Complementarities and Optimal Targeting of Technology Subsidies*

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Abstract

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

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Subsidies are a common policy tool for supporting growth in energy-efficient technologies: the number of government subsidy programs aimed at reducing emissions and promoting low-emissions technologies increased 10% from 2018-2022 (World Bank Group, 2024). Despite some policymakers' preference for direct public support for various low-emissions technologies, relatively little work examines possible interactions between these policies. For example, when low-emissions technologies are complementary goods, subsidizing the adoption of one technology increases demand for its complement, which may influence the efficacy of such a subsidy.

This paper examines how interactions between technologies shape welfare-maximizing policy design,[1] focusing on subsidies for low-emissions technologies when policymakers seek to reduce the externalities that result from the use of older alternatives. We develop a theory of second-best policy for two low-emissions technologies that replace high-emissions technologies with distinct externalities when first-best Pigouvian taxes are infeasible (Bennear and Stavins, 2007; Lipsey and Lancaster, 1956; Pigou, 1920). We demonstrate that the second-best policy regime is a set of subsidies for low-emissions technology which depend on cross-technology substitution patterns. Ignoring these interactions reduces welfare, since inframarginal adoption distorts subsidy effectiveness; instead, the second-best regime targets the more price-responsive technology. Using a combination of revealed and stated preference data from a representative survey of California households, we document a strong complementarity between solar photovoltaics (PVs) and plug-in electric vehicles (PEVs): a 10% price increase in one technology reduces demand for the other by 1–2% among 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 the first-best involves separate policy instruments 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, with a particular emphasis on cases where first-best Pigouvian taxation is infeasible.

[1] Following the public finance literature, we define "optimal policy" to be the policy that maximizes some measure of welfare, inclusive of externalities. The optimal policy can be first-best (unconstrained) or second-best (subject to constraints).

Solar PV and PEVs have received policy attention as technologies 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 direct Pigouvian taxes on emissions.

Second, there are several channels through which residential solar and PEV 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 grid electricity through a program known as net energy metering (NEM). For households with a 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 low-emissions goods.

We extend the optimal taxation literature to examine how complementarities affect second-best policymaking (Lipsey and Lancaster, 1956; Sandmo, 1975; Wijkander, 1985). Our stylized model considers household demand for electricity and transportation, each with low- and high-emissions substitutes, plus a numeraire. High-emissions goods generate differentiated externalities proportional to their aggregate consumption. A social planner sets per-unit taxes or subsidies and redistributes revenues via lump-sum transfers. As a benchmark, the unconstrained case recovers the standard result: optimal policy imposes Pigouvian taxes on externality-generating goods.

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. Second assuming that the the two low-emissions technologies are strong complements, the second-best subsidy will be less (i.e., smaller in magnitude) than the subsidy set ignoring this interaction. 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 low-emissions technology with the greater behavioral response, inclusive of both the resulting direct substitution and indirect impact through the technology complementarity.

Our model highlights the need to consider the full substitution matrix when designing second-best policies for interacting low-emissions technologies. Using a co-adoption framework (Gentzkow, 2007) and data from the 2013 and 2017 waves of the California Vehicle Surveys, we estimate substitution patterns between solar PV and PEVs. We find strong complementarities: a 10% increase in PV prices reduces PV demand by 5.2% and PEV demand by 0.3%, while a 10% increase in PEV prices reduces PEV demand by 4.3% and PV demand by 0.5%. These averages mask heterogeneity, with low-income households having larger cross-price elasticities.

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. Using a different approach, Lyu (2023) finds that solar PV and PEVs are complements in California, a finding we confirm. We build on this literature by drawing out the implications of these empirical complementarities for policymaking and welfare in the presence of externalities.

Although solar PV and PEV adoption have each been studied extensively, existing work typically treats them in isolation. Research on solar PV shows that subsidies increase adoption but that static environmental benefits alone do not justify these policies (Borenstein, 2017; De Groote and Verboven, 2019; Gillingham and Tsvetanov, 2019), while a parallel literature examines how various incentives shape PEV adoption (Muehlegger and Rapson, 2022, 2023; Rapson and Muehlegger, 2023). Our work brings these strands together by highlighting the importance of co-adoption effects when evaluating low-emissions technology subsidies.

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; however, 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 subsidies for solar PV are similarly high: in 2017, global public subsidies for solar PV totaled $61 billion (Taylor, 2020). The location of generous public subsidies for each technology also often overlaps. As shown in Appendix Figure D1, 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 low-emissions technologies take numerous forms. Solar PV and plug-in electric vehicles are both capital-intensive goods, so many public policies aim to reduce the upfront costs of these investments. 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 they 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 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, a relationship that 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.

