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Health Co-Benefits of Sub-National Renewable Energy Policy in the U.S.

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Abstract: State and local policy-makers in the U.S. have shown interest in transitioning electricity systems toward renewable energy sources and in mitigating harmful air pollution. However, the extent to which sub-national renewable energy policies can improve air quality remains unclear. To investigate this issue, we develop a systemic modeling framework that combines economic and air-pollution models to assess the projected sub-national impacts of Renewable Portfolio Standards (RPSs) on air quality and human health, as well as on the economy and on climate change. We contribute to existing RPS cost-benefit literature by providing a comprehensive assessment of economic costs and estimating economy-wide changes in emissions and their impacts, using a general equilibrium modeling approach. This study is also the first to our knowledge to directly compare the health co-benefits of RPSs to those of carbon pricing. We estimate that existing RPSs in the "Rust Belt" region generate a health co-benefit of \$94 per ton CO_2 reduced (\$2–477/tCO_2) in 2030, or 8¢ for each kWh of renewable energy deployed (0.2–40¢/kWh) in 2015 dollars. Our central estimate is 34% larger than total policy costs. We estimate that the central marginal benefit of raising renewable energy requirements exceed the marginal cost, suggesting that strengthening RPSs increases net societal benefits. We also calculate that carbon pricing delivers health co-benefits of \$211/tCO_2 in 2030, 63% greater than the health co-benefit of reducing the same amount of CO_2 through an RPS approach.

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1. Introduction

Policies that address climate change can, as a co-benefit, improve air quality (Smith *et al.*, 2014). In the U.S., air pollution continues to harm human health despite improvements in air quality over the past decades (EPA, 2018b). In 2016, ~93,000 premature deaths and ~1,600,000 years of life lost were attributed to ambient concentrations of fine particulate matter ($PM_{2.5}$) (IHME, 2017), the deadliest form of air pollution (Dockery *et al.*, 1993; WHO, 2006)

Air quality effects can form a large portion of the overall benefits of climate policy. A global summary of previous studies found that estimates of the air quality related health co-benefit of climate policy fell in the range of \$2–196/tCO_2 (Nemet *et al.*, 2010). Health co-benefits can thus be on the same order of magnitude as estimates for the Social Cost of Carbon (SCC) of \$12–123/tCO_2 in 2020 (IWG, 2016). Recent modeling work for the U.S. and other regions has also found that health co-benefits alone can exceed the cost of climate policy (West *et al.*, 2013; Thompson *et al.*, 2014; Shindell *et al.*, 2016; Thompson *et al.*, 2016; EPA, 2015b).

Renewable energy policy is a particularly popular type of climate policy in the U.S. (Leiserowitz *et al.*, 2018), frequently supported for reasons additional to climate change mitigation (Rabe, 2006). Renewable Portfolio Standards (RPSs) are among the most prevalent types of renewable energy policies (Carley and Miller, 2012). An RPS requires electricity suppliers to source a given percent of electricity from eligible renewable power generating technologies. Such policies exist in 29 states and the District of Columbia, and in the European Union, China, India, and elsewhere (IRENA, 2015).

Previous literature on the health co-benefits of U.S. RPSs has focused on national-level effects (Eastin, 2014; Mai *et al.*, 2016; Wiser *et al.*, 2016). State-level regulatory assessments have typically focused on the economic effects of RPSs (Heeter *et al.*, 2014). To our knowledge, only a small number of peer-reviewed studies have estimated state-level air quality impacts (Rouhani *et al.*, 2016; Hannum *et al.*, 2017). Rouhani *et al.* (2016) estimated costs and benefits of an RPS in California using a bottom-up, partial equilibrium model (representing a sub-sector of economy with a large number of discrete technologies) for the power generation mix resulting from different RPS targets. The authors estimated health benefits using marginal benefits per unit of emission abatement from Siler-Evans *et al.* (2013). Hannum *et al.* (2017) used a top-down, computable general equilibrium (CGE) model (providing an economy-wide perspective taking into account market distortions and income effects) to estimate RPS costs in Colorado and the reduced-form air pollution model APEEP to estimate health benefits. Evaluating RPS impacts in other areas of the U.S. continues to be relevant, especially in the absence of federal climate policy. Local effects can differ substantially from national averages, as marginal damages of pollution vary by source and location (Tietenberg, 1995; Siler-Evans *et al.*, 2013; Saari *et al.*, 2015).

A challenge concerning RPS evaluation is the quantification of economic impacts. Modeling studies that estimate the impacts of RPSs have commonly employed partial equilibrium electricity system models (Mai *et al.*, 2016; Rouhani *et al.*, 2016; Wiser *et al.*, 2016). While electricity system models offer detailed bottom-up representation of power markets, they generally preclude considerations of the ripple effects and feedbacks that such policies can cause beyond the electricity sector. An alternative approach is the use of CGE modeling (Thompson *et al.*, 2014; Saari *et al.*, 2015; Hannum *et al.*, 2017). Such models represent the whole economy and capture feedbacks between producers and consumers based on the economic theory of general equilibrium formalized by Arrow and Debreu (1954). While CGE models usually represent energy sector technologies in less detail relative to bottom-up approaches, CGE models enable researchers to estimate the economy-wide costs of climate policy and assess how sector-specific policies influence emissions from unregulated sectors. The U.S. Environmental Protection Agency (EPA) has stated that a general equilibrium approach may be preferable when a policy can be expected to impact a wide number of sectors (EPA, 2014). Previous literature has argued that CGE-based methods are particularly appropriate for analyzing climate policy (Bhattacharyya, 1996; Sue Wing, 2009). To our knowledge, Hannum *et al.* (2017) represents the only sub-national RPS study to quantify future health co-benefits and total economic costs using a general equilibrium approach.

Decision making can also benefit from an understanding of how RPSs compare to alternative policies. Economists often recommend carbon pricing as the most cost-effective climate mitigation policy (Pigou, 1932; Stern, 2006; Stiglitz *et al.*, 2017). Rausch and Mowers (2014) estimated that a carbon price reduces CO_2 emissions at 25% of the cost of an RPS. However, studies that account for air quality effects found that factoring in such co-benefits alters the relative cost-effectiveness of carbon pricing compared to other policies (Boyce and Pastor, 2013; Thompson *et al.*, 2014; Driscoll *et al.*, 2015; Knittel and Sandler, 2011).

Here, we assess future $PM_{2.5}$ related health co-benefits of RPSs in the "Rust-Belt" region, comprised of Pennsylvania, Ohio, Wisconsin, Michigan, Illinois, Indiana, West Virginia, New Jersey, Maryland, and Delaware. We further estimate the total economic costs of this region's RPSs, quantified as the loss of household consumption, a common economic measure for societal policy costs (Paltsev and Carpos, 2013), by using a general equilibrium approach that captures the ripple effects of RPSs beyond the electricity sector. This study also represents, to our knowledge, the first direct comparison of the health co-benefits of RPSs and carbon pricing.

