Fast Subsidies, Furious Emissions: The Double-Edged Impact of EV Policies

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Abstract This paper examines the environmental impact of electric vehicle (EV) subsidies in India, focusing on how they influence air pollution through increased electricity demand. While EVs eliminate tailpipe emissions, their reliance on a fossil-fuel-dominated power grid can inadvertently increase air pollution. Using a social welfare optimization model, this study explores the effects of EV and solar microgrid subsidies on pollution, accounting for production and budget constraints. The analysis reveals that EV subsidies alone may exacerbate pollution without concurrent investments in renewable energy infrastructure. Empirical results show a significant correlation between increased electricity generation and pollutant levels. This research highlights the need for coordinated policy design to ensure that subsidies drive sustainable transitions while minimizing environmental trade-offs.

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1 Introduction

The Indian automobile industry has experienced rapid growth in recent years, with a predominant focus on internal combustion engine vehicles. These vehicles are a primary source of urban pollution and greenhouse gas emissions, putting significant pressure on the industry to transition to zero-emission alternatives such as electric vehicles.Kumar et al. (2021) To address this issue, the Indian government has introduced the Faster Adoption and Manufacturing of Electric Vehicles scheme, which aims to boost the adoption of electric vehicles and build a sustainable ecosystem for the transformation of mobility solutions in the country.Bhaskar (2020)

The adoption of electric vehicles in India faces several challenges, including the high cost of electric vehicles, lack of charging infrastructure, and the purchasing power of Indian consumers.Kumar et al. (2020) Examining these challenges and the potential impact of subsidies on pollution levels is crucial for policymakers to develop effective strategies that can promote the widespread adoption of sustainable transportation solutions in India.

However, the charging infrastructure is primarily based on fossil-fuel based electricity production. This paper aims to explore the impact of electric vehicle subsidies on pollution levels in India, considering the potential emissions from the charging infrastructure required to support the increased adoption of electric vehicles.

1.1 Electric Vehicle Subsidies and Pollution in India

The Indian government has introduced various policies and incentives to encourage the adoption of electric vehicles, including subsidies for both vehicle purchases and the development of charging infrastructure. Bhaskar (2020)Holland et al. (2018)These subsidies have the potential to impact pollution levels in India through two primary mechanisms:

Reduction in emissions from tailpipe: The adoption of electric vehicles can directly reduce the emissions from the transportation sector, as they do not produce any direct emissions during operation. Kumar et al. (2021)This can result in improved air quality in urban areas, particularly in regions with high vehicle density.

Potential increase in emissions from charging infrastructure: The increased adoption of electric vehicles will necessitate the development of a robust charging infrastructure, which may result in additional emissions from the electricity generation required to power these charging stations. Holland et al. (2018) The overall impact on pollution levels will depend on the source of electricity generation, as well as the efficiency of the charging infrastructure.

For this paper, I will be concentrating on the second mechanism. The existing literature suggests that the impact of electric vehicle adoption on pollution levels in India is not straightforward and depends on several factors, including the decarbonization of the electricity grid and the charging patterns of electric vehicle users.Abdul-Manan et al. (2022)

Electrifying passenger road transport in India requires near-term electricity grid decarbonization, as the current electricity generation mix in India is heavily dependent on fossil fuels. Charging electric vehicles during periods of high electricity demand, particularly in regions with a high reliance on coal-fired power plants, can lead to an overall increase in greenhouse gas emissions. On the other hand, charging electric vehicles during periods of low electricity demand or in regions with a higher share of renewable energy sources can result in a significant reduction in emissions.Abdul-Manan et al. (2022)

I will analyse the impact of electric vehicle charging infrastructure on pollution levels in India, taking into account the current electricity generation mix across states and the effect of FAME policies on the demand for electricity. We can infer that an increase in electric vehicles being sold will increase the demand for electricity in tier 1 and tier 2 cities. However, since most of India's electricity is still produced using fossil fuels and renewable energy generation happens through large infrastructure development like dams, wind and solar farms, any increase in demand for electricity will lead to an increase in reliance on fossil fuel infrastructure. There is evidence that to have a successful long-term impact on emissions, rise in EV demand should be coupled with a rise in micro-renewable infrastructure[1].

1.2 FAME Policy

This refers to the Faster Adoption and Manufacturing of Electric Vehicles in India schemes. There have been two phases of this program:

FAME India Scheme Phase I (2015-2019): This initial phase focused on providing demand incentives for electric and hybrid vehicles, supporting pilot projects, and establishing charging infrastructure. Rs. 895 Cr ($108 Million) was earmarked to be spent on this policy.