2.1 Model setup

Consider a model with N identical households where a representative household consumes five goods: low-emissions electricity (x_1), high-emissions electricity (x_2), low-emissions transportation (y_1), high-emissions 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 high-emissions goods produces a differentiated externality, with each externality proportional to the aggregate consumption of that good:[2]

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

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

$$U = u(x_1, x_2, y_1, y_2) - E_x - E_y + \mu \tag{1}$$

where $u(\cdot)$ is a concave, twice continuously differentiable function. Note that while households' utility function depends on the aggregate externalities (E_x and E_y), each of which is a function of all households consumption of high-emissions goods, we assume that households are atomistic and view the aggregate externality as exogenously fixed. Households maximize

[2] We model differentiated externalities to reflect empirical differences between transportation and residential electricity use. Beyond varying greenhouse gas intensities, each entails distinct co-pollutants and spillover costs, with recent work documenting substantial spatial and temporal heterogeneity in these externalities (Gillingham et al., 2024; Holland et al., 2016; Sexton et al., 2021).

their utility subject to the 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. It is therefore 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. *Low-emissions electricity (x_1) is a substitute for high-emissions electricity (x_2) and low-emissions transportation (y_1) is a substitute for high-emissions 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

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

We assume tax revenues are recycled via equal lump-sum transfers.

Following the public finance literature, we assume 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; the disutility from electricity and transportation consumption externalities; income net of household expenditures; and lump-sum transfers of tax revenues:

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

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 optimal policy (6) therefore replicates the well-known result of the "Tingbergen Rule" in the context of two externality market failures.

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

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

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 low-emissions goods are substitutes for the high-emissions goods, the government indirectly targets the externality-producing goods by subsidizing the low-emissions goods, with the subsidy equal to the product of the marginal externality and the degree of substitutability between the low- and high-emissions 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, $\tilde{\Omega}$. The form of the optimal policies given by (9) reveals 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, high-emissions goods is not directly dependent on the price of the low-emissions 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 high-emissions transportation is neither a gross complement nor a substitute for low-emissions electricity implies that the only impact of the low-emissions technology in, say, electricity on the quantity of high-emissions transportation consumed operates through the complementarity of low-emissions electricity and low-emissions 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 low-emissions 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 we assume that own-price demand responses are greater than the cross-price demand responses for the low-emissions technologies.

We now turn to a comparison of the two policy regimes, (8) and (9). We start with comparing the policies for low-emissions electricity, $\tilde{\tau}_1^x$ and $\bar{\tau}_1^x$. Combining Assumptions 1, 2, and 3 gives the following result: accounting for complementarities between low-emissions technologies will result in a lower (i.e., less negative) subsidy rate for low-emissions 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. An analogous condition holds for low-emissions transportation. Accounting for complementarities between low-emissions technologies will result in a lower (i.e., less negative) subsidy rate for low-emissions 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^x changes. See Appendix A.1 for the derivation of (10) and (11).

The results given by (10) and (11) indicate that holding fixed the marginal externalities e_x and e_y, the optimal constrained policy in a given technology will only be larger in magnitude than the naive policy when there is particularly strong substitution between the low-emissions and high-emissions good in that technology. Focusing on the case of subsidies for low-emissions electricity, 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 low-emissions and high-emissions electricity would have to be meaningfully larger than that between low-emissions and high-emissions transportation—holding fixed the marginal externalities—for (10) not to hold and for the optimal constrained policy in low-emissions electricity to be larger than the naive policy. This is evident in the simulated policy regimes in Figure 2a.

Another implication of (10) and (11) that is evident from the simulated policies in Figure 2a is that the stronger the complementarity between the two low-emissions technology, holding fixed own-price elasticities and within technology type substitution, the lower the optimal constrained subsidy. This indicates the potential value of the cross-technology complementarity to policymakers: subsidizing one low-emissions technology increases adoption of the other through the complementarity, which implies that policymakers can achieve the same adoption of one low-emissions technology with a less generous subsidy.

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 low-emissions technologies given by (9). In particular, the optimal constrained policy will be a larger (i.e., more negative) subsidy rate on low-emissions electricity relative to low-emissions transportation, $\bar{\tau}_1^x > \bar{\tau}_1^y$ 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 low-emissions 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 low-emissions 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).