2. Methods

We link a series of models to estimate how climate policy influences the economy, emissions, $PM_{2.5}$ concentrations, human health, and climate. We integrate the MIT U.S. Regional Energy Policy (USREP) model, a CGE model for the US economy, with a reduced-form air pollution model, the Intervention Model for Air Pollution (InMAP). We use USREP to simulate the 2030 economic impacts and CO_2 effects of climate policy. We estimate resulting air pollutant emissions by scaling a base-year emissions inventory to account for changes in the economy simulated by USREP. We then use InMAP to translate emissions to pollution concentrations and premature mortalities. Finally, we estimate the economic benefits of avoided deaths and climate change mitigation, quantified using the Value of Statistical Life (VSL and the Social Cost of Carbon (SCC)). We use these models to evaluate five scenarios designed to explore the impacts of alternative policy options.

The USREP model, which was described in detail in Rausch *et al.* (2010) and Yuan *et al.* (2017), contains 12 regions and aggregates economic activity into 10 economic sectors. Power generating technologies are parameterized based on cost data from the U.S. Energy Information Administration (EIA, 2017a), compiled by Morris *et al.* (2019). Electric vehicles are modeled as in Chen *et al.* (2017). RPS policies are represented in the model using the approach described by Morris *et al.* (2010).

Air pollutant emissions in 2030 are estimated by scaling 2014 emissions from the U.S. National Emissions Inventory (NEI) (EPA, 2017) based on region-specific changes in economic variables in the period from 2014 to 2030 estimated by USREP, following the approach of Thompson *et al.* (2014). First, 2014 emissions are aggregated across pollutant species, time, and space to match the specifications of InMAP (Tessum *et al.*, 2018). Next, we match the EPA Source Classification Codes used to categorize individual emission sources to relevant economic variables estimated by USREP. Unlike Thompson *et al.* (2014), who matched private transportation air pollutant emissions to transportation sector output estimated by USREP, we match private transportation emissions to USREP's estimate of CO_2 emissions of transportation to more accurately represent changes in this sector.

The estimated 2030 emissions are entered into InMAP to estimate 2030 concentrations of $PM_{2.5}$. InMAP simulates the formation of secondary $PM_{2.5}$ and long-range transport of pollution particles using spatially-resolved annual-average physical and chemical information derived from a state-of-the-science Chemical Transport Model (WRF-Chem). InMAP makes simplifying assumptions regarding atmospheric chemistry such as a linear representation of the chemical transformation of emissions into secondary $PM_{2.5}$. The model was described in detail by Tessum *et al.* (2017). InMAP is run statically at a varying spatial-resolution containing up to eight nesting levels, with the largest grid size equal to 288 km^2 and the smallest equal to 1 km^2. We use 2005 historical meteorology from Tessum *et al.* (2015).

InMAP is also used to estimate premature mortalities. We estimate a concentration-response coefficient for the impact of $PM_{2.5}$ concentrations on early deaths by pooling coefficients estimated by Krewski *et al.* (2009) and Lepeule *et al.* (2012) using random effects pooling as described by EPA (2018). To estimate premature deaths in 2030, we scale population and mortality data to 2030 using U.S.-wide and demographic-specific population projections (U.S. Census Bureau, 2012). We further downscale the spatial resolution of InMAP results to the state level to allow the estimation of results specific to political jurisdictions. To do so, we intersect InMAP's variable-resolution grid of mortality estimates with state boundaries. Where state boundaries cross InMAP grid cells, we divide the grid among states and apportion premature mortalities in proportion to area. We treat all lives lost due to 2030 $PM_{2.5}$ concentrations as occurring in 2030. This assumption results in a small overestimate of 2030 co-benefits, as we do not discount premature mortalities occurring later than 2030. A discount rate of 3% and a cessation lag structure used in regulatory analyses (EPA-SAB, 2004) results in an 11% reduction in the dollar value of health co-benefits.

The economic co-benefit of avoided premature mortalities is quantified using the Value of Statistical Life (VSL), consistent with regulatory analyses (EPA, 2015a). We use a range of VSL estimates published by the EPA, equal to \$1–23 million in 2015 dollars (EPA, 2014). The EPA's central estimate, equal to \$8.6 million in 2015 dollars, is used for the central results of this study. We scale VSL estimates by changes in GDP from 2015 to 2030 occurring in each policy scenario, using an income elasticity of 0.4 based on the recommended central value in EPA's Benefits Mapping and Analysis Program-Community Edition model (RTI International, 2015). Finally, we estimate climate change mitigation benefits using CO_2 emission changes estimated by USREP and the EPA's central SCC estimate of \$56.6/tCO_2 in 2030 (2015 dollars) (IWG, 2016). All monetary impacts presented in this paper are expressed in 2015 dollars.

To evaluate alternative policy options, we design five policy scenarios: Business-as-usual (BAU), RPS +50%, RPS +100%, No RPS, and CO_2 price. The BAU scenario reflects current RPS statutes. It simulates a regional RPS for the Rust Belt region, with a renewable requirement equal to the average of the renewable requirements of the existing RPSs in individual Rust Belt states (N.C. Clean Energy Technology Center, 2018), weighted by 2016 electricity sales (EIA, 2017c). We subtract any RPS requirements specific to solar or distributed generation (known as "carve-outs") from the total renewable requirement, as these technologies are not represented in our economic model. These carve-outs represent 5% of the total weighted average renewable requirement in the Rust Belt region (N.C. Clean Energy Technology Center, 2018). The estimated RPS requirement for the Rust Belt equals 6% in 2015 and 13% in 2030. Two additional scenarios (RPS +50% and RPS +100%) test the impacts of strengthening the region's RPSs. These scenarios reflect a gradual increase in the renewable requirement over time to reach a 2030 value that is 50% and 100% larger respectively than the 2030 requirement under BAU. Additionally, we include a counterfactual No RPS scenario. In this scenario, all RPSs in the region are assumed to be repealed as of 2015. Finally, we define a CO_2 price scenario to represent the impact of implementing a carbon price as an alternative to strengthening RPSs. The CO_2 price scenario implements a cap-and-trade system in the Rust Belt in 2020. The cap is specified to be stringent enough to achieve the same amount of cumulative CO_2 reductions as the RPS +100% scenario. The CO_2 price scenario includes a BAU-level RPS, so that it represents the impacts of a CO_2 price in addition to existing RPS policy. For each of these five scenarios, we present our central results as well as two sensitivity cases that change the capital costs of wind turbines by +/- 15% (labeled High Cost and Low Cost).

3. Results

3.1 Emissions

The majority of emission impacts occur in the electricity sector (**Figure 1**). These changes take place as RPS policy causes renewable generation deployment to displace coal- and gas-based generation from the power mix. The percentage of renewable generation estimated by USREP in 2030 is 6%, 13%, 20%, and 26% in the No RPS, BAU, RPS +50% and RPS+100% scenarios, respectively. The share of electricity produced by coal in 2030 is 33%, 29%, 23%, and 17%, respectively. This is equivalent to reductions of 46, 111, and 167 TWh in the BAU, RPS +50% and RPS +100% scenarios relative to No RPS. The 2030 gas share changes from 30% in the No RPS scenario to 26%, 25%, 22% (58, 78, 113 TWh) in the three RPS scenarios respectively. With regard to CO_2 emissions, the three RPS scenarios reduce 2030 emissions in the Rust Belt by 50, 112, 168 Mt CO_2 compared to No RPS (equivalent to 4%, 9%, and 13% respectively).

