IEc

An Assessment of the Health Burden of Ambient $PM_{2.5}$ Concentrations in Virginia

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CHAPTER 1 | INTRODUCTION

Decarbonization policies that promote renewable energy sources and electric mobility have dual benefits – they reduce greenhouse gas (GHG) emissions which contribute to climate change and they reduce emissions of conventional air pollutants such as fine particulate matter ($PM_{2.5}$) that are associated with increases in premature mortality and cardiovascular and respiratory morbidity. The State of Virginia recently enacted the Virginia Clean Economy Act, which requires nearly all coal-fired power plants to close by 2024 and mandates 100 percent renewable energy generation in the state by 2050. The state is considering legislation to adopt California's stringent motor vehicle emissions standards, as allowed under Section 177 of the Clean Air Act (42 U.S.C. §7507). Should this legislation pass, Virginia would become the 14th state to adopt California's standards for Low Emission Vehicles (LEVs), greenhouse gas (GHG) emissions, and Zero Emission Vehicles (ZEVs), joining Maryland, Delaware and many other states in the mid-Atlantic and New England regions. Both of these policy initiatives, along with other transportation reforms, would be expected to generate benefits in terms of reduced GHG emissions and reduced concentrations of pollutants such as $PM_{2.5}$.

Virginia Clinicians for Climate Action (VCCA) is interested in better understanding the public health burden of pollutants such as $PM_{2.5}$ in the state of Virginia. This includes not only the number of premature mortalities, hospital admissions, emergency department (ED) visits, and other morbidity impacts associated with PM levels, but how those effects may be distributed among different communities in the state, including those that are particularly vulnerable or disadvantaged. In addition, they wish to understand the contribution of motor vehicles to the overall $PM_{2.5}$ burden and how policies such as the Section 177 LEV and ZEV programs might reduce that burden. In response, IEc, with assistance from subcontractor SC&A, has prepared a screening assessment of health burden based on relatively current $PM_{2.5}$ levels in the state and conducted a reduced-form analysis of potential impacts of changes in emissions from light duty vehicles on $PM_{2.5}$ concentrations and related morbidity and mortality impacts in the year 2035.

Recent concentrations of fine particulate matter in Virginia are expected to contribute to 3,000 premature deaths, 3,600 hospitalizations, and 1,600 emergency department visits on an annual basis.

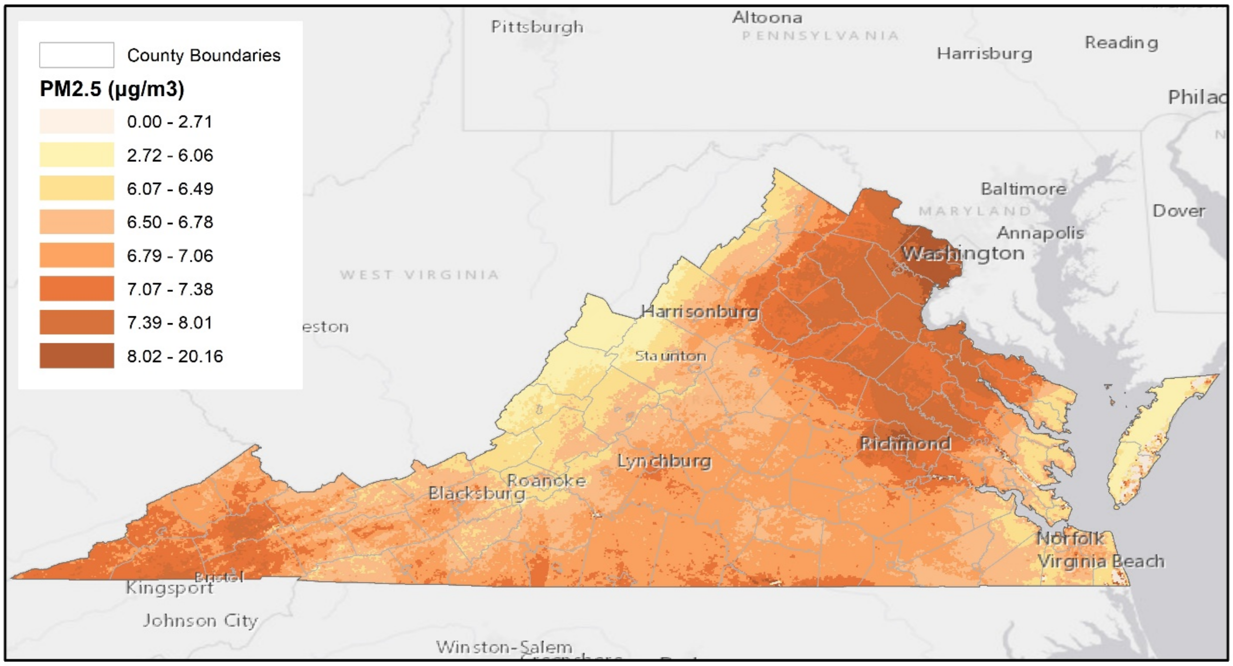
This burden amounts to $23 billion in social welfare costs each year, realized through increased healthcare costs, reduced labor productivity, and reduced personal wellbeing stemming from adverse health effects. The cost of air pollution could be reduced through actions that reduce the emissions of $PM_{2.5}$ and its precursor emissions (e.g., nitrogen oxides, sulfur dioxide, ammonia). The following sections provide additional detail on ambient $PM_{2.5}$ concentrations and $PM_{2.5}$-attributable health burden in Virginia, including impacts specific to the transportation sector.

TOTAL BURDEN

Annual mean $PM_{2.5}$ concentrations have ranged between 6 and 9 µg/m^3 at Virginia air quality monitors between 2016 and 2018.[1] These concentrations, while below the primary U.S. National Ambient Air Quality Standard of 12 µg/m^3, can still pose significant health risks to Virginia residents. Researchers such as Turner et al. (2016), and Di et al. (2017) have continued to observe mortality impacts of fine particle exposure over time, even as $PM_{2.5}$ levels have declined in the U.S. Exhibit 1 presents estimated annual mean $PM_{2.5}$ concentrations in 2018 based on a 2008 modeled 1 km x 1 km air quality surface from Goldberg et al. (2019) scaled to 2018 using $PM_{2.5}$ monitor data in and around Virginia.

[1] See the 2018 Virginia Ambient Air Monitoring Data Report at https://www.deq.virginia.gov/Portals/0/DEQ/Air/AirMonitoring/2018_Virginia_Ambient_Air_Monitoring_Report.pdf.

EXHIBIT 1. ESTIMATED 2018 VIRGINIA $PM_{2.5}$ CONCENTRATIONS



Relative to the dozens of monitoring stations in Virginia, the modeled surface provides substantial spatial heterogeneity in concentrations, with notably high pollutant levels in urban areas including Fairfax County, the City of Richmond, and much of Southwest Virginia. Using U.S. Environmental Protection Agency's (USEPA's) BenMAP-CE software, we estimate the adverse health effects associated with the ambient $PM_{2.5}$ concentrations presented above. The resulting $PM_{2.5}$-attributable health burden associated with these concentrations, which include both anthropogenic and non-anthropogenic fine particles, is presented in Exhibit 2.

EXHIBIT 2. $PM_{2.5}$ ATTRIBUTABLE HEALTH BURDEN IN VIRGINIA (INCLUDES NON-ANTHROPOGENIC $PM_{2.5}$)

HEALTH ENDPOINT	AGES	ANNUAL INCIDENCE	VALUATION (MILLIONS USD 2015$)
Mortality, Adults			
Estimate 1 (Lepeule et al. 2012) (25+)	25+	4,800	$35,000
Estimate 2 (Di et al. 2017) (65+)	65+	2,000	$15,000
Estimate 3 (Turner et al. 2016) (30+)	30+	2,200	$16,000
Mean of estimates 1 and 3		3,000	$22,000
Morbidity effects			
Hospitalizations, cardiovascular[a]	18+	600	$24
Hospitalizations, respiratory	65+	660	$16
Emergency room visits, asthma	All	1,600	$0.68
Stroke[b]	65+	110	$3.1

HEALTH ENDPOINT	AGES	ANNUAL INCIDENCE	VALUATION (MILLIONS USD 2015$)
Low birth weight[c]	0	480	$6.5
New onset asthma[d]	0-17, 35+ (females only)	7,000	$270
Exacerbated asthma[e]	6-18	230,000	$12
Acute bronchitis[f]	8-12	3,600	$1.6
Upper respiratory symptoms[g]	9-11	70,000	$2.2
Lower respiratory symptoms[h]	7-14	46,000	$0.91
Lost work days	18-64	360,000	$66
Minor restricted activity days (MRADs)[i]	18-64	2,100,000	$140
Acute myocardial infarction (non-fatal)	65+	2,200	$280
Total			**$23,000**

[a] Excludes myocardial infarctions, which are estimated separately.
[b] Based on hospital admissions for stroke, ICD-9 codes 430 -436.
[c] We define this endpoiont as a child carried to term (37 - 41 weeks gestation) weighing less than 2500 g at birth. EPA (2019b) finds evidence of $PM_{2.5}$ related birth outcomes to be suggestive, but not sufficient to infer a causal relationship at this time.
[d] The most recent U.S. EPA Integrated Science Assessment for $PM_{2.5}$ determined that there is likely to be a causal relationship between long-term exposure to $PM_{2.5}$ and array of respiratory effects, including the incidence of new cases of-asthma. They note, "Epidemiologic studies provide strong evidence for effects on lung development, with additional evidence for the development of asthma in children due to long-term PM2.5 exposure." (EPA, 2019b)
[e] A worsening of existing asthma cases, including cough, shortness of breath, and wheeze.
[f] Acute bronchitis reflects a doctor-diagnosed case of bronchitis.
[g] Upper respiratory symptoms include one or more of the following: runny or stuffy nose; wet cough; and burning, aching, or red eyes.
[h] Lower respiratory symptoms defined as at least two of the following symptoms: cough, phlegm from chest, pain in chest, or wheezing.
[i] An MRAD is a restricted activity day that does not result in a day of work loss or bed disability but results in minor conditions resulting in a reduction of activity.

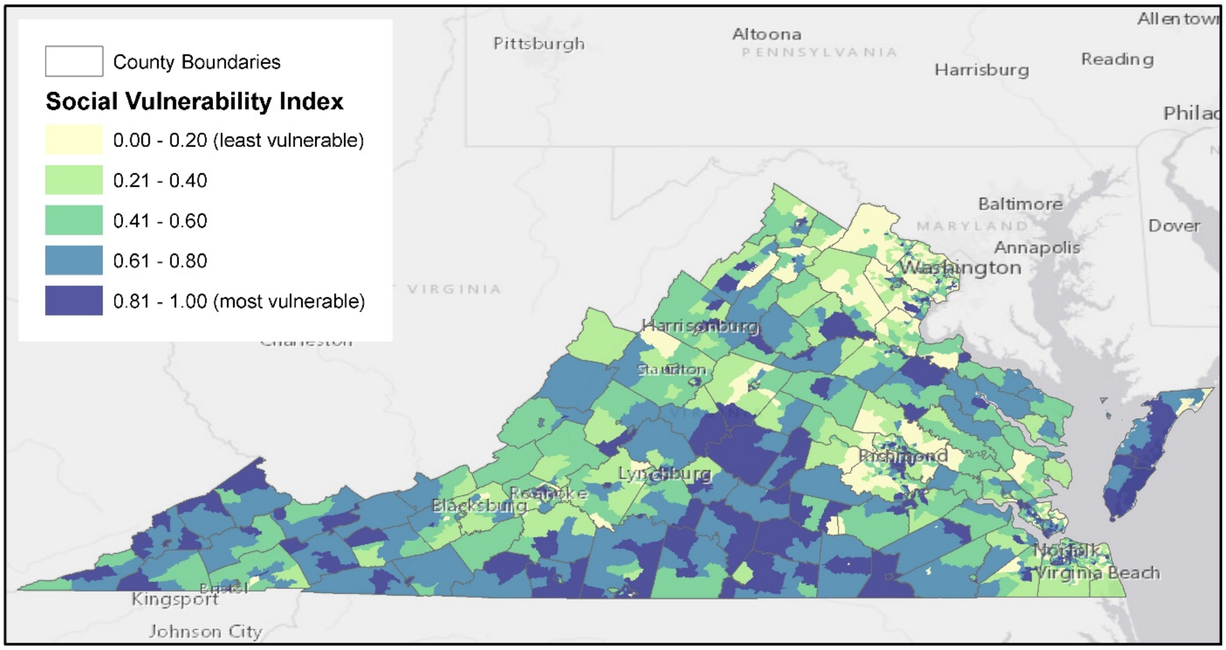
$PM_{2.5}$-attributable health costs are substantial: we estimate thousands of premature deaths, hospitalizations, and emergency room visits are caused by pollutant concentrations in Virginia on an annual basis. In addition, $PM_{2.5}$ is linked to thousands of cases of new onset asthma, and hundreds of thousands of asthma exacerbations and lost work days. Among the 7,000 estimated cases of new onset asthma, roughly 4,000 cases occur in children (ages 0 through 17 years). The economic value of these adverse effects totals $23 billion, driven largely by mortality effects. Notably, the Lepeule-derived mortality estimate (4,800 premature deaths among adults 25 and older) is significantly larger than the estimates from Di et al. (2,000 among adults 65 and older) and Turner et al. (2,200 among adults 30 and older). The difference is explained primarily by the stronger association found in the Lepeule et al. (2012) study between $PM_{2.5}$ concentrations and premature death.

