energies

MDPI

Article

Is It Costly to Transition from Fossil Fuel Energy: A Trade-Off Analysis

Faraz Farhidi [1,2,*] and Zaeng Mawi [2]

[1] NV Energy, Las Vegas, NV 89146, USA
[2] Department of Economics, Georgia State University, Atlanta, GA 30303, USA
* Correspondence: faraz.farhidi@nvenergy.com; Tel.: +1-(702)-409-6803

Abstract: This study aims to evaluate the trade-off between using cheaper and contaminated energy versus cleaner and more expensive energy and ultimately assess their combined effect on social externalities. We estimate the impact of air pollution and income level—mechanisms of energy consumption—on violent crimes and mortality rates. We propose an integrated causal analysis to address an endogeneity concern caused by the energy selection process by employing a difference-in-differences method (DiD) for the mechanism approach using policy changes. We explore the energy variations in neighboring counties caused by the implementation of green act policies to measure violent crimes and mortality rates using air pollution and income as the mechanisms. The results reveal that reducing fossil fuel by one terawatt hour can save 23 lives. Further, lowering nonrenewable energy use reduces 53 rapes yearly by lowering the maximum temperature, whereas decreasing fossil fuel does not negatively impact production and income. Thus, replacing fossil fuel energy with nuclear power is the most effective approach to reduce environmental and social damages caused by energy use.

Keywords: difference if differences; fossil fuel energy; mechanism design; social damage

check for updates

Citation: Farhidi, F.; Mawi, Z. Is It Costly to Transition from Fossil Fuel Energy: A Trade-Off Analysis. *Energies* **2022**, *15*, 7873. https://doi.org/10.3390/en15217873

Academic Editors: Manolis Souliotis, Jose L. Martinez-Ramos and Salem Al-Agtash

Received: 6 September 2022
Accepted: 19 October 2022
Published: 24 October 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Every year, millions of people die because of the effect of air pollution. Further, air pollution has long-term effects on physical and mental health, leading to abnormal, illegal behaviors. Identifying the causes of criminal activities and mortalities, which are referred to as social damages in this paper, would help legislators to control and shift their effects by taking actions that can adequately address these problems, especially the effect of air pollution. Air pollution is a consequence of human activities and is primarily caused by utilizing fossil fuel-based energy. Fossil fuel combustion accounts for half of the greenhouse gas emissions in urban areas. Therefore, it is vital to coordinate the reinforcement of carbon emission mitigation on a global platform [1].

Hanlon [2] and Anderson [3] demonstrated that air pollution substantially affects mortality rates. Heutel and Ruhm [4] disclosed a positive relationship between mortality rates and carbon monoxide, ozone, and particulate matter. The effect of air pollution on human health has been studied thoroughly [5–7]. Castanas and Kampa [8] claimed that air pollution has a severe impact on human health. It affects different organs and systems, causing conditions such as bronchitis in adults, lung cancer, asthmatic attacks, and heart-related diseases.

Air pollution may also affect criminal activities directly or indirectly. Cohn [9] discussed the theoretical background and verified the effect of weather conditions on various types of criminal behaviors. Doshi et al. [10] explored the hypothesis that neurotoxic metals' absorption may be partly responsible for the high and widely varying crime rates in the United States (US). In their study, Herrnstadt and Muehlegger [11] applied data on two million illegal activities reported to the Chicago police department in a 12-year

interval. Consistent with evidence from psychology on the correlation between pollution and aggression, the impact is unique to violent crimes; they could not find any effect of contamination on property crime. Reyes [12,13] explored the impact of childhood lead exposures that do not necessarily occur through inhalation but other routes on individuals' criminal behaviors. These findings on human mortality and illegal activities form a strong claim against air pollution, which is human-made.

There is possible causation between the income level of urban inhabitants and a higher likelihood of illegal activity [14–17]. Further, many studies have examined the relationship between population density and the prevalence of crime [18,19]. Population harms natural resources and the environment itself because of overconsumption [20]. Gainey et al. and Glaeser et al. [21,22] claimed that property rates can influence crimes. Air pollution can affect individuals' income [23–25], housing values [26,27], school productivity [28,29], and city size [30]. Therefore, it might escalate criminal activity indirectly via these factors. Thus, we can find the relationship between illegal activities and air pollution that arises from energy consumption.

This paper aims to measure the impact of energy consumption (fossil fuel-based energy) on key societal externalities—violent crimes and mortality rates—through air pollution and income channels using a newly integrated causal approach. The existing trade-off is a critical controversy among policymakers who support green energy guidelines and enforcements because of climate change and those who are against them because of the possible adverse market effects. Due to the relationship between air pollution and criminal activity, the challenge is to verify whether the results are generalizable and confirm causation. Cheap energy use such as coal leads to higher air pollution than clean energy, such as solar and wind. However, implementing more affordable energy decreases production costs, thus leading to more production, which results in higher income. Higher income leads to a lower illegal activity rate because of the strong relationship between income and criminal activity. Further, higher living standards lead to lower mortality rates, whereas using clean energy adversely affects the production/income channel. Hence, there is a trade-off between using cheap fossil fuel and using more expensive clean energy. Both types of energy may decrease social damages—the first type does so through higher production rates, and the second one does so by reducing air pollution. The current study empirically finds the method that can reduce criminal activity and mortality.

We use yearly county-level data across the US from 2001 to 2015 retrieved from the Energy Information Administration (EIA), Environmental Protection Agency (EPA), Bureau of Labor Statistics (BLS), CDC, LILP, and Uniform Crime Statistics (UCR) to investigate the impact of the proposed energy on social outcomes (EIA: Energy Information Administration; EPA: Environmental Protection Agency; BLS: Bureau of Labor Statistics; CDC: Centers for Disease Control and Prevention; LILP: Lincoln Institute of Land Policy; Uniform Crime Reporting Statistics). To the best of our knowledge, this is the first study to tackle this issue empirically. However, previous studies have demonstrated the impact of air pollution on social externalities and amenities in a metropolitan [31,32]. Thus, in this study, we test the external validity of their results to determine whether the internal validity is reliable. Furthermore, as air pollution is primarily the consequence of energy utilization and has not been studied in the previous literature, it has been added in the current study as the primary cause of social externalities. Due to concerns about the endogeneity of the main variables, we adopt a difference-in-differences approach nested in the policy changes in three states and neighboring counties to evaluate the ultimate impact of energy generation on the results of the study (This is the energy used in a power plant to generate electricity). The states of California, Massachusetts, and Washington initiated Green Act Policies to adopt clean energy instead of fossil fuel-based energy. We explore these policies to verify whether they have led to different energy adaptation patterns from those of the neighboring counties in the adjacent states. Then, we use that gap as the primary exogenous source of variation to validate whether energy consumption induces different air pollution levels and income in the neighboring counties, i.e., treated counties versus control counties. We

find contrasting results in reported violent crimes and mortality rates via air pollution and income channels.