The result (12) implies that the second-best policy will place a larger subsidy on the low-emissions technology with the larger total behavioral response. It is optimal in a constrained environment for the policymaker to place a greater emphasis on the low-emissions technology with the largest marginal externality reduction, inclusive of both externality-generating goods. The relative sizes of the optimal constrained policies depends on the behavioral response from a price change in one low-emissions technology in demand for *both* low-emissions technologies. This is shown for simulated optimal constrained policy portfolios in Figure 2b.

3 Estimates of Substitution between Low-Emissions Technologies

Section 2 highlights the need to consider the full substitution matrix for second-best policies. We estimate a static discrete choice model of household co-adoption of solar PV and PEVs to identify substitution patterns and the potential welfare losses from ignoring these interactions.

3.1 Data on Co-adoption Decisions

We use a unique dataset linking household solar PV adoption with vehicle demand from the 2013 and 2017 waves of the California Energy Commission's (CEC) California Vehicle Survey. These surveys, stratified across major regions in California, collect detailed household demographics—including solar adoption—and elicit vehicle preferences through a discrete choice experiment. This stated preference experiment asks respondents to choose among four hypothetical vehicles across eight choice occasions, with attributes such as price, purchase incentives, fuel type, and vehicle class randomly assigned. To supplement the limited solar information in the survey, we merge county-level solar prices, rebates, and system attributes from Lawrence Berkeley National Laboratory's Tracking the Sun dataset, along with solar output potential measures from the World Bank Group's Global Solar Atlas. We assume solar adoption occurs in the year before survey implementation.

The final dataset consists of 6,754 households (about 12.5% with solar PV) and 8 experimental vehicle choices per respondent. Despite limitations of stated preference data—such as non-incentivized choices and no opt-out—the statewide sampling, rich attribute variation, and integration with solar adoption data make this source well-suited to identify empirical substitution patterns between solar PVs and plug-in electric vehicles (PEVs). We provide additional information on the underlying survey data, ancillary data sources, and final data that we use in our analysis in Appendix B. Full summary statistics for the final dataset are available in Appendix Table D1.

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. 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. $\Gamma_b < 0$ implies substitutability, $\Gamma_b > 0$ implies complementarity, and $\Gamma_b = 0$ implies independence (Gentzkow, 2007). Identifying 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

Applying the discrete choice model (13)–(15) to the California Vehicle Survey requires defining the choice set: respondents choose among eight alternatives per occasion—the four stated-preference vehicle options, each with or without solar PV. We specify a single Γ_b term, which is only nonzero for bundles with both solar PV and a PEV. Since vehicle options vary across occasions, no respondent faces repeated choice sets, which prevents estimation of alternative-specific constants (ξ_j). This may be a concern for identification of the remaining model parameters if unobserved quality correlates with prices, as is common in revealed-preference data.

Fortunately, the nature of the choice experiment and empirical solar PV data aids in identification of the remaining target model parameters, $\begin{bmatrix} \alpha & \theta' & \Gamma_b \end{bmatrix}$. 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 possible given the functional form of (13) and the inclusion of observable product attributes, $\begin{bmatrix} p_{jt} & r_{jt} & X'_{ijt} \end{bmatrix}$, each of which implies an exclusion restriction. 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 an attribute for $j \in b$, observed variation in demand for $k \in b \setminus \{j\}$ will pin down the value of consuming k and j together in bundle b. Our data provides such variation along many dimensions, including solar irradiance, solar panel efficiency, and a number of randomly assigned vehicle attributes 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. The price coefficient, α, is large, precisely estimated, and negative as expected. Importantly, the interaction term, Γ, is positive and statistically-significant. 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.

The positive Γ confirms that solar PV and PEVs are complements; however, the magnitudes of price responses are also informative. On average, a 10% increase in solar PV prices reduces PV consumption by 5.2% and PEV consumption by 0.3%, while a similar 10% increase in PEV prices reduces PEV consumption by 4.3% and PV consumption by 0.5%. This masks substantial heterogeneity by respondent income as shown in Figure 3. Taken together, these findings suggest that the total behavioral response to a price change is greater for solar PV than for PEVs among respondents. In the context of the theoretical results in Section 2, this implies that $\mathcal{D}_{C,x_2}(p_1^x)$ is larger than $\mathcal{D}_{C,y_2}(p_1^y)$, which—assuming equal externalities on the margin—would imply that a policymaker seeking the largest behavioral response should subsidize solar PV adoption more than PEV adoption.

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 technology subsidies. Consumer surplus calculations follow the standard closed-form logit inclusive value formula. Moreover, we use standard estimates from the literature 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 C.

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, netting out 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. 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.