Air pollution related health costs are borne disproportionately by the most socially vulnerable communities in Virginia.

Using the U.S. Centers for Disease Control (CDC) definition of social vulnerability—impacted by factors including socioeconomic status, household composition and disability, minority status and language, and housing type and transportation options—we stratify our estimates of health burden by Social

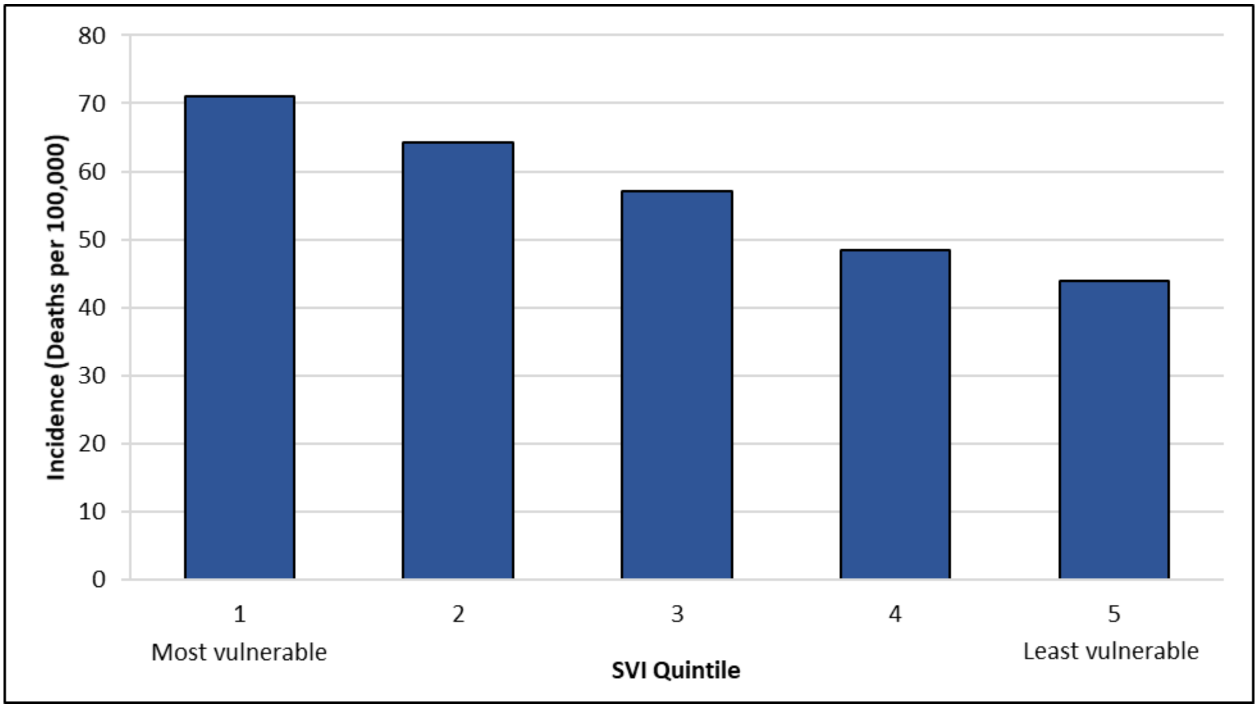
Vulnerability Index (SVI) quintile. Quintile 1 represents the most vulnerable Census tracts and Quintile 5 represents the least vulnerable tracts. Exhibit 3 presents the distribution of SVI in Virginia by Census tract. We highlight CDC's data normalizing SVI values to other Census tracts within the state—0.5 represents the median SVI Census tract in Virginia.

EXHIBIT 3. 2018 SVI BY CENSUS TRACT



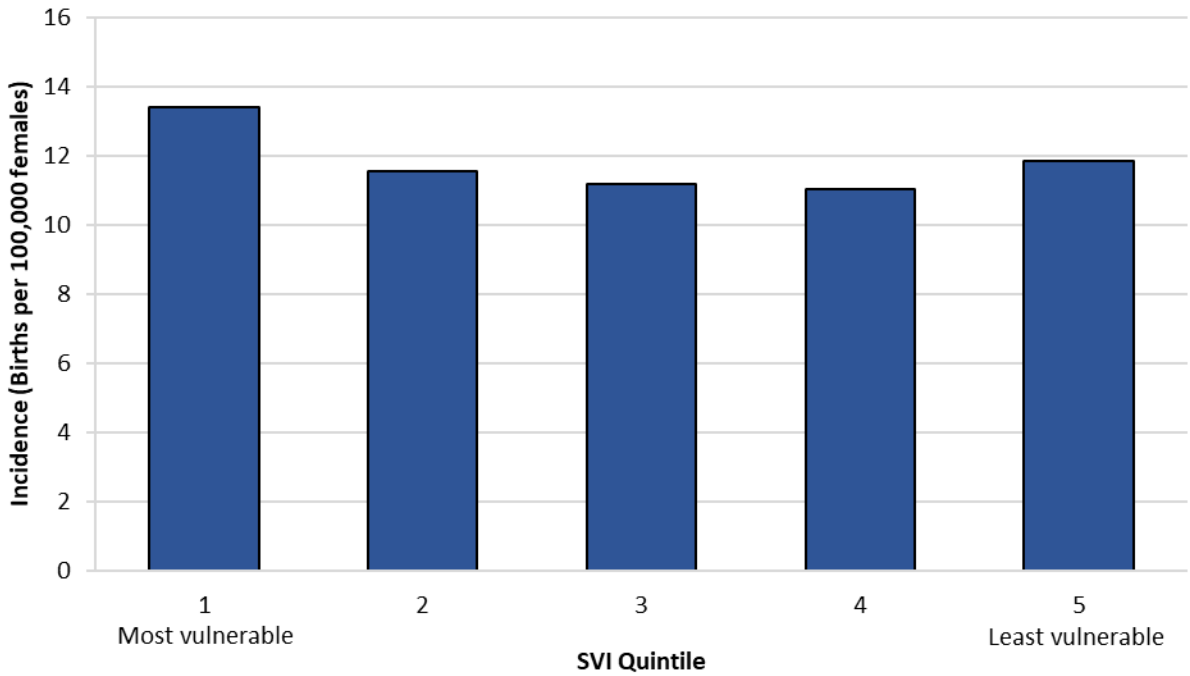
Using the spatial distribution of SVI (Exhibit 3) and our estimated air pollution related deaths (Exhibit 2), we illustrate how these two variables are correlated. For each SVI quintile, we present the statewide air pollution attributable mortality incidence in Exhibit 4, expressed in terms of deaths per 100,000 individuals. Mortality estimates reflect the mean of the three concentration-response functions estimated in BenMAP-CE.

EXHIBIT 4. AIR POLLUTION RELATED DEATHS BY SVI QUINTILE



Overall, we find a strong inverse relationship between estimated air pollution attributable mortality and SVI. That is, mortality incidence associated with air pollution is highest among the most vulnerable populations in Virginia. This is observed even though $PM_{2.5}$ levels are relatively uncorrelated with SVI quintile in Virginia. Rather, the trend in Exhibit 4 largely reflects higher baseline mortality rates in the more vulnerable SVI quintiles. High baseline rates of death are correlated with variables used to construct the SVI, most notably age (most air pollution deaths occur in senior populations) and socioeconomic variables. The risk estimates reported in public health studies and used in the BenMAP-CE tool are typically measured as proportional to a baseline hazard – that is the size of the impact of a change on an exposed population depends in part on the baseline mortality rate in that group. As a result, the same $PM_{2.5}$ concentration can have a larger impact on a community with higher levels of illness and frailty and a higher baseline mortality rate. Conversely, these communities can potentially benefit more than less health challenged communities from similar reductions in exposure. Geographically coarse incidence rate data for most of the morbidity endpoints we analyzed do not facilitate similar analyses for most other health effects in our analysis; however, Exhibit 5 demonstrates how the incremental increase in the incidence rate for low birth weight potentially linked to air pollution is highest in the most vulnerable quintile.

EXHIBIT 5. AIR POLLUTION RELATED TERM LOW BIRTH WEIGHT INCIDENCE BY SVI QUINTILE



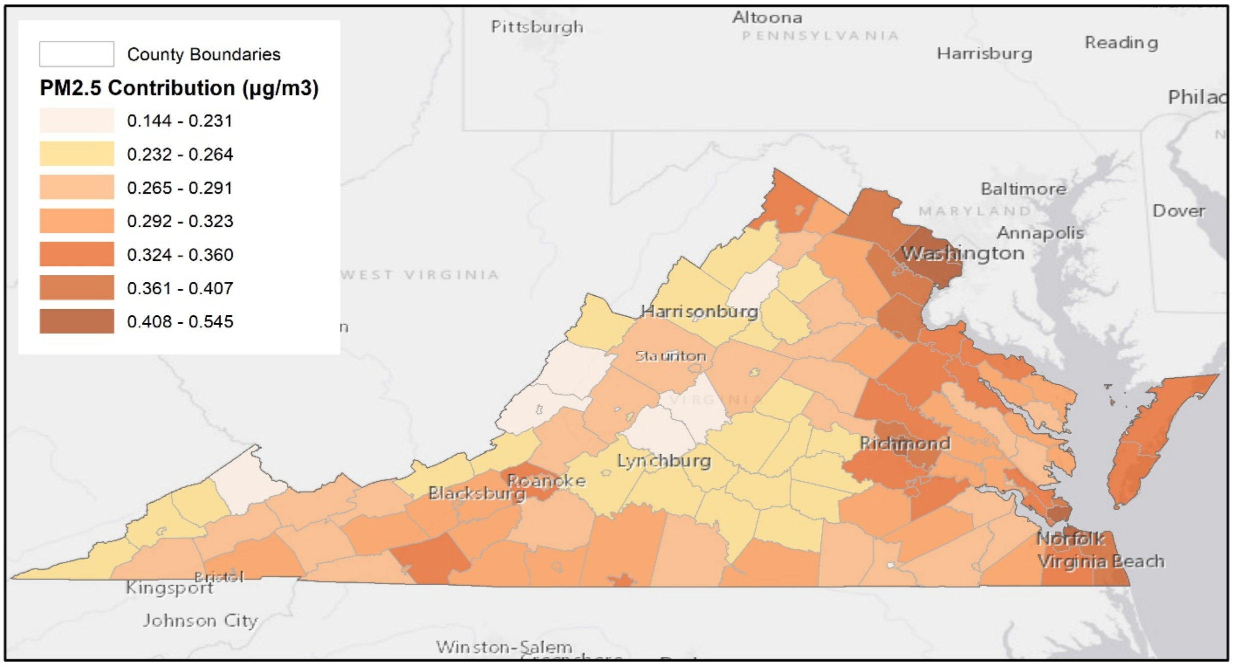
Note: EPA (2019b) finds evidence of PM2.5 related birth outcomes to be suggestive, but not sufficient to infer a causal relationship at this time

Though less pronounced than for mortality, we observe a higher incidence of air pollution attributable low weight births among the most vulnerable Census tracts. Combined, these results suggest that air pollution controls—when designed thoughtfully—may address existing inequalities in health outcomes by reducing the disproportionate burden in vulnerable communities, while also achieving broad-based benefits. We note that data limitations may mask greater inequalities. Most notably, the finding that $PM_{2.5}$ levels are not systematically higher in socially vulnerable communities is somewhat surprising. More localized urban-scale studies of air quality with finer resolution modeling may illustrate "hot spots" of air pollution occurring in poor or otherwise disadvantaged communities (e.g., residences near major roadways) that are not captured in our analysis. Additionally, much of our incidence rate data for morbidity effects are at a relatively coarse spatial scale, and our analysis could benefit from the use of more refined data from the state Department of Health. In the sections that follow, we rely on coarser resolution air quality data. While limiting our ability to better characterize environmental justice concerns, these data facilitate analyzing the subset of $PM_{2.5}$ concentrations attributable to the transportations sector.

