.6    | 3977.8                         | 3983.1     |
| Standard errors in parentheses |        |           | *** p<0.01, ** p<0.05, * p<0.1 |            |

Figure 5 presents four distinct sets of regression coefficients derived from Table 10. Each of these sets exhibits positive values, with coefficients ranging from 0.011 to 0.015. Notably, the second set is characterized by the lowest AIC value.

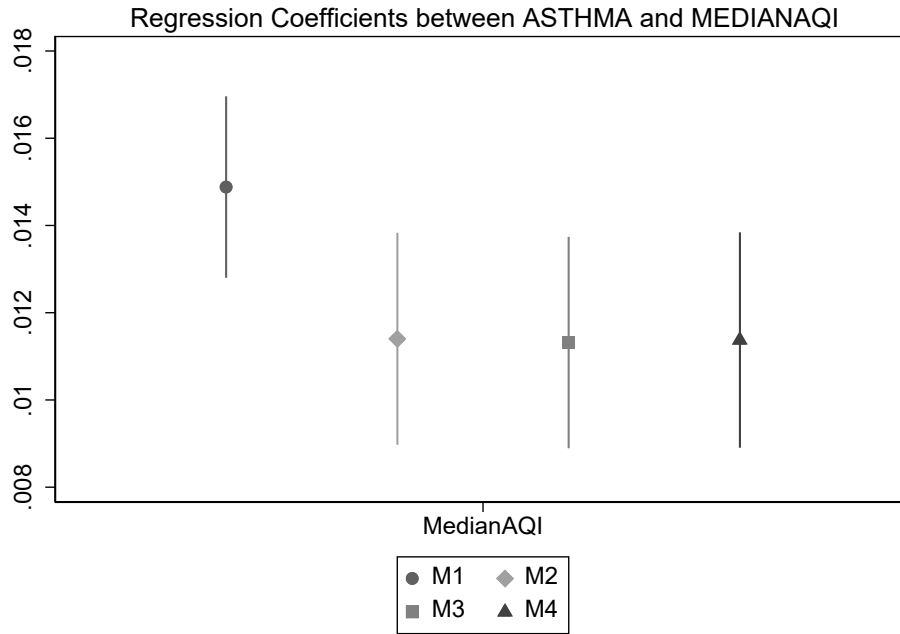


Figure 5 Regression coefficients between ASTHMA and MEDIANAQI

Table 10 GMM Model with IVs between ASTHMA and AQI

|                  | (1)         | (2)         | (3)         | (4)          |
|------------------|-------------|-------------|-------------|--------------|
| VARIABLES        | lnAsthma10K | lnAsthma10K | lnAsthma10K | lnAsthma10K  |
| MedianAQI        | -0.008      | -0.00677    | -0.0081     | -0.00695     |
|                  | -0.00546    | -0.00585    | -0.00604    | -0.00597     |
| lnPopulation     | -0.519*     | -0.158      | -0.157      | -0.0203      |
|                  | -0.29       | -0.269      | -0.272      | -0.285       |
| Popdensity       | -0.000186** | -0.000226** | -0.000226** | -0.000233*** |
|                  | -8.74E-05   | -8.78E-05   | -8.92E-05   | -8.83E-05    |
| COVID            | -0.265***   | -0.265***   | -0.257***   | -0.271***    |
|                  | -0.021      | -0.0275     | -0.0293     | -0.0303      |
| Age65            | -0.0222***  | -0.0153**   | -0.0139*    | -0.0143*     |
|                  | -0.00499    | -0.0072     | -0.00738    | -0.00728     |
| RaceNonWhite     | -0.00636    | -0.00347    | -0.00502    | -0.00488     |
|                  | -0.0102     | -0.0115     | -0.0121     | -0.012       |
| UnemploymentRate |             | 0.0219***   | 0.0229***   | 0.0238***    |
|                  |             | -0.00411    | -0.00424    | -0.00429     |

|                                |        |        |                                |           |
|--------------------------------|--------|--------|--------------------------------|-----------|
| lnIncome                       |        | 0.118  | 0.092                          | 0.112     |
|                                |        | -0.132 | -0.139                         | -0.138    |
| Farm                           |        |        | 0.00578                        | 0.01      |
|                                |        |        | -0.0227                        | -0.0227   |
| Service                        |        |        | 0.00121                        | 0.00128   |
|                                |        |        | -0.000872                      | -0.000863 |
| Homeownership                  |        |        |                                | 0.00427   |
|                                |        |        |                                | -0.00316  |
| Observations                   | 684    | 684    | 684                            | 684       |
| Number of county               | 57     | 57     | 57                             | 57        |
| AIC                            | -614.9 | -672.3 | -653.8                         | -668.4    |
| BIC                            | -587.8 | -636.0 | -608.5                         | -618.6    |
| Standard errors in parentheses |        |        | *** p<0.01, ** p<0.05, * p<0.1 |           |

The results in Table 12 show that without using instrumental variables, the regression coefficient for COPD and PM2.5 is both positive and highly significant, with the fourth group exhibiting the lowest AIC value. The results in Table 13 indicate that when employing instrumental variables, the regression coefficient for COPD and PM2.5 is both positive and highly significant. Additionally, the fourth group exhibits the lowest AIC value. Table 14 presents the results from GMM, where the regression coefficient is positive and, similar to the results obtained using instrumental variables, is highly significant. This supports the findings presented in Table 13.

Table 11 Poisson Model without IVs between COPD and PM25

|              | (1)           | (2)           | (3)           | (4)           |
|--------------|---------------|---------------|---------------|---------------|
| VARIABLES    | COPDVisits10k | COPDVisits10k | COPDVisits10k | COPDVisits10k |
| PM25         | 0.0130***     | 0.0131***     | 0.0127***     | 0.0116***     |
|              | -0.00361      | -0.00334      | -0.00331      | -0.00319      |
| lnPopulation | -0.179        | -0.684        | -0.589        | -0.958*       |
|              | -0.58         | -0.561        | -0.569        | -0.579        |
| Popdensity   | 0.000138**    | -1.37E-05     | 1.59E-05      | 4.03E-05      |
|              | -5.94E-05     | -6.75E-05     | -6.89E-05     | -6.66E-05     |
| COVID        | -0.551***     | -0.624***     | -0.601***     | -0.559***     |
|              | -0.0341       | -0.036        | -0.0345       | -0.0367       |
| Age65        | 0.0279***     | 5.99E-05      | 0.00271       | 0.00151       |

