Designing Dynamic Subsidies to Spur Adoption of New Technologies

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Abstract: We analyze the efficient subsidy for durable good technologies. We theoretically demonstrate that a policy maker faces a tension between intertemporally price discriminating by designing a subsidy that increases over time and taking advantage of future technological progress by designing a subsidy that decreases over time. Using dynamic estimates of household preferences for residential solar in California, we show that the efficient subsidy increases over time. The regulator's spending quintuples when households anticipate future technological progress and future subsidies.

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POLICY MAKERS COMMONLY SUBSIDIZE ADOPTION of durable good technologies. The US government pays hospitals to adopt electronic medical record systems and firms to build renewable energy projects. Subsidies also encourage car buyers to choose electric vehicles, farmers to install more efficient irrigation systems, and households to

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replace their aging appliances. And many governments pay homeowners to install solar panels. These subsidies often evolve over time according to an announced schedule. Policy makers may use these subsidies to increase adoption, but these subsidies also interact with other goals such as limiting public spending: two subsidy trajectories that eventually achieve the same level of adoption could have very different implications for the public purse. In practice, most of these subsidies are either flat or declining over time. Yet the design of an efficient subsidy schedule remains an open policy question.

We fill this gap by investigating how a regulator should design a durable good subsidy that seeks to achieve a target level of adoption by a given date.[1] Potential adopters have heterogeneous, private values for the technology. The regulator values cumulative adoption, dislikes spending public funds, and announces how the subsidy will evolve over time. Given that regulators often want to achieve suboptimal targets, whether for political or budgetary reasons, we remain agnostic about the welfare implications of the adoption target and refer to the "efficient" subsidy as the one that maximizes the regulator's objective subject to the target.[2] We theoretically disentangle the forces that determine whether the efficient subsidy increases or decreases over time, and we combine the theoretical analysis with new dynamic estimates of household preferences for rooftop solar electric systems in order to understand the relative importance of these different forces in a prominent real-world application.

We formally show that the regulator has conflicting interests when designing the efficient subsidy schedule. Of particular note, the regulator wants to offer a low subsidy early, when consumers with particularly high private values for the technology will choose to adopt it. The regulator will then increase the subsidy over time so as to obtain adoption from consumers who are not willing to pay as much for the technology. Within a period, the regulator cannot discriminate between consumers because all adopters receive the same subsidy, but the dynamic nature of the subsidy enables intertemporal price discrimination. By using a low subsidy early and a high subsidy later, the regulator avoids "oversubsidizing" consumers who would be willing to adopt the technology at a low subsidy level and thereby reduces the total cost of achieving a given level of adoption. This price discrimination channel is strong when there are a lot of inframarginal consumers who would adopt even at low subsidy levels and is weak when most consumers

1. We formally demonstrate that our setting is equivalent to one in which the regulator has a fixed budget instead of a fixed adoption target.

2. We refer to our derived subsidy trajectories as "efficient" rather than "optimal" because the policy may not maximize welfare, though we formally demonstrate in app. E.3 that the dynamics of the welfare-maximizing subsidy are qualitatively identical when funds are raised through distortionary taxation. We avoid "cost-effective" in the main analysis because we allow the regulator to derive benefits from cumulative adoption and to dislike concentrating spending in a single period. We briefly describe the cost-effective subsidy in sec. 1.

are on the margin.[3] However, when consumers anticipate future subsidies, some consumers will simply wait for the later, higher subsidies.[4] The regulator can no longer limit the number of inframarginal consumers as sharply merely by delaying higher subsidies for a bit. Consumers' expectations therefore constrain the regulator's ability to intertemporally price discriminate and force the regulator to commit to a flatter subsidy schedule.

In contrast, anticipated improvements in technology usually favor a declining subsidy. As technology improves, more people want to adopt the technology for a given subsidy. If the regulator offered households the same subsidy as in the case without technological change, then later periods would see greater adoption when technological change occurs. The increase in adoption in later periods translates into an increase in subsidy spending in later periods. However, many regulators will prefer to smooth spending over time, whether for budgetary or political reasons. The regulator accomplishes this smoothing by decreasing the subsidy in later periods relative to earlier periods. Technological progress therefore generally favors a subsidy that decreases over time. And endogenizing technological progress strengthens this effect: if the regulator believes that early adoption makes costs decline faster, then the regulator has a stronger incentive to use a relatively high subsidy early so as to stimulate early adoption.[5]

To assess the relative magnitude of these and other competing forces that together determine the shape of the efficient subsidy schedule, we combine our theoretical analysis with a dynamic discrete choice estimation of households' preferences for residential solar systems in California. Beyond learning whether the efficient subsidy increases or decreases over time, we use our theoretical model to decompose the efficient subsidy trajectory into its component drivers in order to understand precisely why the efficient subsidy has its shape. The California Solar Initiative (CSI) included a substantial subsidy for residential photovoltaic (rooftop solar) adoption between 2007 and 2014. This

3. Boomhower and Davis (2014) estimate the fraction of inframarginal adopters in an energy efficiency program in Mexico. They find that more than 65% of households are inframarginal and that about half of adopters would have adopted in the absence of any subsidy. Chandra et al. (2010) find that the majority of Canadian vehicle purchasers who received a rebate for hybrid electric vehicles were inframarginal. Gowrisankaran and Rysman (2012) find that consumers who buy digital camcorders in later periods have lower values for the good than did consumers who purchased in earlier periods.

4. In the theory and simulations, our consumers have rational expectations about the evolution of technology costs and subsidies and attempt to time their adoption of the technology. However, we remain agnostic about whether consumers accurately internalize the present discounted value of the stream of benefits from the technology. This potential undervaluation of a stream of future technology benefits has been discussed at length in the literature on the "energy efficiency paradox" (e.g., Allcott and Greenstone 2012; Busse et al. 2013).

5. We show that endogenizing consumers' willingness to pay for the technology (whether interpreted as peer effects or network effects) is formally equivalent to endogenizing the cost of the technology.

program spent nearly $2.2 billion to obtain 1,940 megawatts (MW) of residential solar capacity. The residential solar subsidy declined step-wise over time from $2.50/watt (W) to zero, with pre-subsidy installation costs over this period declining from around $9/W to around $4/W. We use data on household-level installations, local demographics, solar generation potential, and electricity rates to estimate the distribution of households' benefit of installing solar conditional on household demographics.[6] The estimation assumes that households know the full time path of subsidies and electricity prices but allows solar system prices to evolve stochastically. The estimated preferences show substantial heterogeneity in the private benefit of residential solar systems.

We find that our regulator's efficient subsidy increases over time, even though this type of subsidy is rarely enacted or discussed. An increasing subsidy allows the regulator both to delay spending and to price discriminate by offering a low initial subsidy to consumers who value the technology highly and then raising the subsidy over time to encourage additional consumers to adopt. The benefit of increasing the subsidy over time is tempered by technological change that can make it more cost-effective for the regulator to lower the subsidy in later periods when consumers face a lower private cost of the technology. Across a reasonable range of sensitivity checks, our analysis cannot generate an efficient subsidy that resembles the sharply declining subsidy used by California and many other states to speed adoption of solar power.

Further, whereas previous literature on efficient subsidies has modeled consumers as myopic (e.g., Kalish and Lilien 1983), we show that understanding consumer foresight is critical for designing the efficient subsidy and that facing forward-looking consumers can increase public spending substantially. Consumers' rational expectations of future subsidies limit the regulator's ability to intertemporally price discriminate by offering a low subsidy in early periods and a high subsidy in later periods. In a world without technological progress, this effect increases total spending on solar subsidies by 4% and slows the rate at which the efficient subsidy for solar increases over time. Further, the regulator must offer forward-looking consumers a high subsidy in order to compensate them for forsaking the option to adopt solar at some later time. This effect becomes especially important when households anticipate that technology will improve over time. As a result, the regulator's total spending is 400% greater when households have rational expectations of technological progress in the market for solar as opposed to a world in which technological progress occurs but households are myopic.

