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Environmental Free Riding in Renewable Portfolio Standards

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Abstract: The aim of this paper is to empirically assess the hypothesis on free riding in the implementation of environmental policies. The screening model COBRA is used in order to translate changes in concentrations of particulate matter into health impacts. This is then further converted into health costs to generate a panel data set describing the development of pollution related health costs from 2008 to 2012. The panel data on health costs together with data on renewable energy investments is then used to determine whether the US states engage in free riding in the implementation of the Renewable Portfolio Standards policy. The relationship between the health costs and investments in renewable energy is studied in order to evaluate if later implementation of the policy is less costly in terms of pollution related health costs. The results are contrary to what free riding hypothesis predicts with no evidence of free riding identified in the data. The implications for the future are that there could be a need for greater collaboration in order to take advantage of knowledge spillovers.

Keywords: Renewable Portfolio Standards, free riding, health costs, fine particulate matter, COBRA Screening Model

JEL: Q2, Q4, Q5

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Introduction

Energy production today is still one of the major sources of a large number of pollutants (US Environmental Protection Agency 2004). Pollutants that not only contribute to global warming and environmental destruction, but also have a direct negative impact on the health of the world's population. Therefore, there is a need to reduce these emissions. Currently, there is only one way of doing this while at the same time being able to meet the increasing demand for energy and that is to shift energy production towards renewable sources such as sun and wind. This shift into renewable energy requires costly investments, resulting in a dilemma between economic profitability on one side and health and environment on the other. Short-term higher profits for energy producers through cheaper methods of production are incentives to maintain or even increase the level of emissions.

This conflict is where policies regulating energy production become important. They have the potential of pushing production methods towards more sustainable alternatives through a shift in the incentive balance. However, this requires that the policies are efficiently designed and implemented in order to generate the desired results. In the process of creating such a policy, a number of decisions have to be made. One of these is whether the decision of if and how the policy is implemented should be centralised within the federal government or decentralised among regional authorities. The US Renewable Portfolio Standards (RPS) is a policy that regulates the percentage of energy from renewable sources that utilities must provide. Currently it is implemented gradually on state level by regional governments, but the non-excludability and non-rivalry characteristics of air quality indicate that a federal RPS would perhaps be more efficient.

Air quality is a local public good since pollution flows freely across borders. The non-excludability of air quality implicates that investments in improvement of the air quality in one region not only benefit the people living in the region, but also improve the air quality for non-payers in bordering regions. As people cannot be prevented from breathing the air, air quality is also characterised by non-rivalry. This poses a potential problem for environmental policies aiming for reduction of total air pollution since bordering regions not implementing the policy cannot be excluded from enjoying the benefits. In other words, there is potential for a problem of free riding by regions that choose not to implement the policy. As a consequence, pollution reduction may not be at the level that maximizes total utility in society. The aim of this study is to investigate further if free riding is present when an environmental policy is being implemented gradually on the state level. It is essential to fully understand free riding and economic theory on public goods, in order to analyse efficacy of environmental policies.

The problem of geographical scope of the policy is complicated. Both regional and federal policies that address environmental issues have their respective benefits and caveats. Regardless of which is chosen, it will have implications for the success of the policy. Therefore, it is important to understand the mechanics of the different approaches and the potential problems a country faces when choosing one or the other. Most studies that we are aware of within this field have so far focused on how to design and implement efficient policies regardless of who is responsible for them (e.g. Kotchen 2012). This is why we believe there is a need for further research on the effect of decentralised decision-making when it comes to environmental policies

Further, environmental policies today are often evaluated based on their effect on climate change and costs related to this particular effect. However, in doing so other pollution-related costs are disregarded. These include, among others, the increased health costs from the diseases caused by various pollutants, costs that can be quite significant but also difficult to measure. In this study we choose to use a well-established screening model developed by the US EPA in order to estimate the health costs. The reason for this is that there is an evident risk that important dynamics are disregarded if only costs related to the climate change effect are included in the analysis. We have noted a shift towards a more inclusive approach in recent research, but we believe there is much more to be done within this area.

With this in mind, we decided to investigate how the relationship between investments in renewable energy and pollution-related health costs is affected when a large-scale environmental policy is implemented by different regions of a country individually. More specifically, we will focus on the RPS policy in the US with the purpose of answering the following question:
Is there a free riding problem in terms of health costs related to the introduction of the RPS policy?

Main concepts

Renewable energy sources

Renewable energy is the infinite energy that can supply the needs in a sustainable way. In this paper the following sources have been classified as renewable: solar, wind, tidal, wave, geothermal, hydroelectric, hydrogen and fuel cells as well as biomass. Most of these sources depend directly or indirectly on sunlight. The renewable sources that do not depend on sunlight are geothermal energy, power-derived form the Earth's internal heat, and tidal energy, which is a conversion of gravitational energy. Hydropower is not strictly renewable, since the reservoirs of hydroelectric dams eventually fill up and require an expensive excavation. All of these sources have low environmental costs, but are more expensive than fossil fuels. This will lead to economic dislocations if the renewables are to become the only energy source (National Geographic).

There are some aspects that speak against classifying biomass as a clean energy source. The recent report by Partnership for Policy Integrity (2014), "Trees, Trash, and Toxics: How Biomass Energy Has Become the New Coal" present controversial results on the inefficiency of biomass plants and argues strongly on that this source of energy is harmful for the environment. Biomass facilities are accused of emitting more air pollutants per megawatt hour than those burning coal. Even the cleanest operating biomass plants emit 190 percent more particulate matter than modern coal facilities of the same size. According to the authors of the report this is the result of the lax regulation of bioenergy. The newest biomass facilities are allowed to pollute more than modern coal- and gas-fired plants and are subject to heavy subsidies.

There are two different types of biomass, classified as harmful and beneficial biomass. The effects of biomass combustion range widely, depending on how and where the resources are harvested, how efficiently they are converted to energy and what fuels they substitute. Biomass becomes a non-renewable source if people do not replant the feedstocks as fast as they use them. Therefore the situation is nuanced, as this energy source has a lot of disadvantages and benefits (Union of Concerned Scientists; Childers Andrew 2014).

Particulate matter

Particulate matter (PM) is an air pollution term for a mixture of extremely small particles and liquid droplets. The size of particles varies, and they can be composed of many different types of chemicals and materials. The size of the particles is directly linked to their effects on health. The particles that are 10 micrometres in diameter (PM_{10}) or smaller can pass through the nose and throat and get into the lungs. This paper concentrates on the effect of fine particles ($PM_{2.5}$) due to their significant impact on respiratory and cardiovascular diseases.

Renewable Portfolio Standards

Renewable energy has become an important policy issue. In the beginning of this century the state governments in the US started implementing a plan, Renewable Portfolio Standards, in order to reduce greenhouse gas emissions. The RPS mandate that utilities operating within a state must provide a decided percentage of electricity from renewable energy sources. If a retail provider fails to meet its requirements in a given year, it must pay a penalty proportional to the difference between the target established by the policy and the amount of the renewable electricity it purchased (Johnson 2012). According to Database of State Incentives for Renewables & Efficiency (DSIRE), 38 states currently have enforceable RPS or other mandated renewable capacity policies. Figure 1 presents all the states that implemented the policy and when.

