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An Econometric Analysis of the Effect of Wildfire-Produced Particulate Matter on Solar Energy Production in California

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I. Introduction

On September 18, 2018, the California State Senate passed Senate Bill 100, known as the 100 Percent Clean Energy Act of 2018. This act formally set the goal for "one hundred percent of total retail sales of electricity in California to come from eligible renewable energy resources and zero-carbon resources" by December 31, 2045. [1] This goal requires California to progressively increase its dependence on clean energy sources throughout the coming two decades, with the most recent benchmark of achieving 33% dependence on clean energy sources by 2020. The upcoming deadline that the state faces is December 31, 2024. By then, California should be 40% dependent on clean energies. As of 2020, the state was ahead of schedule, achieving 59% dependence on clean sources at year's end: 10.6% nuclear, 13.9% large hydro, and 34.5% renewables.[2]

The year 2020 was a record-shattering year for wildfires in California, during which over 4.3 million acres burned. 2018 was also a devastating year: nearly 2 million acres were burned by wildfire. 2019, while flanked by two years in which wildfires ravaged the state, only had about 250,000 acres burn.[3] This time span, although short, is representative of the effects of particulate matter on solar energy. An analysis of the effect of wildfire-produced particulate matter on solar energy production is highly relevant to California's efforts to achieve the goals set by the State Senate in the 100 Percent Clean Energy Act of 2018.

Throughout this paper, the term "clean energy" is used to refer to all non-fossil fuel energy sources. "Renewable energy," a subgroup of clean energy, refers specifically to wind and solar energies. Particulate matter, defined as microscopic solid carbon particles released into the atmosphere from wildfires, is included in the air quality measurement $PM_{2.5}$, or particulate matter that is 2.5 micrometers in diameter or smaller. $PM_{2.5}$ contributes to air pollution and decreases solar irradiation, which is the power per unit area of energy received from the sun.

I.A Policy Issue

While the progress that the state has made so far towards becoming 100% reliant on clean energies is commendable, California faces a dilemma that could obstruct it from achieving 100% dependence on clean energy within the next twenty-two years. Wildfire activity in the western United States has increased rapidly over the last two decades.[4] Abatzoglou, Battisti, and Williams state that "absent a massive intervention to modify the intensity and mitigate negative impacts, the western US forest-fire area will continue to increase in the coming decades."[5] Appendix A shows the clear increasing trend of wildfires in the western United States. It is hypothesized that due to the increasing number and intensity of wildfires, and resultingly the

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[1] California, State Legislature, Senate. 100 Percent Clean Energy Act of 2018.
[2] "New Data Indicates California Remains Ahead of Clean Electricity Goals."
[3] California Department of Forestry and Fire Protection (CAL FIRE). "Incidents Overview."
[4] Westerling, A.T. "Increasing Western US Forest Wildfire Activity: Sensitivity to Changes in the Timing of Spring."
[5] Abatzoglou, J.T., Battisti, D.S., Williams, A.P. et al. "Projected Increases in Western US Forest Fire Despite Growing Fuel Constraints."

increased particulate matter in the atmosphere and decreased solar irradiation, solar energy in California will struggle to contribute to the 100 Percent Clean Energy Act's goal of Californian dependence on 100% clean energy by 2045.

I.B Existing Literature

Dumka et al. performed an advanced study testing a similar hypothesis focusing on the Indian subcontinent.[6] Due to India's rapidly increasing population, urbanization, and industrialization, energy demand on the Indian subcontinent has increased significantly. Solar energy is a fast-growing resource in India, but wildfires over the central Himalayan region could obstruct solar energy's contribution to providing energy to satisfy the growing demand. The results of Dumka et al. indicate that smoke and other aerosols weaken solar rays' penetration of the atmosphere, leading to a decrease in the energy production of solar plants.[7]

The Northwest Power and Conservation Council's initial analysis of the 100 Percent Clean Energy Act of 2018 concludes that "massive amounts of…solar resources [make] the management of the power grid more complex and will likely require significantly more resources to be built for reliability."[8] The variability in renewable resource production causes availability of these energies to be "extremely volatile." Ultimately, both Dumka et al. and the Northwest Power and Conservation Council conclude that renewable energies, particularly solar energy, is unreliable due to its sensitivity to uncontrollable forces, such as weather conditions.