Households' rational expectations also reduce the degree to which the regulator can take advantage of technological progress to reduce the total cost of the policy. When households do not anticipate that technology might improve over time, the regulator

6. Because consumers are forward looking, we should not use a static approach to estimate the implications of a change in the subsidy for adoption as, for instance, in Hughes and Podolefsky (2015). Instead, we must recover consumers' structural preferences that will remain stable even when the regulator changes expectations of future subsidies (Lucas 1976).

can take advantage of its understanding of technological progress to reduce spending by 95%. Myopic households actually obtain slightly less surplus in the presence of technological change because the regulator delays their adoption until later periods. However, when households are aware of the possibility of technological progress, the regulator can reduce its spending by only 77%. Households, on the other hand, increase their surplus by $700 million (230%), as technological progress increases the opportunity cost of adopting the technology today, which forces the regulator to offer households a larger subsidy to encourage early adoption.

Finally, whether or not we allow for technological change or household foresight, our benchmark model always generates an efficient subsidy that increases rather than sharply declining like the one enacted in California. Giving the regulator a much stronger desire to smooth spending over time can generate a subsidy that declines over time, but it still does not decline anywhere near as sharply as the actual subsidy. The origin of declining subsidies for solar appears to be a Japanese policy from 1994, which was designed with the idea that high early subsidies would induce technological change (Nemet 2019, 99). We find that the efficient subsidy initially increases over time even under extreme assumptions about the endogeneity of technological change. Further, combining these extreme assumptions with calibrated peer effects still does not suffice to generate a declining schedule. We can, however, generate the type of sharply declining subsidy seen in California if we substantially increase the regulator's value for solar electricity. In particular, our policy maker would need to value solar electricity more than an order of magnitude higher than the estimates of the social value of solar electricity in Baker et al. (2013). The regulator then designs a subsidy schedule that prioritizes obtaining adoption quickly because she does not want to defer the benefits of solar electricity.

Our primary contribution is to ground the design of dynamic subsidy instruments in economic principles. Despite the prevalence of subsidies for durable investments, there has been little formal analysis of these instruments. Kalish and Lilien (1983) argue that learning and word-of-mouth diffusion call for a subsidy that declines over time. We obtain the same result in our analysis of endogenous technology/preferences, although tempered by competition with several forces that push in the opposite direction.[7] Both Kalish and Lilien (1983) and Meyer et al. (1993) informally discuss the logic underpinning our intertemporal price discrimination channel. We formally demonstrate this channel and show how private actors' expectations constrain it. Kremer and Willis (2016) study the efficient subsidy trajectory in the presence of positive spillovers, which act like our endogenously declining costs. They assume homogeneous

7. Kalish and Lilien (1983) assume myopic consumers. Our analysis suggests that both the level and the trajectory of the efficient subsidy will be sensitive to households' expectations about their future preferences for the technology.

private values for the technology and a regulator who differs from consumers only in internalizing spillovers, whereas we emphasize the implications of heterogeneous private values and a regulator who may also care about public spending and about the flow of social benefits from adoption.[8] Finally, Newell et al. (2019) informally argue that, and De Groote and Verboven (2019) calculate that, upfront subsidies may be preferable to production subsidies paid out over time. We formally analyze how to structure the upfront subsidies offered to different possible adopters or projects.[9]

Beyond the literature analyzing subsidy schedules, our analysis builds on both the dynamic public finance and industrial organization literatures. The dynamic public finance literature has long studied a government that commits to a schedule of future taxes in order to satisfy an exogenous revenue requirement (e.g., Judd 1985; Chamley 1986; Chari and Kehoe 1999; Kocherlakota 2010). Instead of considering households that save for the future, we study households that time their adoption of a new technology, and instead of considering a government that commits to future taxes in order to fund a given level of services, we study a government that commits to future subsidies in order to attain a given level of technology diffusion. We mostly follow that literature's treatment of the revenue requirement in leaving the motivation for the technology goal unspecified, but we do analyze welfare-maximizing policy in appendix E.3 (apps. A–E are available online).

Our analysis of one-time adoption decisions echoes the industrial organization literature on monopoly pricing of durable goods.[10] A few papers have explored the conditions under which a monopolist will choose to make all sales in a single instant instead of intertemporally price discriminating (Stokey 1979; Landsberger and Meilijson 1985). Unlike a monopolist, a regulator will often derive benefits from cumulative adoption and may want to avoid spending a lot of money in a single instant. We show that either of these common motivations is sufficient to spread efficient adoption over

8. The intertemporal price discrimination motive can arise only in a setting with heterogeneous private values and a regulator who dislikes spending public funds. In app. E.3, we show that a welfare-maximizing regulator wants to price discriminate if taxation is distortionary.

9. Van Benthem et al. (2008) numerically simulate a subsidy for California solar in a calibrated model with exogenously specified demand, peer effects, and induced technical change. We study a broader regulator objective, and our numerical simulations use dynamically estimated household preferences, allow households to anticipate future subsidies, preferences, and costs, and recognize that households drop out of the market upon adopting solar. The last feature is critical to intertemporal price discrimination.

10. Dupas (2014) considers how learning and reference-dependent preferences interact with subsidy policies when consumers who have already adopted the technology (there, insecticide-treated bed nets) must choose whether to adopt it again. In our application, solar panels can last more than 20 years and a single household has only a single roof. Preferences may depend on market-wide cumulative adoption, but we can ignore the effect of an individual's adoption decisions on the same individual's later preferences.

time, similar to how convex production costs spread out the monopolist's sales in Salant (1989).[11]

The next section describes the model. Section 2 theoretically analyzes the efficient subsidy trajectory. Section 3 introduces the empirical application, including the setting and the data. Section 4 describes the dynamic structural model for estimating the distribution of household values for solar photovoltaics and presents the estimation results. Section 5 combines the empirically estimated distribution of private values with the theoretical analysis in order to explore the determinants of the efficient subsidy trajectory for rooftop solar. Section 6 explores what assumptions might lead the efficient subsidy trajectory to resemble the actual CSI subsidy trajectory. The final section discusses policy implications and directions for future research.

1. MODEL

Our model of technology adoption includes households that are deciding whether to adopt a durable technology and a regulator who encourages technology adoption via subsidies. Each household that has not yet adopted the technology faces a choice in each period whether to adopt the technology and does not face any further choices after adopting the technology. The regulator commits in period 0 to a subsidy schedule, according to which it will offer subsidy s_t to any household that adopts the technology in period $t \in \{0, \dots, T\}$.

Household i values the technology at v_{it} in time t. The household's value $v_{it} = h_{it} + \varepsilon_{i1t}$ depends on potentially time-varying characteristics of the household and of the technology (both captured in h_{it} and including factors like household demographics and changes in the technology's quality) and on shocks to the household's preference for the technology (captured in ε_{i1t}). Every household that adopts the technology at time t receives a subsidy s_t but must pay the technology's cost $C(t, Q_t, \omega_t) \geq 0$, where Q_t is cumulative technology adoption prior to period t and ω_t is a random variable that might, for instance, account for stochastic input costs in the technology's

11. Many authors have also explored how a monopolist should price durable goods when it cannot commit to later periods' prices (e.g., Coase 1972; Stokey 1981). Conlon (2010) quantitatively explores durable good pricing in a dynamic oligopoly model. In considering this literature's implications for actual markets, Waldman (2003) criticizes the assumption that commitments are not possible. He notes that firms often do appear to commit to policies in practice. Similarly, it is easy to provide examples in which policy makers appear to successfully commit to a subsidy schedule. Our theoretical analysis focuses on this environment with commitment (as does the dynamic public finance literature). In our empirical application, we consider policies over relatively short time scales (less than 10 years) that were authorized by legislation, not just by executive action. Regulators have followed through on legislated subsidy schedules for residential solar in many states. Because these schedules are functions of time or of adoption rather than functions of underlying uncertain state variables (such as system cost), this follow-through is more suggestive of commitment than of successfully forecasting equilibrium play.

production. Thus, household i's net benefit of adopting the technology in period t is $v_{it} - C(t, Q_t, \omega_t) + s_t$. If household i does not adopt the technology in a period, then it receives a stochastic benefit ε_{i0t} and has the choice of adopting the technology in the next period. We jointly define the stochastic preference shocks as $\vec{\varepsilon}_{it} = \{\varepsilon_{i1t}, \varepsilon_{i0t}\}$.