FAME India Scheme Phase II (2019-2024): This phase significantly increased the outlay for incentives, expanded the scope to include electric buses, three-wheelers, and four-wheelers, and further emphasized charging infrastructure development. A key goal of FAME II is to support the electrification of public transportation. Rs. 11,500 Cr ($1.39 Billion) was earmarked to be spent on this policy.

The FAME schemes offer financial incentives in the form of subsidies on the purchase price of eligible electric vehicles. The amount of the subsidy varies depending on the type of vehicle and its battery capacity. The schemes also support the development of charging infrastructure through subsidies and other incentives.

The overall aim of the FAME policies is to promote the adoption of electric and hybrid vehicles in India, reduce dependence on fossil fuels, and improve air quality. Ali and Naushad (2022) discusses FAME policies and their role in promoting electric vehicle adoption in India. You can add this document to your library for more detailed information.

2 Model

Consider the problem faced by a social welfare optimizer (like a government) in pursuit of reducing emissions. Around 27% of all emissions come from vehicles, so it should be a good place to start! I propose a model to minimise emissions. My model is constrained by a maximum level of electricity production for the government. My model is also constrained by a budget for subsidies that is determined exogenously. The government chooses subsidies for electric vehicles and small solar plants subject to the production and budget constraints.

My model makes the assumption that splitting the subsidy between EVs and solar-microgrids is an effective strategy.

$$min_{p,s} \;\; E \;\; s.t. \;\; \int_0^{\bar{w}} y(e(p), r(s,c), w)\, dw \leq \bar{y}; \;\; B \geq s + p$$

$$min_{p,s} \;\; V(p) \; + \; G(r(s,c)) \; + O \;\; s.t. \;\; \int_0^{\bar{w}} y(e(p), r(s,c), w)\, dw \leq \bar{y}; \;\; B \geq s + p$$

[1] Alternative Fuels Data Center - US Dept. of Energy

2.1 Variable Definitions

Functions:

$V \longrightarrow$ Vehicular emissions

$G \longrightarrow$ Power generation emissions

$O \longrightarrow$ Other sources of emission

$y \longrightarrow$ Electricity production function

$e \longrightarrow$ Number of EVs

$r \longrightarrow$ Number of small solar plants

Choice variables:

$p \longrightarrow$ Electric vehicle subsidy

$s \longrightarrow$ Small solar subsidy

Parameters:

$c \longrightarrow$ Cost of solar microgrids

$B \longrightarrow$ Total available budget for subsidy

$w \longrightarrow$ Number of hot weather days

2.2 Objective function

$$\begin{aligned} L \ = \ & min_{p,s} \ \ V(p) \ + \ G(r(s,c)) \ + O \\ & + \ \lambda_1(\bar{y} - \int_{w}^{\bar{w}} y(e(p), r(s,c), w)\, dw) \\ & + \ \lambda_2(B \ - p \ - s) \end{aligned}$$

2.3 First order conditions

$$\frac{\partial L}{\partial p} \ = \ \frac{\partial V(p)}{\partial p} \ + \ \lambda_1 \frac{\partial y(e(p), r(s,c))}{\partial e} \frac{\partial e(p)}{\partial p} - \lambda_2 \ \geq \ 0 \tag{1}$$

$$\frac{\partial L}{\partial s} \ = \ \frac{\partial G(r(s,c))}{\partial r} \frac{\partial r(s,c)}{\partial s} \ + \ \lambda_1 \frac{\partial y(e(p), r(s,c))}{\partial e} \frac{\partial e(p)}{\partial p} - \lambda_2 \ \geq \ 0 \tag{2}$$

$$\frac{\partial L}{\partial \lambda_1} \ = \ \bar{y} - \int_{w}^{\bar{w}} y(e(p), r(s,c), w)\, dw) \geq \ 0 \tag{3}$$

$$\frac{\partial L}{\partial \lambda_2} \ = \ B \ - p \ - s \geq \ 0 \tag{4}$$

3 Analysis and Results

3.1 Assumptions to sign the comparative statics

- $\frac{\partial y}{\partial e}\frac{e}{y} > \frac{\partial r}{\partial e}\frac{e}{r}$ - Coal-based power is more responsive to demand from EVs than clean power. This is a fact that has been established in the literature. Primarily, when people substitute to electric vehicles, since they cannot be used for long journeys too much, people tend to make them daily drivers. In which case, since there is a relatively standard office and home timing across a country, many EVs will simultaneously be put on charge. This leads to a requirement for power that has a low response time, which is coal/fossil fuel power.