RPSs are also estimated to lead to an emission leakage effect: a rise in transportation sector emissions that offsets reductions in the electricity sector. In the BAU scenario, emissions of SO_2 and NOx in that sector rise by 3% while primary $PM_{2.5}$ emissions increase by 1% relative to No RPS. This occurs as higher electricity prices caused by RPS policies incentivize households to increase usage of internal combustion engine vehicles relative to electric vehicles. In the BAU scenario, the share of vehicle miles traveled by electric vehicles in 2030 is 4% (compared with 9% in the No RPS), while total vehicle miles traveled are virtually the same. This difference is driven by a 3% increase in the 2030 price of electricity faced by consumers in the Rust Belt under BAU relative to No RPS. This strong response

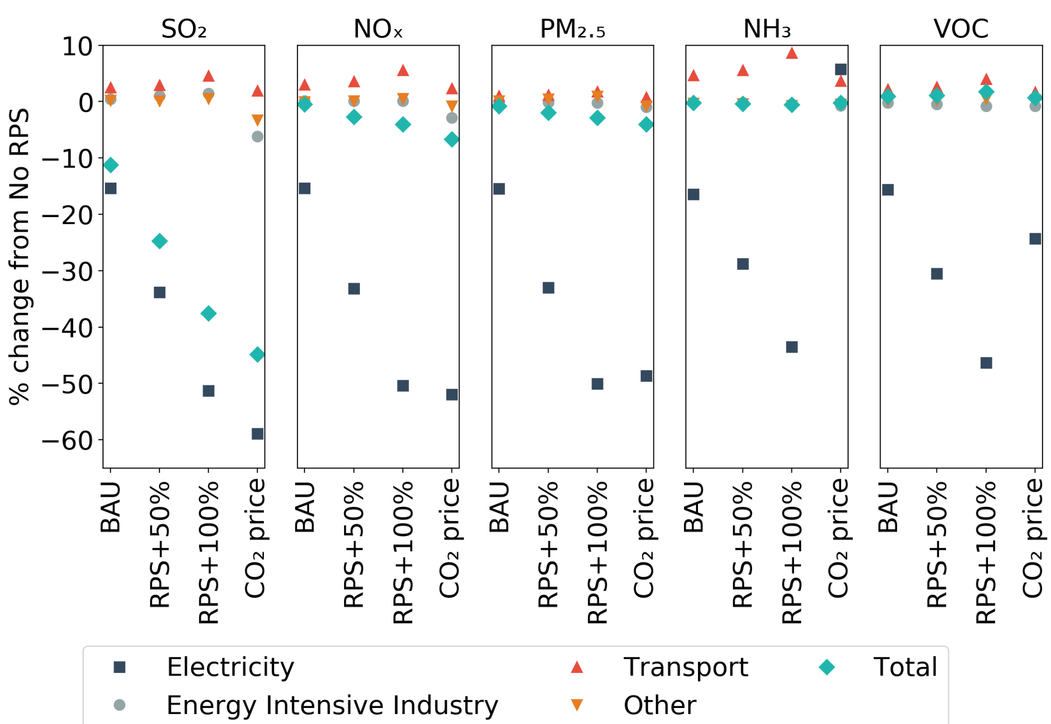

Figure 1. Changes in 2030 emissions by policy scenario, economic sector, and pollutant for the Rust Belt region

in vehicle miles traveled to power price changes occurs because electric vehicles happen to be on the cusp of being competitive against internal combustion engine vehicles in our scenario. As a result, small changes in costs have a relatively large effect on the uptake of electric vehicles. Thus, the magnitude of this result is not generalizable outside of our scenarios.

The CO_2 price scenario, by design, achieves the same emission reductions as the RPS +100% scenario. The reductions required to be achieved by the modeled regional cap-and-trade system are 118 Mt. The CO_2 price generated by the model to achieve these reductions is relatively modest at \$4/tCO_2 in 2030. This scenario exerts qualitatively different effects on the economy. In the electricity sector, the CO_2 price increases the marginal cost of CO_2 emitting technologies based on their CO_2 emission intensity, bolstering the competitiveness of gas relative to coal, thus leading to fuel switching. This scenario results in a 2030 coal share of 8 percent, and an increased gas share of 46 percent, while keeping the renewable share unchanged from the BAU scenario. As a result of the lower amount of coal generation, carbon pricing reduces electricity sector emissions of SO_2 and NOx to a greater degree than the comparable RPS +100% scenario (Figure 1). However, the greater use of gas under carbon pricing results in higher emissions of $PM_{2.5}$, NH_3, and VOCs in the electricity sector compared to RPS +100%.

The CO_2 price scenario lowers emissions in other sectors due to its economy-wide scope. For example, it lowers coal consumption in energy intensive industry. It also partially offsets the increase in transportation sector emissions caused by the BAU RPS.

3.2 $PM_{2.5}$ Concentrations and Mortalities

The effect of our policy scenarios on $PM_{2.5}$ concentrations relative to No RPS mostly occur in the Rust Belt region (**Figure 2**). The relative reductions are largest in Maryland, Delaware, Pennsylvania, Indiana, Ohio, and West Virginia. In the BAU scenario, average population-weighted concentration changes in these states range from -0.14 μg/m^3 in Maryland to -0.10 μg/m^3 in West Virginia.

Concentrations of $PM_{2.5}$ are even lower under the more stringent climate policies. We observe the largest reductions in the CO_2 price scenario. Maryland experiences the greatest decrease in population-weighted concentrations of 0.76 μg/m^3 relative to No RPS. The smallest reduction occurs in Wisconsin and equals 0.06 μg/m^3. Concentrations also decline in downwind states such Virginia (up to -0.5 μg/m^3), followed by New York (up to -0.2 μg/m^3). The location of air quality improvements partially reflects the distribution of coal plants along the Ohio river. These improvements in air quality are estimated to result in 467, 1,350, and 1,999 avoided annual premature mortalities in the Rust Belt in the three RPS scenarios relative to No RPS.