II. Description of the Data

The data used in this analysis come from a variety of sources. The names, locations, and megawatt hour production of solar plants were found on the U.S. Energy Information Administration website. The names and locations of California counties were found on the California state government's website. Weather data, such as average temperature and precipitation per county, were found at the National Center for Environmental Information: National Oceanic and Atmospheric Administration website. Data regarding the particulate matter in Californian counties was found on the United States Environmental Protection Agency website. Information about the number and size of wildfires in California was found on the California Department of Forestry and Fire Protection website. The UV index per month, per county was found at www.weather-us.com.

II.A Descriptive Statistics

The following is an explanation of the variables used in this analysis. A table with descriptive statistics of each variable is shown below.

`solarfarmid`: The numerical distinction between solar farms, ranging 1 to 25. `solarfarmid` is used as the panel variable in the fixed effects regression models.

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[6] Dumka, Umesh Chandra, et al. "Can Forest Fires Be an Important Factor in the Reduction in Solar Power Production in India?"
[7] Ibid.
[8] *California's 100 Percent Clean Energy Act, Part 2*.

yearmonth: The time period associated with each datum, formatted as year followed by month (ex: 201801 for January 2018). The data span January 2018 to December 2020 (201801 to 202012). `yearmonth` is used as the time variable in the fixed effects regression models.

logmegawatthours: The natural log of the total megawatt hours of solar energy produced by solar farm (i) during time period (t). Because the variable `megawatthours` is skewed, `logmegawatthours` = ln(`megawatthours`). Appendix B shows the Kernel density plot of `megawatthours`. There are some instances in which `megawatthours` equals 0; in such cases, `logmegawatthours` is set to ln(4.08) = 1.407. ln(4.08) was chosen as the value for such cases because the lowest naturally occurring value of `megawatthours` is 8.165; the solution to such log(0) instances is to halve the lowest naturally occurring value and take the natural log of that number.

logacres: The natural log of the total acres burned by wildfires that started in county i during time period t. Because the variable `acres` is skewed, `logacres` = ln(`acres`) is created. Appendix C shows the Kernel density plot of `acres`. There are some instances in which `acres` equals 0; for the reasons described above in the description of `logmegawatthours`, in such cases `logacres` is set to equal ln(3) = 1.099.

avgpm: The average particulate matter 2.5 ($PM_{2.5}$) during time period (t) of the county in which solar farm (i) is located.

uv: The average UV index of county (i) during month (t) from the year 2010 to 2020. Because this variable is the average over the course of 10 years, each month has the same UV index over the three years included in our analysis (i.e. $uv_{i201805}$, $uv_{i201905}$, and $uv_{i202005}$ are the same value). This could contribute to internal invalidity.

logprecipitation: The natural log of the total precipitation in county (i) during time period (t). Because the variable `precipitation` is skewed, `logprecipitation` = ln(`precipitation`) is created. Appendix D shows the Kernel density plot of `precipitation`. There are some instances in which `precipitation` equals 0; for the reasons described above in the description of `logmegawatthours`, in such cases `logprecipitation` is set to equal ln(0.005) = -5.298.