[3]For solar PV, we assume a 5 kW system and combine CSI state rebates, federal ITC (30%), and market prices to calculate subsidy ranges for 2013 and 2017, excluding net metering benefits. For PEVs, we report CVRP rebate ranges for BEVs and PHEVs in those years.

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 low-emissions technologies which have several conceptual channels for complementary demand. We develop a theory of optimal (welfare-maximizing) constrained policies when first-best Pigouvian taxation of negative externality-producing substitutes for these two technologies are infeasible. We demonstrate that the optimal second-best policy regime is a set of low-emissions 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 low-emissions goods.

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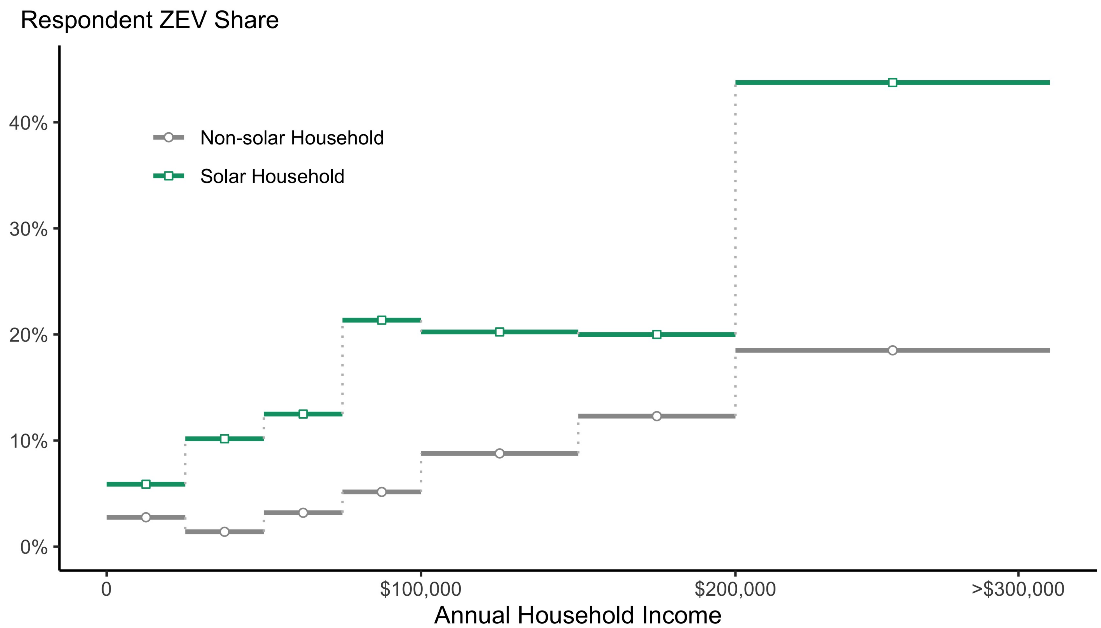
Figures and Tables

