Complementarities and Optimal Targeting of Technology Subsidies*

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Abstract

Policies often implicitly ignore potential interactions between related products. This is particularly true in the case of clean, energy-efficient technologies. We develop a theory of second-best policy for interacting clean technologies where first-best Pigouvian taxation of dirty substitutes is infeasible. Optimal second-best policy involves subsidies that are a function of cross-technology substitution patterns. Ignoring these interactions is welfare-reducing due to infra-marginal take-up of the subsidies and the optimal policy accounts for this by targeting the more price-responsive clean technology. We find evidence of complementarities between solar photovoltaics and plug-in electric vehicles in California, suggesting that policymakers should consider these interactions when setting policy in this context.

Keywords: Clean Technology Policy, Complementary Goods, Optimal Taxation
JEL Codes: H23, Q48, Q58

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Increasing the adoption of clean, energy-efficient technologies is a key step in decarbonizing industrial economies. Subsidies are a common policy tool for supporting growth in clean technologies: according to data collected by the World Bank, the number of government subsidy programs aimed at reducing emissions and promoting clean technologies increased 10% from 2018-2022 (World Bank Group, 2024). Despite policymakers' revealed preference for direct public support for various clean technologies, relatively little work examines possible interactions between these policies. For example, when clean technologies are complementary goods, subsidizing the adoption of one technology increases demand for its complement. As public interest in clean technology adoption increases, the policy debate will prompt questions around the efficacy of these interacting policies.

This paper explores the implications of interactions between technologies for optimal policy design, with a particular focus on new, clean technologies. We focus on potential interactions between policies targeting residential adoption of plug-in electric vehicles (PEV) and distributed solar photovoltaics (PV). We begin by developing a theory of second-best policy for two clean technologies that replace dirty technologies with distinct externalities when first-best Pigouvian taxes are infeasible. We demonstrate that the optimal second-best policy regime is a set of clean technology subsidies which depend on cross-technology substitution patterns. Ignoring these interactions is welfare-reducing due to inframarginal take-up of the clean technology subsidies and the optimal policy regime targets the more price-responsive clean technology. We use a combination of revealed and stated preference data from a representative survey of California households to document a strong complementarity between solar PV and PEVs: a 10% increase in the price of each technology results in a 1-2% decrease in demand for the other clean technology for the most price responsive households.

Economic theory has long held that separate market failures require separate policy instruments. This result, referred to as the "Tinbergen rule" (Tinbergen, 1952), implies that policymakers should adopt a unique policy instrument for each externality-generating technology. However, this result ignores potential interactions between technologies. For example, complementarities are known to influence demand and welfare across many classes of technology (Crawford and Yurukoglu, 2012; Gentzkow, 2007; Samuelson, 1974). In such settings, implementing independent policy instruments aimed at increasing the adoption of complementary technologies ignores potential impacts of each policy instrument on the complementary good. We aim to explore whether the concept of instrument independence holds in the presence of potential spillover effects across different technology market failures.

Solar PV and PEVs are both key technologies to mitigating climate change due to their ability to displace conventional, carbon-intensive forms of electricity generation and transportation. We focus our analysis on these technologies for two reasons. First, these technologies have long been the target of generous public subsidy programs. In the US, state and local governments and electrical utilities provided over $40 billion in upfront subsidies for solar PV adoption from 2000 to 2020 (Barbose et al., 2024). According to the US Department of Energy, over 575 state and federal zero emissions vehicle (ZEV) incentive programs were enacted or renewed over that same period. Policymakers' emphasis on subsidies likely reflects political constraints on the use of first-best policy instruments such as a carbon tax.

Second, there are several channels through which these clean technologies may complement one another. First, there is a technological channel through which solar adoption provides households with relatively low marginal cost electricity for PEV charging, thereby making PEV adoption more attractive. Second, there is a policy channel where solar PV adopting households in many jurisdictions—such as California—are able to reduce their marginal costs for electricity through a program known as net energy metering (NEM). For households with an PEV, this can make PV adoption more appealing as it can help reduce PEV charging costs. In either case, we are likely to observe an increase in adoption of one technology due to a decrease in the price of the other, which is the standard definition of complements: a negative compensated cross-price elasticity of demand (Samuelson, 1974). Finally, it is possible that there are correlations between household demand for each technology and unobservable or observable consumer attributes, such as income or idiosyncratic preferences for clean goods.

We build on the extensive public finance literature on optimal taxation to explore the implications of these potential complementarities for optimal, second-best policymaking (Sandmo, 1975; Wijkander, 1985). We develop a stylized model of demand for household electricity and transportation consumption that allows for the derivation of optimal unconstrained (i.e., first-best) and constrained (i.e., second-best) policy instruments. In the model, a representative household allocates consumption between clean and dirty substitutes for electricity and transportation as well as a numeraire. Each of the two dirty goods produces a differentiated externality, with the externality proportional to the aggregate consumption of that good. A social planner chooses a portfolio of per-unit taxes or subsidies and recycles tax revenues via equal lump-sum transfers. With no constraints on the values of these policy instruments, the model recovers a foundational result: the optimal policy portfolio is to set direct Pigouvian taxes on the externality-producing goods. This first-best policy follows the Tinbergen rule, where the Pigouvian taxes are set independent of one another.

Assuming that direct Pigouvian taxation is infeasible—say, due to political constraints—the model delivers three results. First, the optimal constrained policy is a set of indirect Pigouvian subsidies which account for cross-technology interactions. Thus, the second-best policy no longer treats the two externality problems as independent. Second assuming that the the two clean technologies are complements, the second-best subsidy will be less than the subsidy set ignoring this interaction when the complementarity is sufficiently strong. This comes from the fact that a strong complementarity implies a greater degree of infra-marginal take-up of the subsidies. Finally, the second-best policy regime places a larger subsidy on the clean technology with the greater behavioral response, inclusive of both the resulting direct substitution and indirect impact through the technology complementarity.

A key implication of our stylized model is the importance of considering the full substitution matrix when setting second-best policies for interacting clean technologies. We develop and estimate a simple static discrete choice model of households' co-adoption decisions for solar PV and PEVs in an empirical context. We focus our empirical analysis on the case of California, which has relatively high adoption rates for both technologies and a long history of state-level adoption incentives for various clean technologies.

We develop a flexible model of demand for complementary goods based on Gentzkow (2007) and use data from the 2013 and 2017 waves of the California Vehicle Survey to recover reasonable estimates of empirical substitution patterns between solar PV and PEVs. We find evidence of an empirical complementarity between solar PV and PEVs. We estimate that a 10% increase in solar PV prices leads to a 5.2% decrease in solar PV consumption and a 0.3% decrease in PEV consumption on average. A similar 10% increase in PEV prices leads to a 4.3% decrease in PEV consumption and a 0.5% in PV consumption on average. Interestingly, these average elasticities mask substantial heterogeneity, with low income households—the most price responsive households—reducing consumption by 1-2% in response to a change in the price of the other clean technology.

We contribute to the broad literature on product complementarities, which dates back to early work by Hicks and Allen (1934). More recent empirical work documents demand for bundles of complementary goods in various settings including retail (Dubé, 2004; Hendel, 1999; Iaria and Wang, 2020; Kwak et al., 2015; Lee et al., 2013), automobiles (Manski and Sherman, 1980), telecommunications, (Crawford and Yurukoglu, 2012; Crawford et al., 2018; Grzybowski and Verboven, 2016; Liu et al., 2010), media subscriptions (Gentzkow, 2007; Nevo et al., 2005), gaming (Lee, 2013), and technology adoption (Augereau et al., 2006; Kretschmer et al., 2012). Bollinger et al. (2023) document a strong complementarity between solar PV and residential battery storage. We build on this literature by drawing out the implications of these empirical complementarities for policymaking and welfare in the presence of externalities.

Our work emphasizes the importance of understanding potential cross-technology interactions in the design of subsidy policies. A large and growing literature studies the economics of solar PV policies, focusing primarily on the impact of subsidies on adoption rates, finding that while consumer subsidies have increased the adoption of solar PV, these policies are not justified by the static environmental benefits of adoption alone (Borenstein, 2017; De Groote and Verboven, 2019; Gillingham and Tsvetanov, 2019). Existing work explores the effect of various policy and non-policy incentives on PEV adoption (Muehlegger and Rapson, 2022, 2023; Rapson and Muehlegger, 2023). Our work emphasizes the importance of considering the effects of co-adoption when designing and evaluating clean technology subsidies.

The remainder of the paper is organized as follows. Section 1 provides background information on solar PV and PEV policies in the US. Section 2 develops the stylized model of optimal policy for interacting technologies, including our main theoretical contributions. Section 3 develops and estimates a model of co-adoption for solar and PEVs in California and Section 4 concludes.

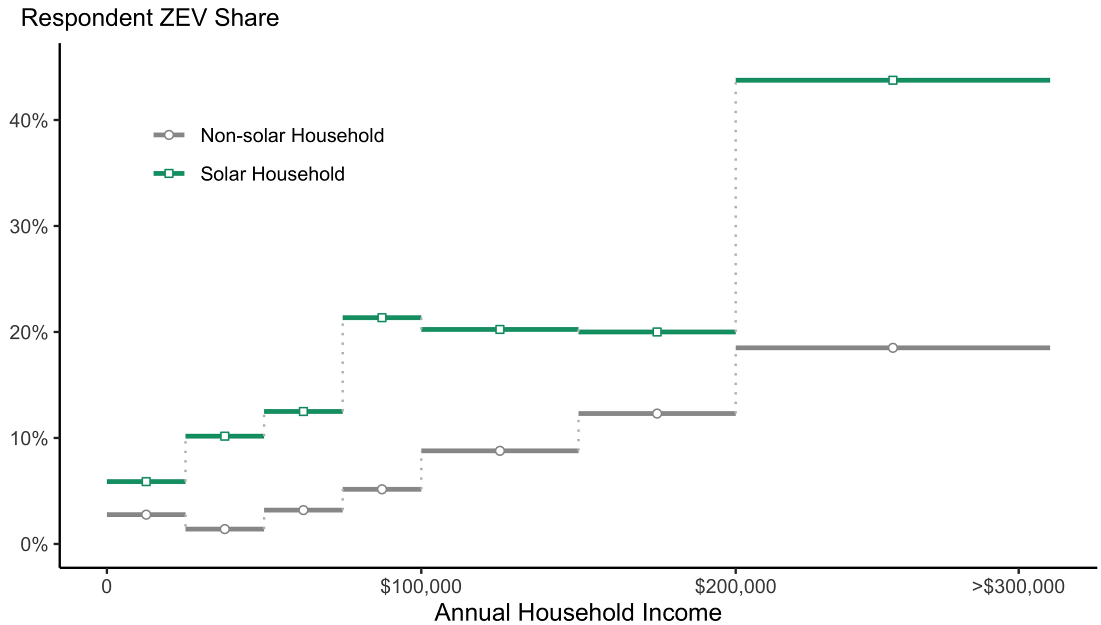
1 Background: Overlapping Incentives for Solar and EVs

The solar and electric vehicle industries have grown rapidly in recent decades. From 2000 to 2022, global solar capacity increased from just under 1 gigawatt to over 1 terrawatt, a 1000-fold increase (IRENA, 2023). PEVs have experienced similar growth, accounting for nearly 20% of global new car sales in 2023, a 10-fold increase from 2018 (International Energy Agency, 2024). These trends of rapid adoption are in large part due to substantial reductions in the costs of these technologies: the price of solar modules—the building blocks of solar PV systems—declined over 99% from 1975 to 2021 (IRENA, 2023; Nemet, 2019) and the price of lithium-ion batteries—a major component to PEVs—decreased 97% from 1991 to 2018 (Ziegler and Trancik, 2021).