The technology's cost may change over time for several different reasons. First, cost may decline exogenously over time: $C_1(t, Q_t, \omega_t) \leq 0$, where the subscript indicates a partial derivative. Second, the technology's cost may also decline as a result of cumulative adoption ($C_2(t, Q_t, \omega_t) \leq 0$) for either of two reasons: cumulative adoption may lower costs through induced technological change or learning by doing, or cumulative adoption may increase households' value for solar through peer effects or network effects.[12] Finally, cost also depends on the stochastic shocks captured by ω_t.

Forward-looking households form expectations over the evolution of technology costs $C(t, Q_t, \omega_t)$, subsidies s_t, and household and technology characteristics h_{it}. We denote the household's time t information set as Ω_t.[13] The household's value of choosing whether to adopt the technology at time t is:

$$V(\Omega_t, \vec{\varepsilon}_{it}) = \max\left\{h_{it} - C(t, Q_t, \omega_t) + s_t + \varepsilon_{i1t}, \beta\,\mathbb{E}[V(\Omega_{t+1}, \vec{\varepsilon}_{i(t+1)})|\Omega_t] + \varepsilon_{i0t}\right\}, \quad (1)$$

where $\beta \in [0, 1)$ is the per-period discount factor and $\mathbb{E}$ is the expectation operator.[14] Forward-looking households have $\beta > 0$ and myopic households have $\beta = 0$.

The regulator commits to a subsidy schedule that will, in expectation, achieve a predetermined level of adoption $\hat{Q}$ after some given time $T > 0$.[15] She knows the true

12. Recall that household i's net benefit for solar is $v_{it} - C(t, Q_t, \omega_t) + s_t$. We can interpret $C_2(t, Q_t, \omega_t) \leq 0$ as indicating an expansive form of peer effects or network effects because a reduction in costs is equivalent to a population-wide increase in the private value of solar.

13. Since technology costs $C(t, Q_t, \omega_t)$ are a function of time, cumulative adoption, and the random variable ω_t, each of these variables is a potential state variable and enters into Ω_t.

14. In order to focus on other effects, we ignore heterogeneity in potential adopters' discount rates. The implications of such heterogeneity depend on whether actors with high discount rates tend to have high or low private values for the technology. The case with a positive correlation between discount rates and private values corresponds to Stokey (1979). The case with a negative correlation arises when adopting the technology provides a stream of benefits that potential adopters discount to a present value. The assumption of a common discount rate corresponds to a well-known aspect of the empirical methodology, in which the econometrician must assume a common discount rate because the discount rate is generally not well identified by the data (Magnac and Thesmar (2002) discuss the conditions under which the discount rate can be identified, and De Groote and Verboven (2019) estimate a homogeneous discount rate in an empirical model of solar installation in Europe).

15. The assumptions of a fixed terminal time T and of a fixed adoption target $\hat{Q}$ are not critical to the theoretical analysis. These assumptions affect the transversality conditions for the regulator's problem, but they do not affect the necessary conditions that are the focus of the analysis. Further, app. E.1 shows that the theoretical analysis is robust to giving the regulator a fixed budget instead of a fixed adoption target. Intuitively, if the budget constraint does not bind, then that

distribution of potential adopters' values but does not know any particular household's value. Because the regulator commits to the subsidy schedule and cannot offer different subsidies to different households in the same period, households do not face any strategic incentives to obscure their technology valuations.

The regulator dislikes spending money. Her distaste for spending money is $G(s_t[Q_{t+1} - Q_t]) > 0$, with $G(\cdot)$ strictly increasing and strictly convex. The convexity of $G(\cdot)$ may reflect political constraints, may reflect that the deadweight loss of taxation increases nonlinearly in revenue requirements, may reflect administrative costs of processing the applications submitted in a given period, or may reflect that each period's spending is subject to a budget. In our application to adoption of solar photovoltaics, the funds for the subsidy were collected from electricity bills in a rolling fashion that required subsidy spending to be smoothed over time.

The regulator also receives instantaneous benefit $B(Q_t) > 0$ from cumulative adoption, with $B(\cdot)$ weakly increasing and weakly concave. In our application to adoption of solar photovoltaics, the benefit function will capture the regulator's value for production of solar electricity. As $B'(\cdot)$ and $G''(\cdot)$ jointly go to zero, the regulator's problem becomes one of minimizing the present cost of subsidy spending, so that the efficient subsidy becomes the cost-effective subsidy and we are back to results familiar from the monopoly pricing literature (Stokey 1979; Landsberger and Meilijson 1985).[16]

When selecting the subsidy trajectory, the regulator has rational expectations about how the technology's cost will evolve and how households will respond to the offered subsidy, though the regulator does not know which precise sequence of shocks to technology and preferences will be realized. At time 0, the regulator chooses the subsidy trajectory $\{s_t\}_{t=0}^{T}$ to maximize

$$\sum_{t=0}^{T}(1 + r)^{-t}\mathbb{E}_0[B(Q_t) - G(s_t[Q_{t+1} - Q_t])],$$

for given discount rate $r > 0$, for given initial adoption $Q_0 \geq 0$, and subject to the constraint that expected terminal adoption $\mathbb{E}_0[Q_{T+1}]$ be at least $\hat{Q} > Q_0$.[17] Potential

setting is equivalent to altering the present setting to allow $\hat{Q}$ free, which would affect the transversality condition but not the other necessary conditions. If the budget constraint does bind, then the problems are effectively identical if we fix $\hat{Q}$ at the value that results from solving the problem with a budget constraint. The only adjustment to the channels analyzed below is to amplify the marginal cost of public funds by the shadow cost of the budget constraint.

16. Imposing $G''(\cdot) > 0$ ensures that standard (Mangasarian) sufficient conditions hold. Appendix E.2 analyzes a case with a linear cost of funds. It shows that the analysis is unchanged as long as $B'(\cdot)$ is sufficiently large relative to the marginal cost of funds: if $B'(\cdot)$ is small, then the regulator might wait until the last instant to incentivize adoption, but if $B'(\cdot)$ is sufficiently large, then the regulator does not want to wait so long.

17. Appendix E.3 extends the analysis to a regulator who chooses the subsidy to maximize welfare, which includes households' surplus from adopting the technology. The most important

adopters' decisions determine how the announced subsidy trajectory affects Q_t. Households expect the subsidy to drop to 0 after time T.

2. THEORETICAL ANALYSIS

We now theoretically analyze the subsidy trajectory that efficiently incentivizes households to adopt a new technology. The theoretical analysis relies on two specializations of the full setting described above, which together eliminate the need for expectation operators. First, we assume that technological progress is deterministic. We therefore drop ω_t from households' cost function, writing $C(t, Q_t)$. Second, we assume that preferences are fixed over time, so that we write v_i instead of v_{it}. Normalizing the measure of potential adopters to 1, the twice-differentiable cumulative distribution function $F(v_i) \in [0,1]$ gives the number of potential adopters who are willing to pay no more than v_i for the technology. Define $f(v_i) \geq 0$ as the density function $F'(v_i)$.

For analytic tractability, we conduct the theoretical analysis in continuous time, with households discounting at rate $\delta > 0$ and the regulator discounting at rate $r > 0$. All other definitions and notation extend in the natural way. We now have $Q_0 \in [0, 1)$ and $\hat{Q} \in (Q_0, 1]$, and we assume that the constraint $Q(T) \geq \hat{Q}$ binds. Note that $\dot{Q}(t)$ gives adoption at time t, where a dot indicates a derivative with respect to time.[18]

Begin by considering households' behavior. Each household i chooses the optimal time Ψ_i to adopt the technology, for given subsidy and cost trajectories:

$$\max_{\Psi_i} e^{-\delta \Psi_i}[v_i - C(\Psi_i, Q(\Psi_i)) + s(\Psi_i)].$$

The first-order necessary condition is[19]

$$\delta[v_i - C(\Psi_i, Q(\Psi_i)) + s(\Psi_i)] = \dot{s}(\Psi_i) - \dot{C}(\Psi_i, Q(\Psi_i)), \tag{2}$$

difference in the solution arises from the welfare-maximizing regulator's choice of $\hat{Q}$. In our numerical application, the calibrated social benefit of solar would lead a welfare-maximizing regulator to choose a much smaller $\hat{Q}$ than the one targeted by the actual regulator.

18. In this deterministic model, the solution does not depend on whether the regulator defines the subsidy as a function of t or of $Q(t)$: the regulator can map one variable into the other.