|                                       |           |            |                                |            |
|---------------------------------------|-----------|------------|--------------------------------|------------|
|                                       | -0.00982  | -0.0114    | -0.0108                        | -0.0113    |
| RaceNonWhite                          | -0.0409** | -0.0854*** | -0.0787***                     | -0.0849*** |
|                                       | -0.0171   | -0.0234    | -0.026                         | -0.0267    |
| UnemploymentRate                      |           | 0.00111    | 0.00163                        | -0.00407   |
|                                       |           | -0.00615   | -0.00587                       | -0.00587   |
| lnIncome                              |           | 0.826***   | 0.686**                        | 0.651**    |
|                                       |           | -0.277     | -0.275                         | -0.269     |
| Farm                                  |           |            | 0.0669                         | 0.0535     |
|                                       |           |            | -0.0465                        | -0.0414    |
| Service                               |           |            | 0.000508                       | 8.41E-05   |
|                                       |           |            | -0.000569                      | -0.000542  |
| Homeownership                         |           |            |                                | -0.0152*** |
|                                       |           |            |                                | -0.00542   |
| Observations                          | 616       | 616        | 616                            | 616        |
| Number of county                      | 56        | 56         | 56                             | 56         |
| AIC                                   | 3795.8    | 3767.8     | 3763.0                         | 3743.1     |
| BIC                                   | 3822.3    | 3803.2     | 3807.2                         | 3791.8     |
| Robust standard errors in parentheses |           |            | *** p<0.01, ** p<0.05, * p<0.1 |            |

Table 12 Poisson Model with IVs between COPD and PM25

|              | (1)           | (2)           | (3)           | (4)           |
|--------------|---------------|---------------|---------------|---------------|
| VARIABLES    | COPDVisits10k | COPDVisits10k | COPDVisits10k | COPDVisits10k |
| PM25         | 0.0145***     | 0.0149***     | 0.0132***     | 0.0129***     |
|              | -0.00547      | -0.00491      | -0.00465      | -0.00432      |
| PM25_resid   | -0.00265      | -0.0031       | -0.00097      | -0.0022       |
|              | -0.00852      | -0.00786      | -0.00772      | -0.00759      |
| lnPopulation | -0.157        | -0.656        | -0.581        | -0.945        |
|              | -0.586        | -0.558        | -0.566        | -0.575        |
| Popdensity   | 0.000139**    | -1.28E-05     | 1.60E-05      | 4.10E-05      |
|              | -5.94E-05     | -6.72E-05     | -6.87E-05     | -6.63E-05     |
| COVID        | -0.558***     | -0.631***     | -0.603***     | -0.564***     |
|              | -0.0407       | -0.0443       | -0.0423       | -0.0417       |
| Age65        | 0.0277***     | -0.000197     | 0.00261       | 0.00127       |
|              | -0.00988      | -0.0116       | -0.011        | -0.0115       |
| RaceNonWhite | -0.0414**     | -0.0857***    | -0.0788***    | -0.0853***    |

|                                       |         |          |           |            |
|---------------------------------------|---------|----------|-----------|------------|
|                                       | -0.0169 | -0.0236  | -0.0261   | -0.0268    |
| UnemploymentRate                      |         | 0.00134  | 0.0017    | -0.00399   |
|                                       |         | -0.0061  | -0.00589  | -0.00584   |
| lnIncome                              |         | 0.827*** | 0.687**   | 0.653**    |
|                                       |         | -0.278   | -0.277    | -0.27      |
| Farm                                  |         |          | 0.0666    | 0.0527     |
|                                       |         |          | -0.0465   | -0.0416    |
| Service                               |         |          | 0.0005    | 6.14E-05   |
|                                       |         |          | -0.000567 | -0.000547  |
| Homeownership                         |         |          |           | -0.0153*** |
|                                       |         |          |           | -0.00557   |
| Observations                          | 616     | 616      | 616       | 616        |
| Number of county                      | 56      | 56       | 56        | 56         |
| AIC                                   | 3797.6  | 3769.6   | 3765.0    | 3745.0     |
| BIC                                   | 3828.5  | 3809.4   | 3813.6    | 3798.1     |
| Robust standard errors in parentheses |         |          |           |            |

Figure 6 shows the four sets of different regression coefficients from Table 13. All four coefficients are positive, ranging from 0.012 to 0.015, with the fourth set having the lowest AIC value.