The policy is a new mechanism to respond to the public demand for electricity supplies that fulfil the requirements of being reliable, inexpensive and environmentally friendly. The main driving force behind the expanding policies has been vividly discussed. According to Johnson (2012), the environmental aspects are secondary factors; the development has been motivated by the economic qualities. The policy has been driving the expansion of important home-grown industries and resulted in net employment gain.

The basics of the policy are the same in every state, but every region tailors it and changes the details. There are some variations in the definition of the renewable sources and what kind of sources has been included. Some states started to differentiate themselves by providing special provisions to the more costly energy sources in order to increase the energy efficiency (Chen et al. 2007).

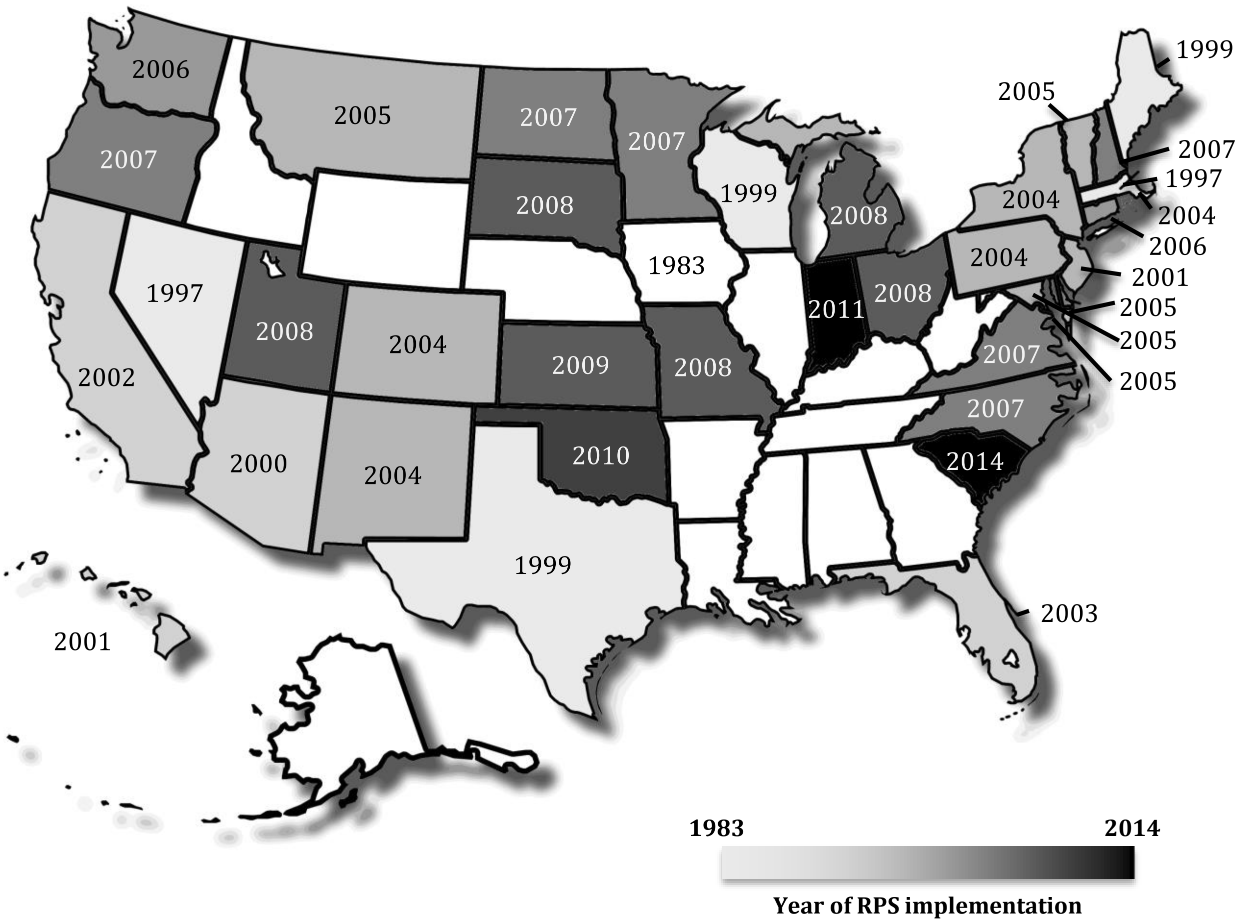

Figure 1. RPS Implementation. States with white colour have not yet implemented the policy. Our own production. Data obtained from DSIRE.

The cooperation between the states has been negligible, which might reduce the positive results of the policy. In order to create a sustainable change, intergovernmental collaboration must be created. There are a lot of implementation challenges, such as for example defining what kind of energy sources should be classified as renewable and deciding the geographical scope of the policy (Cory & Swezey 2007).

COBRA Screening Model

Co- Benefits Risk Assessment (COBRA) Screening Model is a screening model that provides an estimation of health costs as an effect of changes in PM concentrations. This tool delivers estimates of the impact of air pollution emission changes on the PM air pollution concentrations and then translates this into health effects that are monetised. This tool enables policymakers to analyse different scenarios and choose the right policy. It uses existing models and health impact equations, as well as ready for use economic valuations. COBRA is mainly developed for state and local officials, analysts, environmental agencies, energy officials and transportation planners. It has been used in different analyses by state and governmental agencies, such as for example “Retrospective Benefit-Cost Evaluation of US DOE Wind Energy R&D Program.” (US Department of Energy 2010). It should be noted that there are several limitations with this screening model and the economic value of health effects obtained from COBRA will be interpreted as a conservative estimate of the health benefits from reducing emissions (EPA 2014).

Previous research

Previous research on RPS

There are several different studies that focus on the characteristics of RPS, one of the strongest mechanisms in the US to address the climate change (Carley 2009). A quantitative study by Lyon and Yin (2010) identifies the most important characteristics of states that decide to implement RPS. The conclusion is that the adoption of the RPS is more likely in states that have a strong potential in renewables, restructured electricity market and only a small fraction of natural gas in the electricity fuel mix. Additionally a strong democratic presence in the state legislature increases the probability of adoption. The surprising result of the study is that states with worse air quality and higher unemployment rate, generally do not show greater interest in implementing this kind of policies. States with little renewable electricity generation are more likely to adopt the policy. The last factor influencing the adoption of RPS is private interest. The legislation can support some private actors, such as wind farm owners.

There is a lack of consensus on whether the RPS policy is an effective instrument in order to support renewable energy, although the existing analyses of the efficiency of RPS seem to agree on that the success of the policy is dependent on its design and regulatory rules (Langniss and Wiser 2003). Overall the states that have implemented RPS polices have significantly higher renewable energy deployment than states without RPS policies, holding all else constant. The collective results of the models in “State renewable electricity policies: An empirical evaluation” by Carley (2009), are that the policy encourages the total investments and deployments in renewable energy sources, but is not efficient when it comes to the increase of the percentage of renewables in an electricity portfolio of a specific state. A possible explanation of the low rate of renewable energy generation would be the fact that the overall electricity demand is also growing. The increase in total investments in renewable energy is overwhelmed by the growth of the total energy production. All in all, the policy has a positive effect on the investments in renewable energy sources.