Generous public subsidies are another major factor driving increased adoption of these technologies. Consumer subsidies for PEV adoption totaled $43 billion globally in 2022 (International Energy Agency, 2024). Estimates of public support for solar PV are similarly high: in 2017, global public support for solar PV totaled $61 billion (Taylor, 2020). The location of generous public subsidies for each technology also often overlaps. For example, the Inflation Reduction Act of 2022 offers individuals a 30% non-refundable federal tax credit on the cost of an installed solar PV system as well as subsidies of up to $7,500 per PEV for eligible purchases. There is also similar overlap at the state level within the US: as shown in Appendix Figure C1, there is a strong positive relationship between the amount of funding for solar PV adoption and the number of zero-emissions vehicle (ZEV)—which includes PEVs—policies enacted over the period 2000-2020.

Public incentives for clean technologies take numerous forms. Solar PV and plug-in

Figure 1. Co-adoption of ZEVs and Solar PV in California, 2017



Notes: This figure shows the share of respondents in the 2017 California Vehicle Survey that own a zero emissions vehicle (ZEV) within 7 different annual household income bins, separately for households with and without solar installed. Source: 2015-2017 California Vehicle Survey, California Energy Commission.

electric vehicles are both capital-intensive goods, so many public policies aim to reduce the upfront costs of these investments. As demonstrated by the Inflation Reduction Act, these can take the form of either a tax credit offsetting some portion of the investment cost or an upfront cash rebate. Other policies target the value of the technology over time. In the case of solar PV, this includes NEM, feed-in tariffs, and net-billing tariffs, all of which determine some form of compensation for any excess electricity sent from a distributed solar PV system to the grid. Similar policies also exist for electric vehicles, though are less common in practice. These include the introduction of time-of-use pricing for home electricity consumption or PEV-specific retail electricity rates which aim to compensate households for charging vehicles during off peak hours by lowering their marginal charging costs relative to some counterfactual baseline.

The increasing prevalence and coincidence of solar PV and PEV subsidies raises questions around possible interactions between these incentives. There is a natural technical channel through which these two clean technologies may complement one another: solar adoption provides households with relatively low marginal cost electricity for PEV charging, making PEV adoption attractive. Co-adoption may also be made more attractive by policy itself. In jurisdictions where individuals can lower their electricity costs through NEM, feed-in tariffs, or net-billing costs, PEV adoption may become more appealing for PV-owning households and vice versa.

Existing surveys from California, a jurisdiction with substantial adoption as well as public financial support for both technologies, provides suggestive evidence of a complementarity between solar PV and PEVs. The California Center for Sustainable Energy's PEV owner survey indicates that 39% of PEV owners have installed solar PV and a further 17% are planning to adopt solar in the near future. Data from the 2017 wave of the California Energy Commission's California Vehicle Survey finds similar patterns of co-adoption: as shown in Figure 1, solar PV households are nearly four times as likely to own a PEV. Given that these technologies have substantial upfront investment costs, it is possible that this co-adoption is simply a function of income; however, as shown in Figure 1, this relationship holds throughout the income distribution.

In light of this suggestive evidence of complementary demand for these technologies and the substantial overlap in existing, generous public subsidy programs, we seek to better understand the theoretical implications for subsidy design.

2 A Model of Optimal Policy for Interacting Technologies

We develop a stylized model of demand for household electricity and transportation consumption that allows for the derivation of optimal unconstrained (i.e., first-best) and constrained (i.e., second best) policy instruments. While both dirty electricity and transportation generate external climate costs, there are additional, idiosyncratic externalities associated with household electricity and transportation consumption. To account for this, we model households' consumption of each dirty technology as resulting in different externalities.

2.1 Model setup

Consider a model with N identical households where a representative household consumes five goods: clean electricity (x_1), dirty electricity (x_2), clean transportation (y_1), dirty transportation (y_2), and a numeraire (μ). The five goods have prices $\boldsymbol{p} = (p_1^x, p_2^x, p_1^y, p_2^y, 1)$ and the electricity and transportation goods are taxed (or subsidized) at rates $\boldsymbol{\tau} = (\tau_1^x, \tau_2^x, \tau_1^y, \tau_2^y)$. Each of the two dirty goods produces a differentiated externality, with each externality proportional to the aggregate consumption of that good:[1]

$$E_x = e_x N x_2 \qquad\qquad E_y = e_y N y_2$$

The representative household maximizes a utility function which is separable in externalities and linear in μ. The utility function takes the following form

$$U = u(x_1, x_2, y_1, y_2) - N[e_x x_2 + e_y y_2] + \mu \tag{1}$$

where $u(\cdot)$ is a concave, C^2 (i.e., twice continuously differentiable) function. Households maximize their utility subject to the following budget constraint:

$$(p_1^x + \tau_1^x)x_1 + (p_2^x + \tau_2^x)x_2 + (p_1^y + \tau_1^y)y_1 + (p_2^y + \tau_2^y)y_2 + \mu = m \tag{2}$$

where m is the household's total income. We assume that the non-negativity constraint $\mu \geq 0$ is nonbinding. Furthermore, we assume that N is sufficiently large such that households do not internalize their impact on aggregate consumption of the dirty goods (i.e., $\frac{\partial E_x}{\partial x_2} = 0$). With these assumptions, it is possible to write the first-order conditions for the representative household as follows:

$$\begin{aligned} x_1\left(\frac{\partial u}{\partial x_1} - p_1^x - \tau_1^x\right) &= 0 \qquad & x_2\left(\frac{\partial u}{\partial x_2} - p_2^x - \tau_2^x\right) &= 0 \\ y_1\left(\frac{\partial u}{\partial y_1} - p_1^y - \tau_1^y\right) &= 0 \qquad & y_2\left(\frac{\partial u}{\partial y_2} - p_2^y - \tau_2^y\right) &= 0 \end{aligned} \tag{3}$$

The first-order conditions given by (3) imply demand functions that are independent of both income and the total externalities:

$$x_1 = x_1(\boldsymbol{p}, \boldsymbol{\tau}) \qquad x_2 = x_2(\boldsymbol{p}, \boldsymbol{\tau}) \qquad y_1 = y_1(\boldsymbol{p}, \boldsymbol{\tau}) \qquad y_2 = y_2(\boldsymbol{p}, \boldsymbol{\tau})$$

The absence of income effects implies that Hicksian demand functions are equal to Marshallian demand functions. The model setup implies the following assumption:

Assumption 1. *Clean electricity (x_1) is a substitute for dirty electricity (x_2) and clean*

[1] The choice of differentiated externalities is motivated by the empirical differences between transportation and residential electricity consumption externalities. In addition to varying intensities of greenhouse gas emissions associated with consumption of transportation and electricity, each has distinct co-pollutants and spillover costs unique to the technology class. Recent work also documents substantial spatial and temporal heterogeneity in the external costs of dirty versus clean home electricity or transportation consumption (Gillingham et al., 2024; Sexton et al., 2021).

transportation (y_1) is a substitute for dirty transportation (y_2), i.e.

$$\frac{\partial x_1}{\partial p_2^x} > 0 \qquad \frac{\partial x_2}{\partial p_1^x} > 0 \qquad \frac{\partial y_1}{\partial p_2^y} > 0 \qquad \frac{\partial y_2}{\partial p_1^y} > 0$$

2.2 Social Planner's Problem

The government chooses a portfolio of per-unit taxes or subsidies, $\boldsymbol{\tau} = (\tau_1^x, \tau_2^x, \tau_1^y, \tau_2^y) \in \mathbb{R}^4$. For a given portfolio of policies, the government receives tax revenues

$$N[x_1\tau_1^x + x_2\tau_2^x + y_1\tau_1^y + y_2\tau_2^y]$$

For simplicity, we assume tax revenues are recycled via equal lump-sum transfers.