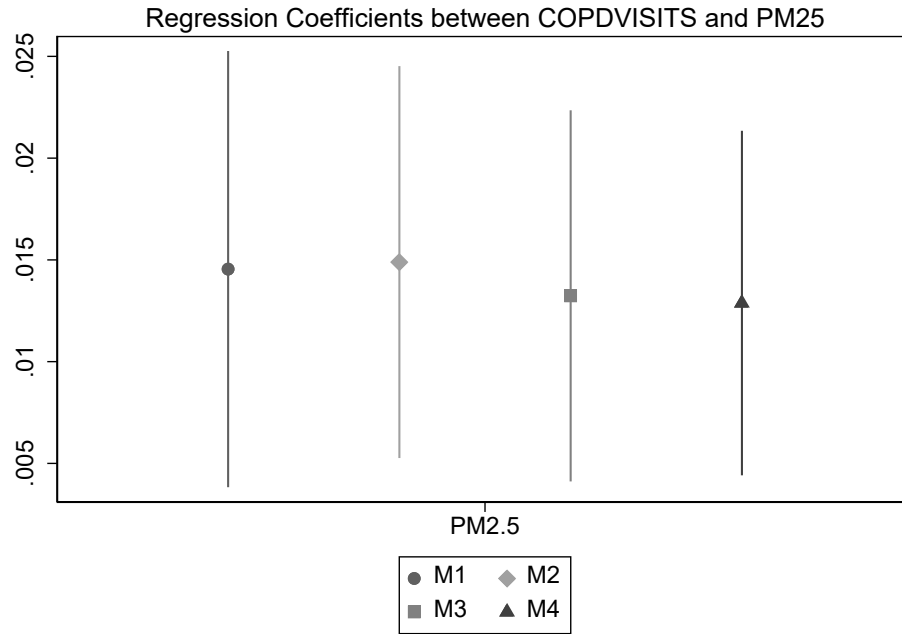


Figure 6 Regression coefficients between COPDVISITS and PM25

Table 13 GMM Model with IVs between COPD and PM25

|                  | (1)             | (2)             | (3)             | (4)             |
|------------------|-----------------|-----------------|-----------------|-----------------|
| VARIABLES        | lnCOPDVisits10k | lnCOPDVisits10k | lnCOPDVisits10k | lnCOPDVisits10k |
| PM25             | 0.0434***       | 0.0404***       | 0.0363***       | 0.0317***       |
|                  | -0.01           | -0.00896        | -0.0089         | -0.00834        |
| lnPopulation     | 0.241           | 0.0206          | 0.0132          | -0.341          |
|                  | -0.342          | -0.357          | -0.349          | -0.351          |
| Popdensity       | 0.000133        | 6.62E-05        | 9.46E-05        | 0.000107        |
|                  | -9.78E-05       | -0.000101       | -9.96E-05       | -9.74E-05       |
| COVID            | -0.691***       | -0.708***       | -0.674***       | -0.630***       |
|                  | -0.0484         | -0.0471         | -0.0481         | -0.046          |
| Age65            | 0.0211***       | 0.0111          | 0.0129          | 0.0127          |
|                  | -0.00625        | -0.00825        | -0.00812        | -0.00793        |
| RaceNonWhite     | -0.0402***      | -0.0528***      | -0.0429***      | -0.0430***      |
|                  | -0.0129         | -0.0143         | -0.0146         | -0.0142         |
| UnemploymentRate |                 | 0.00211         | 0.0023          | -0.00171        |
|                  |                 | -0.00408        | -0.004          | -0.00405        |
| lnIncome         |                 | 0.319**         | 0.201           | 0.166           |

|                                |        |        |                                |            |
|--------------------------------|--------|--------|--------------------------------|------------|
|                                |        | -0.156 | -0.159                         | -0.155     |
| Farm                           |        |        | 0.0706***                      | 0.0603**   |
|                                |        |        | -0.0267                        | -0.0264    |
| Service                        |        |        | -0.000541                      | -0.000785  |
|                                |        |        | -0.00107                       | -0.00105   |
| Homeownership                  |        |        |                                | -0.0113*** |
|                                |        |        |                                | -0.00372   |
| Observations                   | 627    | 627    | 627                            | 627        |
| R-squared                      | 0.4    | 0.419  | 0.444                          | 0.47       |
| Number of county               | 57     | 57     | 57                             | 57         |
| AIC                            | -447.2 | -464.1 | -487.8                         | -515.3     |
| BIC                            | -420.6 | -428.6 | -443.4                         | -466.5     |
| Standard errors in parentheses |        |        | *** p<0.01, ** p<0.05, * p<0.1 |            |

The results in Table 15 indicate that, without using instrumental variables, the regression coefficients for ASTHMA and PM2.5 are both positive and significant, with the second group having the lowest AIC value. The results in Table 16 indicate that when employing instrumental variables, the regression coefficients for ASTHMA and PM2.5 are both positive and highly significant. Similarly, the second group exhibits the lowest AIC value. Table 17 presents the results from GMM, where the regression coefficients are also positive and, as the results obtained using instrumental variables, are highly significant, supporting the findings in Table 16.

Table 14 Poisson Model without IVs between ASTHMA and PM25

|              | (1)          | (2)          | (3)          | (4)          |
|--------------|--------------|--------------|--------------|--------------|
| VARIABLES    | Asthma10k    | Asthma10k    | Asthma10k    | Asthma10k    |
| PM25         | 0.003        | 0.00367**    | 0.00347**    | 0.00349***   |
|              | -0.00192     | -0.00149     | -0.00146     | -0.00132     |
| lnPopulation | -0.227       | 0.266        | 0.284        | 0.199        |
|              | -0.215       | -0.167       | -0.173       | -0.188       |
| Popdensity   | -0.000128*** | -8.75e-05*** | -8.00e-05*** | -7.60e-05*** |
|              | -1.58E-05    | -1.46E-05    | -1.49E-05    | -1.68E-05    |
| COVID        | -0.592***    | -0.558***    | -0.550***    | -0.543***    |
|              | -0.0126      | -0.0134      | -0.0135      | -0.015       |
| Age65        | -0.0259***   | -0.00855*    | -0.00786*    | -0.00827*    |

|                                       |          |           |                                |           |
|---------------------------------------|----------|-----------|--------------------------------|-----------|
|                                       | -0.00367 | -0.00441  | -0.0044                        | -0.00453  |
| RaceNonWhite                          | -0.0141  | 0.000506  | 0.00227                        | 0.0021    |
|                                       | -0.0105  | -0.00718  | -0.00749                       | -0.00779  |
| UnemploymentRate                      |          | 0.0116*** | 0.0119***                      | 0.0109*** |
|                                       |          | -0.00197  | -0.00195                       | -0.00201  |
| lnIncome                              |          | -0.276*** | -0.316***                      | -0.323*** |
|                                       |          | -0.0639   | -0.065                         | -0.0693   |
| Farm                                  |          |           | 0.0206**                       | 0.0173**  |
|                                       |          |           | -0.00868                       | -0.00849  |
| Service                               |          |           | 0.000323*                      | 0.000236  |
|                                       |          |           | -0.000179                      | -0.000189 |
| Homeownership                         |          |           |                                | -0.00300* |
|                                       |          |           |                                | -0.00168  |
| Observations                          | 627      | 627       | 627                            | 627       |
| Number of county                      | 57       | 57        | 57                             | 57        |
| AIC                                   | 3234.6   | 3218.4    | 3221.4                         | 3222.5    |
| BIC                                   | 3261.3   | 3253.9    | 3265.8                         | 3271.4    |
| Robust standard errors in parentheses |          |           | *** p<0.01, ** p<0.05, * p<0.1 |           |

Table 15 Poisson Model with IVs between ASTHMA and PM25

|                  | (1)          | (2)          | (3)          | (4)          |
|------------------|--------------|--------------|--------------|--------------|
| VARIABLES        | Asthma10k    | Asthma10k    | Asthma10k    | Asthma10k    |
| PM25             | 0.00731***   | 0.00926***   | 0.00878***   | 0.00877***   |
|                  | -0.0013      | -0.0012      | -0.00118     | -0.00116     |
| lnPopulation     | -0.181       | 0.331**      | 0.343**      | 0.249        |
|                  | -0.213       | -0.157       | -0.163       | -0.18        |
| Popdensity       | -0.000125*** | -8.52e-05*** | -7.86e-05*** | -7.41e-05*** |
|                  | -1.51E-05    | -1.45E-05    | -1.50E-05    | -1.67E-05    |
| COVID            | -0.608***    | -0.579***    | -0.571***    | -0.564***    |
|                  | -0.0119      | -0.0119      | -0.0121      | -0.014       |
| Age65            | -0.0268***   | -0.00968**   | -0.00903**   | -0.00948**   |
|                  | -0.00356     | -0.00425     | -0.00426     | -0.00435     |
| RaceNonWhite     | -0.0149      | -0.000628    | 0.00105      | 0.000815     |
|                  | -0.0101      | -0.0066      | -0.00694     | -0.00728     |
| UnemploymentRate |              | 0.0122***    | 0.0123***    | 0.0112***    |
|                  |              | -0.0019      | -0.0019      | -0.00195     |