U.S. TRANSPORT EMISSIONS

Emissions from highway vehicles contribute to ambient $PM_{2.5}$ concentrations and resulting adverse health effects in Virginia. Statewide pollutant concentrations include contributions from numerous sources, including transportation emissions both within and outside of state boundaries. In many cases, emissions from bordering and nearby states mix and travel in the atmosphere, resulting in higher ambient $PM_{2.5}$ levels in Virginia. In the state's more densely populated counties, U.S. highway vehicles are responsible for up to 0.5 µg/m^3 of ambient $PM_{2.5}$ levels (5 to 10 percent of the total), as illustrated in Exhibit 6. These county-level estimates, derived using USEPA's COBRA software, represent 2016 emissions and air quality levels.

EXHIBIT 6. $PM_{2.5}$ CONCENTRATIONS ATTRIBUTABLE TO U.S. HIGHWAY VEHICLE EMISSIONS



While these contributions reflect only a fraction of overall $PM_{2.5}$ concentrations, they still result in a measurable transportation-attributable health burden in Virginia. Exhibit 7 summarizes this burden, accounting for highway vehicle emissions in and around Virginia.

EXHIBIT 7. ADVERSE HEALTH EFFECTS IN VIRGINIA STEMMING FROM U.S. HIGHWAY VEHICLE EMISSIONS

HEALTH ENDPOINT	ANNUAL INCIDENCE	VALUATION (MILLIONS USD 2015$)
Mortality		
Estimate 1 (Lepeule et al. 2012)	310	$2,400
Estimate 2 (Di et al. 2017)	130	$1,000
Estimate 3 (Turner et al. 2016)	140	$1,100
Mean estimate	190	$1,500
Morbidity effects		
Hospitalizations, cardiovascular	37	$1.7
Hospitalizations, respiratory	40	$1.1
Emergency room visits, asthma	91	$0.045
Stroke	7.1	$0.24
Low birth weight*	29	$0.45
New onset asthma	450	$19

HEALTH ENDPOINT	ANNUAL INCIDENCE	VALUATION (MILLIONS USD 2015$)
Exacerbated asthma	5,300	$0.31
Acute bronchitis	210	$0.10
Upper respiratory symptoms	3,900	$0.13
Lower respiratory symptoms	2,600	$0.055
Lost work days	21,000	$4.2
Minor restricted activity days	120,000	$8.0
Acute myocardial infarction (non-fatal)	150	$21
Total		**$1,600**

* EPA (2019b) finds evidence of $PM_{2.5}$ related birth outcomes to be suggestive, but not sufficient to infer a causal relationship at this time.
See Exhibit 2 for notes on other health endpoints.

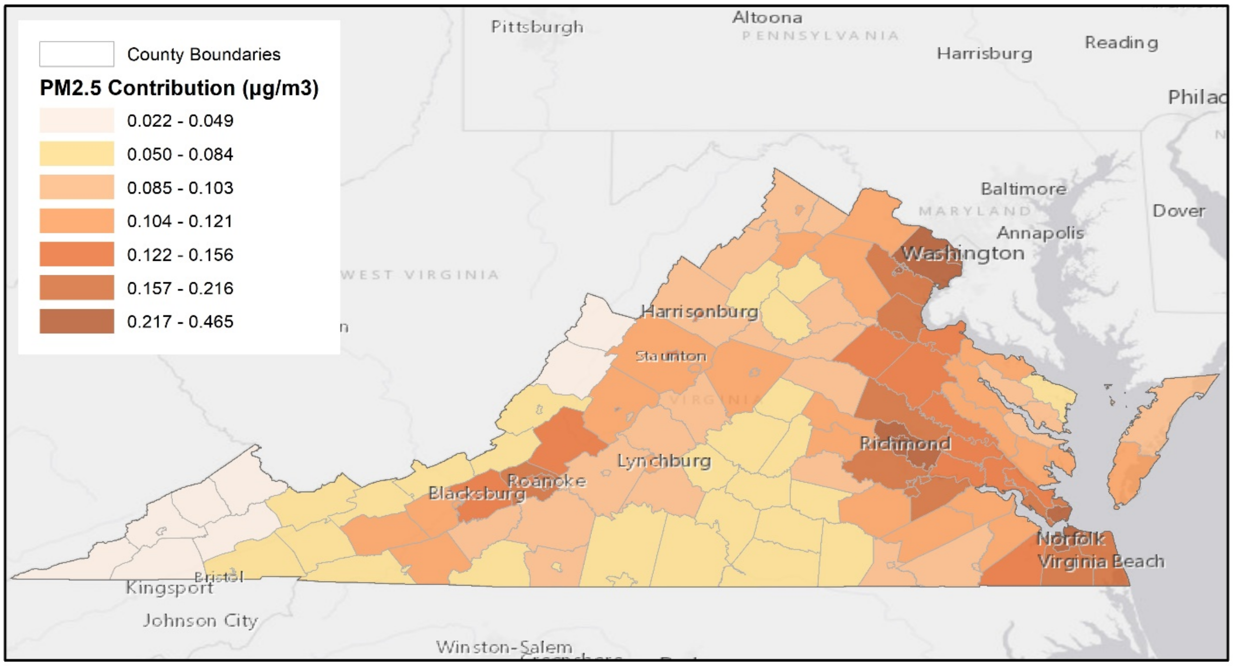
In total, transportation sources are responsible for 190 air pollution related premature deaths annually in Virginia. The total transportation burden ($1.6 billion) represents roughly 7 percent of the total $PM_{2.5}$ attributable burden, and a larger share of the anthropogenic portion of $PM_{2.5}$ concentrations (currently unquantified).

As with total ambient concentrations, we note that emissions from the transportation sector disproportionately impact socially vulnerable communities. The SVI-specific pattern of mortality and low birth weight are comparable to the distributions presented for total $PM_{2.5}$ levels (Exhibits 4 and 5); however, the transportation-specific results suffer from coarser resolution data. We note that distributional concerns may be heightened for transportation given pollutant corridors near major roadways. In many cases, high pollutant concentrations decay rapidly with distance from roadway, requiring highly resolved air quality, population, incidence, and demographic data to analyze.

VA TRANSPORT EMISSIONS

In the previous section, we presented the health burden associated with U.S. emissions from highway vehicles. Absent cooperation with other states and the effects of interstate transport (e.g., Virginia drivers crossing into the District of Columbia), Virginia policymakers are primarily able to influence transportation emissions within the state. These within-state contributions are presented in Exhibit 8 at the county level.

EXHIBIT 8. $PM_{2.5}$ CONCENTRATIONS ATTRIBUTABLE TO VIRGINIA HIGHWAY VEHICLE EMISSIONS



The distribution of $PM_{2.5}$ concentrations linked to VA highway vehicles is comparable to Exhibit 6, which displays the contributions from all U.S. highway vehicles. Transportations sector contributions are highest in Richmond, Norfolk, and Northern Virginia. High concentrations are also observed in Roanoke and along the I-81 corridor in Western Virginia. By definition, the Virginia contributions represent a subset of U.S. contributions. This is most notable in rural counties along the North Carolina border, which are likely affected by transportation emissions in and around nearby cities (e.g., Winston-Salem, Greensboro, Raleigh, Durham). These counties have significantly reduced transportation contributions to $PM_{2.5}$ when excluding non-Virginia emissions. Nonetheless, the transportation-attributable health burden in Virginia is significant when considering emissions within the state. Exhibit 9 presents the health burden estimates associated with Virginia transportation emissions.

EXHIBIT 9. ADVERSE HEALTH EFFECTS IN VIRGINIA STEMMING FROM VA HIGHWAY VEHICLE EMISSIONS

HEALTH ENDPOINT	ANNUAL INCIDENCE	VALUATION (MILLIONS USD 2015$)
Mortality		
Estimate 1 (Lepeule et al. 2012)	150	$1,200
Estimate 2 (Di et al. 2017)	61	$490
Estimate 3 (Turner et al. 2016)	65	$520
Mean estimate	92	$720
Morbidity effects		
Hospitalizations, cardiovascular	18	$0.81

HEALTH ENDPOINT	ANNUAL INCIDENCE	VALUATION (MILLIONS USD 2015$)
Hospitalizations, respiratory	20	$0.55
Emergency room visits, asthma	46	$0.022
Strokes	3.4	$0.12
Low birth weight*	15	$0.23
New onset asthma	220	$9.7
Exacerbated asthma	2,600	$0.16
Acute bronchitis	110	$0.052
Upper respiratory symptoms	1,900	$0.066
Lower respiratory symptoms	1,300	$0.028
Lost work days	10,000	$2.2
Minor restricted activity days	58,000	$4.0
Acute myocardial infarction (non-fatal)	71	$10
Total		**$750**

* EPA (2019b) finds evidence of $PM_{2.5}$ related birth outcomes to be suggestive, but not sufficient to infer a causal relationship at this time.
See Exhibit 2 for notes on each health endpoint.

The overall health burden of vehicle emissions in Virginia is approximately $750 million per year. This represents half of the state-wide burden of vehicle emissions, with the other half originating from vehicles outside of the state. Policymakers may view the $750 million estimate as an upper bound on the potential annual benefits that may be achieved through particulate matter-focused emissions control actions in the transportation sector. Transportation sector policies aimed at lessening emissions of fine particles and their precursors will lessen this statewide burden. Controls aimed at reducing ozone and other criteria pollution and greenhouse gas emissions related controls may yield benefits additional to those related to $PM_{2.5}$. It is also worth noting that Virginia policymaking in this area may produce benefits for neighboring states.

SUMMARY OF HEALTH BURDEN

In summary, we highlight the following results from our review of available data and estimation of health impacts in the State of Virginia:

- Annual mean $PM_{2.5}$ levels observed at air quality monitors in the State of Virginia are recently between 6 and 9 µg/m^3. Concentrations may exceed these values in “hot spots” near roadways or downwind of point sources.
- 3,000 premature deaths or more may be attributed to ambient $PM_{2.5}$ levels in the state. Transportation emissions nationwide account for 190 of these deaths, with 92 resulting from vehicle emissions within the state.
- Ambient $PM_{2.5}$ results in significant adverse health effects among children. These effects include 4,000 cases of new onset asthma, 100,000 instances of respiratory symptoms, and 230,000 asthma exacerbations each year.
- Monetized estimates of social welfare losses from $PM_{2.5}$ exceed $23 billion annually.

- These estimates do not account for the adverse effects of other pollutants, including ozone and nitrogen oxides. Greenhouse gases also pose significant health and environmental risks associated with climate change.
- The most vulnerable Census tracts observe $PM_{2.5}$ attributable mortality incidence rates that are 61 percent higher than analogous rates in the least vulnerable tracts.

CHAPTER 3 | THE BENEFITS OF VEHICLE ELECTRIFICATION

The State of Virginia has proposed legislation to direct the State Air Pollution Control Board to adopt California's stringent motor vehicle emissions standards, as allowed under Section 177 of the Clean Air Act (42 U.S.C. §7507). Passage of this legislation would sync Virginia's vehicle emissions standards (currently aligned with Federal standards) with California's standards for Low Emission Vehicles (LEVs), greenhouse gas (GHG) emissions, and Zero Emission Vehicles (ZEVs). In this chapter, we illustrate the potential benefits of implementing these standards. We present the benefits in one future year, 2035, assuming that vehicle model years 2025-2035 follow the CA standards for the 2025 model year.

ZERO EMISSION VEHICLES PROGRAM

Virginia's proposed adoption of the ZEV portion of the Section 177 waiver would reduce ambient $PM_{2.5}$ concentrations in the state. We model this adoption by assessing how criteria pollutant emissions and resulting $PM_{2.5}$ levels would change with initial adoption of the California ZEV standards for model year 2022. Exhibit 10 presents the projected vehicle fleet in 2035 under a business as usual (BAU) and ZEV scenario.