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
logmegawatthours	900	6.713	2.067	2.1	11.315
logacres	897	2.344	2.291	1.099	11.94
avgpm	900	45.697	21.933	5.778	147.667
uv	900	4.78	1.447	2	9
logprecipitation	900	-1.633	2.655	-5.298	3.041

II.B Correlation Table

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)
(1) logmegawatth~s	1.000				
(2) logacres	0.090	1.000			
(3) avgpm	-0.011	0.124	1.000		
(4) uv	0.249	0.393	0.027	1.000	
(5) logprecipitation	-0.184	-0.367	-0.254	-0.659	1.000

III. Description of the Econometric Model

The data collected for this analysis is panel data, and fixed effects regression models are utilized in this paper. The panel variable is `solarfarmid` and the time variable is `yearmonth`. Variations of two fixed effects regressions will show a) the effect of wildfires on particulate matter and b) the effect of particulate matter on solar energy production.

III.A Estimating Particulate Matter

To quantify the effect of wildfires on particulate matter, we begin with the following regression model:

(1) $$\widehat{avgpm}_{it} = \beta_0 + \beta_1 logacres_{it}$$

Followed by a regression controlling for precipitation:

(2) $$\widehat{avgpm}_{it} = \beta_0 + \beta_1 logacres_{it} + \beta_2 logprecipitation_{it}$$

where β_0 is the constant term and β_1 and β_2 are the coefficient estimations for `logacres` and `logprecipitation`, respectively.

III.B Estimating Solar Energy Production

To quantify the effect of particulate matter on solar energy production, we begin with the following regression model:

(3) $$\widehat{logmegawatthours}_{it} = \beta_0 + \beta_1 avgpm_{it}$$

Followed by a regression controlling for UV and precipitation:

(4) $$\widehat{logmegawatthours}_{it} = \beta_0 + \beta_1 avgpm_{it} + \beta_2 uv_{it} + \beta_3 logprecipitation_{it}$$

where β_0 is the constant term and β_1, β_2, and β_3 are the coefficient estimations for `avgpm`, `uv`, and `logprecipitation`, respectively.

IV. Empirical Results

	(1) $PM_{2.5}$	(2) $PM_{2.5}$
Acres	0.891**	0.126
	(0.385)	(0.402)
Precipitation		-1.633***
		(0.252)
Constant	43.59***	42.72***
	(0.903)	(0.892)
N	897	897
R^2	0.012	0.057

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

	(3) Megawatt hours	(4) Megawatt hours
$PM_{2.5}$	-0.00492***	-0.00427***
	(0.000921)	(0.000546)
UV		0.183***
		(0.00763)
Precipitation		-0.0215**
		(0.0102)
Constant	6.938***	5.999***
	(0.0421)	(0.0315)
N	900	900
R^2	0.026	0.293

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

IV.C.1 Statistical Significance of Regressions Estimating Particulate Matter

Regression (3) looks at just particulate matter to estimate solar energy production. The coefficient is negative and is statistically significant at the $\alpha = 0.01$ level. This indicates that megawatt hour decreases when $PM_{2.5}$ increases. Regression (4) examines the effect of particulate matter on megawatt hours when controlling for UV index and precipitation. In this case, avgpm and uv are statistically significant at the $\alpha = 0.01$ level, while logprecipitation is significant at the $\alpha = 0.05$ level.

IV.D.2 Economic Significance of Regressions Estimating Solar Energy Production

Both regressions indicate that particulate matter negatively affects solar energy production. This conclusion does not change when controlling for UV index and precipitation. Regression (3) demonstrates that when particulate matter increases by 1%, solar energy production decreases by 0.00005 megawatt hours. Regression (4) shows that when controlling for the UV index and precipitation, solar energy production falls by 0.00004 megawatt hours when particulate matter increases by 1%. When holding particulate matter and UV index constant, a 1% increase in precipitation results in a decrease of 0.0002 megawatt hours produced.

V.A Internal Validity

Data is inherently imperfect. So is the dataset used in this analysis. The internal validity of the data is threatened, for example, by the imperfect measure of the UV index of county (i) during time period (t). The only available UV index data that was found on the county level was the average UV index of county i during month t over the course of 2010 through 2020. This means that for county i in month 5, $uv_{i201805}$, $uv_{i201905}$, and $uv_{i202005}$ are the same value. The data could suffer from internal validity because this measure of uv does not provide a perfect explanation of a county's UV index on the megawatt hours of solar energy produced.