|                                       |        |           |                                |           |
|---------------------------------------|--------|-----------|--------------------------------|-----------|
| lnIncome                              |        | -0.270*** | -0.305***                      | -0.313*** |
|                                       |        | -0.0626   | -0.0635                        | -0.0678   |
| Farm                                  |        |           | 0.0182**                       | 0.0145*   |
|                                       |        |           | -0.00872                       | -0.00858  |
| Service                               |        |           | 0.000247                       | 0.000152  |
|                                       |        |           | -0.000179                      | -0.000187 |
| Homeownership                         |        |           |                                | -0.00334* |
|                                       |        |           |                                | -0.00172  |
| Observations                          | 627    | 627       | 627                            | 627       |
| Number of county                      | 57     | 57        | 57                             | 57        |
| AIC                                   | 3235.4 | 3218.3    | 3221.5                         | 3222.7    |
| BIC                                   | 3266.5 | 3258.3    | 3270.4                         | 3276.0    |
| Robust standard errors in parentheses |        |           | *** p<0.01, ** p<0.05, * p<0.1 |           |

Figure 7 presents four distinct sets of regression coefficients derived from Table 3.16. Each of these sets exhibits positive coefficients, with values ranging from 0.007 to 0.01. Notably, the second set is characterized by the lowest AIC value.

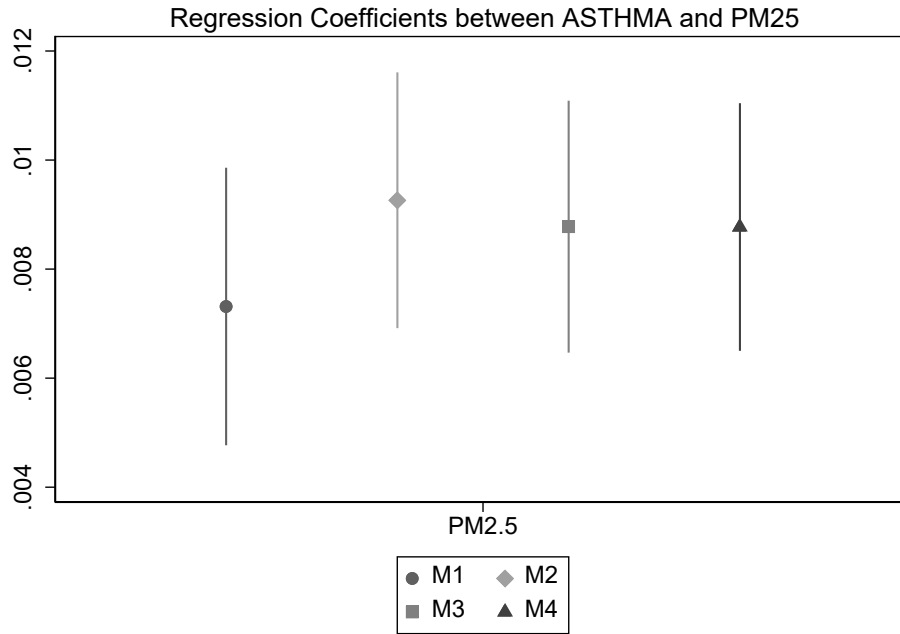


Figure 7 Regression coefficients between ASTHMA and PM25

Table 16 GMM Model with IVs between ASTHMA and PM25

|                  | (1)          | (2)         | (3)         | (4)         |
|------------------|--------------|-------------|-------------|-------------|
| VARIABLES        | lnAsthma10K  | lnAsthma10K | lnAsthma10K | lnAsthma10K |
| PM25             | 0.0236***    | 0.0164***   | 0.0151***   | 0.0142***   |
|                  | -0.00476     | -0.00362    | -0.0036     | -0.0034     |
| lnPopulation     | 0.0375       | 0.415***    | 0.413***    | 0.302**     |
|                  | -0.163       | -0.144      | -0.141      | -0.143      |
| Popdensity       | -0.000126*** | -7.82e-05*  | -7.19e-05*  | -6.74e-05*  |
|                  | -4.65E-05    | -4.08E-05   | -4.03E-05   | -3.97E-05   |
| COVID            | -0.668***    | -0.598***   | -0.587***   | -0.575***   |
|                  | -0.023       | -0.019      | -0.0195     | -0.0188     |
| Age65            | -0.0301***   | -0.0105***  | -0.00991*** | -0.0101***  |
|                  | -0.00297     | -0.00333    | -0.00328    | -0.00324    |
| RaceNonWhite     | -0.0191***   | 8.69E-05    | 0.00209     | 0.00192     |
|                  | -0.00615     | -0.00577    | -0.00589    | -0.0058     |
| UnemploymentRate |              | 0.0124***   | 0.0125***   | 0.0112***   |
|                  |              | -0.00165    | -0.00162    | -0.00165    |

|                                |         |           |                                |            |
|--------------------------------|---------|-----------|--------------------------------|------------|
| lnIncome                       |         | -0.310*** | -0.343***                      | -0.354***  |
|                                |         | -0.0628   | -0.0643                        | -0.0633    |
| Farm                           |         |           | 0.0189*                        | 0.0151     |
|                                |         |           | -0.0108                        | -0.0108    |
| Service                        |         |           | 0.000159                       | 6.65E-05   |
|                                |         |           | -0.000431                      | -0.000427  |
| Homeownership                  |         |           |                                | -0.00380** |
|                                |         |           |                                | -0.00152   |
| Observations                   | 627     | 627       | 627                            | 627        |
| R-squared                      | 0.856   | 0.9       | 0.904                          | 0.906      |
| Number of county               | 57      | 57        | 57                             | 57         |
| AIC                            | -1378.9 | -1602.4   | -1622.8                        | -1640.0    |
| BIC                            | -1352.3 | -1566.9   | -1578.4                        | -1591.1    |
| Standard errors in parentheses |         |           | *** p<0.01, ** p<0.05, * p<0.1 |            |

The findings presented in Table 18 indicate that, in the absence of instrumental variables, the regression coefficients for COPD in relation to O3 are both positive and statistically significant, with the third group exhibiting the lowest AIC value. Conversely, the results in Table 19 demonstrate that when instrumental variables are employed, the regression coefficients for COPD and O3 remain positive and are highly significant, with the fourth group reflecting the lowest AIC value. Furthermore, Table 20 outlines the GMM results, which also reveal a positive regression coefficient; however, only the coefficient from the first group shows mild significance, thereby corroborating the results obtained in Table 19.