The government's problem is to maximize social welfare, which in this case is equivalent to maximizing the representative household's utility. The government therefore chooses $\boldsymbol{\tau}$ to maximize the sum of household utility from consuming electricity and transportation; the disutility from electricity and transportation consumption externalities; income net of household expenditures; and lump-sum transfers of tax revenues:

$$\begin{aligned} W(\boldsymbol{\tau}) = u(x_1, x_2, y_1, y_2) &- N[e_x x_2 + e_y y_2] + m \\ &- (p_1^x + \tau_1^x)x_1 - (p_2^x + \tau_2^x)x_2 - (p_1^y + \tau_1^y)y_1 \\ &- (p_2^y + \tau_2^y)y_2 + \tau_1^x x_1 + \tau_2^x x_2 + \tau_1^y y_1 + \tau_2^y y_2 \end{aligned} \tag{4}$$

subject to the first-order conditions (3). Differentiating (4) and using the household's first-order conditions (3) gives the following first-order conditions for the government's problem:

$$\underbrace{\begin{bmatrix} \frac{\partial x_1}{\partial p_1^x} & \frac{\partial x_2}{\partial p_1^x} & \frac{\partial y_1}{\partial p_1^x} & \frac{\partial y_2}{\partial p_1^x} \\ \frac{\partial x_1}{\partial p_2^x} & \frac{\partial x_2}{\partial p_2^x} & \frac{\partial y_1}{\partial p_2^x} & \frac{\partial y_2}{\partial p_2^x} \\ \frac{\partial x_1}{\partial p_1^y} & \frac{\partial x_2}{\partial p_1^y} & \frac{\partial y_1}{\partial p_1^y} & \frac{\partial y_2}{\partial p_1^y} \\ \frac{\partial x_1}{\partial p_2^y} & \frac{\partial x_2}{\partial p_2^y} & \frac{\partial y_1}{\partial p_2^y} & \frac{\partial y_2}{\partial p_2^y} \end{bmatrix}}_{\equiv \Omega} \begin{bmatrix} \tau_1^x \\ \tau_2^x \\ \tau_1^y \\ \tau_2^y \end{bmatrix} = e_x N \begin{bmatrix} \frac{\partial x_2}{\partial p_1^x} \\ \frac{\partial x_2}{\partial p_2^x} \\ \frac{\partial x_2}{\partial p_1^y} \\ \frac{\partial x_2}{\partial p_2^y} \end{bmatrix} + e_y N \begin{bmatrix} \frac{\partial y_2}{\partial p_1^x} \\ \frac{\partial y_2}{\partial p_2^x} \\ \frac{\partial y_2}{\partial p_1^y} \\ \frac{\partial y_2}{\partial p_2^y} \end{bmatrix} \tag{5}$$

Where we make the standard neoclassical assumption of full tax salience, e.g., $\frac{\partial x_1}{\partial \tau_1^x} = \frac{\partial x_1}{\partial p_1^x}$. Assuming that the substitution matrix, Ω, is non-singular, then we can solve the linear system (5) to find the optimal policy portfolio, $\boldsymbol{\tau}^*$.

2.3 Optimal Unconstrained Policy: Direct Pigouvian Taxation

If there are no constraints on the values of $\boldsymbol{\tau}$, then solving the linear system (5) gives the following portfolio of optimal policies:

$$\tau_1^{x*} = 0 \qquad \tau_2^{x*} = e_x N \qquad \tau_1^{y*} = 0 \qquad \tau_2^{y*} = e_y N \tag{6}$$

With unconstrained policies, we obtain the intuitive result where only direct Pigouvian taxes on the externality-producing goods are necessary. The level of the tax is the marginal external cost of consumption for each of the two dirty technologies, x_2 and y_2. The optimal policy (6) therefore replicates two well-known results: that separate externality market failures require separate policy responses and the optimal policy to correct an externality is to impose a tax equal to the marginal social cost of consuming the externality producing good.

2.4 Optimal Constrained Policy: Indirect Pigouvian Subsidies

We now turn to the case where direct taxation of the externality-producing goods is infeasible, i.e., $\tau_2^x = \tau_2^y = 0$. Such a situation might arise for many reasons, including political constraints on the application of a direct tax. In this case, the government can only regulate the two externalities indirectly through the remaining two goods. The dimensionality of the government's problem is reduced so that they now solve the following linear system

$$\underbrace{\begin{bmatrix} \frac{\partial x_1}{\partial p_1^x} & \frac{\partial y_1}{\partial p_1^x} \\ \frac{\partial x_1}{\partial p_1^y} & \frac{\partial y_1}{\partial p_1^y} \end{bmatrix}}_{\equiv \tilde{\Omega}} \begin{bmatrix} \tau_1^x \\ \tau_1^y \end{bmatrix} = e_x N \begin{bmatrix} \frac{\partial x_2}{\partial p_1^x} \\ \frac{\partial x_2}{\partial p_1^y} \end{bmatrix} + e_y N \begin{bmatrix} \frac{\partial y_2}{\partial p_1^x} \\ \frac{\partial y_2}{\partial p_1^y} \end{bmatrix} \tag{7}$$

We use the linear system (7) to define two distinct policy-setting regimes. The first is a scenario in which the government sets policy ignoring all interactions between the electricity and transportation goods. In this case, the government's problem becomes

$$\begin{bmatrix} \frac{\partial x_1}{\partial p_1^x} & 0 \\ 0 & \frac{\partial y_1}{\partial p_1^y} \end{bmatrix} \begin{bmatrix} \tau_1^x \\ \tau_1^y \end{bmatrix} = e_x N \begin{bmatrix} \frac{\partial x_2}{\partial p_1^x} \\ 0 \end{bmatrix} + e_y N \begin{bmatrix} 0 \\ \frac{\partial y_2}{\partial p_1^y} \end{bmatrix}$$

Ignoring the potential interactions between the two sets of goods (henceforth, the "naive" constrained policy), the government sets the following policies:

$$\tilde{\tau}_1^x = e_x N \left(\frac{\partial x_2}{\partial p_1^x}\right)\left(\frac{\partial x_1}{\partial p_1^x}\right)^{-1} \qquad \tilde{\tau}_1^y = e_y N \left(\frac{\partial y_2}{\partial p_1^y}\right)\left(\frac{\partial y_1}{\partial p_1^y}\right)^{-1} \tag{8}$$

Ignoring the potential for interactions between the two sets of goods and if direct taxation of the externality-producing goods is infeasible, the government sets taxes or subsidies equal to the product of the marginal externality and the degree of complementarity or substitutability between the clean and dirty goods separately for electricity and for transportation. From Assumption 1 and the fact that $\frac{\partial x_1}{\partial p_1^x}, \frac{\partial y_1}{\partial p_1^y} < 0$, we know that (8) gives $\tilde{\tau}_1^x < 0$ and $\tilde{\tau}_1^y < 0$. Thus, since the clean goods are substitutes for the dirty goods, the government indirectly targets the externality-producing goods by subsidizing the clean goods.

We now turn to the case where the government considers potential interactions between the two sets of goods. Solving the system (7) gives the following optimal policies when direct Pigouvian taxation is infeasible:

$$\begin{aligned} \bar{\tau}_1^x &= \frac{e_x N}{|\tilde{\Omega}|}\left(\frac{\partial x_2}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y} - \frac{\partial x_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right) + \frac{e_y N}{|\tilde{\Omega}|}\left(\frac{\partial y_2}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y} - \frac{\partial y_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right) \\ \bar{\tau}_1^y &= \frac{e_x N}{|\tilde{\Omega}|}\left(\frac{\partial x_2}{\partial p_1^y}\frac{\partial x_1}{\partial p_1^x} - \frac{\partial x_2}{\partial p_1^x}\frac{\partial x_1}{\partial p_1^y}\right) + \frac{e_y N}{|\tilde{\Omega}|}\left(\frac{\partial y_2}{\partial p_1^y}\frac{\partial x_1}{\partial p_1^x} - \frac{\partial y_2}{\partial p_1^x}\frac{\partial x_1}{\partial p_1^y}\right) \end{aligned} \tag{9}$$

where $|\tilde{\Omega}|$ is the determinant of the substitution matrix, $\tilde{\Omega}$. While the form of the optimal policies given by (9) does not offer an immediate, intuitive interpretation, it does reveal a key conceptual difference from the optimal policies defined by (6) and (8): when the government takes potential interactions into consideration, the optimal corrective policies no longer treat the two externality problems as independent.

2.5 With Strong Complementarity, Optimal Constrained Policy is Less than Naive Subsidy

Comparing (8) and (9) allows us to determine the impact of ignoring potential interactions between the two sets of goods. If such interactions exist and the government ignores them, the policies given by (8) are sub-optimal. With two additional assumptions, we are able to determine precisely in which way (8) are sub-optimal. In particular, we make the following assumption to simplify the exposition that follows:

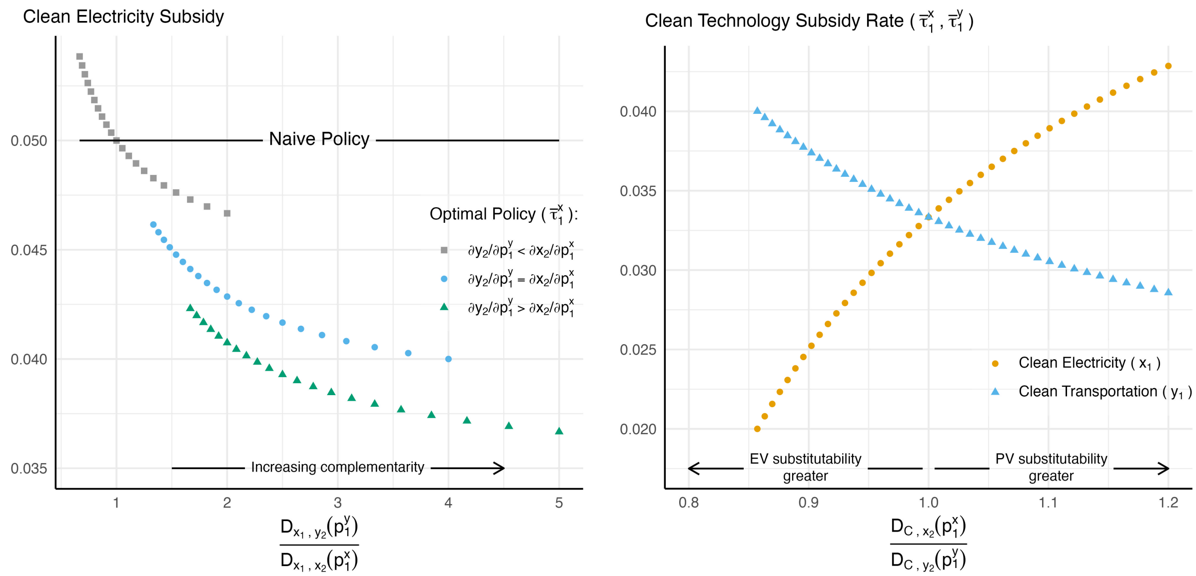
Assumption 2. *Demand for the externality-producing, dirty goods is independent of the price of the clean alternative in the other technology, i.e.,*

$$\frac{\partial x_2}{\partial p_1^y} = \frac{\partial y_2}{\partial p_1^x} = 0$$