The primary contribution of this work is twofold. First, we introduce a modified causal model that is used to conduct our analysis. We take advantage of the mechanism approach and integrate it into a difference-in-differences (DiD) method using a panel fixed-effect model. We then employ a synthetic design to find the year in which the green policies started being effective. In short, we empirically explore four different causal models to address the research problem. Second, we raise and answer a new question in the energy-environment literature by debating the existing trade-off between consuming fossil fuel energy and estimating the trade-off channels to determine the appropriate ones, which, to the best of our knowledge, has not been done yet.

It has been demonstrated that air pollution affects various outcomes, including crime and mortality, but partially comes from energy use. Energy use then affects crime and death through other mechanisms, such as income. Therefore, utilizing one terawatt hour of fossil fuel escalates mortality rates by 23 deaths via the air pollution channel and increases the number of rapes by 53 per county per year via the temperature channel. When fossil fuel-based energy rises, income does not change, thereby neutralizing the income channel. Thus, it does not affect the production process, suggesting that moving away from fossil fuel-based energy will not have a negative impact on the economy because of its positive outcomes.

2. Methodology

Over the past two decades, total reported crimes and mortality rate have declined as negative externalities of air pollution. Moreover, the widespread use of fossil fuel-based energy in the total energy consumption has experienced a downward trend. Due to the impact of economic activities on air pollution and the latter's possible effect on crime rates and mortality through health outcomes or educational quality, we select energy utilization as our independent variable and crime and mortality rates as the dependent variables. Production (total income as a proxy) decreases illicit activities [33], whereas energy consumption might boost illegal endeavors via air pollution. Therefore, the critical issue is whether the overall impact of the energy used in production affects crime rates and mortality, considering both the direct and indirect effects (via air pollution).

Figure 1 displays a summarized identification strategy as a flowchart (This work is the extension of the author's PhD dissertation in 2018 [34]). We demonstrate that energy use affects air pollution and income while influencing the latent variables (criminal activities and mortality rates). Other control variables interact with the study's key variables (independent, dependent, and mechanisms) simultaneously. Moreover, there is a reverse causality between income and energy use, which is a potential bias in any analysis. Another challenge is that various crimes, such as robbery and burglary, might reverse the production effects. A higher income level can impact environmental policies, which can alter air pollution. Therefore, finding a key factor that correlates with production and air pollution is vital for such analysis, but it is not directly linked to criminal activities.

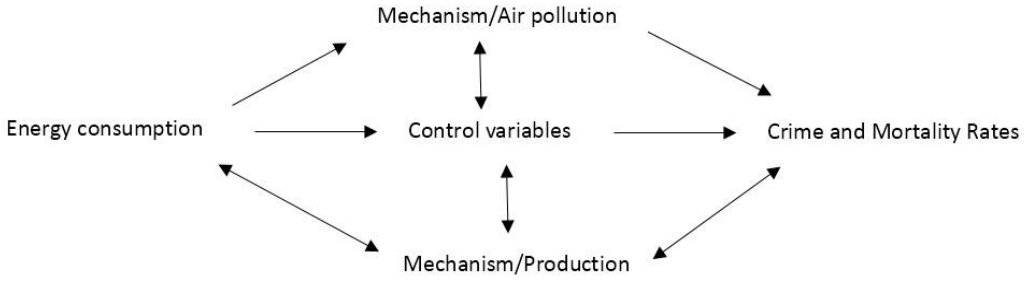


Figure 1. Illustrating the applied empirical model, and the channels of the impacts of each variable on crime and mortality rates.

We employ energy consumption based on county-level data retrieved from the US EIA to address this issue. Air pollution directly affects energy generation; therefore, energy is an influential explanatory variable for air pollution. However, energy use is a primary factor in production, which is indirectly connected to criminal activity. Therefore, air pollution is not the only channel that connects energy consumption to crime and mortality, but production/income also does.

To verify this hypothesis, we apply the mechanism effect approach. We integrate the mechanism method introduced by Imai et al. [35] into the DiD model. The key to understanding the mechanism effect is the following counterfactual inquiry: "How would the outcome differ if the mediator is changed from the control condition to the treatment condition while maintaining the treatment status at the same level?" However, we identify the mechanism's treatments via control conditions, as this study is built on multi-valued treatment and mediator. The mechanism approach is a suitable method for this analysis because air pollution is mainly a consequence of energy utilization. It cannot independently explain the social outcomes (crimes and mortality rates). Thus, pollution is a mediator between the latent variable and the sources of pollution—energy (Temperature is another potential mechanism between energy generation and social externalities, which we use as a control variable).

To measure the mechanism effect, we first verify the impact of energy consumption on the mechanisms—air pollution and income level—which are a proxy for the production level (Equation (1)). Then, we estimate the original model, including all the proposed variables (Equation (3)). The mechanism effect calculates the product of the energy coefficient in the first regression and the mechanism coefficient in the second regression. The variation in the current analysis comes from the states' governments. Each county chooses the type of energy that optimizes its production level based on the availability of natural resources and geographical conditions.

$$\text{Mechanism}_{it} = \alpha_{1i} + \delta_{1t} + \beta_1 \text{Energy}_{it} + \varphi_{1j} X_{ijt} + \varepsilon_{1it} \quad (1)$$

$$\text{Dependent variable}_{it} = \alpha_{2i} + \delta_{2t} + \beta_2 \text{Energy}_{it} + \gamma_1 \text{Mechanism}_{it} + \varphi_{2j} X_{ijt} + \varepsilon_{2it} \quad (2)$$

In the equations above, the dependent variable can be either violent crimes or mortality rates. The mechanism can be air pollution or production. For energy, which is the independent variable, we use fossil fuel-based energy as the proxy. Therefore, we evaluate the above system of equations four different times (each dependent variable with each mechanism separately). In the original model, α is and δ_t are county- and year-fixed effects, respectively. X_{ijt} are covariates controlled for housing prices, the number of police officers, unemployment, temperature, natural gas price, and year trend. As the regional data are correlated with time, we enter the time trend to control such a relationship. We need to isolate the mechanisms from the interaction between the independent and dependent variables to get an accurate result. This assumption might be controversial in this analysis, where the major elements of the study have a strong correlation with each other and control variables simultaneously, which can distort the actual impacts of the treatments. Furthermore, another potential concern is how a county's mediator status impacts a neighboring county's mediator condition.