- $\frac{\partial r}{\partial s} > 0; \frac{\partial^2 r}{\partial s \partial s} < 0$ - There are diminishing returns from solar energy subsidies. Consumers will not shift all their electricity consumption to solar microgrids due to production constraints like the duck curve[2].
- $\frac{\partial^2 y}{\partial r \partial e} = \frac{\partial^2 y}{\partial e \partial r} < 0$ - For this, we can think about Young's theorem and instead of saying that the marginal production of renewable energy changes with number of electric vehicles (a non-intuitive interpretation), we can say that the marginal production increase from electric vehicles changes with increase in solar microgrids. And the direction of this change is negative. This means that as solar microgrids increase, the electricity demand that EVs have on conventional power will decrease!
- $\frac{\partial G}{\partial r} < 0; \frac{\partial^2 G}{\partial r \partial r} < 0$ - This assumption says that there will be compounding increases to substituting demand to solar microgrids on vehicular pollution. While this is not the most intuitive assumption, we can think of this as people being able to use solar power for more than charging their vehicles.
- $\frac{\partial^2 V}{\partial p \partial p} < 0$ - This assumption is justified by the fact that charging stations will not increase at the same rate as electric vehicles. Hence there will be diminishing returns to this substitution to electric vehicles.
- $\frac{\partial^2 y}{\partial r \partial r} < 0$ - This assumptions states that people cannot substitute their entire electricity consumption to solar microgrids. There will continue to be fossil fuel electricity consumption as emergency services, offices, hospitals, etc. will be reliant on coal power.
- $\frac{\partial^2 y}{\partial e \partial w} > 0$ The demand for electricity is increasing in electric vehicles. The marginal increase in demand for electricity for each additional electric vehicle is increasing in each additional bad weather day.

3.2 Comparative Statics

3.2.1 Comparative Static 1: How does generation emission (G) vary with electric vehicle policy subsidy (p)?

$$\frac{\partial G}{\partial p} = \frac{-[-\lambda_1 \frac{\partial^2 y}{\partial r \partial e} \frac{\partial r}{\partial s} \frac{\partial e}{\partial p}]}{\frac{\partial G}{\partial r} \frac{\partial r}{\partial s}} > 0$$

This is an extremely intuitive result from the context and model. Increasing subsidy for electric vehicles increases the pollution from power plants. This result is critical to this model as it makes it incentive compatible for a benevolent social optimizer to not increase electric vehicle subsidy until B=p.

3.2.2 Comparative Static 2: How does small renewable energy (r) increase with electric vehicle subsidy (p)?

$$\frac{\partial p}{\partial s} = \frac{-[-\lambda_1 \frac{\partial^2 y}{\partial e \partial r} \frac{\partial r}{\partial s} \frac{\partial^2 e}{\partial p \partial p} - \frac{\partial^2 y}{\partial e \partial e} s \frac{\partial r}{\partial s}^2]}{\frac{\partial^2 V}{\partial p \partial p} - \lambda_1 \frac{\partial y}{\partial e} \frac{\partial^2 e}{\partial p \partial p} - \lambda_1 \frac{\partial^2 y}{\partial e \partial e}^2} > 0$$

This result is also critical for the government. It states that increasing both subsidies together makes sense for the government.

[2]The Duck curve is making solar energy adoption difficult

3.2.3 Comparative Static 3: How does a change in the maximum possible electricity production impact solar energy subsidy?

$$\frac{\partial \bar{y}*}{\partial s} = \frac{|Det_\theta|}{|BH|} < 0$$

This is a bit of a counter-intuitive result. As the maximum possible electricity production increases when the subsidy on solar energy decreases. Based on the model assumptions, this means that increasing the max production level makes solar subsidies less efficient.

4 Data

I use data from various sources in the Indian government to analyze the impact of electric vehicle subsidies on pollution in India.

4.1 Impact of electricity generation on air pollution

The first thing I do is look at the impact of increased electricity generation and capacity on air quality. I find that increasing electricity generation capacity is correlated significantly with higher particulate matter, nitrogen oxide, and sulfur dioxide emissions. My data is at the national level. Electricity generation here is used interchangeably with coal based electricity generation.