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

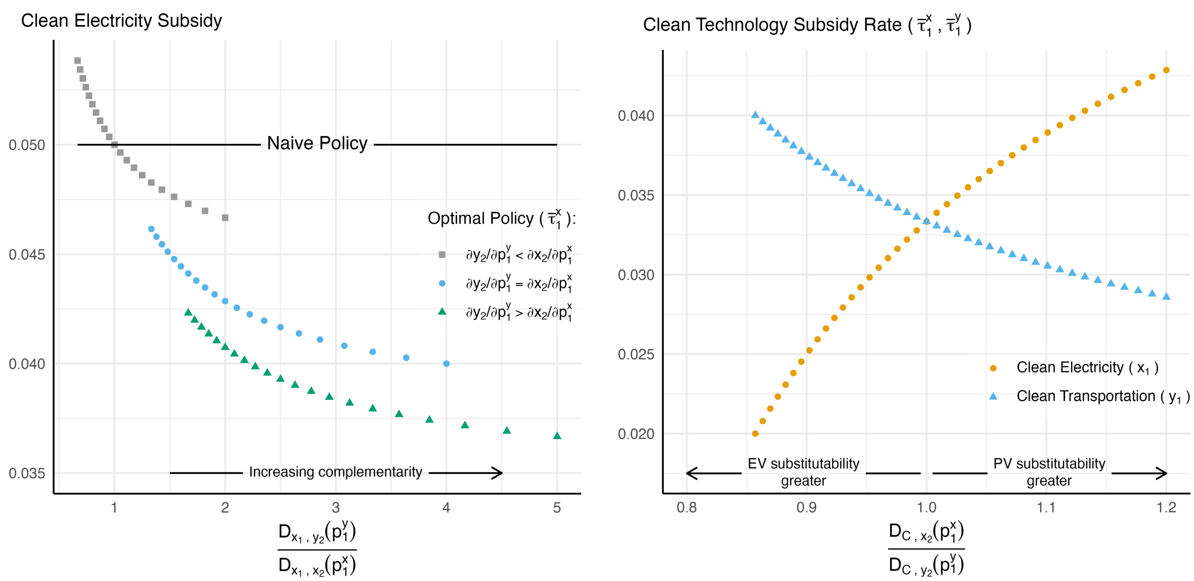


Notes: This figure shows the share of respondents in the 2017 California Vehicle Survey that own a zero emissions vehicle (ZEV) within 7 different annual household income bins, separately for households with and without solar installed. Source: 2015-2017 California Vehicle Survey, California Energy Commission.

Figure 2. Simulated Portfolios of Constrained Policies

(a) Optimal versus Naive Constrained Policy

(b) Optimal Constrained Policies

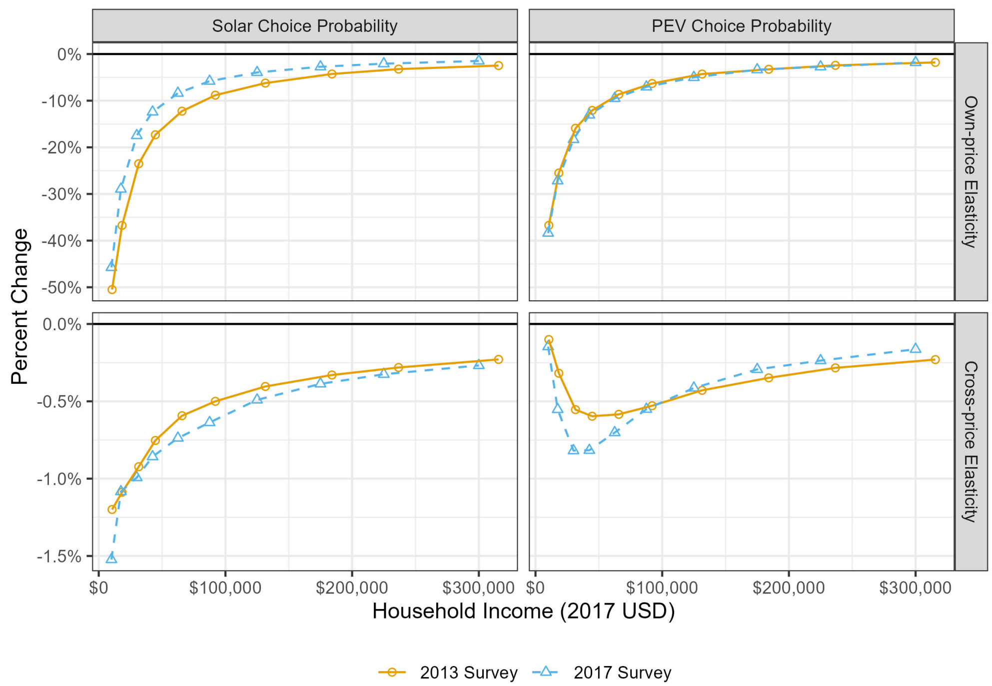


Assumed Parameter Values

		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
Within-technology 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
Cross-technology 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 low-emissions 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 low-emissions electricity and high-emissions 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 low-emissions technologies (x_1 and y_1) and high-emissions 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 $\mathcal{D}_{C,y_2}(p_1^y)$.