Table 17 Poisson Model without IVs between COPD and O3

|              | (1)           | (2)           | (3)           | (4)           |
|--------------|---------------|---------------|---------------|---------------|
| VARIABLES    | COPDVisits10k | COPDVisits10k | COPDVisits10k | COPDVisits10k |
| O3           | 0.00157       | 0.00221**     | 0.00207*      | 0.00195*      |
|              | -0.00113      | -0.00111      | -0.00112      | -0.00108      |
| lnPopulation | -0.157        | -0.673        | -0.58         | -0.965*       |
|              | -0.587        | -0.569        | -0.578        | -0.585        |
| Popdensity   | 0.000117*     | -4.35E-05     | -1.28E-05     | 1.46E-05      |
|              | -5.97E-05     | -6.96E-05     | -7.05E-05     | -6.80E-05     |

|                                       |           |            |                                |            |
|---------------------------------------|-----------|------------|--------------------------------|------------|
| COVID                                 | -0.504*** | -0.581***  | -0.559***                      | -0.519***  |
|                                       | -0.0351   | -0.0333    | -0.0327                        | -0.036     |
| Age65                                 | 0.0316*** | 0.00188    | 0.00458                        | 0.00311    |
|                                       | -0.0102   | -0.0116    | -0.011                         | -0.0115    |
| RaceNonWhite                          | -0.0380** | -0.0857*** | -0.0796***                     | -0.0863*** |
|                                       | -0.0175   | -0.0238    | -0.0263                        | -0.027     |
| UnemploymentRate                      |           | 0.000291   | 0.00086                        | -0.00509   |
|                                       |           | -0.00607   | -0.00577                       | -0.00576   |
| lnIncome                              |           | 0.872***   | 0.730***                       | 0.692***   |
|                                       |           | -0.278     | -0.272                         | -0.268     |
| Farm                                  |           |            | 0.067                          | 0.0527     |
|                                       |           |            | -0.0481                        | -0.0424    |
| Service                               |           |            | 0.000644                       | 0.00019    |
|                                       |           |            | -0.000569                      | -0.000544  |
| Homeownership                         |           |            |                                | -0.0159*** |
|                                       |           |            |                                | -0.00556   |
| Observations                          | 616       | 616        | 616                            | 616        |
| Number of county                      | 56        | 56         | 56                             | 56         |
| AIC                                   | 3811.4    | 3779.9     | 3774.7                         | 3752.4     |
| BIC                                   | 3837.9    | 3815.2     | 3818.9                         | 3801.1     |
| Robust standard errors in parentheses |           |            | *** p<0.01, ** p<0.05, * p<0.1 |            |

Table 18 Poisson Model with IVs between COPD and O3

|              | (1)           | (2)           | (3)           | (4)           |
|--------------|---------------|---------------|---------------|---------------|
| VARIABLES    | COPDVisits10k | COPDVisits10k | COPDVisits10k | COPDVisits10k |
| O3           | 0.00367       | 0.00648***    | 0.00619***    | 0.00573***    |
|              | -0.00243      | -0.00223      | -0.00222      | -0.00217      |
| lnPopulation | -0.0462       | -0.526        | -0.444        | -0.818        |
|              | -0.638        | -0.606        | -0.61         | -0.62         |
| Popdensity   | 0.000107*     | -7.94E-05     | -5.11E-05     | -2.18E-05     |
|              | -5.96E-05     | -6.58E-05     | -6.54E-05     | -6.40E-05     |
| COVID        | -0.507***     | -0.597***     | -0.577***     | -0.538***     |
|              | -0.0367       | -0.0356       | -0.0347       | -0.0376       |

|                                       |           |            |                                |            |
|---------------------------------------|-----------|------------|--------------------------------|------------|
| Age65                                 | 0.0329*** | 0.000394   | 0.00305                        | 0.00187    |
|                                       | -0.0106   | -0.0115    | -0.0109                        | -0.0114    |
| RaceNonWhite                          | -0.0382** | -0.0931*** | -0.0874***                     | -0.0931*** |
|                                       | -0.0176   | -0.024     | -0.0263                        | -0.0274    |
| UnemploymentRate                      |           | -0.000817  | -0.000269                      | -0.00577   |
|                                       |           | -0.00621   | -0.00591                       | -0.00588   |
| lnIncome                              |           | 0.975***   | 0.844***                       | 0.797***   |
|                                       |           | -0.267     | -0.255                         | -0.254     |
| Farm                                  |           |            | 0.0589                         | 0.0463     |
|                                       |           |            | -0.0487                        | -0.0427    |
| Service                               |           |            | 0.000603                       | 0.000174   |
|                                       |           |            | -0.000577                      | -0.00055   |
| Homeownership                         |           |            |                                | -0.0150*** |
|                                       |           |            |                                | -0.0056    |
| Observations                          | 616       | 616        | 616                            | 616        |
| Number of county                      | 56        | 56         | 56                             | 56         |
| AIC                                   | 3811.5    | 3774.7     | 3769.8                         | 3748.7     |
| BIC                                   | 3842.4    | 3814.5     | 3818.4                         | 3801.8     |
| Robust standard errors in parentheses |           |            | *** p<0.01, ** p<0.05, * p<0.1 |            |

Figure 8 illustrates four separate sets of regression coefficients obtained from Table 19. Each set demonstrates positive coefficients, with values spanning from 0.003 to 0.007. It is noteworthy that the fourth set is distinguished by having the lowest AIC value.