19. Define net costs as $z(t, Q(t)) \triangleq C(t, Q(t)) - s(t)$. The necessary condition is sufficient if $\ddot{z}(t) > \delta \dot{z}(t)$ at all t. Substituting from eq. (3), we find that, along an efficient subsidy trajectory, the necessary condition is sufficient if $\ddot{z}(t) > -\delta^2[Y(t) - z(t)]$ at all t. Differentiating eq. (3), we find that the necessary condition is sufficient along an efficient subsidy trajectory if $\dot{Y}(t) < 0$ at all t. We will see that $\dot{Y}(t) < 0$ at any time with strictly positive adoption. Therefore the necessary condition is sufficient along an efficient subsidy trajectory that incentivizes strictly positive adoption at every instant.

where $\dot{C}(t, Q(t))$ indicates the total derivative with respect to time. The left-hand side is the cost of waiting until the next instant: the household delays receiving the instantaneous payoff $v_i - C(t, Q(t)) + s(t)$. The right-hand side is the benefit of waiting: when costs net of the subsidy are decreasing (i.e., when $\dot{C}(t, Q(t)) - \dot{s}(t) < 0$), then the household can save money by adopting the technology later. The optimal time of adoption balances these costs and benefits. As potential adopters become perfectly patient ($\delta \to 0$), the cost of waiting disappears and they delay adoption until net costs reach their minimum. As potential adopters become perfectly impatient ($\delta \to \infty$), they adopt the technology as soon as their net benefit of adoption is positive.

Now consider how the regulator's choice of subsidy trajectory is constrained by the need to induce potential adopters to choose to stop waiting and adopt the technology. Define $Y(t)$ as the private value for which households are just indifferent to adopting or not. The number of households that have adopted the technology by t is $Q(t) = 1 - F(Y(t))$, which implies $\dot{Q}(t) = -f(Y(t))\dot{Y}(t)$. Clearly $\dot{Y}(t) < 0$ in every instant with strictly positive adoption, and we require the regulator to set $\dot{Y}(t) = 0$ whenever the regulator chooses to forgo adoption. Instead of selecting the subsidy at each instant, imagine that the regulator selects the quantity of adoption via $Y(t)$, with the subsidy determined by this choice and by households' equilibrium conditions. Rearranging equation (2), the subsidy must evolve as

$$\dot{s}(t) = \delta[Y(t) - C(t, Q(t)) + s(t)] + \dot{C}(t, Q(t)). \tag{3}$$

The regulator's targeted adoption level constrains both the level of the subsidy and also, for $\delta < \infty$, the change in the subsidy.

We assume that the regulator is able to commit at time 0 to a subsidy schedule. However, the regulator's time 0 choice of subsidy schedule will be dynamically inconsistent: the time 0 regulator commits to offering a given subsidy at time t in part to affect potential adopters at times $w < t$, but once time t arrives, those adoption decisions are in the past and are thus irrelevant to the time t choice of subsidy. The time t regulator has an incentive to offer a larger subsidy at time t because she no longer has to worry about time w households delaying adoption to claim that subsidy. Rather than modeling a dynamic game between the regulator and households, we follow a long tradition in the dynamic public finance literature of assuming commitment (e.g., Judd 1985; Chamley 1986; Chari and Kehoe 1999; Kocherlakota 2010). This assumption suits many cases of technology subsidies.[20]

We can now consider the regulator's problem. Writing $y(t)$ for $\dot{Y}(t)$, the regulator solves

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20. For instance, our empirical application will consider California's subsidies for rooftop photovoltaic (solar) systems. Observers seem to have taken for granted that the regulator would follow its announced subsidy schedule. Also see n. 11 above.

$$\max_{y(t),s_0} \int_0^T e^{-rt}[B(1 - F(Y(t))) - G(-s(t)f(Y(t))y(t))]\mathrm{d}t$$

$$\begin{aligned}
\text{s.t. } \dot{Y}(t) &= y(t) \\
\dot{s}(t) &= \delta[Y(t) - C(t, 1 - F(Y(t))) + s(t)] + \dot{C}(t, 1 - F(Y(t))) \\
y(t) &\leq 0 \\
Y(0) &= F^{-1}(1 - Q_0), Y(T) = F^{-1}(1 - \hat{Q}) \\
s(0) &= s_0, s(T) = C(T, \hat{Q}) - Y(T) + J(Y(T), C(T, \hat{Q})).
\end{aligned}$$

The term $J(v_i, C(T, \hat{Q}))$ is the present value to household i of having the option to adopt the technology at time T, once the subsidy disappears for good. This household adopts the technology at time T if and only if she has not adopted the technology at an earlier date and $v_i - C(T, \hat{Q}) + s(T) \geq J(v_i, C(T, \hat{Q}))$.

Appendix A shows that, at times t with strictly positive adoption (i.e., with $y(t) < 0$), the efficient subsidy must evolve as follows:[21]

$$\begin{aligned}
\dot{s}(t) = {} & [rs(t)G'f(Y(t)) - B'f(Y(t)) + G'\dot{Q}(t) - \dot{\mu}(t) + r\mu(t) \\
& - [s(t)]^2 G''f(Y(t))\ddot{Q}(t) + G'\dot{Q}(t)C_2(t, Q(t))f(Y(t))] \\
& [G'f(Y(t)) + s(t)f(Y(t))G''\dot{Q}(t)]^{-1},
\end{aligned} \tag{4}$$

where the costate variable $\mu(t) \geq 0$ measures the degree to which the regulator is constrained at each instant by private actors' equilibrium behavior and rational expectations (i.e., it measures the cost of keeping promises made to those who adopted the technology in past instants). At time 0, the costate variable $\mu(0) = 0$ because the regulator is not initially constrained by past promises in the first instant.[22] The denominator in (4) is positive, so whether the subsidy increases or decreases over time is determined by the terms in the numerator.

The first term in the numerator, $rs(t)G'f(Y(t)) > 0$, reflects an impatient regulator's desire to delay spending. In order for the regulator to be indifferent to small deviations in her policy trajectory, the social cost of spending must grow at the discount rate r.[23] We call this first force for an increasing subsidy a *Hotelling channel*, due to its

21. If $G''(\cdot) = 0$, then the regulator's objective is linear in the control $y(t)$. One might be concerned that the regulator would then implement a "bang-bang" solution with the subsidy jumping from 0 directly to $s(T)$ at the last possible instant. In fact, app. E.2 shows that the efficient subsidy can still obey eq. (4) because the regulator does not want to delay all adoption until time T when $B'(\cdot)$ is sufficiently large relative to the marginal cost of funds. Numerically, we find that using a linear cost of funds does not significantly change the results.

22. Formally, $\mu(0) = 0$ is the transversality condition corresponding to the choice of s_0.

23. Imagine that the regulator deviates by reducing $Y(t)$ by ϵ and increasing $Y(t + \Delta t)$ by ϵ. And assume for the moment that the regulator's marginal cost of funds is unity (the convex cost

similarity to the Hotelling (1931) analysis of exhaustible resource extraction. It favors a subsidy that increases over time.

Second, the $-B'f(Y(t)) < 0$ reflects that using a larger subsidy today provides benefits tomorrow by raising cumulative adoption.[24] This effect of valuing the total stock of adoption is familiar from Heal (1976) models of resource extraction, in which extraction costs increase in the cumulative quantity extracted. This *adoption benefit channel* favors a decreasing subsidy schedule because it captures the opportunity cost (in forgone social benefits from adoption) of delaying subsidy spending.