EXHIBIT 10. 2035 VEHICLE MILES TRAVELED (VMT) BY VEHICLE AND FUEL TYPE

		2035 VMT (MILLION MILES)		VMT FRACTION	
VEHICLE TYPE	FUEL TYPE	BAU	ZEV	BAU	ZEV
Light duty	Gasoline	90,921	78,390	88.4%	76.2%
	Diesel	1,715	1,481	1.7%	1.4%
	E-85	3,269	2,808	3.2%	2.7%
	Electricity	140	13,366	0.1%	13.0%
Heavy duty	Gasoline	290	290	0.3%	0.3%
	Diesel	6,459	6,459	6.3%	6.3%
	Compressed natural gas	39	39	0.0%	0.0%

Compared to the negligible vehicle miles traveled by electric vehicles under the BAU scenario (0.1 percent), we project that ZEVs will represent 13 percent of all vehicle miles in 2035. This effect is driven by light duty vehicles (LDVs), with the largest switch from gasoline LDVs to ZEVs. We do not model fuel changes within the heavy duty vehicle fleet. Notably, ZEV adoption in the baseline and policy scenarios may differ substantially from our assumed projections (0.1 percent and 13 percent, respectively) depending on a number of factors that might influence ZEV demand (e.g., ZEV subsidies, scrappage programs). To the extent that the ZEV program leads to greater and more rapid ZEV adoption, greater benefits are likely to accrue.

Two competing factors influence criteria pollutant emissions. First, ZEVs emit near-zero pollution relative to internal combustion engines in conventional vehicles.[2] Second, ZEVs increase electricity consumption in Virginia, resulting in increased emissions from electric generating units (EGUs). In 2035, we estimate that ZEV adoption would increase statewide electricity consumption by ZEVs from by a factor of 100 (47,535 to 4,544,498 MWH). As detailed in Appendix A, the reduction in tailpipe emissions greatly outweighs the marginal effects of increased electric generation. As we illustrate below, this is true for every Virginia county. Air quality is expected to improve statewide, even in counties containing EGUs. Additionally, we may be overstating additional EGU emissions given Virginia's recent involvement in the Regional Greenhouse Gas Initiative (RGGI), which places a cap on GHG emissions across participating Northeast and Mid-Atlantic states.[3]

Because of ZEV's reliance on the electric grid, we model ZEV impacts with and without Virginia's adoption of the Clean Economy Act (CEA), signed into law in April 2020. The law requires cleaner energy production in the state: Dominion Energy is required to be 100 percent carbon free by 2045 and Appalachian Power to be 100 percent carbon free by 2050. Exhibit 11 illustrates how the 2035 fuel mix for electric generation is expected to change in Virginia with the adoption of the CEA. The business as usual (BAU) scenario assumes no adoption of the CEA.

EXHIBIT 11. PROJECTED 2035 VIRGINIA FUEL MIX, WITH AND WITHOUT CEA ADOPTION

FUEL	PERCENTAGE OF VIRGINIA'S FUEL MIX	
	BUSINESS AS USUAL SCENARIO	CLEAN ECONOMY ACT SCENARIO
Coal	11%	6%
Natural gas	55%	28%
Nuclear	21%	21%
Renewable sources	13%	45%

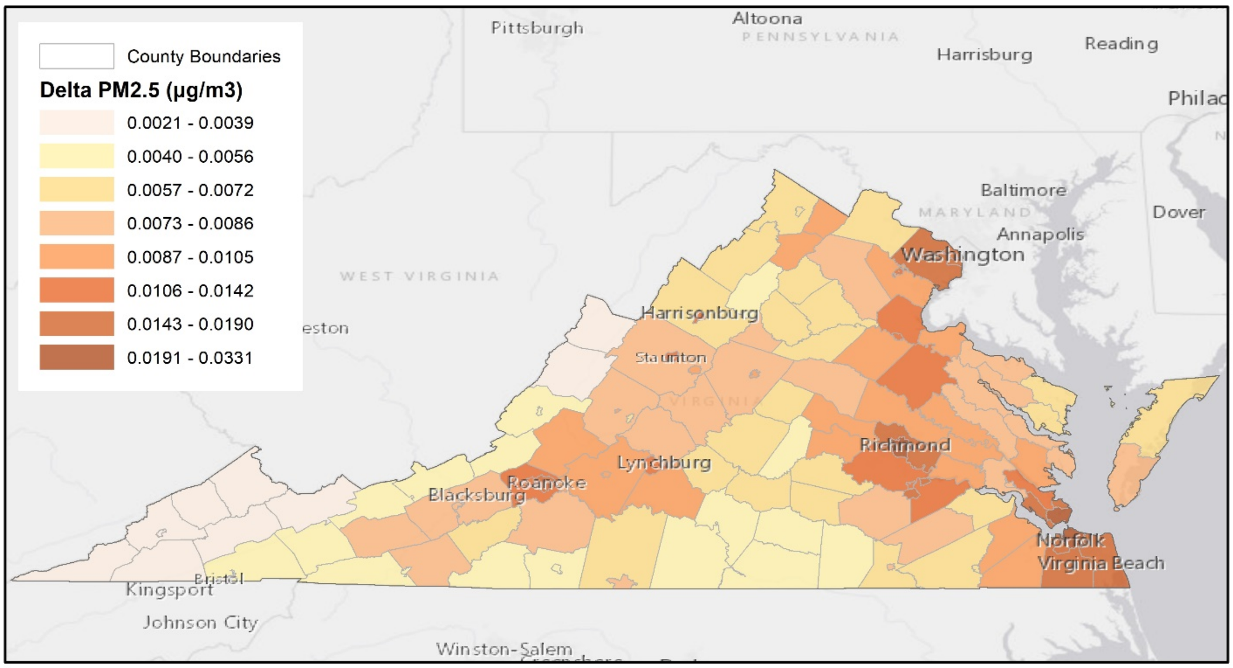
2 We do consider brake and tire wear as a source of emissions from ZEVs and conventional vehicles.

3 Several elements of RGGI present difficulties in modeling emissions changes from EGUs. First, EGUs purchase and trade CO_2 allowances to cover their emissions. Thus, EGUs are not bound to individual caps and may choose to purchase additional credits to cover, for example, increased emissions associated with ZEV electricity demand. Emissions reductions may occur elsewhere in the region. Second, RGGI addresses CO_2 emissions. While directly-emitted PM2.5 and other PM2.5 precursors are co-pollutants of CO2 at EGUs, these sources may choose to purchase CO_2 offset allowances that reduce or sequester CO_2 or CH_4 emissions in the region. Such projects may provide zero or negligible benefits related to reductions in emissions of criteria pollutants. Third, RGGI's cap may be expanded through a Cost Containment Reserve, a mechanism that provides additional allowances in instances where allowance prices exceed predefined price thresholds. Such mechanisms have been triggered in recent years and are difficult to predict/model. Fourth, RGGI allows for EGUs to bank emissions allowances for future years, again presenting modeling difficulties for a given year. Given these limitations and the negligible effects of EGU emissions associated with ZEVs, we do not consider RGGI participation in modeling EGU emissions.

Overall, we model greater reliance on renewable energy sources with the passage of the CEA relative to a no-CEA scenario in 2035. While nuclear power is assumed to comprise a constant 21 percent of the fuel mix, coal and natural gas each nearly halve by 2035. Renewable sources are projected to increase from 13 to 45 percent.

The $PM_{2.5}$ emissions resulting from ZEV program adoption is presented in Exhibit 12. While this graphic assumes passage of the CEA, the no-CEA results are comparable.

EXHIBIT 12. 2035 $PM_{2.5}$ REDUCTIONS FROM ZERO EMISSION VEHICLE PROGRAM (WITH CLEAN ECONOMY ACT PASSAGE)



Overall, $PM_{2.5}$ reductions from ZEV program adoption are greatest in urban Virginia counties. The spatial distribution closely resembles the overall contributions of transport to $PM_{2.5}$—areas with higher vehicle miles traveled (VMT) are most affected by policies to increase ZEV adoption. We note that ZEV adoption is modeled independently of location; however, adoption may be influenced by geographic and socioeconomic factors, including charging infrastructure and affordability.

The estimated health benefits associated with ZEV adoption are summarized in Exhibit 13. These results reflect with-CEA conditions (i.e., a cleaner fuel mix for powering electric vehicles). The associated results without CEA, located in Appendix D, are comparable.

EXHIBIT 13. 2035 PM-RELATED BENEFITS OF ZERO EMISSION VEHICLE PROGRAM ADOPTION, WITH CLEAN ECONOMY ACT

HEALTH ENDPOINT	CHANGE IN ANNUAL INCIDENCE	VALUATION (USD 2015$)
Mortality		
Estimate 1 (Lepeule et al. 2012)	17	$160,000,000
Estimate 2 (Di et al. 2017)	7.7	$72,000,000
Estimate 3 (Turner et al. 2016)	7.3	$69,000,000
Mean estimate	11	$99,000,000
Morbidity effects		
Hospitalizations, cardiovascular	1.7	$77,000
Hospitalizations, respiratory	1.8	$56,000
Emergency room visits, asthma	3.5	$1,700
Stroke	0.37	$13,000
Low birth weight*	1.2	$18,000
New onset asthma	18	$750,000
Exacerbated asthma	210	$13,000
Acute bronchitis	8.3	$4,300
Upper respiratory symptoms	150	$5,500
Lower respiratory symptoms	110	$2,400
Lost work days	760	$160,000
Minor restricted activity days	4,500	$330,000
Acute myocardial infarction (non-fatal)	6.6	$900,000
Total		**$102,000,000**

* EPA (2019b) finds evidence of $PM_{2.5}$ related birth outcomes to be suggestive, but not sufficient to infer a causal relationship at this time.
See Exhibit 2 for notes on each health endpoint.

We estimate that adoption of the ZEV program will result in benefits of roughly $102 million in 2035. As noted above, these benefits are geographically concentrated in urban areas with higher population and vehicle use. Our benefits estimates for 2035 are broadly representative of the annual benefits that may be expected in each subsequent year (2036 and beyond) as ZEVs continue to operate in place of gasoline- and diesel-powered vehicles. Additionally, greater benefits may be achieved with more ambitious ZEV adoption targets. In recent months, the State of California has signaled for an aggressive phase-out of gasoline-powered vehicles, with 100 percent ZEV vehicle sales by 2035. Such policies may result in more rapid adoption of ZEVs nationally and substantially improve health benefits which could be projected under such a scenario.

Comparing these results with the analogous results from the no-CEA scenario (see Appendix D), we observe a slight increase in benefits with CEA passage. This result is due to a cleaner fuel mix used to power the additional electric vehicles in 2035.

LOW EMISSION VEHICLES PROGRAM

In this section, we explore the potential benefits of Virginia's adoption of California's LEV standards. Because the current California LEV standards for criteria pollutants are equivalent to federal standards, we anticipate no $PM_{2.5}$-related health benefits associated with Virginia's adoption of the LEV program. Nonetheless, the LEV scenario is likely to result in significant GHG benefits, pending litigation over California's waiver status. We model Virginia GHG emissions assuming emissions standards under California's "Advanced Clean Car Rules," a part of the LEV III standards passed in 2012. These emissions are compared to emissions under the federal Safer Affordable Fuel-Efficient (SAFE) Vehicles rule (EPA 2020), the emissions standards for GHG emissions and fuel economy for model years 2021 through 2026. We assume that model years 2027-2035 adhere to the more stringent 2026 standards. The results of this emissions modeling are presented in Exhibit 14.