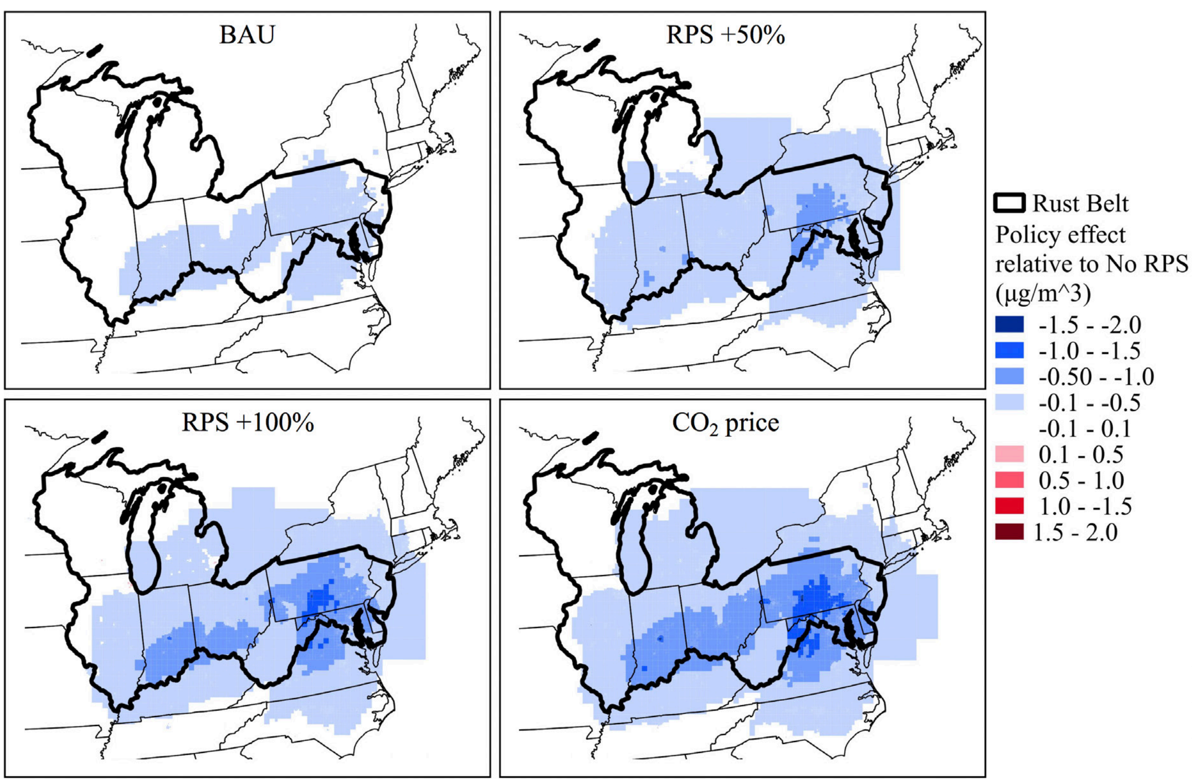

Figure 2. Changes in 2030 $PM_{2.5}$ concentrations by scenario relative to No RPS

3.3 Costs and Benefits

The health co-benefits of existing RPSs in the Rust Belt exceed both the total policy costs and estimated climate benefits according to our central results (**Figure 3**). This finding is robust to the range of different renewable energy costs tested (our Low Cost and High Cost scenarios assume 15% lower or higher wind capital costs respectively). However, the combined uncertainty in the concentration-response coefficient and the VSL leads to a large range of health co-benefit values spanning three orders of magnitude (**Table 1**). Uncertainty in the concentration-response coefficient is based on the coefficient's 95% confidence interval. VSL uncertainty accounts for all values published in EPA (2014). The VSL uncertainty is responsible for more than half of the combined uncertainty reported in Table 1.

The health co-benefits of the BAU, RPS +50%, and RPS +100% scenarios correspond to co-benefits of $94, $120, $119 per ton of CO_2 reduced respectively. These estimates are equivalent to health co-benefits of 8¢, 12¢, and 13¢ per kWh of new renewable generation. In comparison, the economic costs of the three RPS scenarios correspond to 6¢, 5¢, and 6¢ per kWh respectively. In percentage terms, the economic costs represent a decrease in macroeconomic consumption of 0.1%, 0.1%, and 0.2% in the three RPS scenarios relative to No RPS.

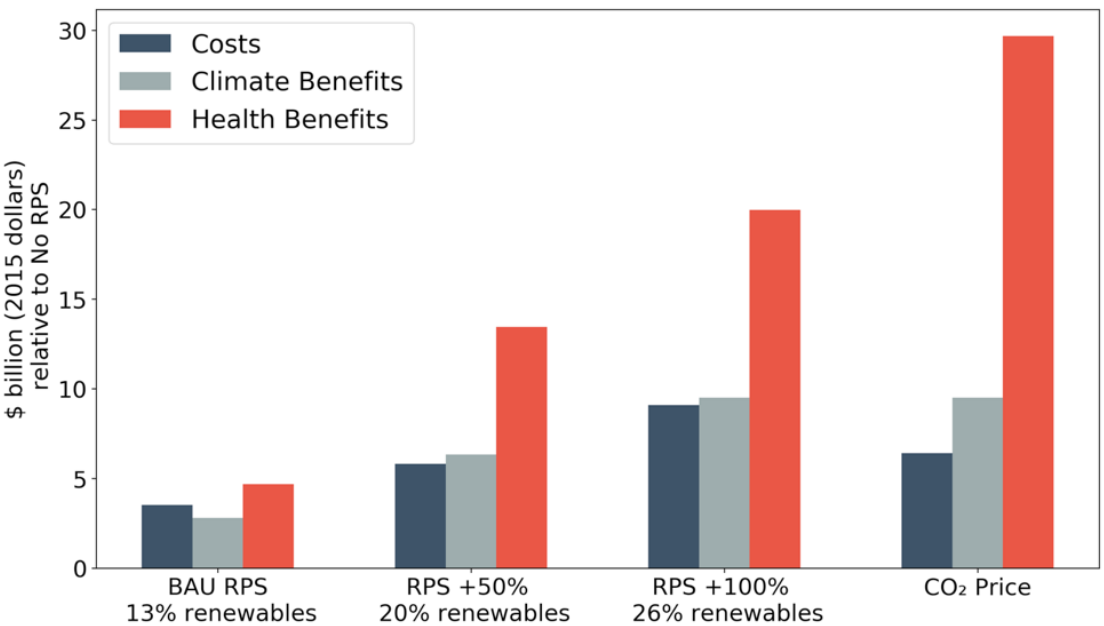

Figure 3. Costs and benefits of RPS and CO_2 pricing scenarios in 2030 relative to No RPS (central results).

Table 1. Costs and benefits in 2030 by policy scenario (billion 2015 dollars). Climate benefit uncertainty includes uncertainty in the discount rate and marginal damages of climate change. The air quality uncertainty includes the 95% confidence interval for the concentration-response coefficient and the full range of values for the Value of Statistical Life reported in EPA (2014).

	Policy Scenarios	Climate Benefits		Health Co-benefits		Costs
Central Results	BAU	$2.8	($0.9–8.6)	$4.7	($0.1–23.7)	$3.5
	RPS +50%	$6.4	($2.0–19.3)	$13.5	($0.3–68.3)	$5.8
	RPS +100%	$9.5	($3.0–29.0)	$20.0	($0.4–101.4)	$9.1
	CO_2 price	$9.5	($3.0–29.0)	$29.7	($0.7–151.0)	$6.4
Low Cost	BAU	$2.9	($0.9–8.7)	$6.0	($0.1–30.5)	$3.4
	RPS +50%	$6.0	($1.9–18.4)	$13.4	($0.3–68.1)	$5.2
	RPS +100%	$8.9	($2.9–27.1)	$18.7	($0.4–95.1)	$7.7
	CO_2 price	$8.9	($2.9–27.1)	$29.3	($0.6–149.2)	$5.9
High Cost	BAU	$2.9	($0.9–8.8)	$4.9	($0.1–24.8)	$5.2
	RPS +50%	$6.6	($2.1–20.2)	$14.3	($0.3–72.4)	$8.0
	RPS +100%	$9.9	($3.2–30.2)	$21.0	($0.5–106.6)	$11.9
	CO_2 price	$9.9	($3.2–30.2)	$32.4	($0.7–165.3)	$8.1

Monetized benefits of CO_2 reductions (referred to here as "climate benefits") are also comparable to policy costs and may substantially exceed them depending on the assumed SCC (Table 1). We quantify the uncertainty in climate benefits using the four alternative SCC assumptions provided by IWG (2016). The high end of the uncertainty range reflects the 95^{th} percentile of the SCC probability distribution, recommended by the IWG as a way to represent the marginal impact of low-probability, high-impact damages caused by climate change. The low end represents the use of a 5% discount rate (relative to the 3% rate used for the central SCC value).