I run the following specifications:

$$Y = \alpha + \beta_i X + \varepsilon_i \tag{5}$$
$$Y = \alpha_j + \beta_i Treatment + \gamma_{ij} \tag{6}$$
$$Y = \alpha + \tau_k + \beta_i Treatment + \delta ik \tag{7}$$

Where, X is Generation or Capacity; Y is SO2, NO2, PM10 or PM2.5 concentration. Treatment here is defined as before and after 2015, the first year of the implementation of the FAME policies. Unfortunately, there isn't a clear way to find exogenous variation using the implementation of this policy. This is due to the fact that the policy was implemented in large cities to begin with. But the timelines are not clearly delineated.

Table 1: Table 1: Summary Stats

	Sum	Mean	SD	Min	Max	N
NO2 (in g/m^3)	23,953	22.28	13.98	1	92	1,075
SO2 (in g/m^3)	11,034	10.37	7.88	2	51	1,064
PM10 (in g/m^3)	113550	104.17	59.13	20	295	1,090
PM2.5 (in g/m^3)	22,383	46.83	27.54	7	167	478
Total Generation in MU	65013451	37623.52	47490.63	0	163447	1,728
Total Capacity in MU	25734839	14892.85	14399.74	3	55,008	1,728

Here I have only included the correlation with SO2 concentration because it is highly significant. The rest of the regressions are included in the appendix. Interestingly, there is a highly significant decrease in PM2.5 and PM10 concentration with increased electricity generation capacity. This is likely due to better combustion efficiencies in newer power plants and tighter regulations surrounding emissions.

Table 2: Regressing Mean so2 on Generation

	(1)	(2)
	Mean so2	Mean so2
Total Generation in MU	0.000***	
	(0.000)	
Log(Total Generation)		3.455***
		(0.854)
Constant	6.703***	-26.305***
	(2.030)	(9.737)
Observations	123	123

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Impact of FAME policy on EV Sales and SO2

In Table 3, there is a significant reduction in SO2 concentration from the policy being in effect. In treatment years, the mean SO2 concentration is is lower by almost 0.8 standard deviations (significant at the 5% level).

Somewhat counterintuitively in Table 4, the policy is highly correlated with lower total sales of EVs overall (significant at the 1% level). But when this effect is disaggregated to the state level, it increases the purchase of EVs in large states with charging infrastructure like Maharashtra, Bihar, Gujarat, Karnataka, Tamil Nadu and Uttar Pradesh.

As seen in table 5, EV sales are also correlated with an increase in PM2.5 concentrations (significant at the 10% level).

Potentially the strongest and most intuitive result is in Table 6, where we see that a 1% increase in total generation of electricity is correlated with 576 more electric vehicles purchased (significant at the 1% level). This result follows the logic that electric vehicles are highly dependent on coal based energy generation. These results are not significant for solar or hydro electric generation.

5 Conclusion

The government of India has spent $1.5 Billion on the FAME policies from 2015 to 2022. More than the amount, this has signaled to state governments that electric cars are the future. However, given the way the current electricity infrastructure is set up, an increase in the number of electric vehicles could lead to increased reliance on fossil fuel based electricity production.

Based on the results from my model, one potential solution to this problem is compounding subsidies of electric vehicles with those on solar microgrids. This would facilitate charging, net metering, and could potentially work towards inculcating behavioral changes to charging and vehicle usage patterns.

While there are potential impacts of the policy to be studied on more local levels (like at the city level since vehicle ownership is concentrated to cities), the impact on air pollution becomes harder to measure as the unit of observation gets smaller.

As for air pollution reduction, we see above that the policy is correlated with a reduction in SO2 concentration. However, the magnitude of the effect is very small. Intuitively, this can be thought of as a high cost low return outcome because it requires a subsidy, purchase of an electric vehicle, usage of infrastructure that may generate other externalities (coal based electricity production) and then results in a reduction in SO2 concentration.