EXHIBIT 14. 2035 VIRGINIA CO_2 EMISSIONS BY VEHICLE TYPE AND POLICY SCENARIO

VEHICLE TYPE	VEHICLE MILES TRAVELED (MILLION MILES)	CO2 EMISSIONS (MILLION TONS)			PERCENTAGE CHANGE IN EMISSIONS
		SAFE	WITH CA WAIVER	CHANGE IN EMISSIONS	
Light duty vehicles	96,045	42.9	37.3	5.6	-12.9%
Heavy duty vehicles	6,787	11.9	11.9	0.0	0.0%
Total	**102,832**	**54.8**	**49.3**	**5.6**	**-10.1%**

In 2035, we estimate that adoption of the more stringent California GHG LEV standards would reduce CO_2 emissions by 5.6 million tons, or roughly 10 percent of total vehicle GHG emissions. These benefits would accrue annually, with some variation by year due to projected VMT and fleet composition. In Exhibit 15, we present the monetized benefits associated with these reductions in CO_2 emissions. Tons of CO_2 are valued using a range of social cost of carbon (SC-CO_2) estimates produced by the Interagency Working Group on the Social Cost of Greenhouse Gases (2016).[4] As described in their 2016 SC-CO_2 update, "the SC-CO_2 is the monetized damages associated with an incremental increase in carbon emissions in a given year. It is intended to include (but is not limited to) changes in net agricultural productivity, human health, property damages from increased flood risk, and the value of ecosystem services due to climate change." Human health impacts could include effects such as increased mortality due to more frequent instances of extreme temperatures (see e.g., Schwartz et al. 2015), increased asthma ED visits due to increases in aeroallergens (Neumann et al. 2019; Anenberg et al. 2017), and increased risks from wildfires and their associated air pollution impacts on health (Ford et al. 2018). We present the Working Group's four recommended SC-CO_2 values to reflect the uncertainty in climate impacts and the important role of discounting in deriving these values. Three estimates reflect the average SC-CO_2 derived from integrated assessment models using discount rates of 2.5, 3, and 5 percent. The fourth "high impact" estimate reflects the marginal damages associated with lower-probability but higher-impact

[4] See https://www.epa.gov/sites/production/files/2016-12/documents/sc_co2_tsd_august_2016.pdf.

outcomes associated with climate change. We update the SC-CO_2 values to 2015 dollars using the Consumer Price Index.

Although there is debate about the appropriate discount rate for the intergenerational impacts of climate change, we use 3% for our primary estimate. This discount rate is a commonly employed rate in the climate impacts literature (e.g., see Goulder and Williams 2012). This rate is also consistent with the consumption rate of interest recommended by federal guidance for benefit cost analysis, known as OMB Circular A-4, to capture "the rate at which 'society' discounts future consumption flows to their present value." OMB based this rate on the real rate of return on long-term government debt averaged over a 30-year period prior to the issuance of Circular A-4 (2003).

EXHIBIT 15. 2035 CLIMATE-RELATED BENEFITS FROM LOW EMISSION VEHICLE PROGRAM ADOPTION

SC-CO_2 BASIS	SC-CO_2 (2015$)	CHANGE IN CO_2 EMISSIONS (MILLION TONS)	BENEFITS OF CO_2 REDUCTIONS IN 2035 (MILLIONS, 2015$)
2035, 5% d.r.	$21	5.6	$120
2035, 3% d.r.	$65		$360
2035, 2.5% d.r.	$92		$520
2035, high impact (95^{th} pct at 3% d.r.)	$198		$1,100
Notes: Benefits estimates are rounded to two significant figures.			

The climate-related benefits from LEV program adoption are substantial. Our central estimate (using a 3 percent discount rate) suggests that associated CO_2 emissions reductions in 2035 will result in $360 million in benefits. This estimate is accompanied by a wide range of possible outcomes, depending upon analytic choices and uncertainty in future climate. Central estimates range from $120 to $520 million using discount rates of 5 and 2.5 percent, respectively, while a high impact scenario results in benefits of $1.1 billion due to the greater marginal costs associated with GHG emissions. Importantly, these benefits estimates are annual – 2034 and 2036 benefits are likely to be similar, with greater benefits accruing as LEVs are adopted more extensively.

SUMMARY

In summary, we highlight the following results from our analysis of Section 177 adoption in the State of Virginia:

- ZEV program adoption would increase the portion of vehicle miles traveled by ZEVs in 2035 from negligible amounts to 13 percent of Virginia's total.
- Urban areas in Virginia would primarily benefit from ZEV adoption due to higher baseline transport-attributable $PM_{2.5}$ concentrations in these areas. Rural areas also observe benefits from ZEV program adoption.
- 10 premature deaths may be avoided annually with adoption of the ZEV program and its resulting reductions in ambient $PM_{2.5}$ levels. Additional benefits may accrue in bordering states.

- Monetized estimates of the ZEV program suggest annual benefits of $102 million annually. These estimates may understate program benefits if ZEV penetration targets exceed our assumed values.
- LEV program adoption would significantly reduce GHG emissions in Virginia. Relative to a no-adoption scenario, light-duty vehicle CO_2 emissions would fall by 13 percent in 2035.
- Annual GHG-related benefits from LEV program adoption are likely to range from $120 to $520 million annually. These benefits may exceed $1 billion annually in lower-probability but higher-impact climate scenarios.

CHAPTER 4 | DISCUSSION

In this report, we present the results of health benefits analyses aimed at (1) assessing the health burden of ambient $PM_{2.5}$ concentrations in Virginia, (2) estimating the transportation-attributable health burden in the state, and (3) quantifying and monetizing the benefits of adopting more stringent vehicle emissions standards under Section 177 of the Clean Air Act.

We find that $PM_{2.5}$ concentrations are fairly similar throughout much of the state and annual average mean levels are generally both below the USEPA national ambient air standard of 12 micrograms per cubic meter and below the World Health Organization standard of 10 micrograms per cubic meter. Nonetheless, public health research has yet to identify a threshold level of $PM_{2.5}$ below which no adverse health effects have been observed, and thus these levels may still pose health risks to Virginia residents. As a result, we estimate a health burden associated with these $PM_{2.5}$ concentrations, some of which we believe may be addressable through effective air quality management efforts.

We note that higher pollutant levels are observed near urban areas. This spatial pattern is driven, in part, by differences in transportation emissions in urban and rural areas. The transportation contribution to $PM_{2.5}$ levels ranges from 0.14 to 0.55 $\mu g/m^3$ in Virginia counties. Notably, roughly half of all transportation-attributable $PM_{2.5}$ levels originate from vehicle emissions outside of Virginia due to pollutant transport in the atmosphere. Similarly, Virginia's emissions are likely to adversely affect bordering states; these impacts are not quantified in this study.

Using these air quality data, we highlight the human health costs associated with ambient $PM_{2.5}$ levels in Virginia. This burden—amounting to roughly 3,000 premature deaths and $23 billion in monetized costs annually—provides rationale for state policymakers to pursue further air quality management actions. Additionally, despite the similarities in $PM_{2.5}$ exposure geographically, underlying baseline health disparities contribute to the most vulnerable census tracts taking on a larger share of the estimated health burden. Higher concentrations in urban areas also provide more room to broadly improve health in these communities.

The transportation sector is responsible for 5 to 10 percent of the overall $PM_{2.5}$ health burden. Vehicle emissions in Virginia result in $750 million in costs annually. As illustrated with the ZEV policy analysis, transportation sector emissions controls may produce significant benefits by reducing this burden. We estimate annual benefits of the ZEV program of $102 million in 2035 using an estimate ZEV penetration rate equating to 13 percent of Virginia VMT in 2035. Greater penetration of ZEVs would result in greater annual benefits. Additional benefits are likely to accrue, including health benefits accruing in bordering states and climate-related benefits associated with reduced GHG emissions. Such benefits may be sizeable. For example, we estimate that the LEV program reduce light-duty vehicle CO_2 emissions would 13 percent in 2035, resulting in annual benefits between $120 to $520 million.

We note several limitations of our analysis. First, we highlight uncertainties with our air quality datasets. The 2008 air quality surface from Goldberg et al. (2019) is scaled to 2018 using $PM_{2.5}$ monitor data in and around Virginia. While 2018 data allow us to "anchor" the modeled surface, more recent air quality modeling may improve our characterization of $PM_{2.5}$ exposure. Additionally, finer scale modeling may provide insights into potential "hot spots" and their relationship with socially vulnerable tool. The air quality modeling used for estimating transport burden and Section 177 impacts (COBRA) is a single reduced form tool based on source-receptor matrix estimates. Photochemical modeling is likely to produce more robust estimates of changes in air quality due to emissions changes from mobile sources.

Second, morbidity data in Virginia is geographically coarse. These rates reflect either regional or national values and do not vary from county to county. Obtaining more refined estimates from state Health Department may elucidate additional variation in health impacts, as is currently possible for mortality endpoints. More refined air quality and incidence data may allow analysts to address potential health impacts among populations living in close proximity (e.g., within 150 m) of roadways.

Third, there are multiple ways to define vulnerable populations. For this screening analysis, we applied the SVI, and index of vulnerability developed by the CDC. Alternative indices of vulnerability exist, such as the SoVI index developed by researchers at the University of South Carolina[5], and analysts can develop their own definitions, depending on the environmental and sociodemographic features that are most relevant to the population being studied. Use of alternative definitions of vulnerable populations could yield different results, pending data availability.

Finally, our analysis does not consider some notable categories of benefits. We focus on $PM_{2.5}$; benefits related to reduced ozone levels are not evaluated, as the complex chemistry of ozone generation is best estimated using more time- and resource-intensive photochemical modeling. Additionally, we do not estimate benefits to residents outside of Virginia. Due to pollutant transport, air quality management actions in Virginia are likely to provide benefits to nearby states. While not the primary focus of this report, we also highlight that investment in public transit and more active modes of transportation are likely to yield significant health benefits. In addition to reducing emissions of harmful pollutants, walking and biking will improve public health, particularly in tandem with LEV and ZEV type programs that reduce exposure of pedestrians and cyclists to harmful pollutants resulting from vehicle emissions (see for example Pucher et al. 2010)

Given these limitations, we recommend several next steps for consideration. First, exploring alternative air quality surfaces and air quality modeling tools would serve as useful sensitivity analyses. Disparities in results may highlight key data gaps and assumptions that could be more closely evaluated. Some air quality surfaces (e.g., Van Donkelaar et al. 2016 1 km surface) and reduced form models (e.g., InMAP, AP3, USEPA benefit per ton estimates, EASIUR) are readily available and familiar to the IEc team.

Second, a closer evaluation of vulnerable communities is warranted if improved data are made available. Obtaining more refined incidence and air quality data could better inform distributional analysis of exposures and risks, e.g., of asthma impacts. Stratifying estimates by relevant socioeconomic indicators may also be possible (e.g., by race, age, or income level).

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[5] http://artsandsciences.sc.edu/geog/hvri/sovi%C2%AE-0

Additionally, VCCA may wish to explore the level of effort required for an analysis of ozone impacts. Combined with $PM_{2.5}$, an ozone health benefits analysis would result in a more comprehensive understanding of the benefits of air quality management actions. Additional health endpoints and epidemiological studies may also be evaluated when considering a second pollutant.

APPENDIX A. EMISSIONS MODELING

The following appendix presents the technical documentation for the emissions modeling discussed in this report. In this analysis, we estimate how highway vehicle emissions of criteria air pollutants might change if Virginia were to adopt the Section 177 waiver which would allow Virginia to adopt California's emission standards for light-duty vehicles. The California Low Emission Vehicle (LEV) III standards and the federal standards for criteria pollutants are essentially aligned by model year 2019, though GHG emissions would diverge, with EPA retracting the latest federal GHG standards. However, since 2022 is the earliest model year that could be affected if Virginia were to adopt the Section 177 waiver within the next year, there would be no emissions impact from the California LEV standards for criteria pollutants. However, if Virginia were to adopt the zero-emission vehicle (ZEV) portion of the Section 177 waiver, criteria pollutant emissions of these criteria pollutant would be affected. An analysis of the criteria pollutant emissions impacts of adopting the California ZEV standards in Virginia starting in model year 2022 is documented below.

ONROAD EMISSIONS

SC&A analyzed onroad emissions from highway vehicles under two scenarios—a baseline and a ZEV scenario. The baseline scenario represents emissions that would be caused by highway vehicles traveling in Virginia for a projection year of 2035. The ZEV scenario represents likely emissions if Virginia were to adopt the ZEV portion of the California vehicle standards. The pollutants included in the analysis are oxides of nitrogen (NO_x), sulfur dioxide (SO_2), ammonia (NH_3), particulate matter with an aerodynamic diameter of 2.5 microns or less ($PM_{2.5}$) and volatile organic compounds (VOC). Emissions from vehicle exhaust, evaporation, and brake and tire wear are included in the onroad emissions. For vehicles powered by electricity, the emissions used to generate the electricity are calculated separately.