Carbon pricing results in greater health co-benefits than the comparable RPS +100% scenario. Since the CO_2 price scenario includes a BAU-level RPS, we estimate the co-benefit of carbon pricing based on the additional health benefits relative to the BAU, resulting in an estimated health co-benefit of of \$211/tCO_2 (the equivalent estimate for the RPS +100% scenario equals \$129/tCO_2). The health co-benefit of the CO_2 price is higher partially due to its stronger effect on coal-fired generation. It is also due to the increase in transportation sector emissions occurring under RPSs, which offsets their overall health co-benefits. In addition, carbon pricing results in lower cost by incentivizing the least-cost CO_2 abatement options. Relative to the BAU, the additional costs of the RPS +100% scenario are twice as large as the costs of carbon pricing.

We test the impact of the emission leakage in the transportation sector under RPSs by recalculating health co-benefits assuming private transportation emissions remain the same as in the No RPS scenario, thus eliminating the effect of RPSs on private transportation emissions. Under this experiment, health co-benefits in the Rust Belt were 35–79% higher depending on the RPS scenario (the BAU scenario exhibited the largest increase). This emission leakage effect is sensitive to the extent to which RPSs increase electricity prices, which is the underlying cause behind the changes in emissions from transportation as discussed previously. Electricity system modeling by Mai *et al.* (2016) estimates that existing RPSs lead to smaller changes in 2030 power prices between +1% and -0.4% depending on region and underlying assumptions.

4. Discussion and Conclusions

Health co-benefits may alone justify the implementation of RPSs or carbon pricing as our central estimates show. This result is consistent with previous literature, which found that the health co-benefits of climate policy (including RPSs and other instruments) tends to exceed policy costs (Thompson *et al.* 2014, 2016; Mai *et al.*, 2016; Wiser *et al.*, 2016; Shindell *et al.*, 2016; West *et al.*, 2013). Our estimated health co-benefits of 8¢/kWh are greater than the national average of 1.2–4.2¢/kWh estimated by Mai *et al.* (2016), consistent with the greater share of coal generation in the Rust Belt region (EIA, 2017b).

We further estimate that increasing the renewable requirement of existing RPSs in the Rust Belt region would increase net societal benefits. As RPS stringency is raised, health co-benefits increase more than costs. The marginal health co-benefits (the incremental co-benefit incurred from the No RPS to the BAU scenario, and so on) are larger than the marginal costs across all RPS scenarios tested.

Our results also demonstrate that there can be meaningful differences between the health co-benefits of alternative climate policies. We find that, to 2030, carbon pricing is more efficient (greater net benefits) relative to an RPS than suggested by cost-per-ton-reduced comparisons that do not consider health co-benefits (*e.g.*, Rausch and Mowers (2014)). Regardless of efficiency, however, RPS policies have been more politically popular, leading to their more frequent implementation (Rabe, 2018). Additionally, while carbon pricing results in higher health co-benefits in 2030, the relative merits of different climate policies would differ in an assessment that includes the full environmental externalities of natural gas extraction (EPA, 2016), the Social Cost of Methane (Marten and Newbold, 2012) or the implications that increasing natural gas consumption may have for long-term policy targets aiming to achieve deep reductions in CO_2 emissions (Erickson *et al.*, 2015).

Several limitations of this work are worth noting. First, we do not attempt to causally attribute the estimated benefits to RPS policies as we do not capture other renewable energy policies that may induce deployment. Instead, the results of this study are indicative of the effects of renewable technology deployment consistent with the requirements of modeled RPS scenarios.

Second, the use of general equilibrium modeling introduces the disadvantage of representing the electricity sector in a top-down fashion, thus omitting details including intra-day power dispatch based on operational limits such as power plant ramping flexibility. Recent work has demonstrated the possibility of leveraging the advantages of both approaches through hybrid approaches that iteratively combine both types of models (Rausch and Mowers, 2014; Tapia-Ahumada *et al.*, 2015). Third, our scenarios do not model air pollution policy in the U.S. such as the emission trading systems for SO_2 and NOx emissions under the Cross-State Air Pollution Rule (CSAPR). This may cause our results to overestimate the effects of climate policies on air pollution if reductions in air pollutant emissions from one source cause the transfer of emission permits, allowing another source to increase emissions, offsetting the original reductions (Groosman *et al.*, 2011). This effect is likely to be limited, however, as emission sources already have access to a surplus number of permits under CSAPR, particularly for SO_2 (EPA, 2018a).

An important area for future work will be to quantify the uncertainty in health effects associated with the choice of air pollution model. While the health co-benefit results presented here compare closely to estimates derived from Chemical Transport Models (Thompson *et al.*, 2014; 2016), we do not quantify uncertainty related to model choice. Subsequent research could apply state-of-the art Chemical Transport Models alongside the type of reduced-form model used in this work to a variety of relevant policies to help understand which atmospheric modeling methodologies are best suited to which types of policy evaluations.

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Appendix A. Additional Sensitivity Analysis

In this Appendix we provide a sensitivity analysis to alternative assumptions for the Concentration-Response Function coefficient, value of statistical life, and timing for mortalities.

A.1 Sensitivity of results to concentration-response uncertainty

Here we present further detail on how our results vary with alternative assumptions for the Concentration-Response Function (CRF) coefficient for the impact of air pollution concentrations on premature mortality. Our main results use a pooled concentration response coefficient calculated using random effects pooling, combining the results of two epidemiological studies by Krewski *et al.* (2009) and Lepeule *et al.* (2012). The estimated pooled coefficient equals 1.092, implying a 9% increase in premature mortalities resulting from a 10 μg/m^3 increase in $PM_{2.5}$ concentrations (with a 95% Confidence Interval of: 1.018–1.171). This compares to 1.06 and 1.14 coefficients estimated by Krewski *et al.* (2009) and Lepeule *et al.* (2012) respectively.

Figure A1 illustrates how the health co-benefits based on the pooled coefficient compare to results derived from the coefficients estimated in each of these studies. As shown, the central estimates derived using the two CRFs from the literature vary by approximately 30% from central estimate using the pooled coefficient.

A.2 Sensitivity of results to Value of Statistical Life assumptions

We further present the sensitivity of the health co-benefit results to the choice of the assumed Value of Statistical Life (VSL) (**Figure A2**). We use the full range of values published by EPA (2014). The range of health co-benefit estimates across all VSLs is approximately 50% larger than the variation resulting from the uncertainty associated with the pooled CRF.

A.3 Sensitivity of results to timing for mortalities

Estimates of the monetary value of premature mortalities depend on when mortalities are assumed to take place in relation to a change in $PM_{2.5}$ concentrations. Our central estimates assume that premature mortalities occur in the same year in which exposure to $PM_{2.5}$ occurs. EPA-SAB (2004) recommended a cessation lag structure where 30% of the mortality changes occur in the first year, 50% occur equally in years 2 through 5, and the remaining 20% occur equally over years 6 through 20. Applying this lag structure and a discount rate of 3% lowers our estimated health co-benefits by 11%. A 7% discount rate would lower our central health co-benefits by 21%.