After estimating each linear equation with the least squares, the product of coefficients method uses $\beta\hat{}1\gamma\hat{}1$ as an estimated mechanism effect. There are two different values for the mechanism effect ($\beta\hat{}1\gamma\hat{}1$)—air pollution and income. If this value is positive and significant for air pollution, utilizing more fossil fuel energy leads to a higher rate of crimes (or mortality) via air pollution. The same explanation is valid for the income channel.

Due to the possible impact of air pollution on mortality and crime rates through channels such as health issues and educational quality, it is essential to find a critical factor that correlates with air pollution but is not a latent variable and use it for the analysis. Specifically, air pollution, mortality rate, and criminal activity are likely to correlate with seasonal trends, coincidental weather conditions, and unobservable occurrences such as

economic activity. In this regard, Beland and Boucher [36] claimed that pollution is affected by political affiliation. Thus, one possible instrument might be political affiliation across states. However, political affiliation cannot be a reliable instrument variable (IV) in this case, as it correlates directly with income and possibly crime rates. Therefore, we cannot have confidence in using this IV for our analysis.

Another serious threat to the mechanism identification is the existence of reverse causality between energy use and income. We cannot address this concern adequately within the structure of the initially proposed method. Further, stakeholders can choose their fossil fuel consumption levels based on geographical boundaries and accessibilities to different energy resources and regulatory requirements. Therefore, there is a selection bias in the fuel type utilization. As earlier attempts to identify the causation between the critical elements of the model are not flawless, we integrate a DiD method to address the endogeneity concern (We explained the difference in differences (DiD) method briefly in the Appendix A). The following model employs relevant energy policy changes in three counties of three states during the research period to conduct a causal analysis. California adopted the Global Warming Solution Act in 2006; Washington implemented the Energy Independence Act in 2006, and Massachusetts passed the Green Communities Act in 2008. Each state has selectively implemented these policies, leading to another endogeneity concern. However, energy availability in each county and state is a function of geographical conditions and natural resources, making the analysis more exogenous. Therefore, we can verify the impact of such energy policy changes on the variables of interest using the following DiD model:

$$\mathrm{Mech}_{it} = \alpha_{3i} + \delta_{3t} + \rho_1 \mathrm{Ener}_{it} + \rho_2 \mathrm{Post}_t + \beta_3 \mathrm{Ener}_t * \mathrm{Post}_t + \varphi_{3j} X_{ijt} + \varepsilon_{3it} \quad (3)$$

$$\mathrm{Dep}_{it} = \alpha_{4i} + \delta_{4t} + \rho_3 \mathrm{Ener}_{it} + \rho_4 \mathrm{Post}_t + \beta_3 \mathrm{Ener}_t * \mathrm{Post}_t + \gamma_2 \mathrm{Mech}_{it} + \varphi_{4j} X_{ijt} + \varepsilon_{4it} \quad (4)$$

α_i and δ_t are the county level and time fixed effect, respectively; Xijts are the covariates that have been controlled; violent crime and mortality rate are our dependent variables. Here, the critical elements of the model are treatment and control variables. Treatment is the interaction of energy and a year dummy (Post) for 16 counties in three treated states (California, Massachusetts, and Washington) from 2008 to 2015. In the placebo test, we can switch the treatment variable to a false treatment (randomly selected counties in three states that did not implement such policies) to falsify the actual impact.

We create a control group comprising 16 counties in eight neighboring states of the treatment (Arizona, Connecticut, Idaho, Nevada, New Hampshire, Oregon, Rhode Island, and Vermont) from 2008 to 2015 to capture any spillover effect. The states of the control counties have not initiated any energy act, although they share borders with the treatment counties. In selecting the neighboring counties, we consider the wind direction to control the spillover effect of air pollution. Thus, the adjacent counties parallel to the wind direction (not in the same direction with the speed of 5 mph and above) are selected in both the treatment and control groups based on the map retrieved from the National Digital Forecast Database and visualized Viegas and Wattenberg (http://hint.fm/wind, accessed on 20 June 2020). Figure 2 is a simple illustration of the wind directions and the neighboring counties of the study.

Figure 3 depicts the fossil fuel energy utilization in the three treatment states combined (California, Massachusetts, and Washington) before and after 2008, and the energy use projection based on the synthetic method. To develop the synthetic control analysis, in addition to the treatment states and income and unemployment rates in nine neighboring control states—Arizona, Connecticut, Idaho, Nevada, New Hampshire, Oregon, Rhode Island, and Vermont—we also use data on fossil fuel utilization. Using the control states' actual data as well as the treatment states' income and employment statistics, we create the synthetic data for the treatment states. Although we do not match the two trends in 2008, we find that fossil fuel energy use started to diverge from 2008, and this gap grew in the following years. Thus, we set up 2008 as the base year for our DiD model to verify the

mechanism effects. The synthetic analysis aims to confirm whether these policy changes have led to different energy utilization; thus, we can employ the energy gap as the primary basis of our evaluation.

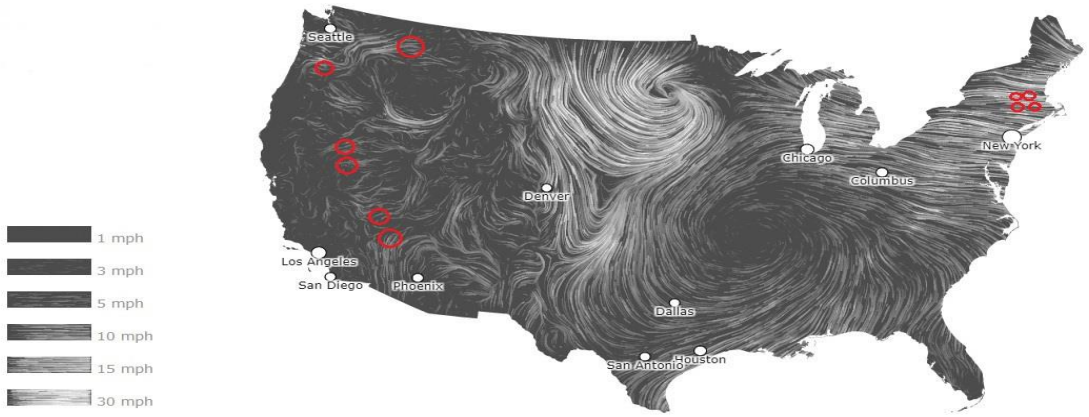


Figure 2. Wind directions in sixteen counties in states of California, Massachusetts, and Washington; and their sixteen neighboring counties in states of Arizona, Connecticut, Idaho, Nevada, New Hampshire, Oregon, Rhode Island, and Vermont.