Air pollution impact on health

The association between PM exposure and mortality and hospital admissions is very strong. (Franklin et al. 2015). Research during the past 10-20 years confirms that air pollution contributes to morbidity and mortality and therefore shortens the life expectancy for those affected by air pollution (Wilson and Spengler 1996). The morbidity and short-term mortality is mostly related to cardiopulmonary diseases, including lung cancer (Holgate et al. 1999). According to the World Health Organization, a time series studies in 90 cities in the US has shown that an increase of 10 $\mu g/m^3$ PM results in 0.27% increase in mortality. Air pollution can both trigger new cases of the diseases and provoke development of chronic diseases, including chronic obstructive pulmonary disease and emphysema. The most significant impact the level of PM in the air has is on asthma attacks, with 6280 attributable new cases among adults per 10 $\mu g/m^3$ PM_{10} in Europe. Air pollutants also harm lung development, creating an additional risk factor for developing lung diseases later in life (PSR 2009).

The fact that PM can travel to other parts of body, for instance blood and heart, results in compelling evidence that exposure of $PM_{2.5}$ contributes to the development of cardiovascular disease and can trigger acute cardiac events (Franklin et al. 2015).

When it comes to the estimation of the health impacts of air pollution, there are several different models and screening models, discussed in the article of Bridges et al. (2015). Although the authors consider them as insufficient in order to properly estimate the exact health damages, inclusion of health costs in energy planning will save both resources and lives. Therefore, the future research should focus on evaluating the credibility of existing screening models and developing methods that are practical and transparent about the assumptions and uncertainties (Bridges et al. 2015).

Previous research on free riding

In economic theory, free riding occurs when a player does not contribute, but still reaps the benefits of the contributions of others. The free riders derive a positive externality from the actions of others. This is especially common if the ancillary good is characterized by non-excludability and non-rivalry and so it is not possible to exclude non-contributors from enjoying the common good. This creates problems since it may reduce the incentives to contribute to the good and thereby reduce the total welfare. Therefore from an economic perspective, free riding is considered as a source of market failure (Kotchen 2012).[1]

[1] It is important to note here that free riding is not exclusively a negative phenomenon. However, we will not focus on the difference between positive and negative free riding in this thesis.

According to the economic-ecological models, free riding occurs when a specific region lets other regions implement new environmental regimes and enjoys a cleaner environment at no cost (Botteon and Carraro 1995). The existing models show that the non-cooperative equilibrium is not an international optimum and that environmental efficiency can only be achieved through cooperation among the involved regions. The reason why an international environmental policy is not yet a factum is that in some cases the costs of implementing the policy may be so high that it makes the region worse off. In this case private good transfers compensating for these costs are required in order to keep the region convinced to cooperate. Additionally there may occur some coalitions involving only subgroups, not all the members/regions involved (Tulkens 1997).

The previous research shows that the characteristics of the agreement itself influence the risk of free riding. In international environmental agreements incomplete contracting can mitigate the free riding problem. Incomplete contracts specify the emissions, but not the amount of investments. The reason why it helps avoiding free riding is due the hold up problem; the participants in the environmental agreement have the opportunity to behave strategically and invest little and save the costs. Therefore they are more likely to participate in the agreement. The participants of the agreement fear that investments today will weaken their bargaining position in the future negotiations. Therefore the coalition is much larger if the contract is not complete and free riding is mitigated, but there is still a risk of underinvestment (Battaglini and Harstad 2015). A free riding problem in the environmental policies of United States can also be mitigated by institutions such as regional offices of US EPA that help to coordinate the management of common properties and help with the exchange of information and develop efficient strategies across the states.

The existing research on the topic of costs of free riding in the implementation of policies in order to stimulate renewable energy sources in Europe by Bigerna et al. (2015) shows that the non-participating countries impose extra costs on the participants of the policy. These costs increase more than proportionally with the non-participating countries' CO_2 emissions and GDP. As long as there are differences between the countries in benefits they get and costs of implementing the policy, there are incentives to behave opportunistically. The temptation to free ride is higher, the smaller the size of the country. The major conclusion of this study is that the majority of countries that participate in the implementation have incentives to behave opportunistically. The authors raise also an issue of efficiency of negative incentives, such as reciprocal measures and penalties, together with positive incentives in order to minimize the risk of free riding (Bigerna et al. 2015).

Research on the economics of leadership in climate change mitigation shows that the first regions that implement an environmental policy contribute to the public good unilaterally and therefore provoke the free rider effect. By starting to mitigate, the leaders engage in a learning process from which the followers can benefit. They test the sustainable technologies and evaluate the efficiency and costs of the policy. In this way they reduce the risks involved with mitigating the climate change. According to Gregor Schwerhoff (2015) the mechanism is to: "…Push the cost-benefit ratio of potential followers over a threshold so that they start mitigating on their own…".

On the other hand, according to the altruistic behaviour theory, contribution is higher when other participants can observe the first contribution before they make their own. The theories suggest that the gradual implementation of an environmental policy may initially result in free riding, but in the end is more efficient when it comes to reducing environmental costs due to the altruistic behaviour (Schwerhoff 2015).

The existing empirical assessments whether the US states engage in free riding through their regulatory enforcement decision do not always find evidence that supports the hypothesis on free riding. The study by Konisky and Woods (2012) attempts to determine the extent to which the US states engage in environmental free riding behaviour by analysing the state enforcement of the federal Clean Water Act directed at major water pollutants. The results of the study are mixed and inconsistent with the free rider hypothesis. A possible explanation of the lack of evidence on collective actions problems could be the existence of effective networks and institutions that help state government agencies work together and mitigate the free rider problem. Additionally there may be other requirements and enforcement regulations with the purpose to limit the pollution, prior to the policy implementation.

Research focus

Limitation of scope

Geographically, we will focus on the United States of America due to the country's political structure with federal states combined with the diversity and size of the country. The federal states are ideal for our approach seeing that they share many institutions and other characteristics that independent countries do not. This means that they can be seen as reasonably comparable and therefore that the disturbances in our analysis become far fewer than they would have been if we had focused on independent countries instead. The sovereignty between the local state governments and the federal government in combination with growing demand for effective actions in order to reduce pollution make this country ideal as an object of environmental policy analysis.

We have also chosen to limit our analysis to the RPS policy. The RPS is not only one of the biggest steps of the US state governments in order to promote renewable energy sources, but also one of the most vividly debated policies in the country (Delmas and Montes-Sancho 2011). There are a lot of discussions taking place concerning the economic consequences of the policy and whether it disrupts the principles of free market that the US stands for. Despite the fact that the policy applies to approximately 40% of the country's electricity capacity, the true impact of the policy is relatively modest, considering the costs. This implies that there is a need for improvement of the policy and a demand for greater collaboration between the states (Chen, Wiser & Nokinger 2007; Delmas and Montes-Sancho 2011). We contribute to the discussion with a new perspective; taking into consideration the health aspects of the state policies that are usually omitted in the existing papers.

Furthermore there are a lot of speculations regarding whether free riding in environmental policymaking is negatively affecting the results of the policy. In this study, we define free riding as waiting with the implementation of the policy, but still enjoying the benefits from improved air quality and knowledge spillovers thanks to other states' implementation of the RPS. We think that the analysis of the externalities will nuance the potential problem of free riding in environmental policymaking.