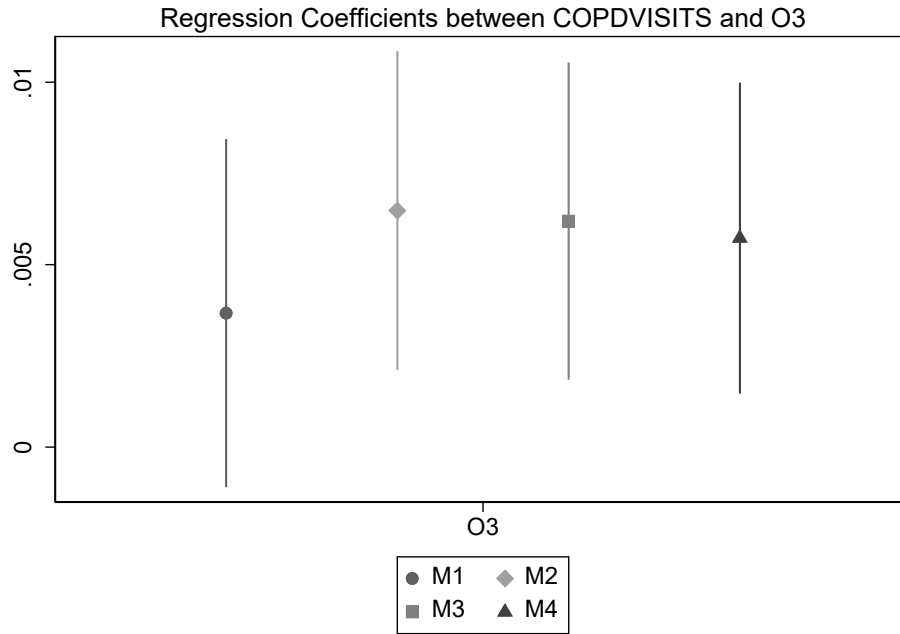


Figure 8 Regression coefficients between COPD visits and O3

Table 19 GMM Model with IVs between COPD and O3

|                  | (1)             | (2)             | (3)             | (4)             |
|------------------|-----------------|-----------------|-----------------|-----------------|
| VARIABLES        | lnCOPDVisits10k | lnCOPDVisits10k | lnCOPDVisits10k | lnCOPDVisits10k |
| O3               | 0.0118*         | 0.00305         | 0.000851        | -0.000668       |
|                  | -0.00681        | -0.00468        | -0.00455        | -0.00457        |
| lnPopulation     | 0.509           | -0.313          | -0.352          | -0.682*         |
|                  | -0.541          | -0.383          | -0.374          | -0.4            |
| Popdensity       | 5.70E-05        | 2.09E-05        | 7.06E-05        | 9.55E-05        |
|                  | -0.000107       | -0.000103       | -0.000103       | -0.000104       |
| COVID            | -0.535***       | -0.558***       | -0.528***       | -0.500***       |
|                  | -0.0314         | -0.0342         | -0.0356         | -0.0376         |
| Age65            | 0.0371***       | 0.0172**        | 0.0192**        | 0.0187**        |
|                  | -0.00789        | -0.0079         | -0.00783        | -0.0078         |
| RaceNonWhite     | -0.0426***      | -0.0506***      | -0.0372**       | -0.0351**       |
|                  | -0.015          | -0.0162         | -0.0168         | -0.0167         |
| UnemploymentRate |                 | -0.00253        | -0.00115        | -0.00392        |
|                  |                 | -0.00404        | -0.00402        | -0.00409        |

|                                |        |        |                                |             |
|--------------------------------|--------|--------|--------------------------------|-------------|
| lnIncome                       |        | 0.343* | 0.162                          | 0.103       |
|                                |        | -0.177 | -0.186                         | -0.187      |
| Farm                           |        |        | 0.0830***                      | 0.0749***   |
|                                |        |        | -0.0269                        | -0.0269     |
| Service                        |        |        | -3.55E-05                      | -0.0003     |
|                                |        |        | -0.00103                       | -0.00103    |
| Homeownership                  |        |        |                                | -0.00998*** |
|                                |        |        |                                | -0.0038     |
| Observations                   | 627    | 627    | 627                            | 627         |
| R-squared                      | 0.306  | 0.458  | 0.473                          | 0.477       |
| Number of county               | 57     | 57     | 57                             | 57          |
| AIC                            | -356.5 | -507.7 | -520.7                         | -523.2      |
| BIC                            | -329.9 | -472.2 | -476.3                         | -474.3      |
| Standard errors in parentheses |        |        | *** p<0.01, ** p<0.05, * p<0.1 |             |

The findings presented in Table 21 indicate that, in the absence of instrumental variables, the regression coefficient for the relationship between ASTHMA and O3 is negative and statistically insignificant. In contrast, the results displayed in Table 22, which incorporate instrumental variables, reveal a positive and highly significant regression coefficient for ASTHMA and O3, with the second group exhibiting the lowest Akaike Information Criterion (AIC) value. Furthermore, Table 23 provides the GMM results, demonstrating that all regression coefficients are positive and highly significant, thereby corroborating the conclusions drawn from Table 22.

Table 20 Poisson Model without IVs between ASTHMA and O3

|              | (1)          | (2)          | (3)          | (4)          |
|--------------|--------------|--------------|--------------|--------------|
| VARIABLES    | Asthma10k    | Asthma10k    | Asthma10k    | Asthma10k    |
| O3           | 0.000317     | -9.50E-05    | -0.000159    | -0.000196    |
|              | -0.000322    | -0.000307    | -0.000293    | -0.000282    |
| lnPopulation | -0.233       | 0.222        | 0.241        | 0.154        |
|              | -0.208       | -0.164       | -0.172       | -0.188       |
| Popdensity   | -0.000132*** | -8.93e-05*** | -8.06e-05*** | -7.62e-05*** |
|              | -1.51E-05    | -1.49E-05    | -1.51E-05    | -1.71E-05    |
| COVID        | -0.580***    | -0.543***    | -0.535***    | -0.527***    |
|              | -0.0103      | -0.0111      | -0.011       | -0.0127      |
| Age65        | -0.0251***   | -0.00796*    | -0.00723*    | -0.00764*    |

|                                       |          |           |                                |           |
|---------------------------------------|----------|-----------|--------------------------------|-----------|
|                                       | -0.00368 | -0.00439  | -0.00439                       | -0.00452  |
| RaceNonWhite                          | -0.0137  | 0.00149   | 0.00346                        | 0.00336   |
|                                       | -0.0103  | -0.00708  | -0.00724                       | -0.00755  |
| UnemploymentRate                      |          | 0.0114*** | 0.0117***                      | 0.0107*** |
|                                       |          | -0.00203  | -0.00201                       | -0.00204  |
| lnIncome                              |          | -0.279*** | -0.323***                      | -0.331*** |
|                                       |          | -0.0646   | -0.0649                        | -0.0697   |
| Farm                                  |          |           | 0.0224***                      | 0.0192**  |
|                                       |          |           | -0.0086                        | -0.00834  |
| Service                               |          |           | 0.000360**                     | 0.000273  |
|                                       |          |           | -0.000173                      | -0.000184 |
| Homeownership                         |          |           |                                | -0.00304* |
|                                       |          |           |                                | -0.00183  |
| Observations                          | 627      | 627       | 627                            | 627       |
| Number of county                      | 57       | 57        | 57                             | 57        |
| AIC                                   | 3235.5   | 3220.0    | 3222.8                         | 3223.9    |
| BIC                                   | 3262.2   | 3255.5    | 3267.2                         | 3272.8    |
| Robust standard errors in parentheses |          |           | *** p<0.01, ** p<0.05, * p<0.1 |           |