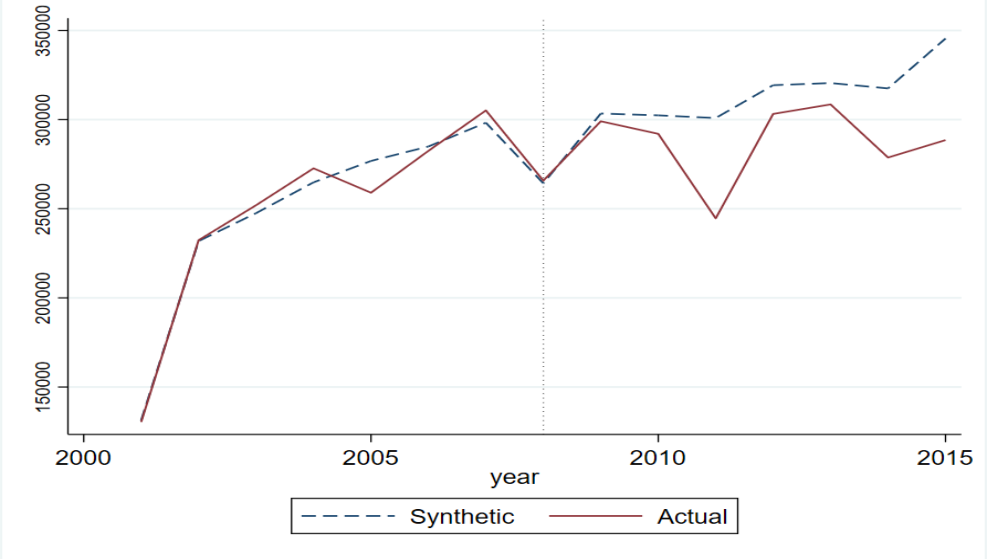


Figure 3. Fossil fuel consumption in three treatment states—California, Massachusetts, and Washington—using actual and synthetic data.

3. Data

We use county-level data for all US states in our original database, including Washington DC, from 2001 to 2015 to examine the relationship between energy utilization and social damages (mortality rate and criminal activities) via air pollution and income. We collect the data for energy consumption from the US Information Administration (EIA) at the US Department of Energy (https://www.eia.gov/electricity/data/eia923/, accessed on 10 February 2017). The energy data are available for all the power plants; the data are extracted from each state's power plant operation report, revealing the electricity they generate and the fuel types they use. The report contains monthly information about the heat and power plants across the US and the fuel type codes for boilers and cooling systems, including the names of the power plants. Based on the data retrieved, we locate each power plant in the corresponding county and add the county name to the dataset. We utilize the input fuel-based energy that the power plants use to generate power but

not the actual electricity that the plants generate as an output because using fossil fuels directly may cause air pollution through the emission of carbon or other toxic particles. The original dataset uses state-level aggregate energy consumption, which is its limitation because it omits the energy utilization of other sectors, such as the motor vehicle. Although we could have collected other sectors' data at the county level and added it to the current data, this addition would have created a new concern because vehicles are mobile across the counties' borders.

The population data, the number of police officers, and reported crime rates are collected from the Federal Bureau of Investigation's online uniform crime statistics (UCR) (https://ucr.fbi.gov/crime-in-the-u.s, accessed on 5 October 2019). Each region's yearly information is publicly available, having two main crime categories—violent crimes (murder, rape, robbery, and aggravated assault) and property crimes (burglary, larceny-theft, motor vehicle theft, and arson). Because one of the concerns is the reverse causality between violent crimes and income levels, we exclude violent robberies to take care of such a potential problem.

We extract the county's mortality rates from the Centers for Disease Control and Prevention Data Center. The Compressed Mortality database contains population and mortality counts for all states and counties in the US. Counts of death are accessible by the underlying cause of death and year at the county level. Data are also available for different races, gender, injury intent, and injury mechanism.

We use particle pollution (Data for PM2.5, CO, NOX, SO2 is also available in our dataset at the state level) (PM10), which is a mixture of airborne liquid droplets and solid particles, as a proxy for air pollution. PM10 varies by geographic location and season and is affected by various weather conditions, such as humidity, temperature, and wind. The particles' major components are carbon, nitrate, sulfate compounds, and crystalline elements, such as ash and soil. We retrieve yearly data on PM10 from the US EPA's database (Data for PM2.5, CO, NOX, SO2 is also available in our dataset at the state level).

We extract and pool the housing price index as a proxy for the housing prices from the Lincoln Institute of Land Policy (https://www.lincolninst.edu/research-data/data-toolkits, accessed on 15 October 2019). Then, we merge the household income data per capita from the US BLS to calculate the production level by multiplying the income per capita by the population (https://www.census.gov/topics/income-poverty/income/data/tables.html, accessed on 25 October 2019). We also use the unemployment rates in different counties, which may play a significant role in the analysis based on its emphasized position and how it can incentivize jobless individuals to commit a crime or deplete their health conditions and exacerbate death rates. Table 1 presents a summary of the statistics we use in the analysis. The data for energy consumption in each county are available at the plant level. To obtain the county-level data, we aggregate the data to find the sum of energy use at the county level. This may cause an issue because of the aggregating of data in panel data analysis. To address this concern, we use the weighted least-squared approach in which the number of energy plants is used as the weight.

Table 1. Summary statistics of the main variables in the model (2001–2015), at the county level.

Type	Variable	Unit	No. Obs.	Mean	SD	Min	Max
Energy-Independent variable	Total Energy	Giga watt hour	12,826	3382.1	6831.9	0.001	173,841.5
	Fossil fuel Energy	Giga watt hour	12,826	2703.9	5944.5	0.0004	173,841.5
	Coal-based Energy	Giga watt hour	12,826	1692.3	5186.2	0	170,140.3
Air Pollution and Income-Mechanisms	PM 10 *	Microgram in cubic meter	3161	21.13	6.94	4.53	67.41
	Income	US Mil $	12,005	8.32×10^3	2.13×10^4	3.50×10^1	5.26×10^5

Table 1. *Cont.*

Type	Variable	Unit	No. Obs.	Mean	SD	Min	Max
Temperature	Max July	Fo	6276	86.1	5.8	63.8	106.3
	Max January	Fo	6276	43.8	12.5	7.4	80.9
Controls	Population	No.	12,136	203,245.1	453,887.1	954	1.01×10^7
	Unemployed Rate	Percentage	12,822	6.91	2.81	1.2	28.9
	Natural Gas Prices	$ per thousand ft3	12,826	9.11	2.47	3.16	47.03
	House Price Index	Ave. price change	12,425	12,887.5	6563.7	1	24,647
Social Externalities-Latent Variables	Violent Crime	No.	12,826	3222.9	10,973.4	1	109,867
	Mortality	No.	12,136	1616.4	3143.5	10	59,883

* PM 10 uses as a proxy for air pollution in this study. ** CDC, FBI (UCR), EPA, EIA, BLS, and LILP have been used as data sources.