BASELINE SCENARIO – MOVES INPUTS

We calculated highway vehicle emissions for this analysis using the US Environmental Protection Agency's (EPA) MOtor Vehicle Emission Simulator (MOVES) model, version MOVES2014b (EPA 2018). A number of local inputs are required to obtain emission results that reflect the vehicle population and activity within a specific county. We obtained the county-level databases containing these MOVES inputs that EPA used in developing the 2017 National Emissions Inventory (EPA 2020a). As the MOVES model runs can be very time-intensive, EPA uses an approach of using representative counties within a state to represent multiple counties in that state with similar vehicle average vehicle ages, fuel composition, and other similar characteristics. We then applied emission factors calculated by modeling the representative county to activity in the other counties within that county group. Because of the short turn-around time for this analysis, SC&A applied this representative county approach for the MOVES modeling for Virginia, using the nine representative counties and the mapping of the Virginia counties to the representative counties developed by EPA to develop emission factors by vehicle type and fuel type.

Starting with the NEI county databases, SC&A updated several inputs to account for differences between 2017 and 2035. One of the inputs is a distribution of registered vehicles by age for the most recent 30 vehicle model years, within a vehicle class. While the average age of vehicles within an area generally remains stable, spikes often occur in certain years due to economic conditions and other factors. Therefore, EPA has created a tool to project these base year local age distributions to distributions for a projection year (EPA 2014a). SC&A used this tool to project the 2017 age distributions for the representative counties to 2035.

SC&A used the 2035 default fuel properties provided for the Virginia representative counties within the MOVES default database as well as the historical meteorological data (temperature and humidity) provided within MOVES.

Vehicles registered within the Northern Virginia counties that are part of the Washington, DC-MD-VA ozone nonattainment area are subject to biennial vehicle emissions inspections (I/M). The data for the I/M program in the representative counties from Northern Virginia was updated to 2035 by adjusting the end model year of the program in these inputs. These counties were also part of the Ozone Transport Commission (OTC) states that adopted the national low emission vehicle (LEV) emission standards starting with model year 1999, while the program started nationally in 2001. Thus, the inputs needed to model these standards for the 1999 and 2000 model years were included with the representative county inputs from Northern Virginia.

Most counties in Virginia had a small population of electric vehicles in 2017 in the MOVES county input databases. For the baseline analysis, we kept the fraction of electric vehicles sold in 2017 as a fraction of light duty vehicle sales constant, as a conservative estimate in the baseline. Vehicle miles traveled (VMT) is the key activity for highway vehicles. We describe the development of the 2035 VMT inputs separately below.

BASELINE SCENARIO - VMT

We used Virginia Department of Transportation's (VDOT) annual report on vehicle miles traveled (VMT) in 2019 in Virginia by county, federal vehicle class, and roadway class (VDOT 2019) as the starting point for VMT data. Virginia Department of Environmental Quality (VDEQ) provided data on Virginia VMT by county and roadway class with a 2017 base year, and projected using VDOT's latest projections to each year through 2040 (VDEQ 2020). SC&A used this data to calculate the annual growth rates from 2019 to 2035 by county and roadway class and then applied these growth rates to the 2019 VDOT VMT data to obtain 2035 VMT by county, roadway class, and vehicle class. We mapped the federal vehicle classes used in the VDOT reporting system to the five Highway Performance Monitoring System (HPMS) vehicle types needed for input to MOVES, then summed the resulting 2035 by county and HPMS vehicle type for input to MOVES.

Following the development of all MOVES inputs for the representative counties, SC&A executed the MOVES model to develop emission factors for these representative counties in 2035. We mapped the resulting emission factors, in units of grams per mile, by representative county, vehicle type, and fuel type to all counties being represented by that county. In addition, we multiplied the baseline 2035 VMT for all counties in Virginia by the fraction of VMT for each by county and vehicle type, based on the MOVES outputs for the representative counties. Then, we multiplied each county's 2035 VMT by vehicle type and fuel type by the vehicle type/fuel type emission factor from the mapped representative county. We calculated emissions for NO_x, SO_2, NH_3, $PM_{2.5}$, and VOC.

ZEV SCENARIO

For the ZEV scenario, the only difference from the inputs discussed above is in the fraction of electric vehicles, as modeled in the MOVES avft input file. For the baseline scenario, we modeled the fraction of electric vehicles in 2017 for all following model years. For the ZEV scenario, for model years 2022 through 2035, we set this fraction to 16 percent, the ZEV VMT fraction provided in EPA's ZEV-AVFT generator (EPA 2014b). This applies to light-duty vehicles and trucks. As with the baseline scenario, we adjusted the fractions of light-duty vehicles and trucks using gas, diesel, or E-85 proportionally downward. We executed the MOVES model using the ZEV avft files for the representative counties and emissions calculated in the same manner as discussed for the baseline scenario.

ELECTRICITY EMISSIONS

With the adoption of California's ZEV requirements, Virginia would benefit from the reduction of fuel combustion in zero-emission vehicles. However, criteria pollutant emissions from electricity generation would be expected to increase in order to supply the electricity needed to power electric vehicles. Therefore, SC&A estimated emissions from electric vehicles for both the baseline scenario and the ZEV scenario.

To estimate electricity emissions, we first estimated the electricity consumed by electric vehicles in Virginia in 2035. As a MOVES output, we converted the VMT allocated to electric vehicles in both scenarios to electricity consumption by multiplying the electric vehicle VMT in each county by a fuel efficiency of 34 kilowatt-hours (kWh) per 100 miles traveled. This fuel efficiency is a conservative estimate based on the range of fuel efficiency of new electric vehicles currently available (DOE 2020). We totaled the estimated electricity consumption from electric vehicles separately for the state for the baseline scenario and the ZEV scenario. For both the baseline and ZEV onroad vehicle emissions scenarios, we calculated electricity emissions for a Business as Usual (BAU) scenario and a Clean Economy Act scenario, as discussed below.

In order to calculate emissions from electricity generation, we needed the amount of generation by fuel or resource. We estimated the projected resource mix or electricity generation by fuel type for the 2035 electricity BAU Scenario primarily from data in the US Energy Information Administration's Annual Energy Outlook (AEO) 2020 (EIA 2020). Based on the AEO data, Virginia is primarily in two electricity market module regions: PJM/Dominion (primarily Dominion Energy) and PJM/West (primarily Appalachian Power). The PJM/Dominion region accounts for approximately 85 percent of the population in Virginia. The AEO 2020 provides the expected electricity generation by fuel type for each of the market module regions for each year through 2050. Using a weighting of 85 percent for the PJM/Dominion region and 15 percent for the PJM/West region, the fuel mix expected to be used to generate Virginia's electricity in 2035 is shown in Exhibit A-1, in the column labeled BAU scenario.

Under Virginia's Clean Economy Act, signed by Governor Northam in April of 2020, Dominion Energy is required to be 100 percent carbon free by 2045 and Appalachian Power to be 100 percent carbon free by 2050. Exhibit A-1 shows the expected electricity generation fuel mix by 2035 with the Clean Economy Act in place. We estimated this mix by applying the weighted renewable percentage required for Dominion and Appalachian Power in 2035, after subtracting out the nuclear energy fraction, which is held constant. We applied the remaining fraction of electricity by fuel type proportionally to the fractions in the BAU scenario.

EXHIBIT A-1. 2035 PROJECTED ELECTRICITY FUEL MIX FOR VIRGINIA AND ELECTRICITY EMISSION FACTORS

FUEL	BAU SCENARIO ELECTRICITY FUEL MIX	CLEAN ECONOMY ACT SCENARIO FUEL MIX	NO_X ELECTRICITY EMISSION FACTOR (LB/MWH)	SO_2 ELECTRICITY EMISSION FACTOR (LB/MWH)
Coal	11%	6%	1.994	0.512
Natural Gas	55%	28%	0.186	0.025
Nuclear	21%	21%	0	0
Renewable Sources	13%	45%	0	0

Next, we calculated statewide electricity emissions that would be expected to occur to meet the electricity demand of the electric vehicles. We obtained emission factors for NO_x and SO_2 for electricity generation in Virginia from EPA's Emissions & Generation Resource Integrated Database (eGRID) for 2018 (EPA2020b). The Virginia statewide emission factors from this source are shown in Exhibit A-1. Emission factors for $PM_{2.5}$, NH_3, and VOC are not included in eGRID. For this analysis, we estimated emission factors for VOC and NH_3 by applying the ratio of VOC or NH_3 fuel-specific emissions from electricity generation in Virginia from EPA's 2017 NEI to the comparable 2017 Virginia NO_x emissions and multiplying by the NO_x emission factors in Exhibit A-1. We estimated the $PM_{2.5}$ emission factors similarly, but using the ratio of $PM_{2.5}$ emissions to SO_2. We then calculated 2035 electricity emissions by multiplying these emissions factors by the corresponding statewide generation by fuel type for each combination of the highway vehicle and electricity scenarios. Finally, we allocated the calculated statewide electricity emissions proportionally to the baseline electricity emission sources in Virginia from the 2028 COBRA database.

RESULTS

Exhibit A-2 summarizes the projected 2035 VMT for light-duty vehicles (LDVs) and heavy-duty vehicles (HDVs) by fuel type under the baseline and ZEV scenarios along with the corresponding fraction of total VMT for each vehicle/fuel type combination. By 2035, with the adoption of the Section 177 waiver, the portion of Virginia's VMT in 2035 expected from electric vehicles increases to approximately 13 percent, decreasing the VMT from LDVs fueled by gas, diesel and E-85. The resulting electricity consumption used to power these electric vehicles is shown in Exhibit A-3.

EXHIBIT A-2. 2035 VMT AND VMT FRACTION BY VEHICLE TYPE AND FUEL TYPE

VEHICLE TYPE	FUEL TYPE	2035 VMT (MILLION MILES)		VMT FRACTION	
		BASE SCENARIO	ZEV SCENARIO	BASE SCENARIO	ZEV SCENARIO
LDV	Gas	90,921	78,390	88.4%	76.2%
LDV	Diesel	1,715	1,481	1.7%	1.4%
LDV	E-85	3,269	2,808	3.2%	2.7%
LDV	Electricity	140	13,366	0.1%	13.0%
HDV	Gas	290	290	0.3%	0.3%
HDV	Diesel	6,459	6,459	6.3%	6.3%
HDV	CNG	39	39	0.0%	0.0%
LDV Subtotal		*96,045*	*96,045*	*93.4%*	*93.4%*
HDV Subtotal		*6,787*	*6,787*	*6.6%*	*6.6%*
Total		**102,832**	**102,832**	**100.0%**	**100.0%**

EXHIBIT A-3. 2035 ELECTRICITY CONSUMPTION BY ELECTRIC VEHICLES IN VIRGINIA

SCENARIO	ELECTRICITY CONSUMPTION (MWH)
Baseline Scenario	47,535
ZEV Scenario	4,544,498

Exhibit A-4 summarizes the expected emissions attributable to highway vehicles in Virginia in 2035. The first two columns of this table indicate the emissions scenario modeled for vehicles and for electricity, for the four possible combinations of vehicle and electricity emissions scenarios.

EXHIBIT A-4. 2035 VIRGINIA STATEWIDE EMISSIONS BY SCENARIO

VEHICLE EMISSIONS SCENARIO	ELECTRICITY EMISSIONS SCENARIO	SOURCE	2035 EMISSIONS (TPY)				
			NO_X	SO_2	NH_3	$PM_{2.5}$	VOC
Base	BAU	Vehicle Emissions	70,725	356	2,480	2,180	102,851
		Electricity Emissions	7.6	1.7	0.3	0.3	0.3
		Total	*70,733*	*357*	*2,480*	*2,180*	*102,851*
Base	Clean Energy Act	Vehicle Emissions	70,725	356	2,480	2,180	102,851
		Electricity Emissions	4.1	0.9	0.2	0.1	0.1

VEHICLE EMISSIONS SCENARIO	ELECTRICITY EMISSIONS SCENARIO	SOURCE	2035 EMISSIONS (TPY)				
			NO_X	SO_2	NH_3	$PM_{2.5}$	VOC
		Total	*70,729*	*357*	*2,480*	*2,180*	*102,851*
ZEV	BAU	Vehicle Emissions	67,191	323	2,181	1,860	95,156
		Electricity Emissions	730.8	159.2	28.9	24.0	24.6
		Total	*67,922*	*482*	*2,210*	*1,884*	*95,181*
ZEV	Clean Energy Act	Vehicle Emissions	67,191	323	2,181	1,860	95,156
		Electricity Emissions	390.2	85.7	15.1	12.9	12.9
		Total	*67,582*	*409*	*2,196*	*1,873*	*95,169*

Exhibit A-5 compares the emissions and VMT in both the base and ZEV scenarios by vehicle type. All of the emission reductions expected from the ZEV scenario are attributable to light duty vehicles (LDVs). This table shows that although heavy-duty vehicles (HDVs) account for only a small share of the statewide VMT, their share of emissions for NO_x, SO_2, and $PM_{2.5}$ is much larger than their VMT share, which tends to dilute the overall emission benefits of the ZEV scenario when evaluated in relation to all highway vehicles.