Table 21 Poisson Model with IVs between ASTHMA and O3

|                  | (1)          | (2)          | (3)          | (4)          |
|------------------|--------------|--------------|--------------|--------------|
| VARIABLES        | Asthma10k    | Asthma10k    | Asthma10k    | Asthma10k    |
| O3               | 0.00359***   | 0.00160***   | 0.00167***   | 0.00152***   |
|                  | -0.000621    | -0.000509    | -0.000495    | -0.00049     |
| lnPopulation     | -0.0336      | 0.287*       | 0.310*       | 0.23         |
|                  | -0.186       | -0.16        | -0.167       | -0.183       |
| Popdensity       | -0.000143*** | -0.000101*** | -9.40e-05*** | -8.93e-05*** |
|                  | -1.57E-05    | -1.63E-05    | -1.65E-05    | -1.85E-05    |
| COVID            | -0.584***    | -0.549***    | -0.542***    | -0.535***    |
|                  | -0.00987     | -0.0108      | -0.0106      | -0.0125      |
| Age65            | -0.0229***   | -0.00838*    | -0.00768*    | -0.00801*    |
|                  | -0.00352     | -0.00439     | -0.00439     | -0.00454     |
| RaceNonWhite     | -0.0166*     | -0.00153     | -2.75E-05    | 0.000135     |
|                  | -0.00986     | -0.00727     | -0.00746     | -0.0077      |
| UnemploymentRate |              | 0.0111***    | 0.0113***    | 0.0104***    |
|                  |              | -0.00199     | -0.00197     | -0.00203     |

|                                       |        |           |                                |           |
|---------------------------------------|--------|-----------|--------------------------------|-----------|
| lnIncome                              |        | -0.244*** | -0.282***                      | -0.292*** |
|                                       |        | -0.0672   | -0.0684                        | -0.0732   |
| Farm                                  |        |           | 0.0198**                       | 0.0172**  |
|                                       |        |           | -0.00865                       | -0.00834  |
| Service                               |        |           | 0.000346*                      | 0.00027   |
|                                       |        |           | -0.000179                      | -0.00019  |
| Homeownership                         |        |           |                                | -0.00267  |
|                                       |        |           |                                | -0.00184  |
| Observations                          | 627    | 627       | 627                            | 627       |
| Number of county                      | 57     | 57        | 57                             | 57        |
| AIC                                   | 3233.0 | 3220.9    | 3223.4                         | 3224.8    |
| BIC                                   | 3264.1 | 3260.8    | 3272.3                         | 3278.0    |
| Robust standard errors in parentheses |        |           | *** p<0.01, ** p<0.05, * p<0.1 |           |

Figure 9 presents four unique sets of regression coefficients obtained from Table 22. Each set demonstrates positive coefficients, with values spanning from 0.001 to 0.004. It is noteworthy that the second set is distinguished by having the lowest AIC value, which holds particular importance in this analysis.

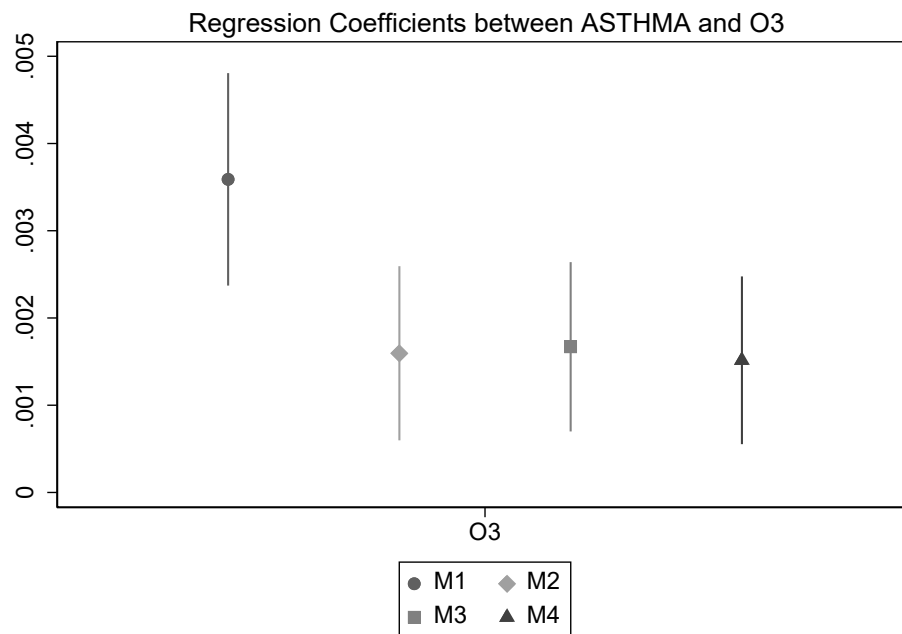


Figure 9 Regression coefficients between ASTHMA and O3

Table 22 GMM Model with IVs between ASTHMA and O3

| VARIABLES                      | (1)          | (2)          | (3)                            | (4)         |
|--------------------------------|--------------|--------------|--------------------------------|-------------|
|                                | lnAsthma10K  | lnAsthma10K  | lnAsthma10K                    | lnAsthma10K |
| O3                             | 0.0112***    | 0.00643***   | 0.00539**                      | 0.00461**   |
|                                | -0.00401     | -0.0023      | -0.00213                       | -0.00205    |
| lnPopulation                   | 0.474        | 0.494***     | 0.464***                       | 0.374**     |
|                                | -0.318       | -0.188       | -0.175                         | -0.179      |
| Popdensity                     | -0.000184*** | -0.000134*** | -0.000122**                    | -0.000113** |
|                                | -6.32E-05    | -5.08E-05    | -4.84E-05                      | -4.65E-05   |
| COVID                          | -0.590***    | -0.556***    | -0.546***                      | -0.538***   |
|                                | -0.0185      | -0.0168      | -0.0166                        | -0.0169     |
| Age65                          | -0.0182***   | -0.00912**   | -0.00848**                     | -0.00848**  |
|                                | -0.00464     | -0.00388     | -0.00367                       | -0.0035     |
| RaceNonWhite                   | -0.0246***   | -0.00858     | -0.0057                        | -0.00431    |
|                                | -0.00883     | -0.00796     | -0.00786                       | -0.00751    |
| UnemploymentRate               |              | 0.00922***   | 0.00971***                     | 0.00924***  |
|                                |              | -0.00199     | -0.00188                       | -0.00184    |
| lnIncome                       |              | -0.196**     | -0.245***                      | -0.268***   |
|                                |              | -0.087       | -0.0869                        | -0.0839     |
| Farm                           |              |              | 0.0156                         | 0.0146      |
|                                |              |              | -0.0126                        | -0.0121     |
| Service                        |              |              | 0.000341                       | 0.000286    |
|                                |              |              | -0.000483                      | -0.000464   |
| Homeownership                  |              |              |                                | -0.00217    |
|                                |              |              |                                | -0.0017     |
| Observations                   | 627          | 627          | 627                            | 627         |
| R-squared                      | 0.745        | 0.861        | 0.877                          | 0.888       |
| Number of county               | 57           | 57           | 57                             | 57          |
| AIC                            | -1021.2      | -1397.7      | -1472.7                        | -1527.9     |
| BIC                            | -994.6       | -1362.2      | -1428.3                        | -1479.0     |
| Standard errors in parentheses |              |              | *** p<0.01, ** p<0.05, * p<0.1 |             |