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

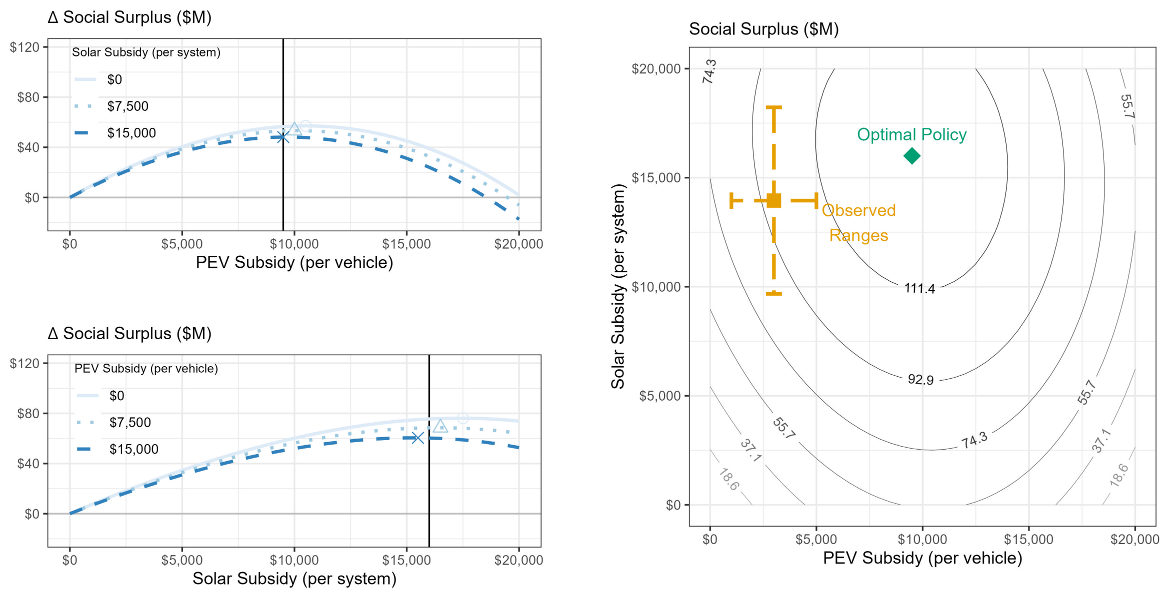


Notes: This figure plots the average relative change in solar photovoltaic (PV) and plug-in electric vehicle (PEV) demand for a 10% change in solar PV and PEV prices as a function of reported household income. Each panel increases the prices of a single low-emissions technology by 10% across all choice 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.

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 low-emissions technology adoption (ΔE), less the impact on government subsidy expenditures (ΔG). We calculate ΔC following the standard formula for inclusive value from Small and Rosen (1981) and ΔG assumes a marginal cost of public funds of 1.0. See Appendix C 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 holding the subsidy in the other low-emissions technology fixed. 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).

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 $\times$ $\mathbb{1}\{$PEV$\}$	0.028 (0.002)	$\mathbb{1}\{$Truck$\}$	−0.692 (0.024)
Income $\times$ $\mathbb{1}\{$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.

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: Data Appendix

—Appendix Section C: Calculating Changes in Environmental Damages

—Appendix Section D: 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 and noting the definition of the substitution matrix as

$$\tilde{\Omega} = \begin{bmatrix} \frac{\partial x_1}{\partial p_1^x} & \frac{\partial y_1}{\partial p_1^x} \\ \frac{\partial x_1}{\partial p_1^y} & \frac{\partial y_1}{\partial p_1^y} \end{bmatrix}$$

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}|) \\
- \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 and again noting the definition of the substitution matrix as

$$
\tilde{\Omega} = \begin{bmatrix} \frac{\partial x_1}{\partial p_1^x} & \frac{\partial y_1}{\partial p_1^x} \\ \frac{\partial x_1}{\partial p_1^y} & \frac{\partial y_1}{\partial p_1^y} \end{bmatrix}
$$

we can show the condition under which the optimal subsidy on one low-emissions 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 low-emissions transportation relative to low-emissions 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 Data Appendix

B.1 Additional Information on Data Sources

We provide information on each of the data sources used in our empirical analysis below.

- *California Energy Commission's (CEC) California Vehicle Survey (CVS):* provides the main data which we use to estimate the choice model in Section 3, including data on a random sample of California households' solar adoption decisions alongside randomized c=vehicle discrete choice experiments. The CEC runs the CVS periodically to understand changes in light-duty vehicle choices within the state and, though early iterations of the survey existed almost three decades ago, we rely on the 2013 and 2017 waves of the CVS as these are largely consistent with one another and therefore allow for analysis across several time periods. The CEC recruits respondent households for the CVS using a combination of address-based sampling and online address-based sampling through a market research panel, with samples stratified across major regions of the state.[2] The CVS survey data include detailed household demographic information, including household income and information on whether a respondent household has installed residential solar. The 2013 and 2017 waves of the CVS also include a stated preference experiment in which respondents are presented with a series of eight choice occasions, each of which involves choosing a preferred option between four different vehicles with randomly varying attributes. The discrete choice experiment includes a rich set of observable attributes, which vary 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. Additional information on these data is available at `https://www.energy.ca.gov/data-reports/surveys/california-vehicle-survey` (last accessed 9/12/2025).