Third, the $G'\dot{Q}(t) \geq 0$ captures the regulator's desire to control total subsidy spending. Recall that $\dot{Q}(t)$ measures new adoption at time t. If the regulator offers a marginally greater subsidy to induce additional adoption at time t, then she must offer that marginally greater subsidy to all adopters, including those who would have adopted at a lower subsidy. But if the regulator waits to offer the marginally greater subsidy in the next instant, then she avoids paying the extra money to the $\dot{Q}(t)$ inframarginal adopters at time t. The more inframarginal adopters there are at time t, the stronger the incentive to wait to offer the higher subsidy. This *price discrimination channel* thus favors an increasing subsidy, with its strength depending on the marginal cost of public funds and on the distribution of households' private values for the technology.[25]

The next two terms in the numerator are $-\dot{\mu}(t) \leq 0$ and $r\mu(t) \geq 0$. As agents become myopic ($\delta \to \infty$), $\mu(t) \to 0$ and $\dot{\mu}(t) \to 0$. These promise-keeping terms thus arise only from agents' attention to the value of waiting to adopt the technology. The costate equation for $\mu(t)$ (derived in app. A) is

$$-\dot{\mu}(t) + r\mu(t) = -G'\dot{Q}(t) + \delta\mu(t).$$

These promise-keeping terms offset the price discrimination channel, leaving only $\delta\mu(t) \geq 0$. We call this net effect of forward-looking agents a *constrained price discrimination channel*. When discussing the price discrimination channel, we described the

of funds enters through other channels) and $C_2 = 0$. The regulator's savings today are $\epsilon\, s(t) f(Y(t))$. The regulator invests this money and earns interest at rate r before spending $\epsilon s(t + \Delta t) f(Y(t))$ to obtain the later adoption. For the regulator to be indifferent to this deviation, it must be true that $\epsilon s(t + \Delta t) f(Y(t)) - \epsilon s(t) f(Y(t)) = r\epsilon s(t) f(Y(t))\Delta t$. Dividing by Δt and taking the limit as Δt goes to zero, we have $\dot{s}(t) = rs(t)$, which matches the first term in (4) once we account for the denominator.

24. In n. 23, the cost of delaying adoption should include $B' f(Y(t))\, \Delta t$. The logic of the footnote would then imply that $\dot{s}(t) = rs(t) - B'$.

25. When the regulator's objective is to maximize welfare, app. E.3 shows that the price discrimination channel arises only if the regulator funds the subsidy through distortionary taxes. The price discrimination channel vanishes if the regulator instead costlessly administers a lump-sum tax.

inframarginal adopters as being all those agents who would have to be paid in time t if the regulator were to raise the time t subsidy but who would have adopted in time t even without the larger subsidy. However, when adopters are forward looking, the relevant set of inframarginal adopters for the time t subsidy actually includes all those who adopted at earlier times: when early adopters may wait for higher subsidies, raising the subsidy paid to time t adopters requires the regulator to also raise the subsidy paid to adopters in earlier instants.[26] If all early adopters were just as inframarginal as the time t adopters, then the regulator would completely lose its ability to price discriminate; however, because adopters are impatient ($\delta > 0$), the regulator need not raise early subsidies by a full dollar when raising the time t subsidy by a dollar. The larger is the discount rate δ, the greater is the regulator's ability to price discriminate in later periods. Importantly, the constrained price discrimination channel is approximately zero near the initial time. Adopters' anticipation of future subsidies therefore does eliminate price discrimination in early instants, which works to tilt the efficient subsidy trajectory downward over those early instants.[27]

The second line of equation (4) contains terms that are critical to the analysis of technical change. The $-[s(t)]^2G''f(Y(t))\ddot{Q}(t)$ captures the regulator's preference for smooth spending over time, driven by the convexity of the cost of public funds. The $\ddot{Q}(t)$ describes how instantaneous adoption changes as time advances. When instantaneous adoption is increasing over time ($\ddot{Q}(t) > 0$), this term favors a decreasing subsidy. Note that $\ddot{Q}(t) = -f(Y(t))\dot{y}(t) - f'(Y(t))[y(t)]^2$. First, if $\dot{y}(t) < 0$, then the measure of private values for which adoption is newly optimal is increasing over time. This case is especially plausible when technological progress, peer effects, or network effects make the value of installing solar increase over time. This greater adoption works to increase subsidy spending, which favors using a declining subsidy in order to smooth spending over time. Second, if $f'(Y(t)) < 0$, then the distribution of private values becomes thicker as more people find adoption to be optimal. For most new technologies, we would think of early adopters as being in the tail of the distribution, so more adopters are on the margin in later instants. In this case, subsidy spending again tends to increase over time, which favors using a declining subsidy schedule. Putting

26. Appendix A shows that $\mu(t) = \int_0^t e^{-(\delta-r)(t-i)}G'\dot{Q}(i)\mathrm{d}i$ and interprets this relationship.

27. The constrained price discrimination channel can also be interpreted in terms of information rents, as in the mechanism design literature. High types are then actors with a high v_i, who adopt before low types under truthful revelation. These high types may pretend to be a lower type by waiting for the larger subsidies offered at later times by a regulator attempting to intertemporally price discriminate. Incentive compatibility constrains intertemporal price discrimination. The fact that the constrained price discrimination channel vanishes at time 0 is another manifestation of the familiar result that there is "no distortion at the top," and the increase in the constrained price discrimination channel over time reflects that lower types can extract less information rent from a regulator attempting to price discriminate.

these pieces together, this *smooth spending channel* favors a decreasing subsidy schedule in the plausible case with $\dot{y}(t) \leq 0$ and $f'(Y(t)) \leq 0$ and vanishes as the marginal cost of public funds becomes constant.

Now consider how anticipated declines in cost affect the efficient subsidy schedule. These cost declines could arise because of technological improvements or could reflect a market-wide increase in the private value of the technology, potentially because of peer effects. First, more strongly declining costs can increase adoption at a given subsidy (especially when households are impatient) and thereby increase the number of inframarginal adopters. This effect amplifies the incentive to price discriminate by using an increasing subsidy schedule. Second, the smooth spending channel depends on both the first and second derivatives of the cost function, via $y(t)$ and $\dot{y}(t)$. Rapid cost declines exacerbate the effect of moving to a thicker part of the distribution of private values (assuming $f'(Y(t)) < 0$), which favors a decreasing subsidy schedule. And if costs are declining at an accelerating rate, then $\dot{y}(t)$ tends to be negative, again favoring a decreasing subsidy schedule. Third, declining costs tend to reduce the level of the subsidy by making it easier to obtain adoption in later instants. This effect weakens the Hotelling channel and thus favors a decreasing subsidy schedule. Combining these pieces, we see that declining costs can strengthen the price discrimination channel that favors an increasing subsidy schedule but otherwise work to make the efficient subsidy decrease over time. The net effect on the efficient subsidy schedule is an empirical question that depends on the relative intensity of these channels in any particular application.

The final term on the second line of equation (4) adjusts the efficient subsidy for the potential endogeneity of net costs, whether due to induced technical change, peer effects, or network effects. When technical change and preferences are purely exogenous, this term vanishes because $C_2(t, Q(t)) = 0$. However, this term is negative when increasing adoption reduces the private cost borne by later adopters or increases later adopters' preference for the technology, because then $C_2(t, Q(t)) < 0$. This *endogenous cost channel* favors a declining subsidy because using a higher subsidy in earlier instants now carries the additional benefit of reducing the private net cost of adoption (and thus reducing the required subsidy) in later instants. Endogenizing either technical change or preferences therefore favors stimulating adoption through a larger early subsidy and taking advantage of lowered costs through a smaller later subsidy.

3. EMPIRICAL SETTING AND DATA

The theoretical analysis shows that the efficient subsidy schedule for a durable technology can be sensitive to whether consumers are forward looking and to the distribution of private values in the population. In order to quantitatively evaluate the determinants of the efficient subsidy schedule in a high-stakes setting, we focus on households' decisions about whether to install solar systems under the California Solar Initiative (CSI). We then pair our preference estimates with a calibrated regulator's objective to evaluate the efficient subsidy policy.

The CSI offered a state subsidy for residential solar installations from 2007 to 2014, administered by the California Public Utilities Commission. This program spent \$2.2 billion to obtain 1,940 MW of solar installations in both residential and commercial properties. We focus on the residential component of the CSI, in which each of the three major California electric utilities (Pacific Gas and Electric [PG&E] San Diego Gas and Electric [SDG&E], and Southern California Edison [SCE]) had subsidies that started at \$2.50/W installed and declined over time to \$0.[28]

We use four data sources to estimate households' preferences for solar during the CSI subsidy period: (1) CSI data on installations and system costs, (2) electricity prices from each of the major utilities, (3) local demographics from the American Community Survey (ACS), and (4) solar radiation data from the National Renewable Energy Laboratory. We detail each of these sources in turn.