In time, the focus is the years 2008-2012. This is mainly due to the fact that data on investments in earlier years is very limited, likely due to a lack of reporting. As a result, earlier data is not meaningful to analyse. Also, a majority of the states that have implemented the RPS have done so after the year 2005. Previous research has shown that it takes some time for a policy to have an effect (Delmas and Montes-Sancho 2011). Therefore, in order to see significant effects of the policy on pollution in these states it makes sense to use data from a few years after the implementation.

We limit our analysis to the effects of fine particulate matter ($PM_{2.5}$) and do not consider other pollutants. This is common for this type of work, focusing on the link between health and pollution, for example ”Seasonal and regional short-term effects of fine particles on hospital admissions in 202 US counties, 1999-2005” (Bell et al. 2008). The screening model that we use in our empirical approach also focuses on $PM_{2.5}$, translating the changes in concentrations in ambient concentrations of $PM_{2.5}$ into changes in health effects and later on, monetary impacts. The main argument for this limitation is the strong association between the fine particles and serious adverse health effects. The particles are able to reach lower regions of respiratory tracts due to their small size. The main sources of these particles are fires, agriculture and stationary fuel combustion. This makes energy production an important source of $PM_{2.5}$ (EPA 2015).

Finally, when it comes to the inclusion of adverse health effects the focus will be on the most significant. These are the impacts on mortality and on hospitalisations due to respiratory and cardiovascular effects. The estimation of costs of mortality takes into account also the most expensive aspects, such as the loss of productivity, making this the clearly dominating part of estimated health costs (EPA 2014). In comparison to these, other adverse health effects apart from hospitalisations cost so little each year that they are hardly worth considering from an economic perspective.

Hypothesis

Our hypothesis is that there are problems associated with the implementation of the RPS. Environmental issues concern the whole nation and therefore an inter-state collaboration is required for a successful execution of environmental policies. The initial hypothesis is that the costs of being an *early adopter* of the policy exceed the costs of adopting the policy when the results of the early implementation can be measured, the costs of being a *late adopter*. In other words the initial speculation is that the policy implementers face a free rider problem.

H_1: There is a free rider problem in RPS implementation.

This hypothesis is derived from the previous research on economics of leadership in climate change mitigation by Schwerhoff (2015). Initially, we hypothesise that the states that decide to not engage in the increased use of renewable energy take advantage of the investments in the green energy of other states without the necessity to incur the same costs when they decide to implement the RPS. Therefore it is logical to assume that the RPS needs to accommodate more federal attributes in order to achieve the environmental goals, if the free riding problem is a reality (Konisky and Woods 2012).

Method

The aim of this paper is to assess if the health costs avoided as an effect of a specific amount of investment in green energy differ depending on the time of RPS implementation. In other words, the goal is to determine if there is a free rider problem in the form of it being more beneficial to implement the policy late in terms of health costs. Accordingly, we have constructed a model of the relationship between health costs avoided as a result of lower concentrations of PM[2] and the investments in green energy in a specific year. The model is studied separately depending on whether the specific state implemented the policy late or early. To obtain a dataset fit for this analysis requires a long procedure of combining data from different sources. We begin by outlining this procedure below since it is of great importance for the analysis. First thereafter we believe that it is meaningful to describe the method of the analysis itself.

Data and Sources

The starting point for our analysis is county-level data on $PM_{2.5}$ concentrations between 2008 and 2012, obtained from the US Environmental Protection Agency database. This is then combined with data on all-cause mortality and hospitalisations due to respiratory diseases to estimate the health impact of changes in $PM_{2.5}$ concentrations. We obtained data on all-cause mortality for 2008-2012 from NCHS Wonder and data on hospitalisations due to cardiovascular and respiratory diagnoses for the same years from US Department of Health & Human Services. The investment data has been obtained from the US Department of Agriculture. These data combine into a dataset that is a strongly balanced panel. For an overview of the data and sources see Table 1 below.

As can be seen in Table 1, the obtained data was available on different aggregation levels. This does not constitute a problem in the final analysis since this is conducted on the state level, but has some implications for the way the data is handled. The fact that the PM2.5 concentrations are only available on county level meant that the only feasible option was to break hospitalisation data down to the county level before estimating the effect on health costs and then aggregate them on the state level. This is the same method used by the COBRA model and any resulting estimation error in the aggregated data should be small. The

[2] In the case of higher concentrations of PM this translates into an increase in costs.

Data	Aggregation level	Source
$PM_{2.5}$ concentrations[3], Emissions	County	United States Environmental Protection Agency
Population	County	United States Census Bureau
All-cause mortality	County	NCHS Wonder
Hospitalisations due to respiratory and cardiovascular diagnoses	State	US Department of Health & Human Services (HCUPnet)
Investments in green energy	County	US Department of Agriculture

Table 1. Overview of data and sources

impact on the final results should also be negligible considering that the hospitalisation costs only constitute 2.02 % of the total estimated health costs, with mortality costs accounting for the rest.

Regarding the investment data it is worth noting that the investments in our dataset are public investments and as such do not include any private investments. This is of course unfortunate since complete data is always preferable, but this is the only data available and it has been frequently used by governmental institutions in order to compare and evaluate environmental policies. The investment data is the basis of the National Mapping Tool, created by the US. Department of Agriculture to compare incentives, policies, investments, standards and emissions. Therefore, we trust that this data, despite being less than optimal, is sufficient to provide useful insight into the area of interest for this paper.

Estimation of health impacts from changes in PM2.5 concentration

Since there is no data on exactly measured pollution related health costs, we are forced to employ an estimation model. For this purpose we use the process outlined in the manual for the COBRA screening model.

[3] There is no data available on $PM_{2.5}$ concentrations in the state of Illinois and therefore we were forced to exclude this state from the analysis.

As mentioned earlier, there is an extensive body of research on the relationship between pollution and various health effects. We take advantage of this previous research and estimate the health impacts of changes in $PM_{2.5}$ concentrations by combining coefficients from eleven existing, similar models (Babin et al. 2007, Bell et al. 2008, Krewski et al. 2009, Kloog et al. 2012, Lepeule et al. 2012, Moolgavkar et al. 2000a, Peng et al. 2008, Peng et al. 2009, Pope et al. 2002, Woodruff et al. 1997 and Zanobetti et al 2009). Following the approach outlined in the COBRA screening model manual (from now on referred to as the COBRA manual), we obtained data on all-cause mortality for 2008-2012 from NCHS Wonder and data on hospitalisations due to cardiovascular and respiratory diagnoses for the same years from HCUPnet.

Since we did not make projections for the future like the COBRA screening model, but rather estimates of historical cost, we were able to use historical data for all the years as baselines instead of mere projections of the development of mortality and hospitalisations. This should increase the accuracy of our approach compared to the COBRA screening model since it eliminates one step of estimation and thus avoids all of the uncertainty related to this particular estimation, thereby reducing total uncertainty.