Table 3: Regressing Mean SO2 on Treatment with FE for Year

	(1)
	Mean SO2
fame	-4.708**
	(2.312)
Year=2015	0.000
	(.)
Year=2016	1.239
	(0.809)
Year=2017	0.333
	(0.635)
Year=2018	1.346
	(0.968)
Year=2019	1.310
	(0.935)
Year=2020	-0.198
	(0.700)
Year=2021	4.718**
	(2.146)
Year=2022	0.000
	(.)
Constant	14.450***
	(1.842)
Observations	107
ρ	0.684
Time Effects	Yes
Fixed effects	No

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regressing EV Sales on Treatment with FE for State

	(1)
	EV Sales
fame	-36950.378***
	(10463.501)
Andhra Pradesh	0.000
	(.)
Assam	7457.100***
	(0.000)
Bihar	13610.900***
	(0.000)
Chhattisgarh	-219.200***
	(0.000)
Delhi	19414.713***
	(3139.050)
Gujarat	9929.300***
	(0.000)
Haryana	789.700***
	(0.000)
Jharkhand	-2947.700***
	(0.000)
Karnataka	23755.300***
	(0.000)
Maharashtra	32328.600***
	(0.000)
Manipur	-7606.000***
	(0.000)
Puducherry	-7220.800***
	(0.000)
Sikkim	-7734.100***
	(0.000)
Tamil Nadu	12936.200***
	(0.000)
Uttar Pradesh	65459.100***
	(0.000)
Uttarakhand	-1974.700***
	(0.000)
Constant	33599.664***
	(7324.451)
Observations	154
ρ	0.000
Time Effects	No
Fixed effects	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Regressing EV Sales on PM2.5 with FE for State

	(1)
EV Sales	0.000*
	(0.000)
Andhra Pradesh	0.000
	(.)
Assam	64.752***
	(0.224)
Bihar	52.155***
	(0.117)
Chhattisgarh	20.019***
	(1.130)
Delhi	85.208***
	(0.200)
Gujarat	22.052***
	(0.484)
Haryana	50.555***
	(0.126)
Jharkhand	25.199***
	(0.659)
Maharashtra	22.530***
	(0.409)
Manipur	20.449***
	(1.196)
Puducherry	24.867***
	(1.185)
Sikkim	39.751***
	(1.203)
Tamil Nadu	-14.820***
	(2.977)
Uttar Pradesh	6.832***
	(0.869)
Uttarakhand	19.116***
	(0.817)
Constant	21.307***
	(1.203)
Observations	67
ρ	0.000
Time Effects	No
Fixed effects	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Regressing EV Sales on Generation with FE for State

	(1)
Log(Total Generation)	57590.554***
	(17331.129)
Andhra Pradesh	0.000
	(.)
Assam	141336.325***
	(41364.728)
Bihar	53744.898***
	(13875.322)
Chhattisgarh	-30133.440***
	(7338.682)
Delhi	146065.492***
	(41220.893)
Gujarat	-18776.629***
	(6626.471)
Haryana	60015.559***
	(17650.565)
Jharkhand	53847.689***
	(15681.934)
Karnataka	17049.139***
	(1608.074)
Maharashtra	-13979.386
	(9178.419)
Manipur	-44298.045***
	(11264.487)
Puducherry	8872.405*
	(4687.115)
Sikkim	44835.655***
	(15591.229)
Tamil Nadu	8899.541***
	(148.295)
Uttar Pradesh	10521.528**
	(4628.002)
Uttarakhand	16017.648***
	(5430.465)
Constant	-638587.483***
	(194273.236)
Observations	108
ρ	0.000
Time Effects	No
Fixed effects	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These findings warrant a deeper exploration into the impact of this policy especially on current levels of pollution.

A Appendix 1: Math

A.1 Second order conditions (via bordered Hessian)

$$|BH| = \begin{vmatrix} 0 & 0 & -\frac{\partial y}{\partial e}\frac{\partial e}{\partial p} & -\frac{\partial y}{\partial r}\frac{\partial r}{\partial s} \\ 0 & 0 & -1 & -1 \\ -\frac{\partial y}{\partial e}\frac{\partial e}{\partial p} & -1 & \frac{\partial^2 V}{\partial p \partial p} - \lambda_1 \frac{\partial^2 y}{\partial e \partial e}\frac{\partial^2 e}{\partial p \partial p}\frac{\partial e}{\partial p} & -{}_1 \frac{\partial^2 y}{\partial e \partial r}\frac{\partial e}{\partial p}\frac{\partial r}{\partial s} \\ -\frac{\partial y}{\partial r}\frac{\partial r}{\partial s} & -1 & -\lambda_1 \frac{\partial^2 y}{\partial r \partial e}\frac{\partial e}{\partial p}\frac{\partial r}{\partial s} & \frac{\partial^2 G}{\partial r \partial r}\frac{\partial^2 r}{\partial s \partial s}\frac{\partial r}{\partial s} - \lambda_1 \frac{\partial^2 y}{\partial r \partial r}\frac{\partial^2 r}{\partial s \partial s}\frac{\partial r}{\partial s} \end{vmatrix}$$