That dirty transportation is neither a gross complement nor a substitute for clean electricity implies that the only impact of the clean technology in, say, electricity on the quantity

Figure 2. Simulated Portfolios of Constrained Policies

(a) Optimal versus Naive Constrained Policy **(b)** Optimal Constrained Policies



Assumed Parameter Values

		Figure 2a	Figure 2b
Marginal externalities	e_x, e_y	0.1	0.1
Number of households	N	1.0	1.0
Own-price derivatives	$\frac{\partial x_1}{\partial p_1^x}, \frac{\partial x_2}{\partial p_2^x}, \frac{\partial y_1}{\partial p_1^y}, \frac{\partial y_2}{\partial p_2^y}$	-2.0	-2.0
Clean-dirty cross-price derivatives	$\frac{\partial x_1}{\partial p_2^x}, \frac{\partial y_1}{\partial p_2^y}$	1.0	1.0
	$\frac{\partial y_2}{\partial p_1^y}$	Varies	1.0
	$\frac{\partial x_2}{\partial p_1^x}$	1.0	Varies
Clean-clean cross-price derivatives	$\frac{\partial x_1}{\partial p_1^y}, \frac{\partial y_1}{\partial p_1^x}$	Varies	Varies

Notes: Figure 2a compares the naive and optimal constrained subsidy policies on clean electricity (x_1) given by (8) and (9), respectively, for different values of the diversion ratios defined in (10). In particular, this figure alters the degree of indirect substitution between clean electricity and dirty transportation (y_2) holding fixed all other components of the substitution matrix, Ω, i.e., the diversion ratio: $\mathcal{D}_{x_1,y_2}(p_1^y) = -\frac{\partial y_2}{\partial p_1^y} \Big/ \frac{\partial x_1}{\partial p_1^y}$. The horizontal axis normalizes different values of $\mathcal{D}_{x_1,y_2}(p_1^y)$ by $\mathcal{D}_{x_1,x_2}(p_1^x)$, the latter of which is held fixed. Figure 2b shows the optimal constrained policies given by (9) for different values of the diversion ratios defined in (12). In particular, this figure alters the degree of substitution—both direct and indirect—between the clean technologies (x_1 and y_1) and dirty electricity (x_2) holding fixed all other components of the substitution matrix, Ω, i.e., the diversion ratio: $\mathcal{D}_{C,x_2}(p_1^x) = -\frac{\partial x_2}{\partial p_1^x} \Big/ \left(\frac{\partial x_1}{\partial p_1^x} + \frac{\partial y_1}{\partial p_1^x}\right)$. The horizontal axis normalizes different values of $\mathcal{D}_{C,x_2}(p_1^x)$ by $\mathcal{D}_{C,y_2}(p_1^y)$.

of dirty transportation consumed operates through the substitutability or complementarity of clean electricity and clean transportation. While this assumption is perhaps restrictive in practice, it likely provides a reasonable approximation to first-order. We make one additional assumption before comparing (8) and (9):

Assumption 3. *The two clean technologies are complements, i.e.,*

$$\frac{\partial x_1}{\partial p_1^x} < \frac{\partial x_1}{\partial p_1^y} < 0 \qquad\qquad \frac{\partial y_1}{\partial p_1^y} < \frac{\partial y_1}{\partial p_1^x} < 0$$

where the assumed concavity of preferences implies that own-price demand responses are greater than the cross-price demand responses for the clean technologies.

We now turn to a comparison of the two policy regimes, (8) and (9). We start with comparing the policies for clean electricity, $\tilde{\tau}_1^x$ and $\bar{\tau}_1^x$. Combining Assumptions 1, 2, and 3 gives the following result: accounting for complementarities between clean technologies will result in a lower (i.e., less negative) subsidy rate for clean electricity when:

$$e_x \mathcal{D}_{x_1,x_2}(p_1^x) < e_y \mathcal{D}_{x_1,y_2}(p_1^y) \tag{10}$$

where $\mathcal{D}_{x_1,x_2}(p_1^x) = -\frac{\partial x_2}{\partial p_1^x} \Big/ \frac{\partial x_1}{\partial p_1^x}$ is a diversion ratio that measures the fraction of individuals shifting from x_1 to x_2 as p_1^x changes and $\mathcal{D}_{x_1,y_2}(p_1^y) = -\frac{\partial y_2}{\partial p_1^y} \Big/ \frac{\partial x_1}{\partial p_1^y}$ is a diversion ratio that measures the fraction of individuals that both shift from x_1 and into y_2 as p_1^y changes. See Appendix A.1 for the derivation of (10).

An analogous condition holds for clean transportation. Accounting for complementarities between clean technologies will result in a lower (i.e., less negative) subsidy rate for clean transportation when:

$$e_y \mathcal{D}_{y_1,y_2}(p_1^y) < e_x \mathcal{D}_{y_1,x_2}(p_1^x) \tag{11}$$

where $\mathcal{D}_{y_1,y_2}(p_1^y) = -\frac{\partial y_2}{\partial p_1^y} \Big/ \frac{\partial y_1}{\partial p_1^y}$ is a diversion ratio that measures the fraction of individuals shifting from y_1 to y_2 as p_1^y changes and $\mathcal{D}_{y_1,x_2}(p_1^x) = -\frac{\partial x_2}{\partial p_1^x} \Big/ \frac{\partial y_1}{\partial p_1^x}$ is a diversion ratio that measures the fraction of individuals that both shift from y_1 and into x_2 as p_1^y changes. See Appendix A.1 for the derivation of (11).

The results given by (10) and (11) imply that accounting for complementarities will result in a lower subsidy rate for a given clean good relative to the naive constrained policy when the direct marginal damages from a change in the price of that clean good are less than the indirect marginal damages from a change in the price of the other clean good due to the complementarity. That is, if fewer people switch from the clean to the dirty good in one technology category due to a change in the price of the clean good than those that switch from the clean good in one technology and into the dirty good in the other technology due to a change in the price of the other clean good, then the optimal constrained policy results in a lower subsidy rate relative to the naive constrained policy.

Put differently, the comparative statics of (10) and (11) indicate that the the optimal constrained policy in a given technology will only be larger than the naive policy that ignores cross-technology complementarities when there is particularly strong substitution between the clean and dirty good in that technology. Focusing on the case of clean electricity subsidies, since $\left|\frac{\partial x_1}{\partial p_1^x}\right| > \left|\frac{\partial x_1}{\partial p_1^y}\right|$, we know that (10) holds for any $\frac{\partial y_2}{\partial p_1^y} \geq \frac{\partial x_2}{\partial p_1^x}$. Indeed, the degree of substitution between clean and dirty electricity would have to be meaningfully larger than that between clean and dirty transportation—holding fixed the marginal externalities—for (10) not to hold and for the optimal constrained policy in clean electricity to be larger than the naive policy. This is evident in the simulated policy regimes in Figure 2a.

More broadly, the results (10) and (11) indicate that the precise way in which (8) are sub-optimal depends on the full substitution matrix and the implications of the technology complementarity for both environmental externalities.

2.6 Optimal Constrained Policies Emphasize Technology with Largest Demand Response

Combining assumptions 1, 2, and 3, we directly compare the optimal constrained policies for the two clean technologies given by (9). In particular, the optimal constrained policy will be a larger (i.e., more negative) subsidy rate on clean transportation relative to clean electricity, $\bar{\tau}_1^x > \bar{\tau}_1^y$ if the following condition holds:

$$e_x \mathcal{D}_{C,x_2}(p_1^x) < e_y \mathcal{D}_{C,y_2}(p_1^y) \tag{12}$$

where $\mathcal{D}_{C,x_2}(p_1^x) = -\frac{\partial x_2}{\partial p_1^x} \Big/ \left(\frac{\partial x_1}{\partial p_1^x} + \frac{\partial y_1}{\partial p_1^x}\right)$ is a diversion ratio that measures the fraction of individuals shifting from clean technologies—either x_1, y_1, or both—and into x_2 as p_1^x changes. Similarly $\mathcal{D}_{C,y_2}(p_1^y) = -\frac{\partial y_2}{\partial p_1^y} \Big/ \left(\frac{\partial x_1}{\partial p_1^y} + \frac{\partial y_1}{\partial p_1^y}\right)$ is a diversion ratio that measures the fraction of individuals shifting from clean technologies—either x_1, y_1, or both—and into y_2 as p_1^y changes. It follows that if (12) does not hold, then $\bar{\tau}_1^x < \bar{\tau}_1^y$. See Appendix A.2 for the derivation of (12).

Thus, when the policymaker takes interactions into consideration, they will place a larger subsidy on the clean technology with the larger behavioral response, inclusive of both the resulting direct substitution away from that clean technology's dirty substitute and the indirect impact on the other technology class due to the complementarity between the two clean technologies. In other words, it is optimal for the policymaker to place a greater emphasis on the technology with the greatest marginal benefit, i.e., the technology that induces a greater behavioral response of households switching from both clean technologies and into the dirty technology for a change in price of that dirty technology's clean substitute. Importantly, the relative sizes of the optimal constrained policies depends on the behavioral response from a price change in one clean technology in demand for *both* clean technologies. This is shown for simulated optimal constrained policy portfolios in Figure 2b.

3 Estimates of Substitution between Clean Technologies

The model in Section 2 highlights the importance of considering the full substitution matrix when setting the second-best policy portfolio in the context of interacting technologies. In this section, we develop and estimate a simple static discrete choice model of households' co-adoption decisions for solar PV and electric vehicles to determine the empirical substitution patterns between these two technologies and, as a result, the likely welfare losses from ignoring these interactions.

3.1 Data on Co-adoption Decisions

Most administrative datasets on clean technology adoption decisions do not include information on co-adoption of different technology types. While it is possible to combine structural assumptions and publicly-available data on unconditional adoption of different technologies to infer substitution patterns across technology types, we leverage a unique dataset that includes information on household-level demand for both solar photovoltaics (PVs) and plug-in electric vehicles (PEVs). In particular, we use data on respondents' solar adoption along with vehicle discrete choice experiments contained in the 2013 and 2017 waves of the California Energy Commission's (CEC) California Vehicle Survey to recover reasonable estimates of empirical substitution patterns between solar PV and PEVs.