As described in the COBRA manual, the data for hospitalisations was somewhat incomplete with some states not reporting hospitalisations. Naturally, we were not able to obtain hospitalisation data for these states as a result[4]. We solved this in the same way as reported in the manual. For the few states with missing data, aggregated regional[5] data was obtained. Then, the number of hospitalisations for states in the same region with reported data was subtracted from the regional data and the residual was distributed in proportion to the population between those states in the region that lacked data. In doing this we assumed that the number of hospitalisations in a state is proportional to the population. This at first seemed like a quite large assumption, but we studied this relationship for all states with reported data and found only minor deviations from the number of hospitalisations they should have had, had the hospitalisations been perfectly proportional to population. Therefore, despite the fact that it

[4] The number of states with missing data is not constant over the years and neither is the states which do not report hospitalisations. On average the number of states concerned lies between two and three per region though, and so the potential for errors is not too large.
[5] There are four US Census designated larger regions in the United States, each comprising several states. These are Northeast, Midwest, West and South.

comes at the price of slightly lower accuracy, we do not believe this assumption to have affected the quality of the data significantly. Further, since the COBRA manual outlines the same approach and has received no criticism for this it appears to be a generally accepted solution to the problem.

Once the baseline data was obtained for each state it was distributed in proportion to population among the counties in that state and converted to an incidence rate[6]. This follows the approach of the COBRA screening model and is also the only feasible method since there is no reported data on hospitalisations available on county level. The estimation of the health impacts was done in five different, non-overlapping, categories; 1. All-cause mortality for all age groups, 2. Hospitalisations due to cardiovascular disease for ages 65 and above, 3. Hospitalisations due to asthma ages 0-18, 4. Hospitalisations due to COPD[7] ages 18-64 and 5. All respiratory diseases ages 65 and over. All of these estimations follow the approach outlined in the COBRA manual.

For both hospitalisations and mortality, the number of cases avoided or incurred due to the change in concentration of $PM_{2.5}$ was estimated with the following air pollutant concentration response function:

$$\Delta y = y_b - y_c = B\left(\exp(\beta_{xb}) - exp(\beta_{xb})\right) = \ y_b * (1 - \frac{1}{\exp(\beta * \Delta x)})$$

Where:

$\Delta y =$ change in the incidence rate

$y_b =$ the baseline incidence (rate)of the health effect, before the change in x

$y_c =$ the incidence (rate)of the health effect after the change in x

$\beta =$ the sensitivity of the health case on change in $PM_{2.5}$

$\Delta x =$ change in $PM_{2.5}$ concentrations

This model is the one used both in the COBRA manual and the studies providing the coefficients. As such, it is one of the most used and researched models for the relationship between pollution and health.

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[6] Number of cases per 100,000 inhabitants throughout this paper.

[7] Chronic obstructive pulmonary disease

Change in all-cause mortality was estimated for each county by applying a weighted average of coefficients from three studies (Krewski et al. 2009, Lepeule et al. 2012 and Woodruff et al. 1997) to the concentration response model above in combination with the baseline incidence rates and changes in $PM_{2.5}$ concentrations. This generated the final estimates of change in mortality per county, which were then aggregated for each state.

The same approach with weighted coefficients was also used for the four categories of hospitalisations. For cardiovascular diseases the studies Zanobetti et al.(2009), Bell et al. (2008), Peng et al. (2008) and Peng et al. (2009) were used. Similarly for asthma we used Babin et al. (2007) and Sheppard (2003), for all respiratory for ages 65 and up Zanobetti et al. (2009) and Kloog et al. (2012) and for COPD we used Moolgavkar (2000a). Then, the county estimates were aggregated per state just like the mortality estimates.

Estimation of Health Costs

The final step of the method of this paper that is based on the COBRA screening model is the estimation of the effect of changes in mortality and hospitalisations on health costs. This is the simplest step of the estimation and it is done in order to create a unified measure of the health effects. To obtain the economic value of the avoided health effects we multiplied the costs assigned to each of the health effects in the COBRA manual with the estimated number of avoided cases for this particular effect per state. These assigned costs can be found in Appendix 7. All of the health costs obtained from the COBRA manual are in 2010 dollars.

Analysis of the relationship between investments and health costs

For our analysis, we define the states that implemented the RPS before the year 2006 as *early adopters*, and all the states that have done so after this point in time as *late adopters*. This division is based on the median year of adoption among the states that have adopted the policy. More precisely, the median time of implementation is in late 2005 and so defining states that implemented the policy later than this year as *late adopters* gives the most even distribution between the two groups.[8]

[8] Simply dividing the states into two groups is not optimal for determining the effect of the timing of policy adoption. However, due to the elimination of variables that are constant over time it is the only method feasible when employing the first difference method which allows for using the largest possible portion of the variation in the data. Therefore, we chose this division despite the fact that designating an index to the states based on when they adopted the policy would provide more accurate results and reduce the risk of any significant results being caused solely by the way the division is made. We solve this by also running a pooled OLS regression

We analysed the relationship between investments in renewable energy and changes in pollution related health costs on a state level by a first-difference regression of the change in health costs on investment data. In order to analyse if there exists a free rider problem we separated our planned regression model into two different ones; one for *early* and one for *late adopters* .We then compared the estimated results for *early* and *late adopters* of the RPS policy to investigate if there are any significant differences and in that case the nature of these.

The used models are dynamic, using distributed lagged variables in order to incorporate the feedback over time. The motivation for using lagged variables is that previous research has shown that it takes time to implement the investments in renewable energy and therefore the most significant results are seen not immediately but after a period of time (Delmas et al. 2011).

*S*tates that have not implemented the policy to date have been tested in the models but are excluded from the presentation of the results. The reason for this is that this group gives results that lack significance and are therefore not comparable to the states that have implemented the policy.

The regression models

The aim of the assessment of the relationship between the health costs avoided and the investments in renewable energy is to identify if the costs avoided are larger if RPS is implemented late. The relationship between the presence of the policy in a specific state and investments in renewable energy sources (see **Appendix 1** for regression)[9] is significantly positive and confirmed by previous research and so we conclude that the investments are related to whether a state has implemented the policy or not.

The first step of our analysis is the study of the relationship between investments in renewable energy and changes in the concentration of $PM_{2.5}$ in the air. The purpose of this is to confirm that investments in renewable energy do indeed affect pollution and thus to ensure that further

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which allows us to create and control for an index for the time of adoption but makes less than optimal use of the variation in the data. As long as the results of the two regressions are consistent with each other, it is likely that the choice of how to divide the states into early and late adopters has no significant effect on the outcome.

[9] Ideally, we would like to control for other factors than unemployment rate in this regression, such as potential in renewables. There is empirical evidence on the significance of these factors (Delmas and Montes-Sancho 2011), but unfortunately we did not have the possibility to obtain the required data. This is most likely also the explanation of the low value of R-squared for this regression.

analysis is warranted. We expect the correlation to be negative due to the aim of investments in renewables being mitigation of air pollution.[10] As a dependent variable we will use the change in $PM_{2.5}$ concentrations within two years of the investment since investments in renewable energy require some time to show an effect. As independent variables we will utilize investments in renewable energy, which is our variable of interest. We will also control for emissions from other sources[11]since these have an enormous effect on the $PM_{2.5}$ concentrations. Finally, we will control for the starting concentrations of PM since these influence the potential for further decreasing the concentrations. The following model summarizes our first regression:

$$PM_{2.5} = \beta_0 + \beta_1 Investments_{it} + \beta_2 Emissions_{it} + \beta_3 Pollution_{it} + \varepsilon \qquad t = 2008, 2011$$

Where:
$Investments_{it} =$ Public investments in renewable energy
$PM_{2.5} =$ Change in concentration of fine particulate matter within two years
$Emissions_{it} =$ Emissions from all sources except energy generation
$Pollution_{it} =$ Particulate matter concentration at time t

The above regression is a simple Pooled OLS regression. The reason for this is that we can reject the null hypothesis of a Lagrange multiplier test at the 1 % level and so using random or fixed effects adds no value. This is in turn most likely due to the fact that emissions data are only available for two years within our time frame of interest, namely 2008 and 2011. This is not optimal but still provides interesting results. We were also able to test the regression for all years 2008 through 2012 without controlling for emissions from other sources. This regression provides similar results and can be found in **Appendix 2**. Finally, it is worth noting that unlike the rest of our regressions, this particular regression is run on county level since that is the level of aggregation of all $PM_{2.5}$ concentration data.