An additional threat to the internal validity is possible simultaneous causality bias in the data. In this study, particulate matter, temperature, and other atmospheric indicators are used to estimate solar energy production. It important to note that it is probable that solar plants are placed in strategic locations with advantageous weather conditions that will maximize megawatt hours production.

For this reason, a robust and diverse sample is necessary. Data was intentionally selected to be diverse and special attention was paid to geography. Future studies could perform similar tests instead using instrumental variables or a differences-in-differences approach to rectify such issues. As in any econometric analysis, a more expansive data set leads to more robust conclusions. Expanding the data by including more years or more counties in California is quite possible. This study analyzes only one solar farm per county but multiple solar farms per county over the course of decades would increase the reliability of our results. Future researchers could study multiple solar farms per county over the course of several decades to achieve more robust results.

V.B External Validity

Appendix E is a map of California with the counties represented in this study outlined in bold black. Of the 58 counties in California, 25 are included in the sample. As seen on the map, every region in California except the Eastern Sierra is represented in this study. Therefore, the results of this study can be applied to the rest of the state. California is a one of the most geographically diverse states with deserts, mountains, valleys, coasts, and forests. Due to California's vast diversity, these results can be applied to other parts of the United States, particularly the western United States. This study is, therefore, externally valid.

VI. Conclusions

The year 2020 was a record-shattering year for wildfires in California, during which over 4.3 million acres burned. 2018 was also a devastating year - nearly 2 million acres were burned by wildfire. 2019, while flanked by two years in which wildfires ravaged the state, only had about 250,000 acres burn.[9] This time span, although short, is representative of the effects of both particulate matter and precipitation on solar energy. The year 2018 had fewer wildfires than 2020 and, therefore, more solar energy was produced. This was because of clearer, less polluted skies in 2018. Given the results of the regressions above, it could be hypothesized that because 2019 experienced the least number of wildfires, it would have experienced the most megawatt hours produced. Following this hypothesis, trailing far behind would be 2018, and 2020 should have produced the least megawatt hours. However, this is not the case: of the three years included in this study, 2019 actually came in *last* in solar energy production. The disconnect between the reality of the data and the results from the regressions are surprising. The reason for this disparity lies in precipitation. In 2019, there was almost twice as much precipitation as in 2018 and nearly three times the amount of precipitation as 2020. Appendix F compares the average acres burned, average megawatt hours produced, average particulate matter, and average precipitation per county for these years.

V.A Policy Implications

The regressions above and evidence between years 2018 and 2020 confirm that particulate matter does negatively affect solar energy production as hypothesized. However, as shown in regressions (2) and (4) and witnessed in 2019, precipitation has a much larger and more influential impact on solar energy production than does wildfire-produced particulate matter. This means that while California should continue dedicating resources to decrease the size and intensity of wildfires in the state, such as proper forest management, there may be only so much that the state can do. The goal of achieving 100% reliance on clean energy by 2045 is still possible, and solar energy will likely be a large component of its success. But as great as the state's efforts are to decrease the effects of wildfires, the balance between precipitation and particulate matter that maximizes solar energy production is delicate.