- *Lawrence Berkeley National Lab's (LBNL) Tracking the Sun Database:* provides system-level data on PV systems annually from state agencies and utilities that administer PV incentive programs, renewable energy credit registration systems, or grid interconnection processes. The public use database includes information on the date of installation, system size, total installed price, total pre-tax rebate value, customer type, zip code, mounting type, and installer name, as well as various technical details about installed hardware, including the energy conversion efficiency (i.e., how much incoming solar

[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.

radiation a panel converts into electrical power), make, and manufacturer of installed PV modules. LBNL processes the source data prior to publishing the public use data, including removing systems with missing size or installation date fields; standardizing installer, module, and inverter manufacturer names; and integrating publicly available equipment specification data with system-level data. We restrict the data to include only residential systems installed in California and further remove any residential systems with capacity exceeding 20 kW and any systems for which we do no observe the installed price.The full sample includes data on over 2.5 million PV systems installed from 2000 to 2021, covering both residential and non-residential systems. Barbose et al. (2022) estimate that the database covers approximately 77% of the total estimated US market for PV systems over 2000-2021. We use these data to generate county-level price estimates for solar PV systems. Additional information on these data is available at https://emp.lbl.gov/tracking-the-sun (last accessed 9/12/2025).

- *World Bank Group's Global Solar Atlas:* provides estimates of the long-term annual average photovoltaic power potential of a 1 kilowatt (kW) capacity PV system in raster data format at a 250-meter resolution. We use these data in combination with administrative boundary data for California Counties from the US Census Bureau to estimate the average annual power production potential for a residential PV system installed in each county. We use these data as an observable, PV-specific shifter of demand for PV-containing bundles. Information on these data is available at https://globalsolaratlas.info/download (last accessed 9/12/2025).

B.2 Constructing Data for Model Estimation

Combining the data that we use in our empirical analysis is relatively straightforward. We are able to harmonize and combine data fields for respondents in the 2013 and 2017 waves of the CVS, including respondent county of residence, actual solar adoption choice, and income. We assign average PV prices generated from the LBNL Tracking the Sun database based on respondents' county of residence and the year of the survey wave, using one-year lagged prices to account for the fact that respondents' solar adoption decisions are not contemporaneous to the vehicle choice experiment. We similarly assign solar irradiance data from the Solar Atlas based on respondents' county of residence.

We combine these solar adoption, price, and irradiance data with the vehicle choice experiment data for each of the 2013 and 2017 waves of the CVS. As discussed above, the vehicle choice experiments include eight distinct choice occasions, each of which involves respondents choosing between four distinct vehicles with randomly assigned vehicle attributes.

For each of the eight choice experiments for all respondents across the two waves, we expand the full choice set to eight alternatives: the four vehicle alternatives from the stated preference experiment, each of which can be consumed with and without solar PV. We then combine the stated choice between the four vehicles on each choice occasion with information on solar adoption to encode respondents' choice of the eight alternatives on each of the eight choice occasions which we observe.

We convert all dollar-denominated fields to 2017 real dollars using the consumer price index (CPI) for all urban consumers. The final discrete choice dataset includes 8 experimental vehicle choices from 6,754 unique respondents, approximately 12.5% of whom have installed solar PV. Appendix Table D1 provides detailed summary statistics for the final discrete choice dataset.

C Estimating Environmental Benefits from Technology Adoption

Counterfactual subsidy policy portfolios generate predicted levels in low-emissions technology adoption. We normalize these predicted levels of low-emissions 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, high-emissions 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 greenhouse gas emissions and other environmental damages from a marginal change in adoption for each technology.

C.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.

C.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.[3] 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). Under these assumptions, replacing an ICE vehicle with a PEV leads to a CO_2 reduction of 3.2 tons/year and 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.

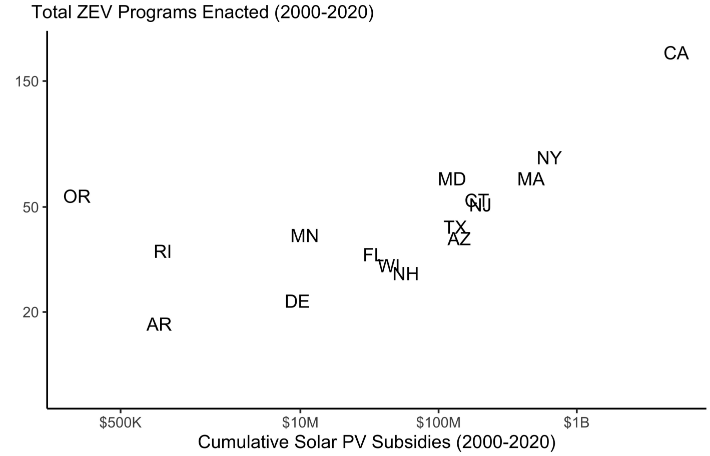
Note that these calculations assume that PEVs replace average gasoline vehicles; however, Xing et al. (2021) find that PEVs tend to replace more fuel efficient ICEs. Based on the findings of Xing et al. (2021), we scale back the sum of the climate and local health benefits of PEV adoption by up to half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