EXHIBIT A-5. 2035 VIRGINIA VMT AND EMISSIONS BY VEHICLE TYPE

	SCENARIO	HDV	LDV	TOTAL	HDV FRACTION	LDV FRACTION
VMT (million miles)	Base and ZEV	6,787	96,045	102,832	6.60%	93.40%
NO_x (tpy)	Base	31,268	39,458	70,725	44.2%	55.8%
	ZEV	31,268	35,924	67,191	46.5%	53.5%
SO_2 (tpy)	Base	99	257	356	27.8%	72.2%
	ZEV	99	224	323	30.6%	69.4%
NH_3 (tpy)	Base	244	2,235	2,480	9.8%	90.2%
	ZEV	244	1,937	2,181	11.2%	88.8%
$PM_{2.5}$ (tpy)	Base	379	1,801	2,180	17.4%	82.6%
	ZEV	379	1,481	1,860	20.4%	79.6%
VOC (tpy)	Base	5,126	97,725	102,851	5.0%	95.0%
	ZEV	5,126	90,030	95,156	5.4%	94.6%

SECTION 177 VEHICLE GREENHOUSE GAS EMISSIONS ANALYSIS

In January 2012, the California Air Resources Board (CARB) approved greenhouse gas (GHG) emission regulations for MY 2017-2025 light-duty vehicles. The regulations were part of the "Advanced Clean Car Rules" that also included the LEV III emission standards for criteria air pollutants and ZEV regulations. The GHG emission regulation was aligned with the federal GHG emissions and fuel economy for model year 2017 through 2025 light-duty vehicles and trucks proposal by the EPA and the National Highway Traffic Safety Administration (NHTSA). When the federal model years 2017-2025 GHG regulation became finalized in August 2012 (EPA 2012), CARB adopted regulatory provisions to the effect that vehicles meeting federal GHG emission standards for model years 2017-2025 are "deemed to comply" with California standards. This approach provided manufacturers a convenient option to comply with one set of rules nationwide.

EPA and the National Highway Traffic Safety Administration (NHTSA) revoked the waiver for California's light-duty vehicle GHG standards on September 27, 2019 (EPA 2019a) and then issued a rule finalized in 2020 known as the Safer Affordable Fuel-Efficient (SAFE) Vehicles rule (EPA 2020c). This SAFE Vehicles rule revises the greenhouse gas (GHG) and Corporate Average Fuel Economy (CAFE) standards for light-duty vehicles and trucks for model years 2021 through 2026. The EPA/NHTSA action revoking California's waiver is currently before the US Court of Appeals for the DC Circuit, and a written briefing is underway but no oral argument has yet been scheduled. Without the waiver in effect, vehicles throughout the country, including those in California and Section 177 states are subject to the less stringent CO2 emission standards and fuel economy standards of the SAFE Vehicles rule.

ANALYSIS OF ONROAD EMISSIONS IN VIRGINIA

As a result of the above, the current CO_2 LDV emissions in Virginia for model years 2021-2025 and beyond are those proscribed within the SAFE Act. The required CO_2 emission rates under this regulation are less stringent than those under the 2012 regulation. The California waiver revocation would need to be reversed before Virginia could implement the more stringent GHG emission standards. This analysis examines the potential CO_2 emission reductions that could occur in Virginia in 2035 if the California GHG waiver were reinstated and Virginia were to adopt the Section 177 waiver for these GHG standards.

The baseline in this analysis are the CO_2 emissions that would be expected to occur under the SAFE rule. Exhibit A-6 summarizes the fleetwide CO_2 emission requirements by model year under the SAFE rule.

EXHIBIT A-6. 2020 SAFE RULE ESTIMATED FLEETWIDE FINAL CO_2 EMISSION REQUIREMENTS

VEHICLE CATEGORY	MODEL YEAR					
	2021	2022	2023	2024	2025	2026
Passenger cars (CO_2, g/mi)	183	180	177	174	171	168
Light trucks (CO_2, g/mi)	264	259	255	251	247	243

The reduced GHG emission scenario represents the expected 2035 emissions in Virginia with the 2012 CO_2 emission standards reinstated in California and adopted by Virginia via Section 177. Exhibit A-7 shows the projected fleet-wide CO_2 emission compliance levels under the original 2012 rule.

EXHIBIT A-7. 2012 RULE FLEETWIDE CO_2 EMISSION STANDARDS

VEHICLE CATEGORY	MODEL YEAR					
	2021	2022	2023	2024	2025	2026
Passenger cars (CO_2, g/mi)	172	164	157	150	143	143
Light trucks (CO_2, g/mi)	249	237	225	214	203	203

The current version of EPA's MOVES model, version MOVES2014b (EPA 2018), includes the provisions of the 2012 GHG standards. Therefore, this represented the controlled or Section 177 GHG scenario. We calculated CO_2 emissions for Virginia in the same manner as discussed for the criteria pollutant analysis, but with output at the model year level. We then calculated CO_2 emission rates by model year for each representative county, vehicle category, and fuel type. We adjusted these emission rates by the ratio of the SAFE CO_2 standards to the ratio of the corresponding 2012 rule CO_2 standard. We multiplied these revised SAFE emission standards by the VMT at the county, vehicle category, and fuel type level for all counties in Virginia to develop an estimate of emissions statewide under the SAFE rule. We assumed emissions prior to the 2021 model year to be the same in both scenarios, and assumed the 2026 standards from Exhibits A-6 and A-7 to apply to model years 2027 through 2035.

Exhibit A-8 summarizes the projected 2035 VMT and CO_2 emissions under the baseline scenario with the SAFE rule in effect and under a scenario where California's GHG waiver is reinstated and Virginia adopts the Section 177 waiver for GHGs.

EXHIBIT A-8. 2035 VIRGINIA CO_2 EMISSIONS UNDER SAFE AND WITH A SECTION 177 GHG WAIVER

VEHICLE TYPE	VMT (MILLION MILES)	CO_2 EMISSIONS (TPY) UNDER SAFE	CO_2 EMISSIONS (TPY) WITH CA WAIVER	PERCENTAGE CHANGE IN EMISSIONS
LDV	96,045	42,880,673	37,343,508	12.9%
HDV	6,787	11,928,461	11,928,461	0.0%
Total	**102,832**	**54,809,135**	**49,271,969**	**10.1%**

APPENDIX B. AIR QUALITY MODELING

EPA's Co-Benefits Risk Assessment Health Impacts Screening and Mapping tool (COBRA) provides screening-level, reduced-form estimates of how changes in air pollution emissions will impact ambient air quality, and can further translate the air quality change into health effect burden and valuation (EPA 2020). COBRA provides baseline emissions of multiple pollutants (NO_2, SO_2, NH_3, SOA, $PM_{2.5}$, and VOCs) for multiple years (2016, 2023, and 2028). It further allows users to develop scenarios by modifying emissions across 14 categories (called "tiers") to model how these changes affect air quality. COBRA then calculates changes in air quality between the baseline scenario and the control scenario using a source-receptor matrix to translate the various pollutant emissions changes into ambient $PM_{2.5}$ concentrations. We use COBRA to generate air quality surfaces of ambient $PM_{2.5}$ concentrations (in $\mu g/m^3$) under multiple policy scenarios across the state of Virginia, at the county level. We used BenMAP-CE for further health benefits analysis, rather than COBRA's screening tool, for a more spatially-resolved analysis and for use of supporting datasets.

BURDEN ANALYSIS

We first use COBRA to determine the burden of the transport sector on overall air quality in Virginia. Using COBRA's built in emissions inventory for 2016 as a baseline, we zeroed all emissions in Tier 11 ("highway vehicles") within the state of Virginia, and ran the resulting emissions inventory through COBRA to yield an air quality surface. We repeated this process, zeroing all highway vehicle emissions for the country as a whole in 2016, to account for emissions outside of Virginia that impact Virginia's air quality.

SECTION 177 ANALYSIS

We also use COBRA to set up various analyses regarding the adoption of California's vehicle emissions standards under Section 177 of the Clean Air Act. We set up four emissions scenarios in Virginia, described below:

1. Baseline scenario (no Section 177 adoption) without Clean Economy Act (CEA) adoption
2. Zero Emissions Vehicle (ZEV) scenario without CEA adoption
3. Baseline scenario with CEA adoption
4. ZEV Scenario with CEA adoption

These scenarios are described in more detail in Appendix A. Vehicle emissions data provided by SC&A were modeled for the year 2035 and include highway vehicle emissions and electricity emissions associated with powering electric vehicles via electric generating unit deltas across different scenarios. We used these datasets to substitute COBRA's 2028 inventory baseline Tier 11 ("highway vehicle") emissions and adjust a subset of Tier 1 ("Fuel Combustion: Electric Utility") emissions in Virginia.

To model changes in $PM_{2.5}$ concentrations resulting from Virginia adoption Section 177, we ran two scenarios through COBRA modeling emission changes under the Section 177 ZEV scenario compared to the baseline: the first assumes no CEA adoption; the second assumes CEA adoption. We used the COBRA outputs of these two runs to generate resulting health burden associated with adopting Section 177 in Virginia.

APPENDIX C. HEALTH BENEFITS ESTIMATION

The following appendix describes the methodology for calculating the health impacts and economic values of air quality and changes in air quality in Virginia. In total we performed five health benefits analyses:

1. The total health burden of current $PM_{2.5}$ concentrations in Virginia;
2. The health burden of US transport emissions;
3. The health burden of Virginia transport emissions;
4. The benefit of adopting the ZEV vehicle regulations without adopting the CEA; and
5. The benefit of adopting the ZEV vehicle regulations and the CEA.

For these analyses, we use the USEPA's Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE) version 1.5.2.0, an open-source program employed by USEPA for their regulatory impact analyses. The remainder of this appendix provides an overview of our approach, including our data sources for key inputs such as population, baseline incidence rates, and concentration-response functions from the epidemiological literature. Finally, we provide an overview of our valuation approach.

OVERVIEW OF APPROACH

We use BenMAP-CE to estimate the impact of $PM_{2.5}$ concentrations on morbidity and mortality health endpoints by assessing the difference in the risk of those endpoints under the baseline and control (i.e., policy) scenarios. BenMAP-CE relies on health impact functions to quantify the change in incidence of adverse health impacts stemming from changes in ambient pollutant concentrations:

$$\Delta y = y_o \cdot \left(1 - e^{-\beta \cdot \Delta PM}\right) \cdot Pop$$

where Δy is the change in the incidence of the adverse health effect, y_o is the baseline incidence rate for the health effect, beta (β) is a coefficient derived from a relative risk (RR) estimate associated with a change in exposure (i.e., pollutant concentration) as expressed in concentration-response functions, ΔPM is the change in concentrations of fine particulate matter, and Pop is the exposed population.[6]

DATA INPUTS

We draw upon multiple data sources to parameterize and implement the generic health impact function presented above. These data sources are described below.

[6] Based upon the functional form of the underlying concentration-response function, the functional form of the health impact function may differ. ΔPM may also be replaced by concentrations of other pollutants (e.g., ozone) or conditions (e.g., temperature).

POPULATION

For the transport burden analyses (bullets two and three above), we rely upon the 2010 Census tract population data, disaggregated by age, gender, race and ethnicity. We use the Woods and Poole (2015) county-level forecasts, developed by age, gender, race and ethnicity, to project the census tract population through the year 2050 (see the BenMAP-CE User Manual for details on the Woods and Poole (2015) methods). We use the 2016 projected census tract population as the final input for the transport burden analyses.