The CEC runs the California Vehicle Survey periodically to understand changes in light-duty vehicle (LDV) choices within the state. Though early iterations of the survey existed almost three decades ago, the CEC completed previous waves of the survey in its current form in 2013, 2017, and 2019, each of which included revealed and stated preference surveys for both the residential and commercial LDV sectors in California. Respondent households were recruited for each wave of the survey using a combination of address-based sampling and online address-based sampling through a market research panel. Samples were stratified across major regions of the state.[2] The surveys solicited detailed household demographic data, including household income and information on whether a respondent household has

[2]For example, in the 2017 iteration of the survey, samples were stratified by the following six regions: San Francisco, Sacramento, Central Valley, Los Angeles, San Diego, and the rest of the state.

installed residential solar. The revealed preference component of the survey elicited respondents' preferences for different vehicles and vehicle attributes by asking a series of questions about their current vehicle and their next vehicle decision.

Each wave of the California Vehicle Survey also included a stated preference experiment in which respondents were presented with a series of eight choice occasions, each of which involved choosing a preferred option between four different vehicles with randomly varying attributes. This discrete choice experiment included a rich set of observable attributes which varied randomly across each vehicle, including price; available rebates or other non-pecuniary incentives; fuel type (e.g., plug-in hybrid electric vehicle or gasoline internal combustion engine); vehicle type (e.g., compact car, SUV, or pickup truck); and other physical and performance attributes for each alternative. While the 2013 and 2017 waves of the California Vehicle Survey asked respondents to make contemporaneous selections in the experiment, the 2019 wave asked respondents to evaluate the hypothetical alternatives as if they were selecting their next vehicle in 3-5 years.

We combine the discrete choice experiments from the 2013 and 2017 California Vehicle Survey waves with information on respondent demographics and solar adoption to understand the relationship between household preferences for different vehicles and solar PV. Since the 2019 wave introduces a choice experiment about a hypothetical future vehicle purchase, we view this as inconsistent with the design of the 2013 and 2017 waves and therefore omit the 2019 data from our empirical analysis. While the stated preference data for vehicle demand provide empirically-plausible, random variation in prices and vehicle attributes, the California Vehicle Survey data contains little information on respondents' solar PV systems. As a result, we combine these survey data with additional data on county-level average prices, consumer rebates, and product attributes for residential solar PV systems from the Lawrence Berkeley National Laboratory's Tracking the Sun Database. We do so using respondents' reported county of residence and assuming that households adopt solar in the year prior to the California Vehicle Survey's implementation, a flawed but necessary assumption given the lack of information on the timing of solar adoption in the survey data. We bring in additional data from the World Bank Group's Global Solar Atlas to capture cross-sectional variation in production potential for residential solar across California.

While there are a number of limitations to relying on these stated preference data, including the fact that choices were not incentivized and respondents were unable to opt out of selecting a vehicle alternative, we view them as reasonable approximations to consumer demand in this context. In particular, the statewide sampling approach, the ability to observe multiple choices per respondent, and the rich variation in vehicle attributes and pricing—which avoids standard identification challenges with revealed preference data in this context—combined with the availability of information about solar PV adoption make these data uniquely suited to recover empirical estimates of consumers' preferences for bundles of these technologies. The final discrete choice dataset includes 8 experimental vehicle choices from 6,754 unique respondents, approximately 12.5% of whom have installed solar PV.

3.2 Demand for Bundles of Technologies

We adopt the framework of Gentzkow (2007), which allows for potential complementarity between goods in a standard discrete choice model of demand by modeling household demand for bundles of different products. In particular, we index households by $i \in \{1, ..., N\}$, goods by $j = \{1, ..., J\}$, and the possible bundles of goods by $b \in \{1, ..., 2^J\}$. Household i's indirect utility from consuming bundle b at time t is therefore:

$$u_{ibt} = \sum_{j \in b} \bar{u}_{ijt} + \Gamma_b + \varepsilon_{ibt} \tag{13}$$

where $\bar{u}_{ijt}$ is the contribution of product $j \in b$ to household indirect utility from consuming bundle b; Γ_b is the difference between the base utility of bundle b and the sum of the individual contributions of constituent products, j; and ε_{ibt} is an idiosyncratic shock to preferences for each bundle.

The bundle-specific term, Γ_b, by construction captures the utility from the interaction between the constituent products that define each bundle. We assume that this interaction term is zero for singleton bundles, i.e.,

$$\Gamma_b = \begin{cases} 0 & \text{if } |b| = 1 \\ \Gamma_b & \text{otherwise} \end{cases} \tag{14}$$

Note that the construction of (14) makes no assumption on the sign of the interaction term Γ_b for non-singleton bundles. This term, which measures the extent to which the utility of consuming a good $j \in b$ changes when consumed with $b \setminus \{j\}$, can be positive, zero-valued, or negative. Intuitively, $\Gamma_b < 0$ implies that individuals experience disutility from interaction of products within a bundle. Similarly, $\Gamma_b > 0$ implies a positive preference for the interaction of products within a bundle. Gentzkow (2007) validates this logic by proving the value of Γ_b is a sufficient statistic for substitution patterns between goods in b: $\Gamma_b < 0$ implies substitutability, $\Gamma_b > 0$ implies complementarity, and $\Gamma_b = 0$ implies independence. Determining the sign of the interaction term Γ_b is therefore a key objective of this empirical exercise.

We parameterize each product's contribution to indirect utility as

$$\bar{u}_{ijt} = \alpha_i(p_{jt} - r_{jt}) + \theta' X_{ijt} + \xi_j \tag{15}$$

where p_{jt} is the price of product j at time t; r_{jt} is the rebate received on product j at time t; X_{ijt} is a vector of observable attributes that (possibly) varies over respondents, products, and time; and ξ_j is a measure of product j's time-invariant, unobservable quality.

We assume that the idiosyncratic preference shock, ε_{ibt}, is an independently and identically distributed random variable that follows a type-I extreme value distribution, which allows for closed-form, model-implied choice probabilities across technology bundles which we can take to the data in estimation. We parameterize heterogeneity in respondents' price sensitivity as follows: $\alpha_i = \alpha/y_i$, where y_i is observed consumer income. The probability that individual i consumes bundle b on choice occasion t is therefore given by:

$$p_{ibt}(\alpha, \theta, \Gamma_b) = Pr(b \in \arg\max_{c \in \mathcal{C}} u_{ict}) = \frac{\exp(u_{ibt}(\alpha, \theta, \Gamma_b))}{\sum_{c \in \mathcal{C}} \exp(u_{ict}(\alpha, \theta, \Gamma_b))} \tag{16}$$

where $\mathcal{C} = \{1, ..., 2^J\}$ is the choice set of possible bundles. Estimation then proceeds via maximum likelihood, with the log likelihood defined as

$$\mathcal{L}(\alpha, \theta, \Gamma_b) = \sum_i \sum_b \sum_t y_{ibt} \log(p_{ibt}(\alpha, \theta, \Gamma_b))$$

where y_{ibt} is an indicator that equals 1 if individual i selects bundle b on choice occasion t and zero otherwise.

3.3 Estimation and Identification

Taking the discrete choice model defined by (13), (14), and (15) to the California Vehicle Survey data requires defining the choice set. Respondents select one of eight alternatives, which vary across the eight choice occasions that we observe for each respondent: the four vehicle alternatives from the stated preference experiment, each of which can be consumed with and without solar PV. Given this definition of the choice set, we define a single Γ_b term, which is possibly non-zero for alternative bundles containing solar PV and a PEV and is constrained to zero for all other singleton and non-singleton bundles. Since the four vehicle alternatives vary across all choice occasions, it is important to note that there are no repeat choice sets either within or across individuals. As a result, we are unable to estimate alternative-specific constants—the time-invariant measure of unobservable quality, ξ_j, in (15) above. This might be a concern for identification of the remaining model parameters if, for

Table 1. Demand Estimates

	Estimate (SE)		Estimate (SE)
Common Parameters		***Vehicle Attributes***	
(Price – Subsidy) / Income	−1.904 (0.033)	Acceleration Rate	−0.060 (0.002)
Complementarity Term (Γ)	0.771 (0.030)	Fueling Time	−0.139 (0.004)
		Fuel Cost/Mile	−0.047 (0.015)
Solar PV Attributes		Miles/Gallon	0.391 (0.018)
$\mathbb{1}$\{Solar PV\}	−6.374 (0.404)	Range	0.533 (0.012)
Solar Radiation	0.058 (0.018)	Trunk Space	0.198 (0.013)
Module Efficiency	0.205 (0.012)	Vehicle Age	−0.037 (0.004)
		$\mathbb{1}$\{Small Car\}	−0.157 (0.015)
Income Interactions		$\mathbb{1}$\{SUV\}	−0.039 (0.022)
Income × $\mathbb{1}$\{PEV\}	0.028 (0.002)	$\mathbb{1}$\{Truck\}	−0.692 (0.024)
Income × $\mathbb{1}$\{Solar PV\}	0.015 (0.002)	$\mathbb{1}$\{Van\}	−1.280 (0.036)
		$\mathbb{1}$\{PEV\}	−0.213 (0.032)
		$\mathbb{1}$\{Hybrid\}	0.130 (0.014)
Log Likelihood		−85 665.49	
Individuals		6754	
Choices		54 032	

Notes: This table reports parameter estimates from the discrete choice model of demand for bundles of technologies estimated using microdata from the 2013 and 2017 waves of the California Vehicle Survey. Prices, income, and other monetary terms are converted to 2017 USD and are normalized by $10,000 for parameter readability. Parameters are estimated via maximum likelihood estimation. Asymptotic standard errors are reported in parentheses.

example, we think the unobservable ξ_j is correlated with prices as is common in revealed preference demand data.

Fortunately, the nature of the choice experiment and empirical solar PV data aids in identification of the remaining target model parameters, $\begin{bmatrix}\alpha & \theta' & \Gamma_b\end{bmatrix}$. In particular, the price coefficient, α, is identified from the random variation in prices and rebates in the vehicle discrete choice experiment as well as the plausibly exogenous variation in available rebates for solar PV adoption across California counties. Solar adoption rebates vary both over space and time in California and is analogous to a shift in solar firms' supply curve holding demand fixed assuming the standard statutory-incidence irrelevance result. This variation is used elsewhere in the literature estimating solar installation demand Gillingham and Tsvetanov (2019); Pless and van Benthem (2019). Identification of the parameters θ follows again from the random variation in observable vehicle attributes in the choice experiment.