The CSI provides data on all applications for residential solar subsidies under the program. These data include the application date, the household's zip code and utility, the subsidy received, and an extensive set of solar system characteristics, including system size, manufacturer, installer, and cost. Figure 1*A* shows the evolution of subsidies and pre-subsidy average system costs from July 2007 through May 2012 (when our estimation window ends).[29] The general patterns are similar across the utilities. The cost of an average system does not change much in the initial periods when silicon costs are increasing and then declines over the majority of our estimation time frame as technology advances and silicon costs fall. CSI subsidies decrease in a step-wise pattern, with the steps occurring at different times in each utility.[30]

Electricity price data come from each utility's rate statements. Electricity prices in California are based on a household's usage relative to a baseline. During this time period, the marginal price of electricity is low up to the baseline and then increases steeply in monthly usage. Because solar was most cost-effective for households with high monthly electricity usage, we follow Hughes and Podolefsky (2015) and use the average

28. Subsidies in the CSI were determined based on cumulative adoption thresholds within each utility rather than precise dates. In order to avoid substantial complications in our dynamic estimation, we assume that households had rational expectations over the pace of adoptions in their utility district, which allowed them to know the dates at which the subsidy level would change rather than just the cumulative adoption quantity. We discuss this assumption in more detail in app. B.2.

29. The average system costs are based on the average cost per watt in each month for each utility multiplied by the median system size over the full period for all utilities of 5.4 kilowatts. There was also a 30% federal tax subsidy available for residential solar installation during this period that is not reflected in fig. 1.

30. Figure B1 (figs. B1, B2, C3, D4, D5 are available online) shows how installation counts in each utility varied over time.

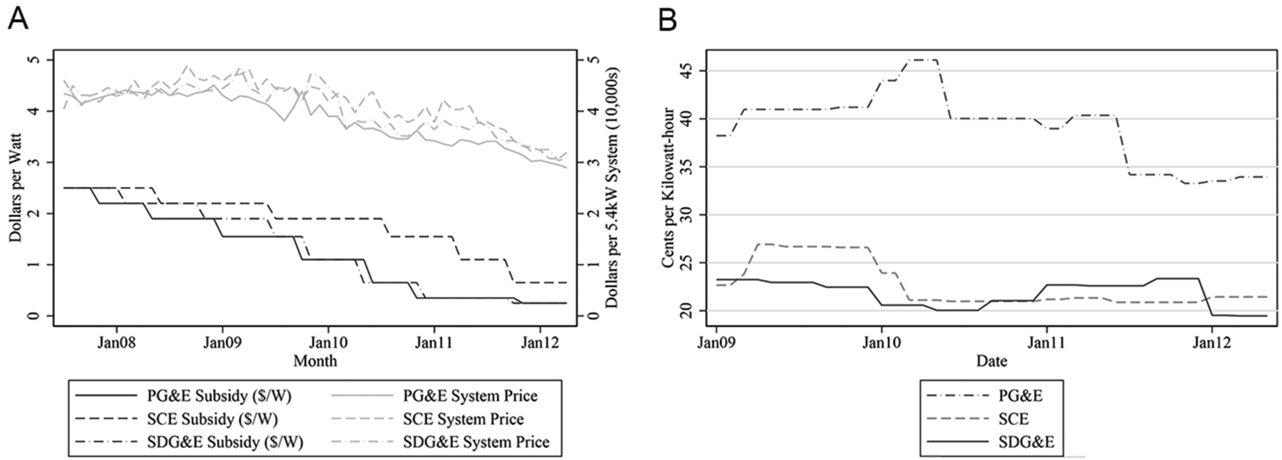

Figure 1. The evolution of the subsidy and average pre-subsidy system cost (*A*) and electricity prices (*B*) by utility over time. In panel *A*, the dark lower lines are the subsidy levels in dollars per watt (*left axis*) for each utility. The lighter upper lines show the average system prices per 5.4 kW system in tens of thousands of dollars (*right axis*) by utility. Electricity prices are the average marginal electricity price per kilowatt-hour for usage over 200% of baseline. Data details are in app. B.2. Color version available as an online enhancement.

of the marginal price per kilowatt-hour for usage over 200% of baseline.[31] Figure 1*B* shows the evolution of electricity prices in each utility over our estimation window. Prices for usage over 200% of baseline are substantially higher in PG&E than in the other two utilities, although this difference decreases somewhat over time.

We use demographic data at the block group level from the American Community Survey to allow preferences for solar to vary with consumer demographics. We focus on the demographics of owner-occupied households in each zip code under the assumption that all residential households that install solar systems are owner-occupied. Given the short panel of solar installation data, we do not allow demographics to vary over time. We supplement the demographic data with information from the California Secretary of State's office on Barack Obama's share of votes in the 2012 presidential election at the precinct level. Finally, in order to account for geographic variation in solar generation potential across California, we construct the median solar direct normal irradiation at the zip code level from National Renewable Energy Laboratory data.

Table 1 summarizes the household data. Column 1 presents the average demographics for owner-occupied housing in the three California utilities in our sample. Column 2 presents average demographics for zip codes with households that install solar, weighted by the number of installations in each zip code. We see that households that install solar live, on average, in zip codes with slightly higher income and more expensive homes than owner-occupied households overall. Households that installed solar systems also live in zip codes with greater median solar direct normal irradiance than households overall, which means that they are generally in areas with greater solar electricity generation potential. Households that install solar systems live in precincts that voted for Barack Obama at slightly lower rates than owner-occupied households overall, perhaps reflecting their higher income and home values or perhaps reflecting how political preferences are correlated with solar radiation in California. Finally, households that install solar live in zip codes with approximately the same education, household size, and number of mortgages as owner-occupied households overall.[32]

We limit our analysis to households in California zip codes that fall within one (and only one) of the three major utilities in order to have accurate information on the subsidies faced by households in each period. We begin our estimation window when the cap on the federal subsidy was removed in January 2009 because it was unclear whether

31. Appendix B.2 provides details on exactly how electricity rates are constructed. During this period, California's net metering policy ensured that electricity generated from rooftop solar was valued at the retail price of electricity (see Borenstein 2017). Our analysis of the dynamics of the efficient up-front subsidy could be applied to production subsidies such as a net metering policy if we think of the subsidy as the present value of future production subsidies and assume that households are grandfathered into any changes in the policy. See Burr (2014) and De Groote and Verboven (2019) for comparisons of up-front and production subsidies.

32. Appendix B.2 provides additional details about how we handle potential complications in the data.

Table 1. Demographic Summary Statistics

	Average Owner-Occupied Household Demographics	
	Overall (1)	Install Solar (2)
Household income ($)	88,664	95,929
Home value ($)	476,483	512,723
Median solar radiation (kWh/m^2/day)	5.86	6.04
Democratic vote share	.59	.55
Years of schooling	13.6	13.8
Number of mortgages (0/1/2+)	.94	.96
Number of household members	2.6	2.6
Count	4,104,377	49,765

Note. Data are at the block group level except for installations and solar radiation, which are at the zip code level, and Democratic vote share, which is at the precinct level. Owner-occupied households are assumed to have the average demographics of their zip code, weighted across block groups. Solar radiation is direct normal irradiance.

households would have anticipated this federal policy change ahead of time. We end our estimation window before the solar subsidy expires in the first utility (PG&E) because we do not have information on solar system prices after subsidy funds expire. These restrictions leave us with an estimation window of January 2009 through March 2012.

4. ECONOMETRICS

We estimate a dynamic model of residential solar system demand in order to understand how California households value residential solar and how different subsidy trajectories may change their installation decisions. It is important to use a dynamic model of residential solar adoption because a static model would misestimate the benefits to households of adopting: some households that value solar above the current system cost will choose not to install now as they wait for technology to advance and for costs to drop (see Aguirregabiria and Nevo 2013). Correctly accounting for the value of waiting for lower prices is critical to understanding the trade-offs regulators face in structuring solar subsidies. Our demand estimation approach is consistent with previous literature that has modeled residential solar installation decisions as a dynamic decision (e.g., Burr 2014; Reddix 2014; Feger et al. 2017; De Groote and Verboven 2019). In appendix B.1, we provide reduced-form evidence that households are indeed forward looking when deciding whether to install solar systems.