A.4 References to Appendix A

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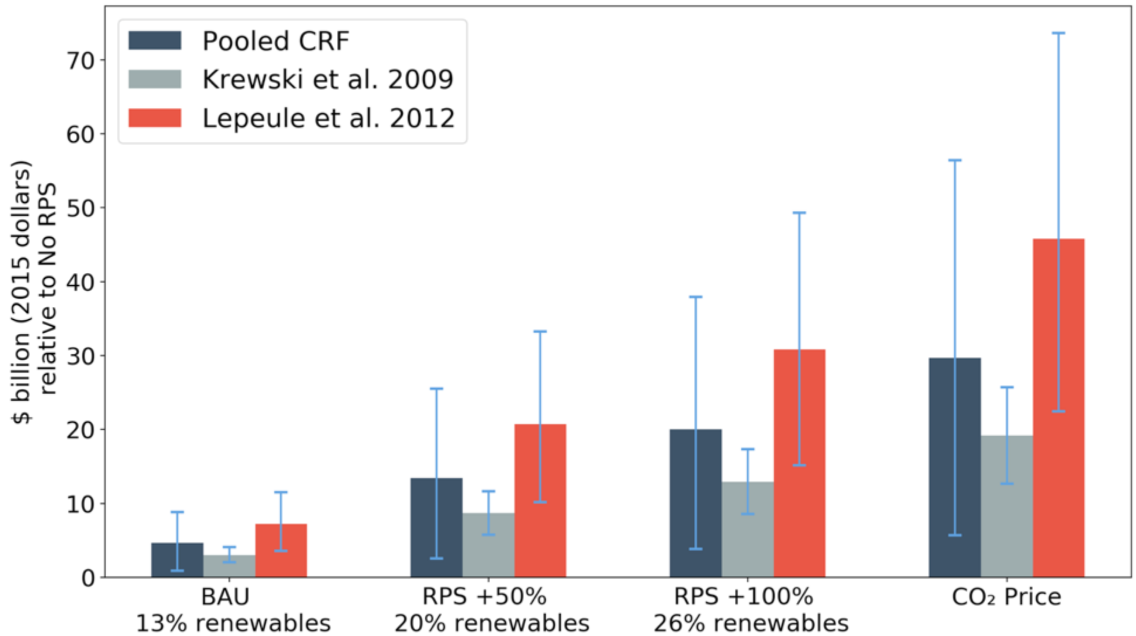

Figure A1. Health co-benefits in 2030 by scenario relative to No RPS for alternative concentration-response assumptions.

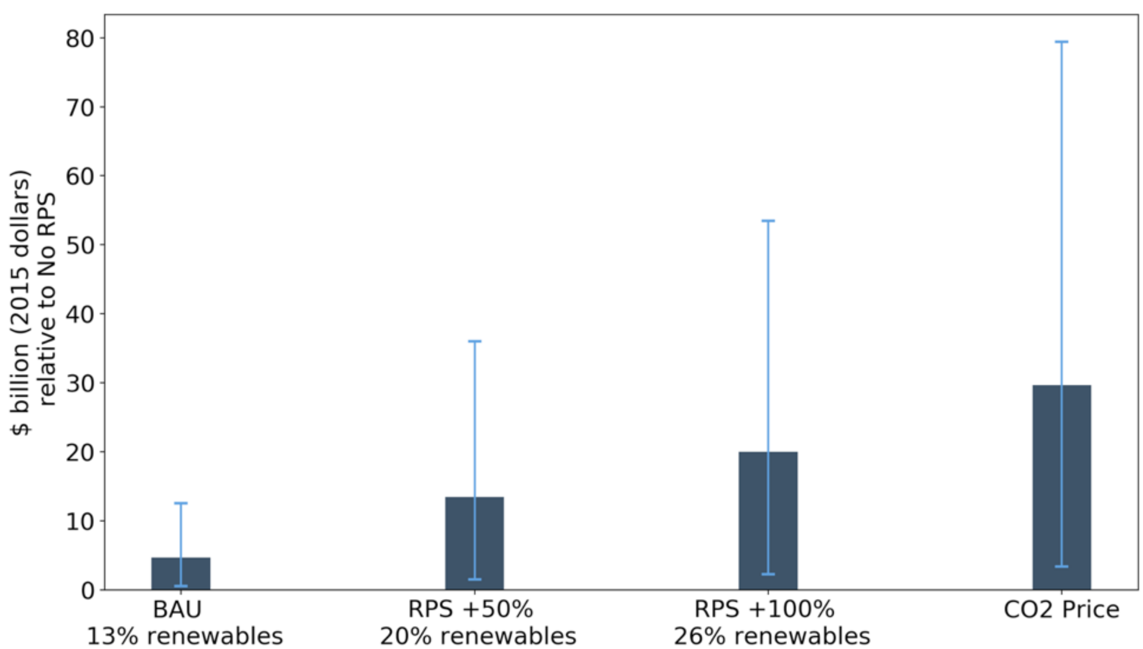

Figure A2. Health co-benefits in 2030 by scenario relative to No RPS including the range of VSL estimates published by EPA (2014).

Appendix B. Ohio Case Study

Emil Dimanchev, Sergey Paltsev, Mei Yuan and Noelle E. Selin

B.1 Introduction

Renewable energy policy is on the agenda of the current 133rd General Assembly of the Ohio legislature. In April 2019, Representatives Jamie Callender and Shane Wilkin introduced House Bill 6. The bill proposes a Clean Air Program that would offer financial support for nuclear plants in the state. In addition, House Bill 6 repeals Ohio's Renewable Portfolio Standard (RPS) – also referred to as the Alternative Energy Portfolio Standard – as proposed in the version reported by the House Energy and Natural Resources Committee.

The future of Ohio's RPS may have important implications for air quality in the state. Emissions from power plants have been estimated to result in 4,000 premature deaths in Ohio in 2005, more than in any other state (Caiazzo *et al.*, 2013). The EPA has determined Cleveland to be in non-attainment of the National Ambient Air Quality Standard for $PM_{2.5}$ under the Clean Air Act. Thus, approximately 10% of the state's population is exposed to $PM_{2.5}$ concentrations that exceed national health-based standards.

Here, we explore the potential air quality health benefits and the economy-wide costs of Ohio's RPS. This analysis applies the modeling framework developed and described previously in this report. In what follows, we describe how we apply this methodology to Ohio, and present results for the impacts of Ohio's RPS on power generation, air pollutant emissions, $PM_{2.5}$ concentrations, and avoided premature mortalities. Finally, we compare the monetized value of premature mortalities avoided by the RPS to the total economy-wide cost of the RPS.

B.2 Methods

We apply the modeling framework discussed earlier in this report to estimate Ohio's RPS costs and benefits in 2030. Here, we use a more granular, 30-region version of the MIT United States Regional Energy Policy (USREP) model, which allows us to model Ohio as a separate jurisdiction and thus estimate impacts specific to the state.

We evaluate RPS impacts by modeling two policy scenarios: BAU and NoRPS. The BAU scenario reflects existing RPS requirements (N.C. Clean Energy Technology Center, 2018) up to 2030. Solar-carveouts were excluded from our scenarios as USREP does not represent solar. We estimate the impacts of the BAU scenario by comparing its results to the NoRPS scenario, which assumes that Ohio's RPS is repealed.