4. Results and Discussion

Before diving into the primary analysis, we discuss the reason for the mechanism design through a straightforward analysis. If energy use impacts social damages (only) via mechanisms, adding mechanisms to the equation should remove the energy impact on the latent variables (societal externalities). Conversely, when we remove mechanisms from the main equations, the dependent variable should be affected by energy consumption. Table 2 reports this argument in three steps, including mechanisms and control variables for the primary regression. The independent variable in the first three columns of the table is fossil fuel energy, but it is replaced by nuclear power in the last three columns. In all the six regressions, the dependent variable is death rates. We find that when there are no mechanisms or controls, fossil fuel energy increases death rates. Including the mechanisms removes this effect. However, there is an opposite relationship between nuclear energy and death rates, and the relationship fades away by including the mediation variables. Table 2 confirms the efficacy of our mechanisms, which determine the relationship between energy and social damages.

Following the proposed steps and using the yearly data of collected counties in the US from 2001 to 2015, we report the preliminary results, without integrating the policy changes into the DiD method in Table 3 using the original mechanism model (Equations (1) and (2)). The error terms are clustered at the county level. Table 3 presents the impacts of the empirical model's main elements on social damages (violent crimes and mortality). Increasing total energy consumption by one terawatt hour escalates air pollution by 0.1, but it does not affect income level, as speculated. However, more than six residents die due to the consequences of an increase in air pollution by one unit, although there is no noticeable impact on violent crimes. The effect of higher living standards (higher income) is as expected, where higher income leads to lower crimes and death rates.

We can calculate the effect of fossil fuel consumption on the latent variables through the mechanisms. Because fossil fuel utilization does not affect income, the income channel is neutralized. The same argument is valid for the air pollution channel when the latent variable is violent crimes. Therefore, based on this approach, the only legitimate channel from fossil fuel use to mortality rates is air pollution. By calculating this impact, we find that when fossil fuel energy use increases by one terawatt hour, almost one resident dies because of the values presented in Table 3. However, due to the concerns about the existing endogeneity in the original mechanism model and the potential interactions between the mechanisms, we cannot draw such conclusions unless we employ an exogenous variation.

Table 2. Preliminary analysis with and without mechanisms and control variables to verify the mechanism approach effectiveness: county-level.

	Dependent Variable: Death Rates					
	Fossil Fuel Energy			**Nuclear Energy**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Energy	0.0032 *	0.007	−0.005	−0.037 **	−0.027 *	−0.019
	(0.0019)	(0.006)	(0.005)	(0.017)	(0.016)	(0.017)
Mechanisms *	No	Yes	Yes	No	Yes	Yes
Controls **	No	No	Yes	No	No	Yes
Fes ***	Yes	Yes	Yes	Yes	Yes	Yes
N	12,136	1156	1555	421	62	62

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. * Air pollution, income, and temperature. ** Population, housing price index, unemployment rate, natural gas price, and year trend. *** County and year fixed effects.

Table 3. Using the original mechanism approach (Equations (1) and (2)), when air pollution and income level are the mechanism and fossil fuel consumption is the independent variable: county-level.

	Main Regressions (Equation (2))		**Mechanisms (Equation (1))**	
	(1)	**(2)**	**(3)**	**(4)**
	No. Deaths	**No. Violent Crime**	**Air Pollution**	**Income**
Fossil fuel	−0.005	−0.211	0.0001 *	−0.012
(Giga watthour)	(0.005)	(0.142)	(0.000)	(0.066)
Air pollution	5.62 *	−60.50		109.4
(PPM)	(3.04)	(114.09)		(78.62)
Income	−0.056 ***	−0.333 ***	0.0001 *	
(Million $)	(0.012)	(0.087)	(0.000)	
Temperature	−1.53	11.36	0.034	77.72 *
(Fahrenheit)	(2.81)	(117.12)	(0.048)	(46.04)
Controls *	Yes	Yes	Yes	Yes
Fixed Effects **	Yes	Yes	Yes	Yes
N	1555	1555	1555	1555
R2	0.999	0.654	0.855	0.987

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. * Population, housing price index, unemployment rate, natural gas price, and year trend. ** County and year fixed effects.

We are interested in the sign of the impact (positive or negative) and the exact level of point estimates. Based on our initial claim, the existing trade-off between lower pollution and higher income makes the ultimate impact unclear. Table 4 presents the main results of the integrated mechanism analysis using the DiD method. The first two columns reflect the main regressions when the dependent variables are death rates and violent crimes. The third column presents the impact of the energy green act policies on air pollution—the first mechanism—in the treatment counties, and the last column presents the same effects on the income channel of these counties.

Table 4. Using the integrated mechanism approach based on DiD method (Equations (3) and (4)), when air pollution and income level are the mechanism and fossil fuel consumption is the independent variable: county-level.

	Main Regressions (Equation (4))		**Mechanisms (Equation (3))**	
	(1) Deaths	**(2) Violent Crime**	**(3) Air Pollution**	**(4) Income**
Fossil fuel	0.154 **	−12.38 *	0.0008	−1.141
Treated counties	(0.075)	(6.74)	(0.001)	(0.935)
After	−1808	11,506	3.67	5030
	(1439)	(44,371)	(22.03)	(17,294)
After×reated	−0.010	−27.27 ***	−0.0016 **	−0.511
	(0.062)	(7.01)	(0.001)	(0.522)
Air pollution	14.67 **	−300.1		−3.88
	(7.24)	(247.7)		(85.32)
Income	−0.0485 ***	−0.351	−0.00001	
	(0.015)	(0.469)	(0.000)	
Controls *	Yes	Yes	Yes	Yes
Fixed Effects **	Yes	Yes	Yes	Yes
N	141	141	141	141
R2	0.998	0.811	0.915	0.992

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. * Population, housing price index, unemployment rate, natural gas price, and year trend. ** County and year fixed effects.

We do not control the number of police officers because of the following reasons. First, it reduces the sample size by more than two-thirds, making the DiD approach ineffective. Second, the number of police officers can be predicted by the population, income, and housing prices (as a source of property tax) used in the analysis, thereby decreasing the importance of using it. Third, the number of police officers does not play any role in mortality rates, making the main equations incomparable. Lastly, the number of enforcement law officers does not necessarily decrease criminal activities [37]; thus, we drop this variable in our analysis, knowing it would not bias the results.