For the total health burden (bullet one above), we also use the 2010 Census tract population data, however, the air quality surface for this assessment is specified using a 1 km by 1 km grid. We used R and ArcGIS to generate a 1 km population dataset from the census tract population using the area-weighted distribution of the census tract grids. To reduce file size, we aggregate the population across race and ethnicity, leaving the population disaggregated only by age and gender. As a result, we cannot apply the Woods and Poole (2015) county-level forecasts, and use the 2010 1 km population as the final input for the total burden analysis.

For the ZEV benefits analysis, with and without CEA adoption (bullets four and five above), we use the 2035 county-level population data built into BenMAP-CE. These data reflect 2010 Census count population estimates projected using Woods and Poole values.

BASELINE INCIDENCE

We rely primarily upon the morbidity and mortality incidence data built into BenMAP-CE (see the BenMAP-CE User Manual for details on BenMAP-CE datasets). This includes: the 2014 county-level incidence rates for hospitalizations and emergency department visits; the 2000 county-level incidence rates for acute bronchitis and work loss days; the 2008 national prevalence rates of asthma (for asthma exacerbation endpoints) and upper respiratory symptoms; and the 2020 county-level mortality incidence rates.

There are three incidence health endpoints which do not have incidence data incorporated into the BenMAP-CE configuration, stroke, new onset asthma, and low term birth weight. We derive stroke national annual incidence rates from Yao et al. (2019), which analyzes the temporal trends in rates of first stroke hospitalization and 30-day mortality between Black and White Medicare enrollees. We derive new onset asthma national annual incidence rates from Winer et al. (2012), which estimates the incidence of asthma in children and adults from the Behavioral Risk Factor Surveillance System Asthma Call-Back Survey (BRFSS ACBS). For new onset asthma endpoint, we also incorporate the 2018 National Health Interview Survey (NHIS) prevalence of asthma to ensure that the concentration-response function is applied only to the portion of the population that does not already suffer from asthma. We develop the term low birth weight incidence from 2017 Virginia county-level birth, pre-term birth, and low birth weight rates provided by the Virginia Department of Health.

CONCENTRATION-RESPONSE FUNCTIONS

We utilize morbidity and mortality health impact functions for our benefits analyses. We use a subset of the USEPA standard morbidity functions pre-loaded into BenMAP-CE that are considered to be ‘core’ health impact functions used in USEPA regulatory analyses. We subset the standard functions using the

.cfgx and .apvx BenMAP-CE configuration files available on the USEPA website.[7] We also include five health impact functions developed for the incidence endpoints of stroke, new onset asthma, and term low birth weight. Additional detail on the low birth weight endpoint is provided below. Exhibit C-1 lists the full set of 55 functions used in our analyses.

EXHIBIT C-1. HEALTH IMPACT FUNCTIONS

AUTHOR	YEAR	ENDPOINT GROUP	AGE RANGE
Dockery et al.	1996	Acute Bronchitis	8-12
Ostro and Rothschild	1989	Minor Restricted Activity Days	18-64
Mar et al.	2004	Asthma Exacerbation, Cough	6-18
Ostro et al.	2001	Asthma Exacerbation, Cough	6-18
Mar et al.	2004	Asthma Exacerbation, Shortness of Breath	6-18
Ostro et al.	2001	Asthma Exacerbation, Shortness of Breath	6-18
Ostro et al.	2001	Asthma Exacerbation, Wheeze	6-18
Mar et al.	2010	Emergency Room Visits, Asthma	0-99
Slaughter et al.	2005	Emergency Room Visits, Asthma	0-99
Moolgavkar	2000	Hospital Admissions, Chronic Lung Disease	18-64
Moolgavkar	2000	Hospital Admissions, All Cardiovascular (less Myocardial Infarctions)	18-64
Bell et al.	2008	Hospital Admissions, All Cardiovascular (less Myocardial Infarctions)	65-99
Peng et al.	2008	Hospital Admissions, All Cardiovascular (less Myocardial Infarctions)	65-99
Peng et al.	2009	Hospital Admissions, All Cardiovascular (less Myocardial Infarctions)	65-99
Zanobetti et al.	2009	Hospital Admissions, All Cardiovascular (less Myocardial Infarctions)	65-99
Zanobetti et al.	2009	Hospital Admissions, All Respiratory	65-99
Sheppard	2003	Hospital Admissions, Asthma	0-64
Schwartz and Neas	2000	Lower Respiratory Symptoms	7-14
Pope et al.	1991	Upper Respiratory Symptoms	9-11
Ostro	1987	Work Loss Days	18-64
Kloog et al.	2012	Hospital Admissions, All Respiratory	65-99
Glad et al.	2012	Emergency Room Visits, Asthma	0-99
Peters et al.	2001	Acute Myocardial Infarction, Nonfatal	18-24
Peters et al.	2001	Acute Myocardial Infarction, Nonfatal	25-44
Peters et al.	2001	Acute Myocardial Infarction, Nonfatal	45-54
Peters et al.	2001	Acute Myocardial Infarction, Nonfatal	55-64
Peters et al.	2001	Acute Myocardial Infarction, Nonfatal	65-99
Di	2017	Mortality, All Cause	65-99
Turner	2016	Mortality, All Cause	30-99
Lepeule et al.	2012	Mortality, All Cause	25-99

[7] The USEPA BenMAP-CE configuration, pooling and valuation setup can be found here: https://www.epa.gov/benmap/benmap-community-edition Select the U.S. EPA approach for quantifying and valuing PM effects to download the cfgx and apvx BenMAP-CE files, or use this link: https://www.epa.gov/sites/production/files/2017-07/pm_cfgx_apvx_files_0.zip

AUTHOR	YEAR	ENDPOINT GROUP	AGE RANGE
Kloog et al.	2012	Incidence, Stroke	65-99
Khreis et al.	2017	Incidence, Asthma	0-17
Young et al.	2014	Incidence, Asthma	35-64 (Female only)
Young et al.	2014	Incidence, Asthma	65-99 (Female only)
Sun et al.	2016	Term Low Birth Weight	0-99 (Female only)

Low Birth Weight

Researchers have developed an extensive literature studying the potential impacts of $PM_{2.5}$ exposures to pregnant women on a variety of pregnancy outcomes, including low birth weight (LBW), defined as a singleton birth weighing less than 2500 g. The most recent Integrated Science Assessment for $PM_{2.5}$ prepared by EPA (2019) classifies the evidence of $PM_{2.5}$ impacts on pregnancy and birth outcomes as suggestive but insufficient to infer a relationship, though the authors cite "strong supporting evidence from low birth weight [studies]." Among other issues, the ISA document cites concerns over uncertainties in exposure assessment, key exposure windows, and limited data on the biological mechanism of these effects. However, a number of meta-analyses have been conducted over the past decade (e.g., Sun et al., 2016; Dadvand et al., 2013, Sapkota et al., 2012) that attempt to control for methodological differences such as exposure assessment, and several of these have found overall positive associations between $PM_{2.5}$ exposure at any time during pregnancy and LBW. Some researchers including Perera (2019) have advocated including LBW as a $PM_{2.5}$-related endpoint in benefits analyses involving impacts on children's health (2020). Given the higher level of uncertainty related to this endpoint, we do not include these results as part of our primary analysis, but include consideration of the LBW endpoint as reflective of potential uncertainty in the $PM_{2.5}$ health burden. We developed a health impact function for this endpoint based on the results of the Sun et al., 2016 meta-analysis.

VALUATION

We value mortality using the value per statistical life (VSL) estimate used by USEPA and included in the BenMAP-CE program. Mirroring the concentration-response functions, we value the morbidity endpoints using a subset of the USEPA standard valuation functions that are considered to be 'core' valuation functions used in USEPA regulatory analyses. We subset the standard functions using the .apvx BenMAP-CE configuration files available on the USEPA website.[4] To limit the results, we opt for valuation estimates with a three percent discount rate (excluding seven percent values). We further apply a three percent discount rate to mortality valuation (multiplier of 0.90606) to reflect EPA's cessation lag methodology. For VSL and other willingness to pay estimates, we further apply BenMAP-CE's default income growth adjustments for the relevant years (through 2015 for the burden analyses, through 2026—the last projection year in BenMAP-CE—for the Section 177 analyses).

For the three incidence endpoints which do not have a corresponding valuation functions within BenMAP-CE (new onset asthma, stroke incidence, and LBW), we derive cost-of-illness and/or willingness-to-pay estimates from the available literature. Exhibit C-2 details the economic values corresponding to each endpoint (not yet adjusted for income growth).

EXHIBIT C-2. VALUATION FUNCTIONS

HEALTH ENDPOINT GROUP	AGE RANGE	VALUATION, COST PER CASE (2015$)
Mortality, All Cause	0-99	$8,705,114
Acute Bronchitis	0-17	$490
Acute Myocardial Infarction, Nonfatal 3% Discount Rate (Russell 1998)	0-24	$38,253
Acute Myocardial Infarction, Nonfatal 3% Discount Rate (Russell 1998)	25-44	$38,253
Acute Myocardial Infarction, Nonfatal 3% Discount Rate (Russell 1998)	45-54	$38,253
Acute Myocardial Infarction, Nonfatal 3% Discount Rate (Russell 1998)	55-64	$38,253
Acute Myocardial Infarction, Nonfatal 3% Discount Rate (Russell 1998)	65-99	$38,253
Acute Myocardial Infarction, Nonfatal 3% Discount Rate (Wittels 1990)	0-24	$187,530
Acute Myocardial Infarction, Nonfatal 3% Discount Rate (Wittels 1990)	25-44	$187,530
Acute Myocardial Infarction, Nonfatal 3% Discount Rate (Wittels 1990)	45-54	$187,530
Acute Myocardial Infarction, Nonfatal 3% Discount Rate (Wittels 1990)	55-64	$187,530
Acute Myocardial Infarction, Nonfatal 3% Discount Rate (Wittels 1990)	65-99	$187,530
Minor Restricted Activity Days	18-99	$70
Asthma Exacerbation	0-17	$59
Emergency Room Visits, Asthma	0-99	$534
Emergency Room Visits, Asthma	0-99	$447
Hospital Admissions, Asthma	0-64	$16,655
Hospital Admissions, All Respiratory	65-99	$35,402
Hospital Admissions, Chronic Lung Disease	18-64	$21,989
Lower Respiratory Symptoms	0-17	$21
Hospital Admissions, All Cardiovascular	18-64	$45,659
Hospital Admissions, All Cardiovascular	65-99	$42,642
Upper Respiratory Symptoms	0-17	$34
Work Loss Days	18-65	*Calculated using median income & wage index
Incidence, Stroke	18-99	$33,962
Incidence, Asthma	0-12	$17,629
Incidence, Asthma	4-21	$16,425
Incidence, Asthma	35-99	$16,741
Term Low Birth Weight	0-1	$15,560

APPENDIX D. ADDITIONAL RESULTS

This brief appendix includes a table of ZEV program benefits assuming no passage of the Clean Economy Act (CEA). These results are similar in magnitude to the with-CEA results presented in the main text and are presented in Exhibit D-1 below.

EXHIBIT D-1. 2035 BENEFITS OF ZERO EMISSION VEHICLE PROGRAM ADOPTION, WITHOUT CLEAN ECONOMY ACT

HEALTH ENDPOINT	CHANGE IN ANNUAL INCIDENCE	VALUATION (USD 2015$)
Mortality		
Estimate 1 (Lepeule et al. 2012)	16	$150,000,000
Estimate 2 (Di et al. 2017)	7.4	$70,000,000
Estimate 3 (Turner et al. 2016)	7.1	$67,000,000
Mean estimate	10	$96,000,000
Morbidity effects		
Hospitalizations, cardiovascular	1.7	$74,000
Hospitalizations, respiratory	1.8	$54,000
Emergency room visits, asthma	3.4	$1,700
Stroke	0.36	$12,000
Low birth weight*	1.1	$17,000
New onset asthma	17	$730,000
Exacerbated asthma	200	$13,000
Acute bronchitis	8.0	$4,200
Upper respiratory symptoms	150	$5,300
Lower respiratory symptoms	100	$2,300
Lost work days	740	$150,000
Minor restricted activity days	4,300	$320,000
Acute myocardial infarction (non-fatal)	6.4	$880,000
Total		**$99,000,000**

* USEPA finds evidence of $PM_{2.5}$ related birth outcomes to be suggestive, but not sufficient to infer a causal relationship at this time.
See Exhibit 2 for notes on each health endpoint.

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