Unfortunately, precipitation is the one factor that *cannot* be controlled. While small amounts of precipitation create clear skies, which then maximize solar energy production, as

[9] California Department of Forestry and Fire Protection (CAL FIRE). "Incidents Overview."

seen in 2018, too much precipitation can cloud the skies and deplete solar energy production, as witnessed in 2019. California is currently at risk of exactly this: 2023 has experienced unexpected amounts of precipitation, with some experts claiming that California's drought is "effectively over."[10] The extreme amounts of precipitation received in the first quarter of this year may negatively affect the amount of solar energy produced. Fortunately, the highest solar energy production months in California are May through September.[11]

The extreme amounts of precipitation received in the first quarter of 2023 may result in a mild wildfire season in the Western United States, which will result in lower levels of particulate matter and ultimately result in higher levels of solar energy production. However, this is yet to be seen; while 2023 has received precipitation at opportune times, other years will not receive precipitation, resulting in more intense wildfire seasons and higher particulate matter, or will receive precipitation during the peak solar energy production window, which will result in cloudy skies. What the years 2018, 2019, and 2020 testify and what is reiterated now in 2023 is that solar energy production is ultimately too unreliable to serve as the foundation of the state's lofty energy goals.

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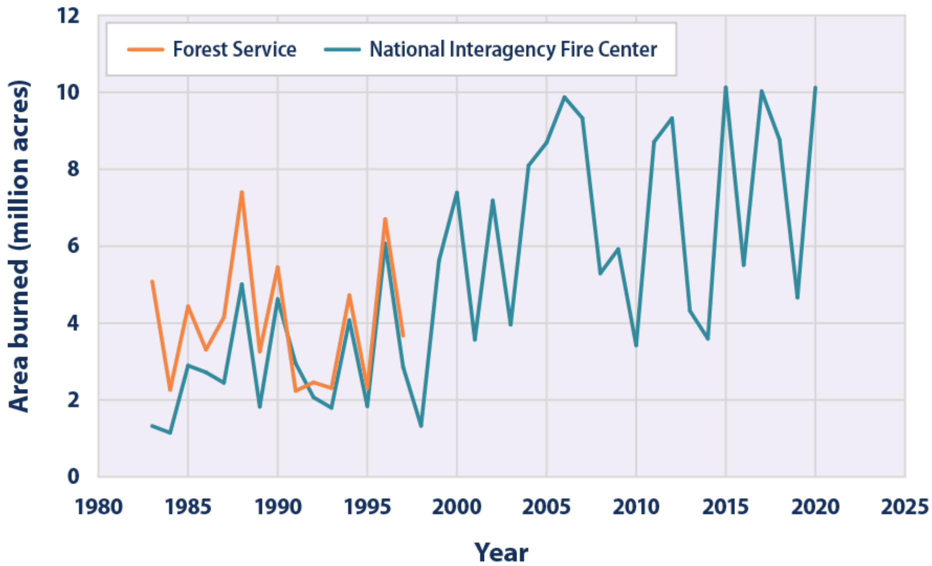
[10] Adams, A. B. (2023, March 12). *CA Drought: Recent Storms Put the 'Nail in the Coffin' for Drought.*

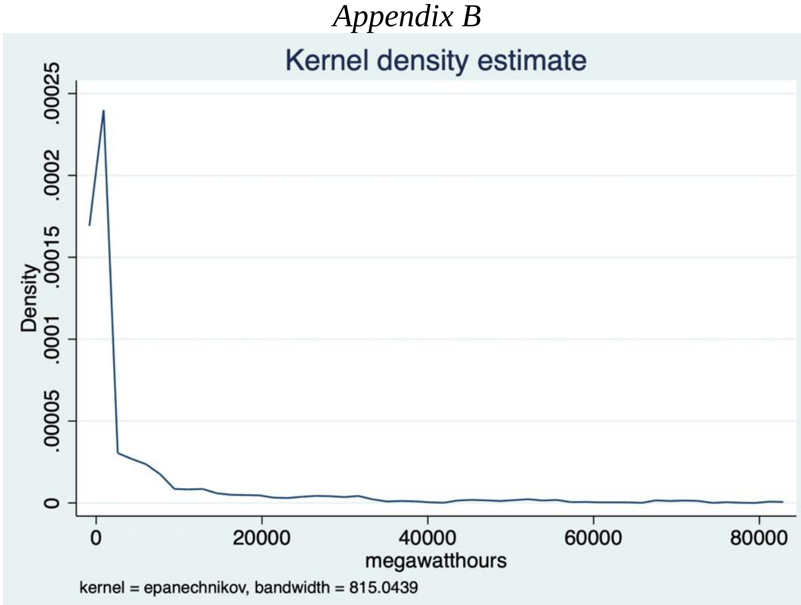
[11] "Why Is Spring the Best Time to Go Solar in California?" (2023, 29 March).