We find that, on average, a terawatt hour reduction in fossil fuel use due to the green policies decreases air pollution by 1.5 units in the treated counties at the 94% confidence level. Moreover, there is no meaningful impact on the income level, although its magnitude is negative. However, 15 residents die when air pollution increases by one unit. Thus, a reduction in fossil fuel energy consumption by one terawatt hour can save 23 people. Further, it does not have a significant effect via the income channel. We can compute the outcome confidence level for each channel—the coefficient's confidence level of the independent variable multiplied by the coefficient's confidence level of the mechanism of the dependent variable. This value is above 90% for the air pollution channel but less than 8% for the income channel.

One of this model's issues is the interaction among the mechanisms, which may distort the ultimate impacts. To check if such an effect exists, we perform a DiD analysis. The impact of differences in income caused by the policy changes in the affected counties on air pollution is examined. The results are presented in Table 5. We find that there is no spillover effect between income and air pollution from implementing green energy policies. Considering only the magnitude of these effects, we find that even the impacts of each other's mechanisms are in a different direction, balancing out any possible bias.

Although we do not get any meaningful impact from energy reforms on violent crimes when air pollution is the mechanism, we examine any wave on the activities via temperature, as previous studies have suggested. Here, air pollution is replaced by temperature (the maximum temperature in July) as the mechanism, but income remains the other crucial channel of influence. Table 6 summarizes the results. There is still no significant effect on violent crimes in general through income and temperature channels, but there is an impact on a subcategory of violent crime—rape. When temperature rises by

one degree (Fahrenheit), 61 more rapes occur. However, one terawatt hour reduction in fossil fuel energy utilization decreases temperature by 1.3 degrees Fahrenheit. Therefore, the ultimate result of one terawatt hour of fossil fuel-based energy's overall effect is to mitigate the number of rapes by almost 53 cases yearly in the treated counties. Further, there is no negative impact on the income level. We report the analysis for rape because it is the only crime with a significant result in this category. There is also evidence of the impact of temperature on violent crimes, such as rape and assault, due to a deterioration of the nervous system.

Table 5. Finding the potential interactions of the mechanisms on each other to isolate the effect of the fossil fuel energy on the latent variables—death and violent crime rates—through the mechanisms.

	(1) **Air Pollution**	**(2)** **Income**
Income treated counties	−0.0001	
	(0.0002)	
After × treated income	−0.00003	
	(0.0001)	
After	9.13	9300
	(22.46)	(17,846)
Air pollution treated counties		−240.9
		(235.9)
After × treated pollution		95.86
		(115.34)
N	141	141
R2	0.914	0.992

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. * Population, housing price index, unemployment rate, natural gas price, and year trend. ** County and year fixed effects.

Table 6. Using the integrated mechanism approach based on DiD method (Equations (3) and (4)), when temperature and income level are the mechanism and fossil fuel consumption is the independent variable: county-level.

	Main Regressions (Equation (4))		**Mechanisms (Equation (3))**	
	(1) **Rape**	**(2)** **Violent Crime**	**(3)** **Temperature**	**(4)** **Income**
Fossil fuel	0.386	−12.38 *	−0.0002	−1.141
Treated counties	(0.669)	(6.74)	(0.001)	(0.935)
After	3435	11,506	−1.589	5030
	(3666)	(44,371)	(20.696)	(17,294)
After × treated	1.195 *	−27.27 ***	−0.0015 **	−0.511
	(0.665)	(7.01)	(0.001)	(0.522)
Temperature	60.98 *	147.0		67.11
	(33.98)	(285.9)		(88.54)
Income	−0.0062	−0.351	0.0001	
	(0.031)	(0.469)	(0.000)	
Controls *	Yes	Yes	Yes	Yes
Fixed Effects **	Yes	Yes	Yes	Yes
N	141	141	141	141
R2	0.744	0.811	0.846	0.992

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. * Population, housing price index, unemployment rate, natural gas price, and year trend. ** County and year fixed effects.

Table 6 reveals that green energy policies help lower temperature, which is an enormous result of fighting global warming. Our analysis demonstrates that moving away from fossil fuel-based energy is not having a negative effect on the economy, but it has several benefits for the environment and society. Although some energy-related policies changed during the treatment years, our focus is not on their effectiveness but on the energy use itself. The main reason for using the synthetic analysis is the mixed policy-year effect.

5. Robustness Check

This brief test replaces the treatment counties with a false treatment—16 random counties in three randomly selected states, Alaska, Colorado, and North Dakota, which legislated clean energy policies. Tables 7 and 8 present the results of the tests. We find that the effects of the energy changes on the mechanisms—air pollution, income level, and temperature (for violent crime)—are neutralized. Further, we still find some impacts of air pollution and income on death rates.

Table 7. Placebo test to detect the true effect in Table 3 with the randomly selected 16 counties from Alaska, Colorado, and North Dakota, instead of the treatment counties in California, Massachusetts, and Washington.

	Main Regressions (Equation (4))		**Mechanisms (Equation (3))**	
	(1) Deaths	**(2) Violent Crime**	**(3) Air Pollution**	**(4) Income**
Fossil fuel faked	0.094 *	−0.304	0.0007	−2.229 ***
treated counties	(0.052)	(1.005)	(0.001)	(0.685)
After	−1755 *	42,453	−3.88	−6293
	(1041)	(31,212)	(18.94)	(13,038)
After × faked	−0.089 ***	−0.659	0.0003	0.315
treated	(0.023)	(0.658)	(0.000)	(0.446)
Air Pollution	5.95	−201.2		40.58
	(5.04)	(154.1)		(60.93)
Income	−0.029 **	0.119	0.0001	
	(0.014)	(0.340)	(0.000)	
Controls *	Yes	Yes	Yes	Yes
Fixed Effects **	Yes	Yes	Yes	Yes
N	164	164	164	164
R2	0.998	0.771	0.893	0.992

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. * Population, housing price index, unemployment rate, natural gas price, and year trend. ** County and year fixed effects.

Table 8. Placebo test to detect the true effect in Table 6 with the randomly selected 16 counties from Alaska, Colorado, and North Dakota instead of the treatment counties in California, Massachusetts, and Washington.