4.1. Estimation Framework

Our empirical estimation parameterizes the household technology demand model presented in section 1, without the simplifications made in the theoretical analysis. Households are assumed to be forward looking and to value solar adoption in period t at

$v_{it} = h_{it} + \varepsilon_{i1t}$, which should be thought of as the expected present discounted value of the stream of benefits from installing residential solar plus the up-front net benefit from installing solar. The up-front net benefit from installing solar is the current social, aesthetic, or reputational benefits to the household net of any nonmonetary fixed costs of researching solar systems or providers and the disruption of the solar installation process. For many households, the up-front nonmonetary cost of installing solar is likely to be large, which would make the up-front net benefit negative.

We parameterize the model in four key ways. First, we assume that $\vec{\varepsilon}_{it}$ is distributed i.i.d. extreme value type I and that $h_{it} = X_{it}'\gamma$, where X_{it} includes observable characteristics of the household and the technology. Allowing for heterogeneity in preferences based on observable differences across households allows us to understand the shape of the full distribution of solar system valuations, which we have shown is an important input to the regulator's efficient subsidy.

Second, we introduce a parameter α_i that measures the disutility of spending money, which may vary by household, and we include the federal subsidy on solar that reduces the technology's cost by a fixed fraction ϕ. The average system cost (net of subsidies) in a given period changes household utility by $\alpha_i[(1-\phi)C(t, Q_t, \omega_{it}) - s_{it}]$, where α_i is expected to be negative and costs and subsidies are allowed to vary by electric utility.[33] We model households as responding to the system cost of an average size system, with heterogeneity in the α_i and h_{it} parameters capturing the fact that some households purchase systems with different sizes.[34]

Third, we specify how households form beliefs about the evolution of the states in Ω. We assume that technology costs evolve according to a first-order Markov process and that households understand that process. We also assume that technology costs evolve exogenously rather than depending upon the installed base of the technology. As a result, we have $C_{i(t+1)} = \kappa_0 + \kappa_1 C_{it} + \omega_{it}$, where ω_{it} is normally distributed and where we collapse the remaining cost function arguments into the subscript on C.[35] We assume that households know the full time path of subsidies and household preference shifters (such as electricity prices) from the beginning of the estimation window and form rational expectations over the evolution of system costs.

33. This formulation assumes that the pass-through for the CSI subsidy is 100%. This assumption is consistent with recent empirical evidence in Pless and van Benthem (2019). While perfect competition would generate 100% pass-through, it is not necessary. Borenstein (2017) discusses the difficulty of estimating pass-through in this market.

34. In our analysis of the impact of alternative subsidy paths on adoption, this assumption will mean that while we may overestimate the number of households of a certain type that respond to the subsidy by changing when they adopt solar, we are correctly estimating the total kilowatts of solar that are installed at different time periods.

35. The parameters κ_0 and κ_1 are estimated from the observed system cost evolution: $C_{i,t+1} = 6.468 \times 10^{-4} + 0.9925 \times C_{it} + \omega_{it}$, where the standard deviation of ω_{it} is 0.1611.

Finally, many owner-occupied households do not actually face the choice of installing residential solar. This may be because they live in a condominium or other multi-family dwelling and therefore do not have the right to install solar on their roof, or it may be because their roof's slope, orientation, and shading are not conducive to solar. We therefore also include a variable ζ_i that is the probability that a household is able to consider residential solar. This variable is fixed over time and can be thought of as a permanent, random shock to the household's preference for residential solar.[36]

We estimate the model via maximum likelihood. The likelihood function in each period is

$$L_t = \Pi_{i=1}^{N_t}\left\{\left[\zeta_i\left(\frac{\exp(X_{it}'\gamma + \alpha_i\tilde{C}_{it})}{\exp(X_{it}'\gamma + \alpha_i\tilde{C}_{it}) + \exp(\beta\,\mathbb{E}[V(\Omega_{t+1}|\Omega_t)])}\right)\right]^{1\{i \text{ adopts in } t\}}\right.$$
$$\left.*\left[(1-\zeta_i) + \zeta_i\left(\frac{\exp(\beta\,\mathbb{E}[V(\Omega_{t+1}|\Omega_t)])}{\exp(X_{it}'\gamma + \alpha_i\tilde{C}_{it}) + \exp(\beta\,\mathbb{E}[V(\Omega_{t+1}|\Omega_t)])}\right)\right]^{1\{i \text{ does not adopt in } t\}}\right\}, \tag{5}$$

where $\tilde{C}_{it} \triangleq (1-\phi)C_{it} - s_{it}$ is the net-of-subsidy cost of installing solar and N_t is the number of households that have not yet installed solar at the start of period t. In this formulation, the probability of adopting solar is equal to the probability ζ_i of considering solar times the probability of adopting solar conditional on considering it. The probability of not adopting solar is equal to the probability of not considering solar plus the product of the probability of considering solar and the probability of not adopting solar conditional on considering it. When we estimate a model assuming that the probability of considering solar is the same across households, the point estimate is 0.0660, but the variation in the data is not sufficient to pin down a precise estimate. We therefore estimate our remaining parameters assuming that 6.6% of the households that have not yet installed solar at the start of our time frame have $\zeta_i = 1$ and that ζ_i is independent of other household characteristics. We conduct extensive sensitivity checks of this assumption in appendix B.3. Neither the estimation results nor the conclusions of our simulations are fundamentally affected by the assumed percentage of households that consider adopting solar.

At each step of the likelihood maximization, we obtain the value function (1) in two steps: we first solve for the value function that holds upon the end of the subsidy program by solving for the fixed point of (1) with all current and future CSI subsidies fixed at zero, and we then solve for the value function in each period during the CSI by stepping backward from this solution. Households make an installation decision every month, using a monthly discount factor of 0.99 (for an annual discount rate of approximately 12%, which is roughly consistent with Busse et al. [2013] and De Groote and

36. We discuss the role of the serial correlation that ζ_i introduces into the household's preference shocks in app. B.3.

Verboven [2019]).[37] Standard errors are calculated as the square root of the inverse of the outer product of the Jacobian.

4.2. Identification

The CSI provides data on the applications to install solar, which includes information on the system's cost and the household's zip code but not the household's demographics. In order to estimate our model, we organize our data so that we have a count of the number of adopters and nonadopters in each period for each demographic bin in each utility.[38] To do this, we assume that solar adoptions within a zip code are randomly distributed across demographic bins within each block group and then aggregate the total number of households that adopt or do not adopt each period within each demographic bin in each utility.[39] This approach is similar to Nevo (2001) and Berry et al. (2004). There are over 2,500 zip codes in California, so identification of the demographic preference coefficients comes from the fact that, for instance, zip codes with high home prices have higher rates of solar installation conditional on solar costs than do zip codes with low home prices.

Identification of the cost parameters and of the demographic differences in the preference for solar systems and for spending should be thought of somewhat differently. Cost changes at the utility level are coming largely from changes in subsidies and changes in panel costs via technological advancement, input costs, and exchange rates. This means that unobserved shocks to local adoption are likely to be uncorrelated with average utility-level solar system costs.[40] We therefore argue that we are estimating the causal effect of changes in system costs on adoption.[41] However, we do not

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37. Estimation and simulation results are fundamentally unchanged with alternative discount rate assumptions (see app. B.3).

38. We divide solar radiation into quintiles, home values into four bins (less than \$200,000, \$200,000–\$500,000, \$500,000–\$1 million, and greater than \$1 million), and education into three bins (high school or less, more than high school to college completion, more than college).

39. Unfortunately, the joint distribution of demographics is not available at the zip code level in the ACS. To capture some of the correlation between demographic characteristics, we assume that adopters are drawn from the unconditional distribution of demographic characteristics in each block group within a zip code. Thus, if one block group has, on average, higher income and education while another block group has, on average, lower income and education, this tendency for income and education to be correlated will be captured in our simulations even though we do not know the actual covariance between income and education within a block group.

40. If there is imperfect competition among local solar installers, then local system costs could be correlated with local demand over the full period. We mitigate this concern by using monthly average costs by utility.

41. One might be concerned about the identification of the system cost coefficient if upcoming declines in the subsidy increase current demand for solar systems and thereby increase current installation costs. There are two reasons why this concern may not be severe. First, what mattered for whether a household received a subsidy was the date that the household applied for

claim that our estimates of the relationship between household demographics and preferences are causal. For example, while we are estimating how changes in the cost of a solar system will affect adoption and how this effect will vary over households with different home values, our estimates should not be interpreted as suggesting how a change in housing values will affect solar installation rates. This is because households in zip codes with high home values will differ from households in zip codes with low home values in unobservable ways that we are not capturing. We need causal estimates only for the effect of system cost on adoption because we will study policies that change net-of-subsidy costs, not demographics. We include demographic characteristics in order to better understand the density of consumer preferences, regardless of whether the shape of that density is being determined by observed or unobserved demographics.