VI. Appendix

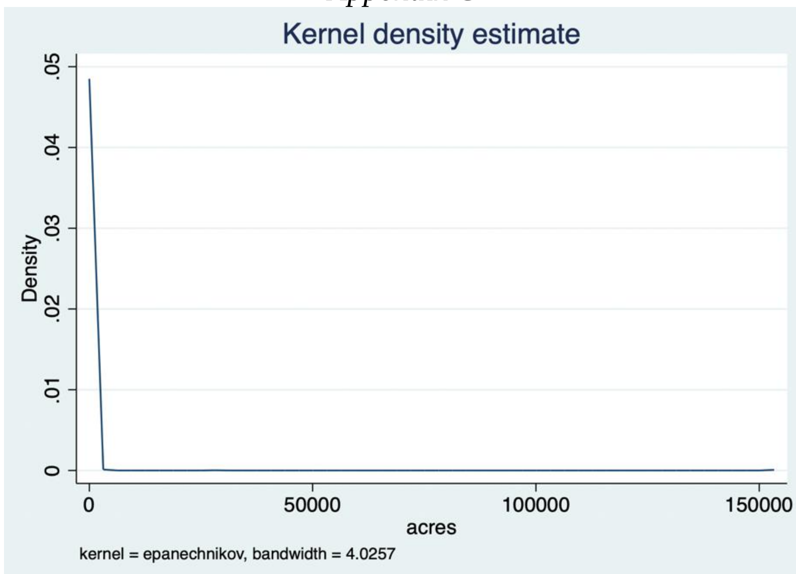
Appendix A



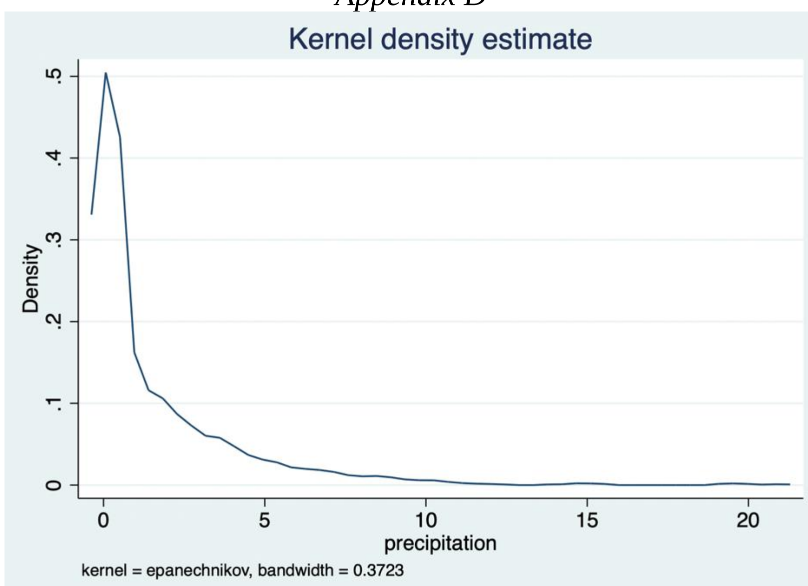
Appendix B



Appendix C



Appendix D



Appendix E

Appendix F

year	acres	megawat~s	avgpm	precipita~n
2018	1110.082	6498.637	48.93051	1.447233
2019	179.7592	5458.153	38.17737	2.310033
2020	1661.323	5903.387	49.9834	.8636333

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