Identification of the interaction term, Γ_b, is non-trivial, but is possible with reasonable exclusion restrictions. In particular, with the inclusion of observable product attributes, $\begin{bmatrix}p_{jt} & r_{jt} & X'_{ijt}\end{bmatrix}$, which only shift the utility of adoption for one good $j \in b$ implicitly functions as an exclusion restriction which aids in identification of the interaction term Γ_b. Since these product-specific attributes only enter $\bar{u}_{ijt}$ in (13), we can separately identify Γ_b using observed realizations of these product-specific attributes and choices for all bundles: for any two realizations of a non-trivial attribute for a specific good $j \in b$, observed variation in demand for goods $k \in b \setminus \{j\}$ will pin down the value of consuming k and j together in bundle b, i.e., Γ_b. Our data provides such variation along many dimensions. For example, the amount of solar irradiance a respondent's home county receives plausibly only affects their utility of solar adoption, so any change in PEV adoption that we observe at different realizations of solar irradiance can be attributed to interaction between consuming solar PV and PEVs together. A similar argument holds for the random vehicle attributes in the discrete choice experiment, such as a vehicle's acceleration rate or trunk space.

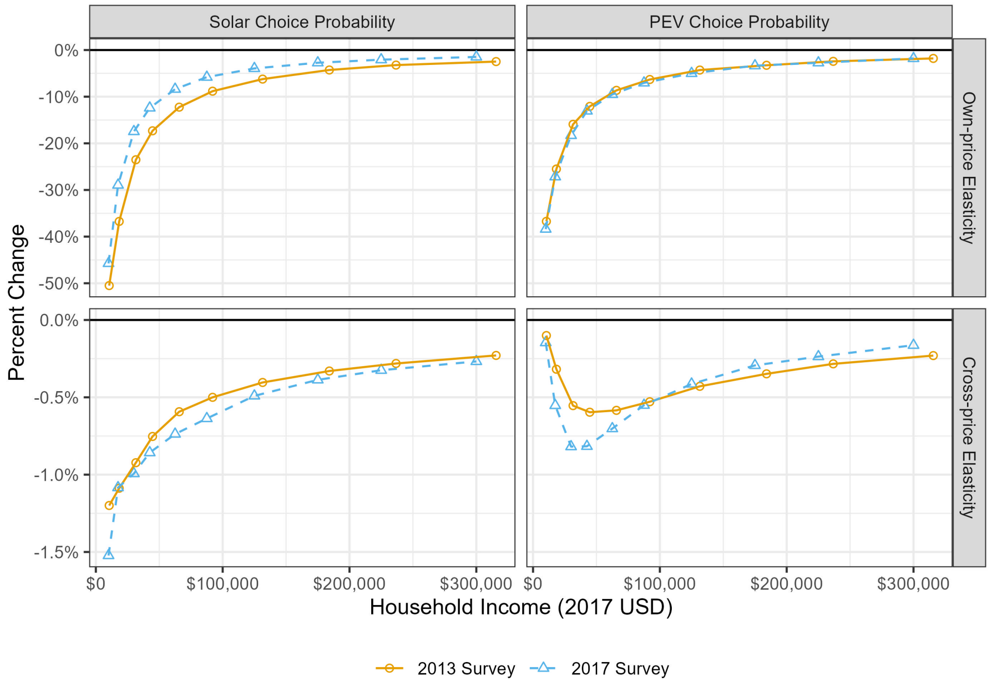
3.4 Results

We present parameter estimates and standard errors for the empirical co-adoption model in Table 1. In general, all parameter estimates are precisely estimated and have the expected sign. The price coefficient, α, is large, precisely estimated, and negative as expected. Importantly, the interaction term, Γ, is positive and large-in-magnitude. This term, which measures the utility that respondents experience from consuming solar PV and PEVs together, is a sufficient statistic for the substitution patterns between these technologies. In this case, the positive value of Γ implies that solar PV and PEVs are complementary technologies.

The remaining parameters on solar PV and vehicle attributes all have the expected sign. Interestingly, respondents appear to experience considerable disutility from consuming solar beyond the expense of the technology, though this is in part offset by higher demand for solar among high income households. Unsurprisingly, respondents' demand for solar appears higher in areas that receive greater solar irradiance, in-line with existing literature, and when higher efficiency solar modules are marketed. On the vehicle attribute side, consumers similarly appear to dislike PEVs, with a strong, positive correlation between PEV utility and income. Consumers generally prefer more efficient, faster, and newer vehicle models.

While the positive value of Γ is sufficient to conclude that solar PV and PEVs are complements, the magnitudes of specific price responses may be of independent interest, particularly given that the comparative statics in Section 2 depend on these values. We therefore calculate own- and cross-price elasticities from separate 10% increases in the prices of all solar PVs and PEVs in our choice dataset. On average, a 10% increase in solar PV prices across the board leads to a 5.2% decrease in solar PV consumption and a 0.3% decrease in PEV consumption. A similar 10% increase in all PEV prices leads to a 4.3% decrease in PEV consumption and a 0.5% decrease in solar PV consumption on average. Interestingly,

Figure 3. Relative Change in Demand from a 10% Increase in Solar or PEV Prices



Notes: This figure plots the average relative change in solar photovoltaic (PV) and plug-in electric vehicle (PEV) demand for a 10% change in solar PV and PEV prices as a function of reported household income. Each panel increases the prices of a single clean technology by 10% across all choice occasions facing that technology, holding all other prices fixed. The left panels plot the relative change in the probability a household chooses a bundle containing solar when solar PV prices increase (upper left) and when PEV prices increase (lower left). The right panels plot the relative change in the probability a household chooses a bundle containing PEV when PEV prices increase (upper right) and when solar PV prices increase (lower right). Note the differences in the vertical axis scales between the own-price elasticities in the upper panels and the cross-price elasticities in the lower panels.

this masks substantial heterogeneity by respondent income as shown in Figure 3

3.5 Policy Counterfactuals

We explore the implications of the results reported in Table 1 by calculating changes in social surplus from different subsidy levels and policy-setting regimes. Given the lack of a supply model, we focus on changes in consumer surplus, environmental damages, and government subsidy expenditures from a baseline scenario with no clean technology subsidies. Consumer surplus calculations follow the standard closed-form logit inclusive value formula. Moreover, we use existing estimates of the marginal environmental benefit of adoption solar PV and PEVs as well as a series of assumptions to calculate (avoided) environmental damages associated with different subsidy regimes. Additional information on this calculation is available in Appendix B.

Figure 4 reports results from two distinct subsidy-setting counterfactual exercises. In Figure 4a, we replicate the "naive" policy-setting regime that implicitly ignores cross-technology complementarities: we hold the subsidy-level in one technology fixed and look at changes in social surplus from different subsidy levels in the other technology, ignoring any surplus gains from the fixed, non-zero subsidy. This exercise empirically validates the result from Section 2.5: ignoring the complementarity results in setting a higher-than-optimal subsidy, unless the subsidy in the other technology is sufficiently high.

Figure 4b empirically validates the result from Section 2.6: the optimal second-best subsidy portfolio places a greater emphasis on the technology with the largest behavioral response, which as shown in Figure 3 is solar PV in the context of the California Vehicle Survey. Moreover, we compare the model-implied optimal subsidy portfolio with the observed ranges of available upfront subsidies for each technology in California during the two waves of the California Vehicle Survey that we use in our empirical exercise.[3] Taking the midpoints of both ranges of observed solar PV and PEV subsidies, we find a loss of approximately 20% the maximum available social surplus, suggesting large potential welfare gains from setting subsidy policies in conjunction with one another in practice.

It is important to note that these counterfactual simulations are only illustrative: there are several welfare-relevant margins for which we do not account (for example, producer surplus) and there are important limitations to relying on these survey data as we discuss above. Moreover, our calculation of the ranges of different subsidy levels observed in practice rely on a series of assumptions and ignore important subsidy categories such as net energy metering on the solar side. Nonetheless, we view these counterfactual results as demonstrating a key point: that the theoretical results of Section 2 likely have empirical relevance in practice.

4 Discussion and Conclusion

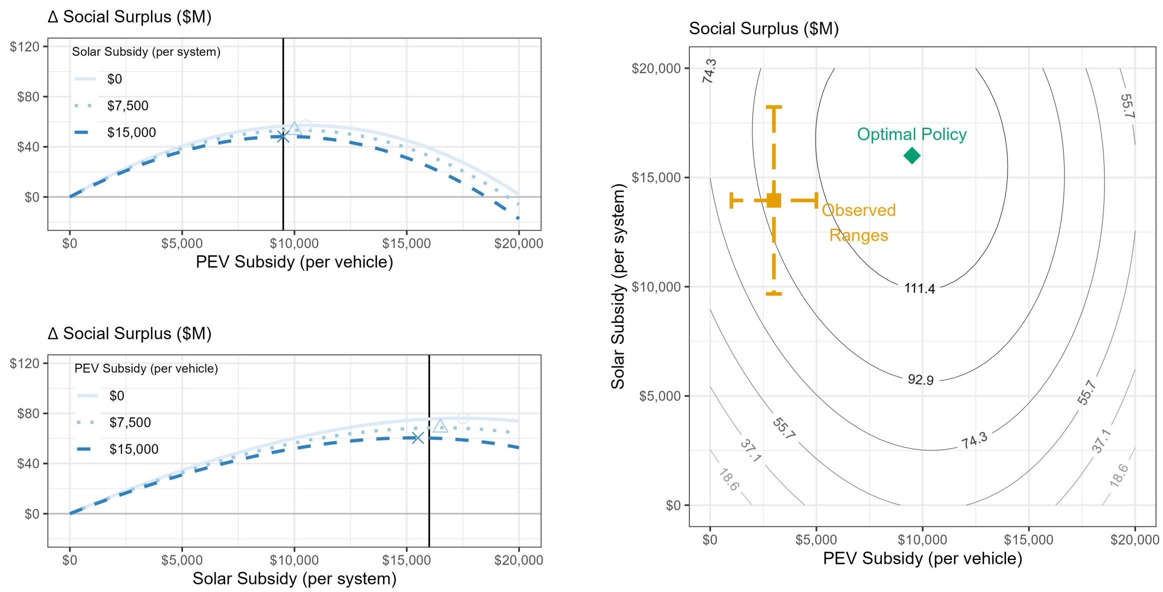
We explore the implications of interactions between different technologies for the design of policies aimed at increasing demand for these goods. We focus on potential interactions between policies targeting residential adoption of solar PV and PEVs, two clean technologies which have several conceptual channels for complementary demand. We develop a theory of optimal constrained policies when first-best Pigouvian taxation of negative externality-

[3]In particular, for solar PV we assume a system size of 5 kW and use maximum available state-level rebates available through the California Solar Initiative, prices in the main estimation data, and the 30% federal Investment Tax Credit to calculate minimum and maximum available solar subsidies per system for 2013 and 2017. Note that this does not include and flow benefits from net energy metering policies. For PEVs, we report the maximum and minimum available rebates from the California Clean Vehicle Rebate Program (CVRP) for battery electric and plug-in hybrid vehicles for 2013 and 2017.