	Main Regressions (Equation (4))		**Mechanisms (Equation (3))**	
	(1) Deaths	**(2) Violent Crime**	**(3) Air Pollution**	**(4) Income**
Fossil fuel faked	−0.096	−0.304	0.0009	−2.229 ***
treated counties	(0.064)	(1.005)	(0.000)	(0.685)
After	190.7	42,453 *	−17.98	−6293
	(3263)	(31,212)	(14.53)	(13,038)
After × faked	0.018	−0.659	−0.0001	0.315
treated	(0.071)	(0.658)	(0.000)	(0.446)
Temperature	30.84	114.7		35.90
	(34.08)	(290.4)		(83.35)
Income	0.0005	0.119	0.00005	
	(0.021)	(0.340)	(0.000)	
Controls *	Yes	Yes	Yes	Yes
Fixed Effects **	Yes	Yes	Yes	Yes
N	164	164	164	164
R2	0.821	0.771	0.864	0.992

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. * Population, housing price index, unemployment rate, natural gas price, and year trend. ** County and year fixed effects.

6. Conclusions and Policy Implications

This paper aims to study the trade-off between using cheaper and contaminated energy to produce more and using cleaner and more expensive to pollute less. We conclude that using more nonrenewable and cheap energy increases mortality rates and rape cases. Additionally, replacing fossil fuel energy imposes almost no economic cost but reduces environmental damage, whereas air pollution increases mortality rates, but income reduces

them. The results reveal that the air pollution channel outweighs the income channel when the latent variable is mortality rates. We find the same pattern after replacing air pollution with temperature and keeping the income mediator and using rape as the dependent variable. Reducing fossil fuel energy by one terawatt hour decreases the maximum temperature by more than one degree Fahrenheit. Surprisingly, replacing fossil fuel with renewable energy does not significantly reduce social damages, but nuclear power does. Thus, our focus should be on nuclear power in all the clean energy categories.

If we follow Fang et al. [38] and consider the long-term social costs, finding that the cost per crime would be about $29,000 in the US. Over the past two decades, more than ten million crimes have been committed yearly. Therefore, the long-term loss in the whole economy caused by criminal activities is more than $290 billion; reducing crime rates by only 1% can save $3 billion yearly. The roughly calculated amount gives us an incentive to understand the social cost hidden in violent crimes such as rape, which we do not include in our economic analysis. In addition to the benefits of lower mortality rates caused by energy regime changes, social damages have to be considered to achieve a more accurate cost–benefit analysis. In the US, each life value is around $9 million. Further, many consequences of global warming can be avoided by replacing fossil fuel energy, suggesting an even higher amount of neglected social expenses in our cost analysis of choosing the type of energy to consume. The proposed results underestimate the environmental and social costs of fossil fuel energy because of the study period. Compared with that of clean energy, there has been a monetary spike in utilizing fossil fuel energy in recent years, which makes the energy transition even more economically, environmentally, and socially beneficial. Thus, it is essential to formulate policies to stimulate this transition to lower social damages while it does not cost the US economy significantly at the national level. Specifically, it has been shown that the green policies become the center of attention when people's lives are in imminent danger [39].

Author Contributions: Conceptualization, F.F.; methodology, F.F.; software, F.F.; validation, F.F.; formal analysis, F.F.; investigation, F.F.; resources, F.F.; data curation, F.F. and Z.M.; writing—original draft preparation, F.F.; writing—review and editing, F.F.; visualization, F.F.; supervision, F.F.; project administration, F.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The links to publicly archived datasets analyzed during the study have cited in the text, data section. To regenerate the results, authors have made their polished data available at the following link. https://www.dropbox.com/s/upi8u9qilqisy5h/Energy%20Data%20-%20Final.csv?dl=0 (accessed on 1 June 2022).

Acknowledgments: Authors want to thank Spencer Banzhaf, Paul Ferraro, and Garth Heutel, for their comments in developing this study.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. DiD Method

Let's say we have a treatment group (T) and a control group (C). An incident happened in year Y which affected T but not C. Now, the underlying premise is that the incident may change the trend in T after year Y, but does not impact C during the same period (there is no spill-over effect, no movement between C and T after that, and so on; if there is we need to isolate that effect, e.g., controlling for migration, tech spill over and etc.) Consider the below equation:

$$y_{it} = \beta_0 + \beta_1 * T_{it} + \beta_2 * After_t + \beta_3 * After_t * T_{it} + \varepsilon_{it}$$

In the above equation, β_0 is the effect/size of the control group before the incident in year Y; $\beta_0 + \beta_1$ is the effect/size of the treatment group before the incident; $\beta_0 + \beta_2$ is the effect/size of the control group after the incident (the new trend (β_2) is going to add

to the before trend (β_0) and construct the trend after the incident); the idea is to add a trend variable to both groups (T and C), to set a benchmark for both of them after time Y, denoting are following the same trend after year T. $\beta_0 + \beta_1 + \beta_2 + \beta_3$ is the effect/size of the treatment both after the incident. Table A1 summarizes how the final impact is calculated:

Table A1. Calculating the DiD impact.

	Before (B)	**After (A)**	**Difference**
Control group (C)	CB: β_0	CA: $\beta_0 + \beta_2$	CA–CB: β_2
Treatment group (T)	TB: $\beta_0 + \beta_1$	TA: $\beta_0 + \beta_1 + \beta_2 + \beta_3$	TA–TB: $\beta_2 + \beta_3$
Difference	TB–CB: β_1	TA–CA: $\beta_1 + \beta_3$	DiD: β_3

Therefore, the impact of that incident (if there would be a significant impact), is captured by β_3 which is the interaction between the trend after that incident and the treatment after that incident.