### ***Model Selection***

Like the model selection process discussed in Chapter Two, we employ the Akaike Information Criterion to identify the most suitable model. AIC serves as a statistical metric for model selection, providing an estimation of the relative quality of various statistical models in relation to a specific

dataset. This criterion aids in discerning the model that achieves an optimal balance between fit adequacy and model complexity. While AIC does not function as a hypothesis test, it offers a structured methodology for comparing models and selecting the one that is most likely to generalize effectively to new, unseen data. By synthesizing the findings from the 18 tables presented in the preceding section, it is evident that the models with the lowest AIC values in each respective table are Model 4 in Table 7, Model 2 in Table 10, Model 4 in Table 13, Model 2 in Table 16, Model 4 in Table 19, and Model 2 in Table 22. These results are documented in the six tables provided in the previous section.

### ***Robustness Check***

Robustness checks for GMM involve assessing the stability and reliability of GMM results by altering model specifications or estimation techniques. This process is crucial for confirming that the research conclusions are not unduly affected by specific decisions made during the analytical process. Additionally, it serves to validate the chosen model specifications and estimation methods, thereby confirming that the research outcomes are not merely a product of analytical choices. By establishing robustness, the credibility and persuasive power of the research findings are significantly enhanced. The preceding findings indicate that GMM is employed to assess the efficacy of the Poisson control function model. An examination of the results presented in Tables 8, 14, 17, 20, and 23 reveals that GMM serves as a highly effective instrument for stability testing and has been instrumental in the context of this research. The results of GMM are comparable to those of the Poisson model; however, the significance is not as robust as that of the Poisson model. Nevertheless, this method can bolster the validity of the findings obtained from the Poisson model.

### ***Bootstrapping Method***

We use a bootstrap method to correct the biased standard errors and use 500 resampling in bootstrap. We only choose the models with the lowest AIC values and the results are as follows,

Table 23 Bootstrapping Method Results

| Poisson_IVs               | COPD_AQI  | ASTHMA_AQI | COPD_PM25 | ASTHMA_PM25 | COPD_O3   | ASTHMA_O3 |
|---------------------------|-----------|------------|-----------|-------------|-----------|-----------|
| Model                     | Model 4   | Model 2    | Model 4   | Model 2     | Model 4   | Model 2   |
| Coefficients              | 0.0183438 | 0.0114027  | 0.0128796 | 0.0092626   | 0.0057276 | 0.0015957 |
| Bootstrap standard errors | 0.0032718 | 0.0012913  | 0.004289  | 0.001173    | 0.0022143 | 0.0005052 |

As shown in Table 24, using bootstrapping methods to correct standard errors in the Poisson model, both the sign and significance level for key independent variables remain the same. The results of this method show that the Poisson model is convincing and serves as an effective tool.

### Discussion and Policy Recommendation

This chapter examines the empirical relationship between two categories of respiratory diseases and three indicators of air quality. The analysis employs a two-stage methodology, beginning with fixed effects panel regression in the first stage, followed by instrumental variable techniques and a Poisson control function model in the second stage. A total of four distinct sets of control variables are utilized to derive the regression results. The findings indicate a significant coefficient for the proportion of electric vehicles relative to gasoline-powered vehicles, as well as a positive correlation between the three air quality indicators and health outcomes. Additionally, the AIC values for each variable set are compared, leading to the identification of the optimal set characterized by the lowest AIC value. A comparative analysis of the Generalized Method of Moments and Poisson control function models further validated the efficacy of the instrumental variable approach. The standard variance was optimized through the Bootstrapping method, which mitigates bias in the Poisson regression results. While the findings are largely consistent with the initial hypotheses, several limitations persist. Firstly, the sample size is insufficiently large. Secondly, there are gaps in the data, and other factors influencing respiratory diseases, such as industrial and household pollution, have not been accounted for. Moreover, the instrumental variables employed in the model require further validation, and the control variables necessitate empirical data to assess their validity. Although the results generally support the hypotheses, future

research is anticipated to utilize diverse datasets and sample sizes for similar investigations. Furthermore, the Difference-in-Differences (DID) approach is recognized as a valuable empirical research tool for this study.

As of 2024, the proportion of electric vehicles in California remains relatively low; however, this study offers valuable insights for future research on electric vehicles. Policymakers should acknowledge that, in the long term, the adoption of electric vehicles is an inevitable trend. In regions of California with a high ratio of renewable energy, the market potential for electric vehicles is expected to be substantial, particularly regarding health benefits. Consequently, the government should implement additional policies and support mechanisms to encourage the widespread adoption of electric vehicles.

## **Conclusion**

This chapter provides a comprehensive introduction to the improvements in air quality resulting from the adoption of electric vehicles in California and their potential health impacts. First, we briefly review the research literature on the relationship between air pollution and health, as well as the direct environmental impacts and indirect health effects associated with the implementation of electric vehicles over the past decade. Currently, many scholars support the positive effects of electric vehicles on both air quality and public health. Based on existing data and historical literature, we propose two hypotheses. Next, we outline the stages of data introduction, model establishment, and result interpretation. By employing a Poisson control function model with instrumental variables, we obtained results that align closely with our hypotheses. The findings indicate a significant positive correlation between three different air quality indicators and two types of respiratory diseases. Additionally, by comparing the regression coefficients of four distinct groups of control variables, we identify the model with the lowest AIC value. At the conclusion of the article, we conduct a robustness check using the GMM method and optimize the standard errors using the Bootstrapping Method.

In summary, this chapter encapsulates the essence of the entire dissertation and serves as a bridge to the cost-benefit analysis presented in the next chapter. Due to incomplete data and model biases, the conclusions drawn require further validation. Although the large-scale adoption of

electric vehicles encounters numerous challenges—ranging from policy-related issues and technical obstacles to local protectionism and political ideologies—humanity is striving to embrace electric vehicles from the perspective of sustainable development, continuously fostering conditions for better utilization of electric vehicles worldwide.

## Appendices

Table A. Value for RateEV\_Gas

| F value    | AQI_Model 1 | PM25_Model 4 | O3_Model 3 |
|------------|-------------|--------------|------------|
| RateEV_Gas | 8.53        | 7.67         | 4.17       |

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