Figure 4. Changes in Social Surplus Relative to No Subsidy Baseline

(a) Subsidies Set Independently

(b) Subsidies Set Together



Notes: This figure plots the change in social surplus from different subsidy levels and policy-setting regimes based on the model estimates reported in Table 1. Changes in social surplus are calculated as the sum of changes in consumer surplus (ΔC) and changes in environmental externalities due to clean technology adoption (ΔE), less the impact on government subsidy expenditures (ΔG). We calculate ΔC following the standard McFadden inclusive value formula and ΔG assumes a marginal cost of public funds of 1.0. See Appendix B for more details on our calculation of ΔE. Changes in social surplus are relative to a no subsidy baseline. Figure 4a reports changes in social surplus from adjusting a single subsidy. Figure 4a represents the naive subsidy-setting regime by ignoring any surplus changes relative to the baseline of no subsidies that come from the other technology. Figure 4b shows the change in social surplus relative to a baseline of no subsidies for different combinations of solar and PEV subsidies. The "Observed Ranges" correspond to the maximum available upfront subsidies for each technology in California during 2013 and 2017 (see text for further discussion).

producing substitutes for these two technologies are infeasible. We demonstrate that the optimal second-best policy regime is a set of clean technology subsidies which depend on cross-technology substitution patterns. Ignoring these interactions can lead policymakers to set subsidies inefficiently high and to forgo potential welfare gains from optimally allocating subsidies towards the more influential market. We demonstrate the relevance of these theoretical findings by developing and estimating a model of PV and PEV co-adoption in California, finding evidence of a strong complementarity. These findings suggest that policymakers should consider potential spillover effects in related markets when creating policies to increase the adoption of clean goods.

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Online Appendix for "Complementarities and Optimal Targeting of Technology Subsidies"

Jacob T. Bradt and Frank Pinter[1]

The following appendices are **for online publication only**:

—Appendix Section A: Stylized Model Derivations

—Appendix Section B: Calculating Changes in Environmental Damages

—Appendix Section C: Supplemental Figures and Tables

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A Stylized Model Derivations

A.1 Comparing Naive and Optimal Constrained Subsidies

Combining Assumptions 1, 2, and 3, we can show the condition under which accounting for interactions results in a lower (i.e., less negative) subsidy rate on electricity:

$$
\begin{aligned}
\tilde{\tau}_1^x &< \bar{\tau}_1^x \\
e_x N \left(\frac{\partial x_2}{\partial p_1^x}\right)\left(\frac{\partial x_1}{\partial p_1^x}\right)^{-1} &< \frac{e_x N}{|\tilde{\Omega}|}\left(\frac{\partial x_2}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y}\right) + \frac{e_y N}{|\tilde{\Omega}|}\left(-\frac{\partial y_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right) && \text{(by (8), (9), Assumption 2)} \\
\left(\frac{\partial x_1}{\partial p_1^x}\right)^{-1} &< \frac{1}{|\tilde{\Omega}|}\left(\frac{\partial y_1}{\partial p_1^y}\right) + \frac{e_y}{e_x|\tilde{\Omega}|}\left(\frac{\partial x_2}{\partial p_1^x}\right)^{-1}\left(-\frac{\partial y_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right) && \text{(by Assumption 1)} \\
1 &> \frac{1}{|\tilde{\Omega}|}\left(\frac{\partial x_1}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y}\right) - \frac{e_y}{e_x|\tilde{\Omega}|}\left(\frac{\partial x_1}{\partial p_1^x}\frac{\partial y_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right)\left(\frac{\partial x_2}{\partial p_1^x}\right)^{-1} && \text{(by concavity of pref.)} \\
\frac{\partial x_1}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y} - \frac{\partial y_1}{\partial p_1^x}\frac{\partial x_1}{\partial p_1^y} &> \frac{\partial x_1}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y} - \frac{e_y}{e_x}\left(\frac{\partial x_1}{\partial p_1^x}\frac{\partial y_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right)\left(\frac{\partial x_2}{\partial p_1^x}\right)^{-1} && \text{(by definition of } |\tilde{\Omega}|\text{)} \\
-\frac{\partial y_1}{\partial p_1^x}\frac{\partial x_1}{\partial p_1^y} &> -\frac{e_y}{e_x}\left(\frac{\partial x_1}{\partial p_1^x}\frac{\partial y_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right)\left(\frac{\partial x_2}{\partial p_1^x}\right)^{-1} \\
\frac{\partial x_1}{\partial p_1^y} &> \frac{e_y}{e_x}\left(\frac{\partial x_1}{\partial p_1^x}\frac{\partial y_2}{\partial p_1^y}\right)\left(\frac{\partial x_2}{\partial p_1^x}\right)^{-1} && \text{(by Assumption 3)} \\
\frac{\partial x_1}{\partial p_1^y}\left(\frac{\partial x_1}{\partial p_1^x}\right)^{-1} &< \frac{e_y}{e_x}\left(\frac{\partial y_2}{\partial p_1^y}\right)\left(\frac{\partial x_2}{\partial p_1^x}\right)^{-1} && \text{(by concavity of pref.)} \\
e_x\left(\frac{\partial x_2}{\partial p_1^x}\right)\left(\frac{\partial x_1}{\partial p_1^x}\right)^{-1} &> e_y\left(\frac{\partial y_2}{\partial p_1^y}\right)\left(\frac{\partial x_1}{\partial p_1^y}\right)^{-1} && \text{(by Assumptions 1, 3)} \\
e_x\underbrace{\left(-\frac{\partial x_2}{\partial p_1^x}\right)\left(\frac{\partial x_1}{\partial p_1^x}\right)^{-1}}_{\equiv \mathcal{D}_{x_1,x_2}(p_1^x)} &< e_y\underbrace{\left(-\frac{\partial y_2}{\partial p_1^y}\right)\left(\frac{\partial x_1}{\partial p_1^y}\right)^{-1}}_{\equiv \mathcal{D}_{x_1,y_2}(p_1^y)}
\end{aligned}
$$

which is the condition given by (10). We can show that an analogous condition holds for household transportation. Combining Assumptions 1, 2, and 3, we can show the condition under which accounting for interactions results in a higher (i.e., more negative) subsidy rate on transportation:

$$
\begin{aligned}
\tilde{\tau}_1^y &< \bar{\tau}_1^y \\
e_y N \left(\frac{\partial y_2}{\partial p_1^y} \right) \left(\frac{\partial y_1}{\partial p_1^y} \right)^{-1} &< \frac{e_x N}{|\tilde{\Omega}|} \left(- \frac{\partial x_2}{\partial p_1^x} \frac{\partial x_1}{\partial p_1^y} \right) + \frac{e_y N}{|\tilde{\Omega}|} \left(\frac{\partial y_2}{\partial p_1^y} \frac{\partial x_1}{\partial p_1^x} \right) && \text{(by (8), (9), Assumption 2)} \\
\left(\frac{\partial y_1}{\partial p_1^y} \right)^{-1} &< \frac{1}{|\tilde{\Omega}|} \left(\frac{\partial x_1}{\partial p_1^x} \right) + \frac{e_x}{e_y |\tilde{\Omega}|} \left(\frac{\partial y_2}{\partial p_1^y} \right)^{-1} \left(- \frac{\partial x_2}{\partial p_1^x} \frac{\partial x_1}{\partial p_1^y} \right) && \text{(by Assumption 1)} \\
1 &> \frac{1}{|\tilde{\Omega}|} \left(\frac{\partial x_1}{\partial p_1^x} \frac{\partial y_1}{\partial p_1^y} \right) - \frac{e_x}{e_y |\tilde{\Omega}|} \left(\frac{\partial y_1}{\partial p_1^y} \frac{\partial x_2}{\partial p_1^x} \frac{\partial x_1}{\partial p_1^y} \right) \left(\frac{\partial y_2}{\partial p_1^y} \right)^{-1} && \text{(by concavity of pref.)} \\
\frac{\partial x_1}{\partial p_1^x} \frac{\partial y_1}{\partial p_1^y} - \frac{\partial y_1}{\partial p_1^x} \frac{\partial x_1}{\partial p_1^y} &< \frac{\partial x_1}{\partial p_1^x} \frac{\partial y_1}{\partial p_1^y} - \frac{e_x}{e_y} \left(\frac{\partial y_1}{\partial p_1^y} \frac{\partial x_2}{\partial p_1^x} \frac{\partial x_1}{\partial p_1^y} \right) \left(\frac{\partial y_2}{\partial p_1^y} \right)^{-1} && \text{(by definition of } |\tilde{\Omega}|\text{)} \\
- \frac{\partial y_1}{\partial p_1^x} \frac{\partial x_1}{\partial p_1^y} &> - \frac{e_x}{e_y} \left(\frac{\partial y_1}{\partial p_1^y} \frac{\partial x_2}{\partial p_1^x} \frac{\partial x_1}{\partial p_1^y} \right) \left(\frac{\partial y_2}{\partial p_1^y} \right)^{-1} \\
\frac{\partial y_1}{\partial p_1^x} &> \frac{e_x}{e_y} \left(\frac{\partial y_1}{\partial p_1^y} \frac{\partial x_2}{\partial p_1^x} \right) \left(\frac{\partial y_2}{\partial p_1^y} \right)^{-1} && \text{(by Assumption 3)} \\
\frac{\partial y_1}{\partial p_1^x} \left(\frac{\partial y_1}{\partial p_1^y} \right)^{-1} &< \frac{e_x}{e_y} \left(\frac{\partial x_2}{\partial p_1^x} \right) \left(\frac{\partial y_2}{\partial p_1^y} \right)^{-1} && \text{(by concavity of pref.)} \\
e_y \left(\frac{\partial y_2}{\partial p_1^y} \right) \left(\frac{\partial y_1}{\partial p_1^y} \right)^{-1} &> e_x \left(\frac{\partial x_2}{\partial p_1^x} \right) \left(\frac{\partial y_1}{\partial p_1^x} \right)^{-1} && \text{(by Assumptions 1, 3)} \\
e_y \underbrace{\left(- \frac{\partial y_2}{\partial p_1^y} \right) \left(\frac{\partial y_1}{\partial p_1^y} \right)^{-1}}_{\equiv \mathcal{D}_{y_1, y_2}(p_1^y)} &< e_x \underbrace{\left(- \frac{\partial x_2}{\partial p_1^x} \right) \left(\frac{\partial y_1}{\partial p_1^x} \right)^{-1}}_{\equiv \mathcal{D}_{y_1, x_2}(p_1^x)}
\end{aligned}
$$

which is the condition given by (11).