$$|BH| < 0$$

A.2 Matrices to apply IFT via Cramer's Rule

$$-D_\theta = \begin{vmatrix} \lambda_1 \frac{\partial^2 y}{\partial e \partial r}\frac{\partial r}{\partial c}\frac{\partial e}{\partial p} & \lambda_1 \frac{\partial^2 y}{\partial e \partial w}\frac{\partial r}{\partial s} & 0 & 0 \\ -[\frac{\partial^2 G}{\partial r \partial r}\frac{\partial r}{\partial s}\frac{\partial r}{\partial c} + \frac{\partial^2 r}{\partial s \partial c}\frac{\partial G}{\partial r}]+ & & & \\ \lambda_1 \frac{\partial^2 y}{\partial r \partial r}\frac{\partial r}{\partial s}\frac{\partial r}{\partial c} + \lambda_1 \frac{\partial y}{\partial r}\frac{\partial^2 r}{\partial s \partial c} & \lambda_1 \frac{\partial^2 y}{\partial e \partial w}\frac{\partial r}{\partial s} & 0 & 0 \\ \frac{\partial y}{\partial r}\frac{\partial r}{\partial c} & \frac{\partial y}{\partial w} & 0 & -1 \\ 0 & 0 & -1 & 0 \end{vmatrix}$$

$$D_x = \begin{vmatrix} \frac{\partial^2 V}{\partial p \partial p} - \lambda_1 \frac{\partial^2 y}{\partial e \partial e}\frac{\partial^2 e}{\partial p \partial p}\frac{\partial e}{\partial p} & -{}_1 \frac{\partial^2 y}{\partial e \partial r}\frac{\partial e}{\partial p}\frac{\partial r}{\partial s} & -\frac{\partial y}{\partial e}\frac{\partial e}{\partial p} & -1 \\ -\lambda_1 \frac{\partial^2 y}{\partial e \partial r}\frac{\partial e}{\partial p}\frac{\partial r}{\partial s} & \frac{\partial^2 G}{\partial r \partial r}\frac{\partial^2 r}{\partial s \partial s}\frac{\partial r}{\partial s} & & \\ -\lambda_1 \frac{\partial^2 y}{\partial r \partial r}\frac{\partial^2 r}{\partial s \partial s}\frac{\partial r}{\partial s} & -\frac{\partial y}{\partial r}\frac{\partial r}{\partial s} & -1 & \\ -\frac{\partial y}{\partial e}\frac{\partial e}{\partial p} & -\frac{\partial y}{\partial r}\frac{\partial r}{\partial s} & 0 & 0 \\ -1 & -1 & 0 & 0 \end{vmatrix}$$

Similarly, we can assume that emissions decrease linearly in number of electric vehicles (e(p)).

Putting these graphs together, we can infer that emissions are a decreasing concave function of electric vehicle subsidy.

A.3 Production under uncertainty

Consider the case of uncertainty in weather. If we consider $\bar{w}$ the number of hot weather days, based on the government's expectation $E(y|\bar{w})$, we can treat s as the the risk premium paid by the government to diversify from a risky (y) to a sure asset (r).

Recall, the government's objective is to minimise emissions. $min_{p,s} \;\; V(p) + G(r(s,c)) + O \;\; s.t. \;\; \int_0^{\bar{w}} y(e(p), r(s,c), w)\, dw \leq \bar{y}; \;\;\; B \geq s + p$

From the government's perspective, $\frac{\partial y}{\partial e} > 0$ but $\frac{\partial y}{\partial r} < 0$ so in order to keep $E(y) < \bar{y}$ a risk averse government should invest in EVs and small solar.

A.4 Deterministic model of emission reduction

While the conclusion of this model is deterministic, I have included it here for the sake of completeness. We see here that if we assume subsidy increases electric vehicles on the road and that electric vehicles decrease emissions, we can see that electric vehicle subsidies have a substitution effect on emissions for electricity generation.