Modeling an RPS at the state level presents an additional challenge of accurately representing this policy in a Computable General Equilibrium (CGE) model such as USREP. USREP simulates an RPS as a requirement for a certain share of generation within a given jurisdiction to be renewable (in reality, RPSs place a renewable requirement on consumption rather than generation). While this approach is suitable to modeling RPSs on a regional level, it may misrepresent RPS impacts at the state level. This is because utilities can meet RPS requirements by purchasing Renewable Energy Credits (RECs) from out-of-state. RPSs therefore do not necessarily lead to renewable energy deployment in the implementing jurisdiction. In Ohio, load serving entities have surrendered RECs from a number of neighboring states to comply with the RPS (**Table B1**) (PUCO, 2018)

To account for the impact of out-of-state REC purchases, we implement hypothetical renewable generation requirements in Indiana, Kentucky, West Virginia, and Pennsylvania (for Pennsylvania we implement a renewable requirement on top of the existing RPS), which are proportional to each state's contribution listed in Table B1. Ohio's renewable generation requirement is specified to equal 24% of the total Ohio RPS.

B.3 Results

B.3.1 Electricity generation effects

Figure B1 displays the effects of the RPS on electricity generation, USREP estimates an increase in wind generation in the states from which Ohio sources its RECs. In total, the model estimates that the BAU scenario results in 11 TWh of wind generation relative to NoRPS in 2030 in these states. In addition to this new wind generation, Ohio's RPS is met with existing hydro generation in Kentucky and West Virginia, consistent with historical compliance (PUCO, 2018). Coal generation drops by 19 TWh in affected states in total. Generation from other technologies remains relatively unaffected. The model estimates a small increase in coal combustion in Pennsylvania, which is driven by regional electricity trading effects.

It is worth noting that these power market impact results are somewhat in contrast to our finding for the Rust Belt region in the main portion of this report, where we found that new renewable generation displaces both coal and gas generation from the power mix. However, our results for Ohio are largely consistent with findings by Buonocore *et al.* (2016) who found that renewable deployment in Northern Ohio displaces mostly coal generation using a more detailed representation of power sector dispatch. Coal plants

Table B1. Share of RECs surrendered for 2017 compliance with Ohio's AEPS

	Percent of all RECs (non-solar)
Ohio	24
Indiana	30
Kentucky	21
West Virginia	15
Pennsylvania	9

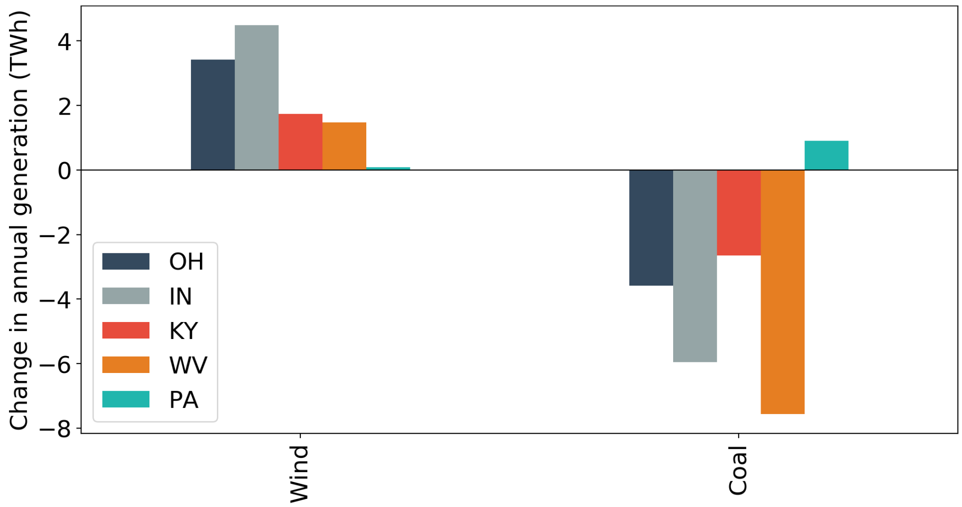

Figure B1. Changes in electricity generation in BAU scenario relative to NoRPS.

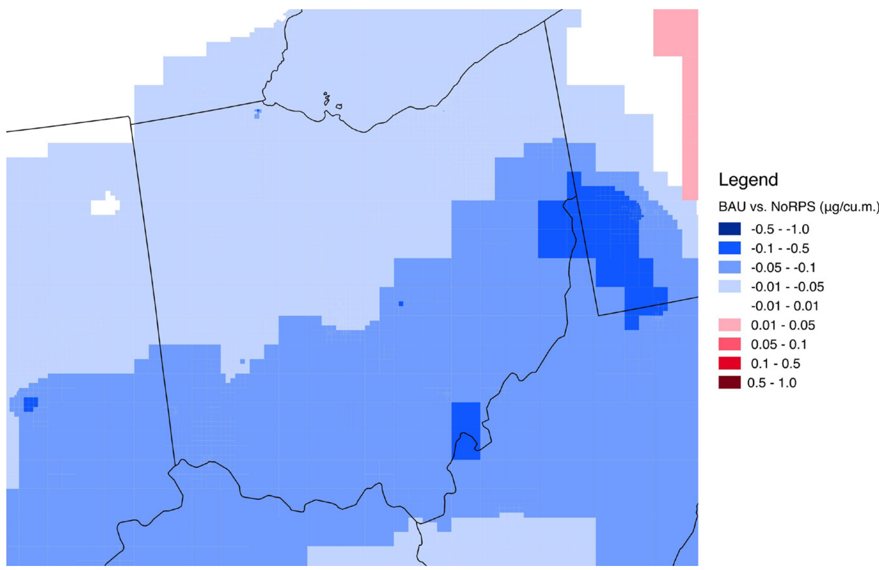

Figure B2. Changes in 2030 $PM_{2.5}$ concentrations (µg/m³) in BAU scenario relative to No RPS.

generally have higher cycling costs compared to gas plants (Kumar *et al.*, 2012) suggesting that, all else being equal, increasing penetration of variable renewable energy affects the revenues of coal plants more than gas plants. Whether renewable generation displaces coal or gas generation will vary depending on the plant costs and operational characteristics in each state. Differences between our results here and for the Rust Belt region are somewhat consistent with differences between estimated renewable impacts in Ohio and in the region as a whole: Buonocore *et al.* (2016) found that in Pennsylvania and New Jersey (two states included in our Rust Belt region) new wind plants displaced more natural gas generation than coal.

B.3.2 Emission effects

As a result of the reduction in coal generation, the RPS leads to a reduction in emissions of air pollutants. As emission reductions are being driven by less coal combustion, the majority of the impacts are reflected in the emissions of SO_2. In Ohio, 2030 SO_2 emissions are lower in the BAU by 2% relative to No RPS. In Indiana, Kentucky and West Virginia, emissions are lower by 3%, 2%, and 7% respectively, reflective of the changes in coal combustion discussed above. Emissions of SO_2 in Pennsylvania increase by 6% as a result of the increased coal use.

B.3.3 $PM_{2.5}$ concentration and mortality effects

We use the InMAP model to estimate how changes in emissions translate to changes in concentrations of $PM_{2.5}$ (**Figure B2**). We estimate the RPS reduces $PM_{2.5}$ concentrations throughout Ohio. Across the state, $PM_{2.5}$ concentrations in 2030 are lower in the BAU by 0.04 µg/m³ on a population-weighted average basis. This relatively small impact reflects the weak stringency of Ohio's RPS.