Once we have established that investments do affect concentrations of $PM_{2.5}$[12], we move on to our main analysis. This is a first difference regression of pollution related health costs on

[10] In practice, there is mixed evidence (e.g. Delmas et al. 2011) on whether this is actually the case and therefore we are interested in investigating this relationship in our data.
[11] These sources include all types of traffic, fires and industry. All data is collected from the 2008 and 2011 emissions inventories created by the US EPA.
[12] This was the result after testing the first model.

investments, including lagged variables. The aim of differentiating our panel data over time is to decrease the likelihood of bias by controlling for unobserved, time-constant factors that affect the health impacts of concentration in PM. An example of such factors is the geographic conditions of a specific state. This statistical technique is efficient for our analysis, because our explanatory variable of interest *(Investments)* fluctuates vividly over time and so the variation over time is large within each state. Therefore, the risk that the estimation of the effect of *Investments* on the health effect will become imprecise is low. Another aspect that makes this more efficient than fixed effects regression is the fact that idiosyncratic errors follow a random walk and that the changes in residuals, Δu_{it}, are serially uncorrelated. We verified this by a regression, where Δuhat was regressed on the Δuhat from the previous period, for example $\Delta uhat1 = uhat_{year\ 2011} - uhat_{year\ 2010.}$ The regression can be found in **Appendix 3**.

Additionally we choose to control for whether the state has neighbours that have implemented the policy and therefore enjoys clean air at no cost. According to the free riding theory, the states that have many neighbours that have implemented RPS should see greater decreases of the health costs due to the positive externalities from decreased pollution in other states and knowledge spillovers, given a certain level of investments. It is not possible to control for the use of biomass or other state specific characteristics of the RPS that are known to affect the efficacy of the policy due to the nature of the first difference regression. Also, controlling for the inclusion of biomass is not meaningful since all states include this in RPS and so there is no variation. However, since we would only be interested in controlling for these and not their individual effect, this is not a problem since any potential bias caused by them is eliminated when first differencing the data.

One factor we would have liked to control for but failed to obtain data for is the number of other policies directed at reducing pollution. There are other policies besides the RPS that have been shown to have a significant effect on PM, and so we would need to control for these in order to isolate the effect of the RPS. We did attempt to obtain data on this, but there is no comprehensive data on this and due to the various regional policies and policies changing over time it was not possible for us to gather the data manually. This does of course imply that there is some omitted variable bias in the model and room for future improvement, but we still expect it to provide useful insights in its current form.

The most important assumption in order to achieve a consistent FD estimator is the strict exogeneity assumption. We assume that there is no correlation between the remaining idiosyncratic error and the explanatory variables in each period of time. Furthermore we assume that all the classical linear assumptions are valid. The estimated model is the following:

$$\Delta Totalcosts = \alpha_0 + \beta_1 \Delta Investments_t + \beta_2 \Delta lag1_t + \beta_3 \Delta lag2_t + \beta_4 \Delta Neighbours + \varepsilon$$

Where:

$Totalcosts$= Pollution related health costs

$Investments_{t1} =$ investments in renewable energy

$Neighbours =$ number of neighbouring states with RPS

The fact that it is interesting to test the significance of whether a state is an *early* or *late adopter*, forced us to combine the above model with a Pooled Ordinary Least Squares method to analyse this specific relationship. Additionally we took the opportunity to also control for specific characteristics of the policy by adding the control variable *Goal*, which is defined as the goal percentage of renewables of total energy production within each state. This control variable is clearly correlated with the health effects of the RPS policy since states set very different goals, ranging from the percentage of renewables already produced in the state to very ambitious goals of above 30 %. In this case we assume that the classical linear assumptions are fulfilled. The model can be seen below.

$$Totalcosts = \beta_0 + \beta_1 Adopter + \beta_2 Investments + \beta_3 lag1 + \beta_4 lag2 + \beta_5 Neighbours + \beta_6 Goal + \varepsilon$$

Where:

$Totalcosts =$ Pollution related health costs

$Adopter$ = Dummy variable equal to 0 for early adopter and equal to 1 for late adopter

$Investments =$ Investments in renewable energy

lag1 and lag2 = Investments in the previous year and two years ago respectively

$Neighbours =$ number of neighbouring states with RPS

$Goal =$ The goal of RPS in a specific state, the decided share of energy that must come from renewable energy sources

Tests

Using the Breusch-Pagan test we cannot reject linear forms of heteroskedasticity in the residuals of the regressions. The same result has been achieved using a White test; we can reject the null hypothesis of homoskedasticity at 1 % significance level. Since both of these tests indicate that the data suffers from some degree of heteroskedasticity, robust standard errors have been used in all regressions in order to correct for this.

Analysis

Pollution and investments in renewable energy

The results of the regression of *PM2.5*[13] on *Investments* fulfil the expectations of a significant negative correlation between the variables while controlling for emissions from other sources. An increase in investments in renewable energy by one dollar is expected to decrease the concentration of fine particles in the air by 1.14e-08 μg/m^3 considering a constant level of emissions from sources other than energy production. The coefficient as such is of no use in our further analysis, but the fact that it is highly significant indicates that it is meaningful to continue the analysis.

Variables	**PM2.5**
Investments	-1.14e-08***
	(2.04e-09)
Emissions	1.39e-05
	(1.66e-05)
Pollution	-0.498***
	(0.0208)
Constant	0.0303
	(0.106)
Observations	1,888
R-squared	0.307

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 2. Regression of PM2.5 on Investments.

Comparison of *early* and *late adopters*

Continuing our analysis, we wish to test a null hypothesis against the alternate hypothesis: *H_1: There is a free rider problem in RPS policy implementation*. This is done separately for the two groups *early* and *late adopters* and in practice we can reject the null hypothesis if *late adopters* experience significantly larger decreases in pollution related health costs compared to *early adopters* at the same level of investments. Statistically, this is equivalent to *late*

[13] The change in pollution from the year of the investments to two years in the future.

adopters having significantly more negative coefficients on investments in the same year and previous years compared to *early adopters*.

Table 2 shows the results of the regressions for the two groups. From this, it is evident that we cannot reject the null hypothesis of no free riding problem existing since *early adopters* appear to exhibit more negative relationship between investments and health costs. However, it is only the coefficients for the investments two years earlier that are significant at the 1% level for both groups. Therefore, the conclusions we can draw from these results are rather limited for other time periods.