A.2 Comparing Optimal Constrained Subsidies across Technologies

Combining assumptions 1, 2, and 3, we can show the condition under which the optimal subsidy on one clean technology exceeds the other under the first-best policy constraint. For example, the optimal constrained policy portfolio will be a larger (i.e., more negative) subsidy rate on clean transportation relative to clean electricity if:

$$
\begin{aligned}
\bar{\tau}_1^x &> \bar{\tau}_1^y \\
\frac{e_x N}{|\tilde{\Omega}|}\left(\frac{\partial x_2}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y}\right) + \frac{e_y N}{|\tilde{\Omega}|}\left(-\frac{\partial y_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right) &> \frac{e_x N}{|\tilde{\Omega}|}\left(-\frac{\partial x_2}{\partial p_1^x}\frac{\partial x_1}{\partial p_1^y}\right) + \frac{e_y N}{|\tilde{\Omega}|}\left(\frac{\partial y_2}{\partial p_1^y}\frac{\partial x_1}{\partial p_1^x}\right) \\
e_x\left(\frac{\partial x_2}{\partial p_1^x}\right)\left(\frac{\partial y_1}{\partial p_1^y}+\frac{\partial x_1}{\partial p_1^y}\right) &> e_y\left(\frac{\partial y_2}{\partial p_1^y}\right)\left(\frac{\partial x_1}{\partial p_1^x}+\frac{\partial y_1}{\partial p_1^x}\right) \\
e_x\left(\frac{\partial x_2}{\partial p_1^x}\right)\left(\frac{\partial x_1}{\partial p_1^x}+\frac{\partial y_1}{\partial p_1^x}\right)^{-1} &> e_y\left(\frac{\partial y_2}{\partial p_1^y}\right)\left(\frac{\partial y_1}{\partial p_1^y}+\frac{\partial x_1}{\partial p_1^y}\right)^{-1} \\
e_x\underbrace{\left(-\frac{\partial x_2}{\partial p_1^x}\right)\left(\frac{\partial x_1}{\partial p_1^x}+\frac{\partial y_1}{\partial p_1^x}\right)^{-1}}_{\equiv \mathcal{D}_{C,x_2}(p_1^x)} &< e_y\underbrace{\left(-\frac{\partial y_2}{\partial p_1^y}\right)\left(\frac{\partial y_1}{\partial p_1^y}+\frac{\partial x_1}{\partial p_1^y}\right)^{-1}}_{\equiv \mathcal{D}_{C,y_2}(p_1^y)}
\end{aligned}
$$

which is the condition given by (12).

B Estimating Changes in Environmental Damages from Clean Technology Adoption

Counterfactual subsidy policy portfolios generate predicted levels in clean technology adoption. We normalize these predicted levels of clean technology adoption relative to adoption levels at a no-subsidy baseline. Given that a key policy justification for incentivizing the adoption of solar PV and PEVs is to replace consumption of legacy, dirty electricity sources, we use the quantities of solar PV and PEV adoption for each counterfactual policy portfolio to conduct a back-of-the-envelope calculation of any changes in environmental damages relative to the no-subsidy baseline. This requires estimates of the change in climate and other environmental damages from a marginal change in adoption for each technology.

B.1 Environmental Benefits of Solar Adoption

The external social benefits of solar PV subsidies are a function of the quantity of solar PV adopted due to subsidies, the amount of electricity produced by these systems, and the external damages associated with alternative electricity generation sources displaced by this additional solar capacity. I use estimates of the marginal environmental benefits of additional solar capacity in the US from Sexton et al. (2021). These estimates account for both the marginal external damages from harmful local air pollutants as well as carbon dioxide. Using rich data on electricity generation, solar insolation, and air pollution transport, Sexton et al. (2021) produce spatially-differentiated estimates of the marginal environmental benefits of additional solar capacity that account for substantial heterogeneity in solar generation, displaced pollution emissions, and marginal costs of electricity over space and time. These off-the-shelf estimates therefore allow me to account for variation across the state of California in not only the lifetime generation potential of additional solar capacity, but also characteristics of the electricity grid.

B.2 Environmental Benefits of PEV Adoption

We focus on capturing the environmental benefits of PEVs relative to gasoline vehicles, assuming that each PEV adopted offsets an internal combustion engine vehicle. Environmental benefits come through reductions in both CO_2 emissions and harmful local air pollutants. We monetize these benefits using the social cost of carbon and estimates of the health benefits of reduced exposure to harmful local air pollutants.

First we consider the carbon reduction benefits. A typical gasoline vehicle in the US emits 4.6 tons of CO_2 annually based on an assumption of average vehicle miles traveled of 11,500[2] We further assume an emissions reduction factor of 70%, a vehicle lifetime of 12 years, and a social cost of carbon of $185 per ton of CO_2 (Rennert et al., 2022). With these assumptions, we estimate that replacing an ICE vehicle with a PEV leads to a CO_2 reduction of 3.2 tons/year, which we estimate provides a present discounted benefit of approximately $7,100.

The local air pollution benefits from PEV adoption are due to a decline in $PM_2.5$, NO_x, and VOC emissions. Estimates of the health costs of different pollutants from the US EPA and Holland et al. (2016) place the total health benefit of replacing a gasoline vehicle with a PEV at approximately $12,000.

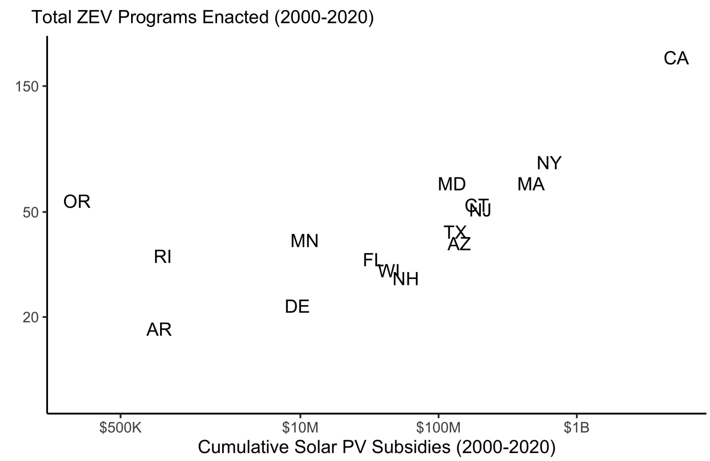
Note that these calculations assume that PEVs replace average gasoline vehicles; however, Xing et al. (2021) find that PEVs tend to replace more fuel efficient ICEs. Based on the findings of Xing et al. (2021), we scale back the sum of the climate and local health benefits of PEV adoption by up to half in the results that we report in the main text (Figure 4

[2]Estimate retrieved from US Department of Energy, Alternative Fuels Data Center: https://afdc.energy.gov/data (last retrieved, 4/21/2025).

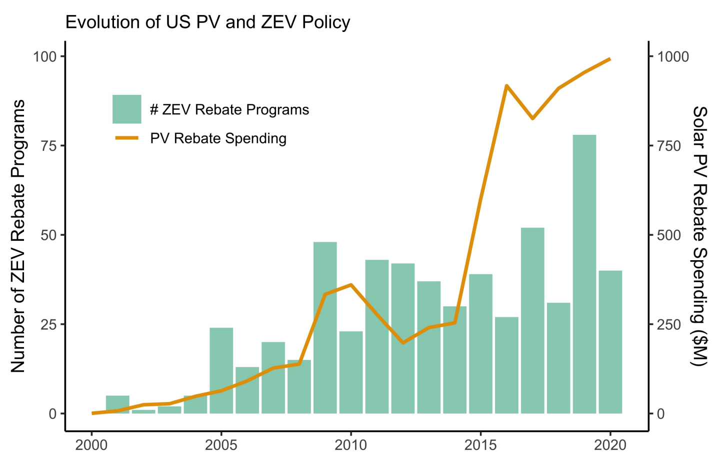
C Supplemental Figures and Tables

Figure C1. US State-level Solar PV and Zero Emissions Vehicle (ZEV) Incentives

(a) Cumulative solar PV subsidies and ZEV programs enacted by state, 2000-2020.



(b) Total solar PV subsidies and ZEV programs enacted by year, 2000-2020.



Notes: This figure shows the evolution of state-level solar PV and zero emissions vehicle (ZEV) incentive programs from 2000 to 2020. Panel (a) shows variation in these incentive programs across different states over time, demonstrating a strong positive relationship between the extent to which these two technologies are subsidized over space. Panel (b) shows variation in these incentive programs by year, showing the total dollar value of solar PV incentives and the number of ZEV incentive programs enacted by US states by year. Note that ZEV include plug-in electric vehicles (PEVs)—battery electric vehicles and plug-in hybrid electric vehicles—as well as other zero- or low-emissions vehicles such as hydrogen fuel cell vehicles. The vast majority of ZEVs are PEVs. Data come from Lawrence Berkeley National Laboratory and the US Department of Energy.

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