References

1. Crichton, R.; Farhidi, F.; Patel, A.; Ellegate, N. Clearing up the benefits of a fossil fuel sector diversified board: A climate change mitigation strategy. *Bus. Soc. Rev.* **2021**, *126*, 433–453. [CrossRef]
2. Hanlon, W.W. *Pollution and Mortality in the 19th Century*; No. w21647; National Bureau of Economic Research: Cambridge, MA, USA, 2015.
3. Anderson, M.L. As the Wind Blows: The Effects of Long-Term Exposure to Air Pollution on Mortality. *J. Eur. Econ. Assoc.* **2019**, *18*, 1886–1927. [CrossRef] [PubMed]
4. Heutel, G.; Ruhm, C.J. Air pollution and procyclical mortality. *J. Assoc. Environ. Resour. Econ.* **2016**, *3*, 667–706. [CrossRef]
5. Burnett, R.T.; Calle, E.E.; Ito, K.; Krewski, D.; Pope, C.A., III; Thun, M.J.; Thurston, G.D. Lung cancer, cardio-pulmonary mortality, and long-term exposure to fine particulate air pollution. *JAMA* **2002**, *287*, 1132–1141.
6. Künzli, N.; Kaiser, R.; Medina, S.; Studnicka, M.; Chanel, O.; Filliger, P.; Herry, M.; Horak, F., Jr.; Puybonnieux-Texier, V.; Quénel, P.; et al. Public-health impact of outdoor and traffic-related air pollution: A European assessment. *Lancet* **2000**, *356*, 795–801. [CrossRef]
7. Folinsbee, L.J. Human health effects of air pollution. *Environ. Health Perspect.* **1993**, *100*, 45. [CrossRef]
8. Kampa, M.; Castanas, E. Human health effects of air pollution. *Environ. Pollut.* **2008**, *151*, 362–367. [CrossRef]
9. Cohn, E.G. Weather and crime. *Br. J. Criminol.* **1990**, *30*, 51–64. [CrossRef]
10. Doshi, A.; Hone, B.T.; Masters, R.D. Environmental pollution, neurotoxicity, and criminal violence. *Environ. Toxicol.* **1998**, 13–48.
11. Herrnstadt, E.; Muehlegger, E. *Air Pollution and Criminal Activity: Evidence from Chicago Microdata (No. w21787)*; National Bureau of Economic Research: Cambridge, MA, USA, 2015.
12. Reyes, J.W. Environmental Policy as Social Policy? The Impact of Childhood Lead Exposure on Crime. *BE J. Econ. Anal. Policy* **2007**, *7*. [CrossRef]
13. Reyes, J.W. Lead Exposure And Behavior: Effects On Antisocial And Risky Behavior Among Children And Adolescents. *Econ. Inq.* **2015**, *53*, 1580–1605. [CrossRef]
14. Freeman, R.B. The Relation of Criminal Activity to Black Youth Employment. *Rev. Black Political Econ.* **1987**, *16*, 99–107. [CrossRef]
15. Grogger, J. Market Wages and Youth Crime. *J. Labor Econ.* **1998**, *16*, 756–791. [CrossRef]
16. Viscusi, W.K. The Risks and Rewards of Criminal Activity: A Comprehensive Test of Criminal Deterrence. *J. Labor Econ.* **1986**, *4*, 317–340. [CrossRef]
17. Gould, E.; Weinberg, B.; Mustard, D.B. Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997. *Rev. Econ. Stat.* **2002**, *84*, 45–61. [CrossRef]
18. Glaeser, E.L.; Sacerdote, B. Why Is There More Crime in Cities? *J. Political Econ.* **1999**, *107*, S225. [CrossRef]
19. McDonald, J.F.; McMillen, D.P. *Urban Economics and Real Estate: Theory and Policy*; John Wiley & Sons: Hoboken, NJ, USA, 2010.
20. Farhidi, F. Solar impacts on the sustainability of economic growth. *Renew. Sustain. Energy Rev.* **2017**, *77*, 440–450. [CrossRef]
21. Gainey, R.R.; Sun, I.Y.; Triplett, R. Neighborhood characteristics and crime: A test of Sampson and Groves' model of social disorganization. *W. Criminol. Rev.* **2004**, *5*, 1.
22. Glaeser, E.L.; Sacerdote, B.; Scheinkman, J. Crime and Social Interactions. *Q. J. Econ.* **1996**, *111*, 507–548. [CrossRef]
23. Carson, R.T.; Jeon, Y.; Mccubbin, D.R. The relationship between air pollution emissions and income: US Data. *Environ. Dev. Econ.* **1997**, *2*, 433–450. [CrossRef]
24. Selden, T.M.; Song, D. Environmental quality and development: Is there a Kuznets curve for air pollution emissions? *J. Environ. Econ. Manag.* **1994**, *27*, 147–162. [CrossRef]
25. Isen, A.; Rossin-Slater, M.; Walker, W.R. Every breath you take—Every dollar you'll make: The long-term conse-quences of the clean air act of 1970. *J. Political Econ.* **2017**, *125*, 848–902. [CrossRef]

26. Anderson, R.J., Jr.; Crocker, T.D. Air pollution and residential property values. *Urban Stud.* **1971**, *8*, 171–180. [CrossRef]
27. Ridker, R.G.; Henning, J.A. The Determinants of Residential Property Values with Special Reference to Air Pollution. *Rev. Econ. Stat.* **1967**, *49*, 246. [CrossRef]
28. Currie, J.; Hanushek, E.A.; Kahn, E.M.; Neidell, M.; Rivkin, S.G. Does pollution increase school absences? *Rev. Econ. Stat.* **2009**, *91*, 682–694. [CrossRef]
29. Sanders, N.J. What Doesn't Kill You Makes You Weaker: Prenatal Pollution Exposure and Educational Outcomes. *J. Hum. Resour.* **2012**, *47*, 826–850. [CrossRef]
30. Grimm, N.B.; Faeth, S.H.; Golubiewski, N.E.; Redman, C.L.; Wu, J.; Bai, X.; Briggs, J.M. Global Change and the Ecology of Cities. *Science* **2008**, *319*, 756–760. [CrossRef]
31. Herrnstadt, E.; Heyes, A.; Muehlegger, E.; Saberian, S. Air Pollution as a Cause of Violent Crime: Evidence from Los Angeles and Chicago. 2016; *manuscript in preparation*.
32. Liu, B. Essays on the Effect of Pollution and Weather on Behavior. Ph.D. Thesis, Georgia State University, Atlanta, GA, USA, 2017.
33. Hansen, K.; Machin, S. Spatial Crime Patterns and the Introduction of the UK Minimum Wage*. *Oxf. Bull. Econ. Stat.* **2002**, *64*, 677–697. [CrossRef]
34. Farhidi, F. Essays in Environmental and Energy Economics. Ph.D. Thesis, Georgia State University, Atlanta, GA, USA, 2018. [CrossRef]
35. Imai, K.; Keele, L.; Tingley, D. A general approach to causal mediation analysis. *Psychol. Methods* **2010**, *15*, 309–334. [CrossRef]
36. Beland, L.P.; Boucher, V. Polluting politics. *Econ. Lett.* **2015**, *137*, 176–181. [CrossRef]
37. Farhidi, F. *Do We Need More Cops? An Analysis of the Determinants of Metro Crime Rates*; SSRN Working Papers; SSRN: Rochester, NY, USA, 2020.
38. McCollister, K.E.; French, M.T.; Fang, H. The cost of crime to society: New crime-specific estimates for policy and program evaluation. *Drug Alcohol Depend.* **2010**, *108*, 98–109. [CrossRef] [PubMed]
39. Farhidi, F.; Madani, K.; Crichton, R. Have extreme events awakened us? *Sustainability* **2022**, *14*, 7417. [CrossRef]