A conclusion we can draw despite the lack of significance is that the empirical results do not succeed in supporting theoretical expectations generated by the free rider argument. There is also mixed evidence when it comes to the actual effect of the investments in green energy on pollution related health costs and the first difference estimation does not indicate that it is beneficial to wait with the implementation of the policy. Though some care should be taken in drawing further conclusions due to the lack of significant coefficients, from the results above it appears as though the more *early adopters* invest in green energy, the higher pay-off they get in terms of health costs. The effect appears to be of lower magnitude when it comes to the *late adopters*. When it comes to the relationship between pollution related health costs and number of neighbours with RPS, we cannot find any significant effect.

We also see tendencies consistent with the above effect when the year of RPS adoption is incorporated directly as a variable in a Pooled OLS regression. Then, later adoption of the policy appears to have a significant positive effect on health costs, indicating that *late adopters* benefit from smaller decreases in health costs for a given level of investments. This regression can be found in **Appendix 4**.

Based on the results above we cannot reject the null hypothesis that is built upon the existing theory on free rider problem. This would not have changed even if all the coefficients below had been significant.

Variables	Early Adopter ΔTotalcosts	Late Adopter ΔTotalcosts
ΔInvestments	-242.3	152.4***
	(291.2)	(18.96)
Δlag1	930.2*	107.3***
	(497.7)	(30.64)
Δlag2	-8,814***	-487.0***
	(2,745)	(53.85)
ΔNeighbours	-1.336e+09	7.271e+08
	(3.871e+09)	(6.699e+09)
Constant	-9.045e+08	5.711e+08
	(4.000e+09)	(2.320e+09)
Observations	84	64
R-squared	0.395	0.379

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1*

Table 3. The main regression

Pooled OLS and incorporating a variable for *early* or *late adopters*

As can be seen in Table 3 below, a pooled OLS regression incorporating the adopter variable produces similar results to those of the first difference regression above. The coefficient on the variable adopter is positive, large and significant at the 5 % level. This indicates that adopting the policy late leads to high pollution related health costs compared to implementing the policy early. Such a result means we cannot reject the null hypothesis using this method either. The significance of the adopter coefficient makes it more probable that the results above are correct despite the fact that we cannot test the coefficients in these regressions directly against each other. When it comes to the relationship between pollution related health costs and RPS Goal, we cannot find any significant effect. This is also valid for the number of neighbours that have implemented the policy.

To ensure that the results are not only due to the way the states were distributed between *early* and *late adopter*s we also ran a Pooled OLS regression incorporating an index for the time of policy implementation instead of a dummy variable for *early* or *late adopters*. The results of this regression can be found in Appendix 4. In general, they lead to the same conclusions as the regressions above with earlier adopters seeing larger positive effects and thus no

Variables	Totalcosts
Adopter	1.192e+10**
	(5.661e+09)
Investments	86.10
	(103.1)
lag1	-194.8
	(174.9)
lag2	33.87
	(69.69)
Neighbours	2.149e+09
	(1.510e+09)
Goal	2.234e+08
	(3.802e+08)
Constant	-2.571e+10**
	(1.043e+10)
Observations	130
R-squared	0.059

Robust standard errors in parentheses
*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 4. Pooled OLS regression of Totalcosts on Adopter

possibility of rejecting the null hypothesis. Therefore, it is reasonable to believe that the way the states are classified as *early* or *late adopters* has had no significant effect on the results.

Discussion

In this section, we will discuss possible explanations for the results and the absence of evidence for a free riding problem. We will also touch upon the contribution of this study and the implications for future research.

The results of our analysis are mixed, but in general we do not find any evidence for a free riding problem in terms of health costs in the implementation of the RPS policy. Rather, we find tendencies for *early adopters* to have a greater decrease in pollution-related health costs for the same level of investments in renewable energy.

The reasons for these tendencies we can of course only speculate on, but it is possible that it is related to *early adopters* having more experience with the policy and therefore having learnt more, making them more efficient. This in turn would indicate that *late adopters* are not taking advantage of the experience of earlier adopters to the extent possible. Furthermore it is also possible that the *early adopters* have greater potential in renewables and therefore are successful implementers, while *late adopters* do not enjoy the same potential and therefore are less successful. This argument is consistent with the previous research on RPS by Delmas and Montes-Sancho (2011). If this is indeed the case, it would imply that it is beneficial to implement these kind of policies on state level in order to maximize the benefits of the investments. If the *early adopters* really do have greater potential in renewables, it would mean that RPS stimulates competition and benefits the states that are abundant in the required resources and therefore leads to a potentially more efficient allocation of resources.

There is also a possibility that the characteristics of the RPS make this specific policy resistant to the free rider problem. Implementation of the policy can be comparable with an incomplete contract, where the state governments decide independently the amount invested. It would indicate that the states that have potential and resources to be successful in reality implement the policy. Those who wait with the implementation do it due to the lack of possibility and required means. The design of the policy and the implementation, as well as the definition of renewable sources in a specific state, also have an impact on how successful the policy is in practice. All the renewable sources have both advantages and drawbacks. Biomass is the source that has the most ambiguous impact on the environment. It is possible that states investing in harmful biomass as a result of the policy experience negative health effects after implementing the policy. Biomass is now heavily subsidized in the US and therefore the risk that states that decided to implement the policy late are investing in this source is high and may be the explanation for the high health costs of late implementation of RPS.

The lack of evidence on free riding in this study could also be due to different characteristics of the data and the method chosen. It is possible that using other measures of the success of the policy or different definitions of free riding would generate different results and conclusions. Further research is needed for conclusive evidence on whether free riding is an issue in environmental policies or not.

Further, there are some drawbacks with our analysis that should not be ignored. The health costs from COBRA screening model, used in the analysis, are only estimations of the true costs. The nature of the health effects means that it is impossible to measure their costs exactly, but as suggested by the previous research there is still great room for the improvement of screening models that calculate the health costs of reduction in pollution. A more precise estimation of the health costs will make the future analysis more reliable.

The major drawback of the study is the lack of the private investments data in renewable energy sources. We still believe that the obtained data on public investments provides useful insights but nonetheless, including private investments would most certainly improve the quality of the analysis.

We think that this study puts the problem of free riding in environmental policy-making in a new light and shows that there is room for improvement in the existing theory. Empirical evidence on the presence of free riding problem in RPS policy implementation has not been found. Instead, we see the opposite pattern; in terms of health costs it appears to be more profitable to implement the policy early. Our study is not the first that finds no empirical support for existing free riding theory in environmental policies in the US. The study by Konisky and Woods (2012) finds similar results for water pollution under the Clean Water Act.

The gradual implementation of the environmental policy on the state level might be beneficial in aspects of efficient resource allocation since states which have larger potential in renewables implement the policy earlier. The benefits of the early adoption of the policy implementation indicate that conditions for information transparency and technological knowledge spillovers should be improved in the RPS implementation, since today *late ado*pters do not appear to take full advantage of the existing knowledge and technology. The results show that the role of institutions that manage the collaboration of different states in policy implementation is of great importance.

Contribution

First and foremost, according to our knowledge, there is only one other study that focuses on the free riding hypothesis in environmental policies, and none that do so with a focus on health costs and RPS implementation. Our calculations in line with the guidelines of the COBRA screening model show that there are significant health costs avoided by investments in renewable energy sources and reduction of pollution that should be considered in the economic-environmental discussions and environmental cost-benefits analysis. We can see a clear pattern that the costs are dependent on the time of the implementation of the policy. This has implications for when and how the policy should be implemented and acts as an indication for areas of future research.