This is a stage 0 version of the model presented in this paper.

$$L \;=\; min_p \;\; V(p) \;+\; G(r(c)) \;+O \;+\; \lambda(\bar{y} - \int_0^{\bar{w}} y(e(p), r(c), w)\, dw)$$
$$\frac{\partial L}{\partial p} = \frac{\partial V}{\partial p} - \lambda \frac{\partial y}{\partial e}\frac{\partial e}{\partial p} \geq 0$$

This model is straightforward and tells us that increasing the subsidy on vehicles will lead to an increase in the demand for electricity.

A.5 Signing the Lagrange multipliers λ_1 and λ_2

Using the first order conditions, we can determine the value of λ_1 and substitute this to find the value of λ_2

$$\lambda_1 = \frac{\frac{\partial G}{\partial r}\frac{\partial r}{\partial s} - \frac{\partial V}{\partial p}}{\int_0^{\bar{w}} (\frac{\partial y}{\partial r}\frac{\partial r}{\partial s} - \frac{\partial y}{\partial e}\frac{\partial e}{\partial p}) dw} = \frac{(-)}{(-)} > 0 \tag{8}$$
$$\lambda_2 = \frac{\partial G}{\partial r}\frac{\partial r}{\partial s} - \frac{\frac{\partial G}{\partial r}\frac{\partial r}{\partial s} - \frac{\partial V}{\partial p}}{\int_0^{\bar{w}} (\frac{\partial y}{\partial r}\frac{\partial r}{\partial s} - \frac{\partial y}{\partial e}\frac{\partial e}{\partial p}) dw} \int_0^{\bar{w}} (\frac{\partial y}{\partial r}\frac{\partial r}{\partial s}) dw = \frac{(-)}{(-)} > 0 \tag{9}$$

B Appendix 2: Tables

Table 7: Regressing Mean no2 on Generation

	(1) Mean no2	(2) Mean no2
Total Generation in MU	-0.000 (0.000)	
Log(Total Generation)		-5.089 (4.194)
Constant	31.624*** (6.711)	82.285* (47.040)
Observations	123	123

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Regressing Mean pm10 on Generation

	(1) Mean pm10	(2) Mean pm10
Total Generation in MU	-0.000	
	(0.000)	
Log(Total Generation)		-18.134*
		(10.949)
Constant	129.436***	314.970**
	(20.725)	(123.213)
Observations	123	123

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Regressing Mean pm25 on Generation

	(1) Mean pm25	(2) Mean pm25
Total Generation in MU	-0.000**	
	(0.000)	
Log(Total Generation)		-16.081***
		(4.060)
Constant	72.712***	231.596***
	(9.468)	(43.101)
Observations	79	79

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Regressing Mean no2 on Treatment

	(1) Mean no2
treatment	0.000
	(.)
Constant	26.930***
	(3.072)
Observations	123

Standard errors in parentheses

Data: websuse nlswork

Second line note

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Regressing Mean pm10 on Treatment

	(1)
	Mean pm10
treatment	0.000
	(.)
Constant	117.810***
	(11.350)
Observations	123

Standard errors in parentheses
Data: websuse nlswork
Second line note
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Regressing Mean pm25 on Treatment

	(1)
	Mean pm25
treatment	0.000
	(.)
Constant	55.855***
	(6.008)
Observations	79

Standard errors in parentheses
Data: websuse nlswork
Second line note
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Regressing Mean no2 on Capacity

	(1)	(2)
	Mean no2	Mean no2
Total Capacity in MU	-0.000	
	(0.000)	
Log(Total Capacity)		-4.092
		(3.889)
Constant	31.977***	65.921*
	(5.638)	(38.601)
Observations	123	123

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Regressing Mean pm10 on Capacity

	(1) Mean pm10	(2) Mean pm10
Total Capacity in MU	-0.001**	
	(0.000)	
Log(Total Capacity)		-18.732**
		(8.833)
Constant	136.656***	296.206***
	(17.203)	(88.624)
Observations	123	123

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Regressing Mean pm25 on Capacity

	(1) Mean pm25	(2) Mean pm25
Total Capacity in MU	-0.001*	
	(0.000)	
Log(Total Capacity)		-16.645***
		(4.567)
Constant	71.528***	214.638***
	(10.209)	(43.391)
Observations	79	79

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Regressing Mean so2 on Capacity

	(1) Mean so2	(2) Mean so2
Total Capacity in MU	0.000**	
	(0.000)	
Log(Total Capacity)		2.838***
		(1.012)
Constant	7.951***	-15.777
	(1.943)	(10.015)
Observations	123	123

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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