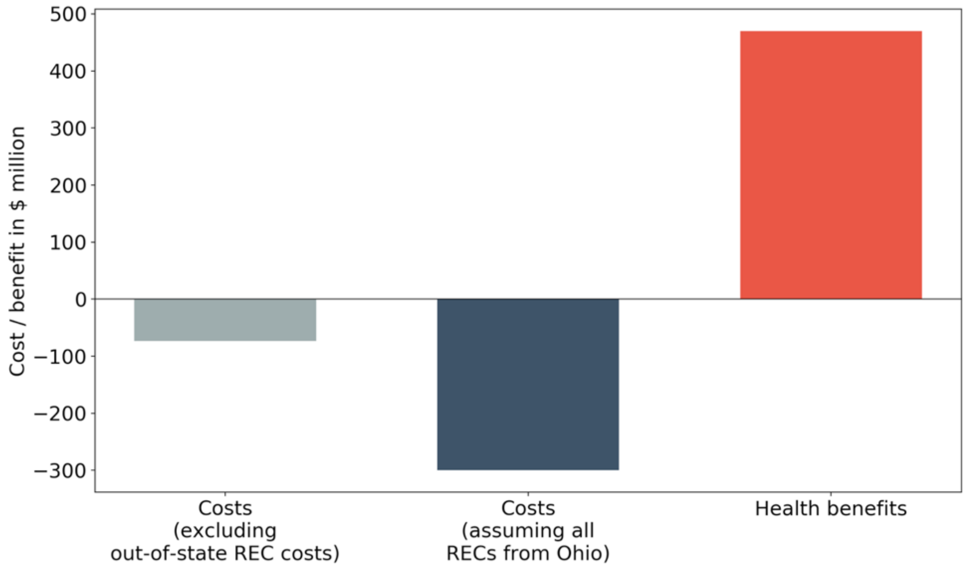

Figure B3: Costs and benefits of RPS in 2030 relative to No RPS (central results), 2015 dollars.

This reduction in $PM_{2.5}$ concentrations is estimated to result in approximately 50 avoided premature mortalities per year in Ohio. This result is based on our pooled concentration response function (CRF) described in the main body of this report. The 95% confidence interval associated with this CRF results in an uncertainty range between 9 and 93 avoided premature mortalities. Using alternative CRF assumptions from Krewski *et al.* (2009) or Lepeule *et al.* (2012) results in 32 (95% confidence interval of 21–42) and 75 (37–121) avoided premature mortalities, respectively.

B.3.4 Costs and benefits

Total economic costs are estimated as the annual change in household consumption between the BAU and the NoRPS scenarios. Changes in household consumption are a common way to measure total macroeconomic costs (Paltsev and Carpos, 2013). RPS costs are to a large extent driven by the cost of acquiring RECs, the corresponding impact on electricity prices, and the ripple effects of higher electricity prices on the rest of the economy (as well as other second-order effects such as the impact of changes in renewable and coal generation on these industries and supply chains).

Cost estimates are presented in **Figure B3**. Our BAU scenario implies a cost of Ohio's RPS of $70 million (gray bar). However, this is an underestimate as our implementation of RPS policy in USREP effectively assumes that Ohio electricity ratepayers do not bear the cost of out-of-state RECs. To more closely represent the RPS cost to Ohio, we model a renewable generation requirement in Ohio equivalent to the total RPS requirement of 12% in 2030. This assumes that all RECs come from in-state and more accurately represents the impact of REC purchases on Ohio's electricity price in our model. Under this case, our BAU RPS scenario implies a cost to Ohio of $300 million in 2030 relative to No RPS (blue bar). This modeling case may overestimate costs somewhat as it assumes that RECs come from more expensive generation in Ohio (as opposed to cheaper REC sources such as existing hydropower in West Virginia and Kentucky). Overall, the cost of Ohio's RPS may lie between the gray and the blue bars (the first two bars in Figure B3). It bears mentioning that in relative terms, $300 million is a relatively small reduction in total household consumption of 0.06% (less than one tenth of one percent).

For the air quality related health benefits of Ohio's RPS, we estimate that as the RPS avoids 50 premature mortalities per year, it results in an annual monetized benefit of $470 million in 2030, based on our Value of Statistical Life (VSL) assumption discussed previously. This is equivalent to approximately $0.03 for each of the 18 kWh of renewable generation supported by the RPS in 2030. As noted earlier, this is the benefit incurred by Ohio specifically. We estimate that the total benefit of Ohio's RPS to Ohio and all surrounding states that experience improvements in air quality is equal to $800 million in 2030. These benefit estimates are subject to uncertainty, particularly, in our CRF and VSL assumptions as discussed in detail in the main section of the report. Considering the full uncertainty in the CRF (95% confidence interval) and the VSL assumptions (all values published by the EPA), we estimate a large uncertainty range around our central $470 million estimate of $10–2,390 million.

B.4 Discussion and Conclusions

We find that the air pollution-related health benefits of Ohio's RPS are of a magnitude that justifies their consideration in state policy making. Our best estimate of the 2030 RPS health benefit to Ohio of $470 million exceeds our more conservative estimate of the 2030 total economy-wide cost of $300 million. This is consistent with our findings above for the Rust Belt and previous research (Thompson *et al.*, 2014, 2016; Mai *et al.*, 2016; Wiser *et al.*, 2016; Shindell *et al.*, 2016; West *et al.*, 2013; EPA, 2015), which shows that health benefits for greenhouse gas reduction policies tend to exceed policy costs.

The health benefits of Ohio's RPS, estimated here at $0.03/kWh, are of the same order of magnitude as previous estimates. Jaramillo and Muller (2016) estimated that power plant emissions impose a health-related externality of $0.05/kWh or $0.09/kWh (depending on the assumed relationship between air pollution exposure and mortality). Levy *et al.* (2009) estimated the health-related externality of coal plants at $0.14/kWh (median across the U.S.), with larger values estimated for Ohio. Mai *et al.* (2016) estimated cumulative national average health benefits of RPSs up to 2050 of $0.01–0.04/kWh. Our estimate for Ohio is smaller than some of these previous findings, in part because we estimate health benefits specific to Ohio. As shown in our results above, some of the air quality improvements from Ohio's RPS occur in neighboring states.

This analysis further suggests that Ohio benefits from out-of-state deployment of renewables. As Ohio's air quality is impacted by power plant emissions originating from neighboring states, so changes in the energy mixes of its neighbors can lead to better air quality for Ohio residents. This is particularly the case in large populated areas close to state borders such as Cincinnati. Although some states have designed their RPSs to encourage in-state renewable investments (Mack *et al.*, 2011), this analysis shows that out-of-state renewable generation can also be beneficial to individual states due to its effects on regional air quality.

The limitations of our modeling of Rust Belt RPS effects presented in the main body of this report also apply to this case study. Most notably, these results should be viewed as indicative of the general magnitude of health benefits and costs, rather than as deterministic forecasts of policy impacts. A limitation specific to this state-level case study is that estimating RPS air quality impacts in a given state is relatively dependent on where emission reductions occur. Our economy-wide model does not aim to represent which coal plants, in which parts of the region studied, will be impacted by RPS legislation. Future work on state-specific impacts will likely benefit from the use of more detailed power system models using plant-level data.

B.5 References to Appendix B

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