Secondly the unique feature of the method is the use of health costs avoided as a measure of the efficiency of the RPS policy. It shows to be not only a reasonable measure, but also a feasible one. Health effects are known to be one of the most important results of environmental investments and should be used in not only environmental policy evaluation, but in general cost-benefits analysis of environmental dilemmas. So far, this has only been done to a limited extent due to measurement issues, but this study shows that it is possible to find significant results using estimated health costs.

Finally, this study uses the COBRA screening model in an innovative way. In contrast to the existing research, this paper does not focus on projecting the future, but uses the screening model in order to perform a cost-benefits analysis based on the past. Therefore we think that the health costs estimation in this research is more reliable than those produced by the screening model, because they are based on actual numbers, not forecasts.

Further research

The findings together with the limited scope of this paper, highlight several areas that could benefit from closer examination. The environment of implementation and specific characteristics of the policy seem to have a significant influence on the environmental and economic results. Therefore it would be interesting to study further how specific attributes of the policy influence social benefits. We think that it would also be interesting to study the impacts on a smaller scale, for instance on the county level. We conclude that the differences in implementation strategies between the regions, such as different definitions of renewable energy sources, are very important when it comes to the results of the policy.

In order to make a clear inference as to whether there is a free riding problem in RPS implementation, the relationship between investments and other externalities avoided, not only health impacts, needs to be studied. The optimal solution is to take into consideration both economic, environmental and social costs in the analysis. Furthermore it could also be useful to compare the costs avoided in the US with the costs avoided in other countries that implemented policies similar to the RPS policy on national level.

Finally, this study highlights that the existing theory on free riding in environmental context should be discussed further. The countries that implement the policy late enjoy the social benefits at no cost due to other regions investing in renewable energy sources. However, it would seem like later on, they need to pay extra to achieve the same results, in terms of health benefits, as the *early adopters*. We think that it is of greatest importance to investigate the inefficiency of late implementation of environmental policies further and compare the effects of late and early adoption in terms of efficiency and effectiveness.

Conclusion

The main conclusion of this thesis is that we cannot reject the null hypothesis that there is no free riding problem in RPS implementation. Regardless of how we specify *early* or *late adopters* the regressions consistently show the same pattern with no evidence of free riding. This is consistent with the results of the rather limited previous research within this field in the US. However, the point of time of introduction of RPS seems to have an effect on the future success of the policy. Additionally, significant desirable effects of the policy are achieved not directly, but after a period of time after the investment in renewable energy.

According to our results the relationship between health costs avoided and investments in renewable energy sources is a negative one and of larger magnitude for *early adopters* than for *late adopters.* This indicates that *early adopters* are more successful in the implementation of the policy. Theoretically, *late adopters* should enjoy larger decreases in health costs for a given level of investments if free riding is present. We conclude that the *late adopters* are not efficient when it comes to the implementation of RPS. The most probable explanation for the lack of efficiency in the late implementation of RPS is the absence of knowledge spillovers and *late adopters* failing to take advantage of positive externalities. Therefore we conclude that the institutions working towards greater cooperation and a consistent framework of the policy will increase the efficiency of RPS, as air pollution is not limited by the political boundaries.

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Appendices

Appendix 1: Pooled OLS regression of Investments on whether RPS has been implemented or not

Appendix 2: Pooled OLS regression of Pollution change on Investments

Appendix 3: Test for serial correlation of residuals in the regression of particulate matter on investments

Appendix 4: Pooled OLS regression of Investments in renewable energy sources on total costs of respiratory diseases with an index

Appendix 5: Summary of *Investments*

Appendix 6: Summary of health costs

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Appendix 1: Pooled OLS regression of Investments on whether RPS has been implemented or not

Variables	Investments
RPS	3.811e+06**
	(1.901e+06)
Unemploymentrate	-972,945
	(1.134e+06)
Constant	9.488e+06
	(9.393e+06)
Observations	186
R-squared	0.011

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Investments = Investments in renewable energy

RPS = dummy variable, *RPS* =1 if a specific state has implemented the policy;

RPS = 0 if a specific state has not implemented the policy

Unemploymentrate= Unemployment rate in the state

Appendix 2: Pooled OLS regression of Pollution change on Investments

Variables	Pollution change
Investments	-1.64e-08***
	(2.67e-09)
Pollution1	-0.348***
	(0.0177)
Constant	-0.398***
	(0.0844)
Observations	3,663
R-squared	0.159

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Appendix 3: Test for serial correlation of residuals in the regression of particulate matter on investments

Variables	uhat
uhat1	0.0441
	(0.112)
Constant	-1.579e+09
	(5.785e+09)
Observations	64
R-squared	0.002

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Uhat = residuals
Uhat1= residuals from previous period

Appendix 4: Pooled OLS regression of Investments in renewable energy sources on total costs of respiratory diseases with an index

Variables	Totalcosts
Year of RPS adoption	3.897e+08**
	(1.898e+08)
Investments	80.26
	(95.37)
lag1	47.82
	(111.2)
lag2	-159.7*
	(92.07)
Constant	-8.683e+09***
	(2.219e+09)
Observations	188
R-squared	0.025

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Investments = Investments in renewable energy

Totalcosts = Total costs of respiratory diseases

Year of RPS adoption = Year the state implemented RPS

Appendix 5: Summary of *Total costs*

	Total costs			
	Percentiles	Smallest		
1 %	**-1.74e+11**	**-2.17e+11**		
5 %	**-4.62e+10**	**-1.85e+11**		
10 %	**-2.83e+10**	**-1.74e+11**	Obs	250
25 %	**-8.97e+09**	**-1.43e+11**	Sum of Wgt.	250
50 %	**-3.74e+09**		Mean	-1.00e+10
		Largest	Std. Dev. 2.97e+10	
75 %	**-3.99e+08**	**3.88e+10**	Variance	8.81e+20
90 %	**1.73e+09**	**4.20e+10**	Skewness	4.015991
95 %	**1.12e+10**	**4.72e+10**	Kurtosis	23.28018
99 %	**4.20e+10**	**4.82e+10**		

Appendix 6: Summary of *Investments*

	Investments			
	Percentiles	Smallest		
1 %	**0**	0		
5 %	**0**	0		
10 %	**0**	0	Obs	250
25 %	**45954.56**	0	Sum of Wgt.	250
50 %	**454385.7**		Mean	4568608
		Largest	Std. Dev.	1.95e+07
75 %	**1769557**	9.02e+07	Variance	3 .82e+14
90 %	**5847238**	1.11e+08	Skewness	7.439605
95 %	**1.39e+07**	1.54e+08	Kurtosis	64.15123
99 %	**1.11e+08**	2.04e+08		

Appendix 7: Table of assigned health costs

Health impact	Costs (USD, year 2010)
Hospitalisation Asthma 0-17	15430
Hospitalisation COPD 18-64	20349
Hospitalisation All Cardiovascular 18-64	41002
Hospitalisation All Cardiovascular 65 +	38618
Hospitalisation All Respiratory 65 +	32697
Infant Mortality	9401680
Adult Mortality	8434924
All Mortality	8918302