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

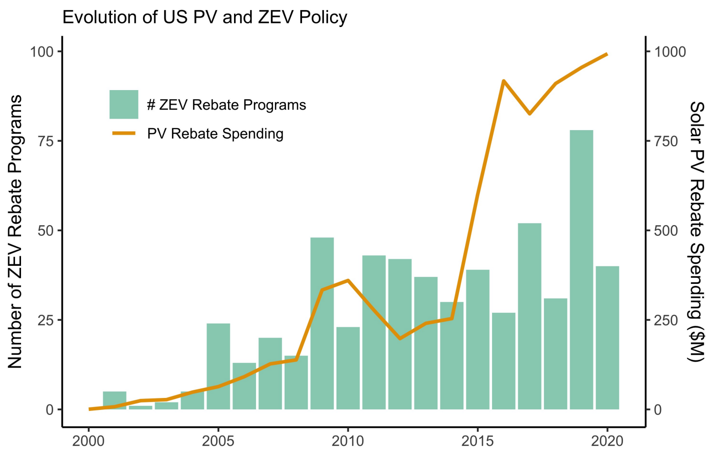
D Supplemental Figures and Tables

Figure D1. 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 photovoltaic (PV) and zero emissions vehicle (ZEV) incentive programs from 2000 to 2020. Note: comprehensive expenditure data are unavailable for many plug-in electric vehicle (PEV)/ZEV incentive programs, so we compare solar PV expenditures with the number of PEV/ZEV. 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.

Table D1. Summary Statistics

	N	Mean	SD	Non-solar Respondents Mean	Non-solar Respondents SD	Solar Respondents Mean	Solar Respondents SD
Respondent-level Variables							
Income ($10,000)	6,754	11.26	7.36	10.85	7.16	14.07	8.10
Solar Household (0/1)	6,754	0.13	0.33	0.00	0.00	1.00	0.00
Solar Price ($10,000)	6,754	4.02	2.00	4.05	2.03	3.78	1.77
Solar Rebate ($10,000)	6,754	1.47	1.17	1.49	1.19	1.34	1.01
PV Output (100 kWh/kWp)	6,754	18.16	0.77	18.17	0.77	18.15	0.75
PV Efficiency (%)	6,754	17.43	1.24	17.39	1.25	17.70	1.19
Vehicle-level Variables							
Vehicle Price ($10,000)	216,128	3.56	2.87	3.50	2.88	3.96	2.78
Vehicle Rebate ($10,000)	216,128	0.04	0.13	0.04	0.13	0.05	0.14
Acceleration Rate (seconds)	216,128	8.39	2.48	8.40	2.48	8.29	2.46
Refueling Time (minutes)	216,128	109.62	311.55	110.62	316.13	102.65	277.43
Cost per Mile ($/mi.)	216,128	0.14	0.08	0.14	0.08	0.14	0.08
Miles per Gallon	216,128	34.76	20.01	34.50	19.70	36.64	21.95
Range (mi.)	216,128	417.39	190.74	417.05	189.18	419.70	201.33
Trunk Space (ft.^{3})	216,128	33.36	40.91	33.92	41.45	29.42	36.75
Vehicle Age (years)	216,128	1.22	2.16	1.24	2.20	1.06	1.90
Small/Compact Car (0/1)	216,128	0.29	0.45	0.28	0.45	0.30	0.46
SUV (0/1)	216,128	0.23	0.42	0.23	0.42	0.21	0.41
Pickup Truck (0/1)	216,128	0.09	0.29	0.09	0.29	0.09	0.29
Minivan/van (0/1)	216,128	0.09	0.28	0.09	0.28	0.09	0.28
Plug-in Electric Vehicle (0/1)	216,128	0.19	0.39	0.18	0.39	0.24	0.43
Non-PEV Hybrid (0/1)	216,128	0.25	0.43	0.25	0.43	0.24	0.43

Summary statistics for the final dataset used to estimate the discrete choice model in Section 3. All monetary figures are in 2017 USD. 'Non-solar respondents' and 'solar respondents' are households that report no solar and solar adoption, respectively. The respondent-level variables are constant within respondents across choice occasions, whereas the vehicle-level variables vary across respondents, choice occasions, and vehicle alternatives. See Section 3 and Appendix Section B for additional information about these data.

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