Finally, we include a quadratic time trend in our estimation to allow for the fact that solar system quality was probably increasing over this time period. It is possible that this time trend also captures changing preferences for solar, such as would come from peer effects (Bollinger and Gillingham 2012).

4.3. Preference Estimates

The dynamic empirical model generates estimates of households' valuation of residential solar systems that we will use to quantitatively evaluate the efficient subsidy trajectory. Table 2 presents the estimated coefficients, including the preference for installing a solar system of the median size and the preference for system costs. Both the preference for solar and the disutility of spending vary by demographic group. The average household that considers installing solar has a negative valuation of solar, even after controlling for the fact that most households do not consider installing solar systems. This result is intuitive because the decision to adopt solar comes with substantial nonmonetary costs of researching whether solar is a good option for the household, of finding an installer to evaluate the home, of understanding whether financing is available to help with the up-front cost of solar, and of going through the installation process. Many households will likely perceive this cost of investigating solar to be substantial enough that they would require a considerable up-front payment to even evaluate whether solar is a reasonable option for them.

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the subsidy rather than the installation date. The household (or the installer) could then delay installing solar until the backlog of pending installations had subsided. In our data, we observe average delays between subsidy application and completed installation of approximately four months, with some delays lasting well over a year. These delays suggest an ability of installers to smooth demand spikes. Second, Pless and van Benthem (2019) find nearly 100% pass-through of subsidies for systems purchased by homeowners. If substantial system cost increases were occurring before subsidy changes, then their estimate of pass-through should have been substantially smaller than 100%.

Table 2. Dynamic Demand Estimates

	Estimate	SE
Preference for solar:		
Constant	−10.6419***	(.5305)
Median radiation (kWh/m^2/day/10)	4.7961***	(.1166)
Electricity price ($ per kWh)	4.0510***	(.2631)
log(home value ($ millions))	.7711***	(.1564)
Years of schooling	.0986***	(.0331)
SCE	.2885***	(.0476)
SDG&E	1.2944***	(.0606)
Time trend	.1247***	(.0027)
Time trend^2	−.0021***	(.0001)
Preference for solar costs:		
Cost ($10,000s)	−.5175***	(.2416)
Cost ($10,000s) × log(home value ($ millions))	−.1105**	(.0732)
Cost ($10,000s) × years of schooling	−.0300*	(.0154)
Log-likelihood	−268,399	
Months	41	
Percentage who consider solar	6.6	

Note. Results of dynamic discrete choice estimation on data from Southern California Edison (SCE), San Diego Gas and Electric (SDG&E), and Pacific Gas and Electric (PG&E, the omitted utility in the fixed effects). Standard errors in parentheses.

* $p < .1$.
** $p < .05$.
*** $p < .01$.

The benefit of installing solar is strongly increasing in the solar radiation in the household's zip code, likely because the quantity of radiation directly determines the quantity of electricity generated and thus the electricity savings from installing solar. Preferences for solar are also strongly increasing in the electricity price faced by households, which reflects the fact that solar generation directly offsets electricity expenses under net metering policies (see Borenstein 2017). Households with higher home values have a higher value for solar, likely because these homes have more potential roof space for solar panels and have better access to financing for solar panels. More educated households also have a higher value for solar, perhaps reflecting differences in the cost of collecting information about the costs and benefits of solar. The magnitudes of the effects of radiation and electricity prices on preferences are substantially larger than those of home values and education: the difference in the preference for solar between the highest and lowest radiation bins is comparable to the difference in the preference for solar between the highest and lowest electricity prices in the data, whereas the difference in preference between the highest and lowest home value and education bins is approximately half that size.[42] We take this result as strong evidence that the economic viability of solar in terms of generating electricity for offsetting expensive electric bills is a more important determinant of preferences for solar adoption than are other differences between demographic groups.

We also find that preferences for solar are significantly different across utilities. In particular, households in the SCE utility district have a slightly higher preference for solar than in the PG&E utility district (the omitted category). Households in the SDG&E utility district have a substantially higher preference for solar. This may be because of the better alignment of wealthy households in high-radiation areas in the two southern utility districts relative to PG&E, where the wealthiest households are concentrated in the relatively foggy Bay Area.

Importantly, we also find that preferences for solar are increasing over time at a decreasing rate. In our baseline simulation results, we interpret this time trend as capturing unobservable changes in system quality, as would be expected of a new technology. However, this trend could also arise from changing consumer preferences over time, for instance, if increased information about solar panels increases consumers' willingness to pay. We eliminate this trend in counterfactual simulations that hold technology constant at its initial level. We also quantitatively assess the implications of attributing either all or part of the time trend to peer effects.

We find that households get disutility from the net-of-subsidy cost of installing solar and that a household's cost sensitivity increases with both home value and schooling. This somewhat counterintuitive result likely arises for two reasons. First, we are modeling the households' sensitivity to the total cost of an average-sized solar system, and households in more expensive homes or with more education may be installing larger systems and therefore facing a larger total cost of installing solar (and a larger benefit of per-kilowatt subsidies). Second, households with more education may be more informed about solar subsidy price changes and therefore better able to time their purchases in response to price changes, making them effectively more price sensitive. The effect of education on price sensitivity is similar to the effect of home value, with the highest value group increasing price sensitivity by approximately one-third relative to

42. The highest radiation zip codes receive 0.7240 tenths of a kilowatt-hour (kWh) per square meter per day of radiation whereas the lowest radiation zip codes only receive 0.5012. Therefore, the difference in preference for solar between these zip codes for otherwise identical households is $4.7961 \cdot (0.7240 - 0.5012) = 1.0686$. The highest electricity price in the data is 0.4613 $/kWh and the lowest is 0.1927 $/kWh. Therefore, the difference in preference for solar between these zip codes for otherwise identical households is $4.0510 \cdot (0.4613 - 0.1927) = 1.0881$. The difference in preference for solar between otherwise identical households with the highest and lowest home values and education in our data is $0.7711 \cdot (\log(1) - \log(0.2)) = 0.5390$ and $0.0986 \cdot 6 = 0.5916$, respectively.

the lowest value group.[43] Overall, our model suggests that a 10% increase in the first period's subsidy leads to a 0.5% increase in total installations over the life of the subsidy, whereas a 10% increase in the subsidy in all periods leads to a 4.2% increase in installations over the life of the subsidy. This overall elasticity is in line with Pless and van Benthem (2019), who find price elasticities between −0.42 and −0.85 in California, and with Gillingham and Tsvetanov (2019), who find a price elasticity of −0.65 in Connecticut.

We tested models with other combinations of demographics. Log home value has a larger and more statistically significant effect on preferences than log income, and heterogeneity in preferences based on income is very small and statistically insignificant when home values are already included. Solar radiation and electricity prices do not have a large or statistically significant effect on price sensitivity, which is reasonable because radiation and electricity prices both increase the long-run returns to a solar system but have no impact on the up-front cost of the system. Whether a household voted Democratic, the number of mortgages on the home, and the number of household members do not statistically significantly impact either households' preferences for solar or their sensitivity to system cost once we control for the other demographics. Appendix B.3 presents additional sensitivity checks of the model specification.

Before moving on to our simulations of the efficient subsidy for rooftop solar, it is helpful to compare our estimates to prior work on the CSI. Hughes and Podolefsky (2015) use a reduced-form, static analysis on a slightly longer estimation window to estimate the impact of CSI subsidies on solar system adoption. They find that solar installation in California would have been 53% lower in the absence of subsidies. Using our estimates, we find that solar installation would have been 60% lower in the absence of subsidies. The fact that Hughes and Podolefsky (2015) reach a very similar conclusion despite using a different methodology with a different sample suggests that our model is in line with the literature's understanding of the aggregate effects of the CSI subsidy.

5. RESULTS: THE EFFICIENT SUBSIDY FOR ROOFTOP SOLAR

We now use our structural estimates of household values for solar to simulate the efficient subsidy trajectory. The analysis in section 2 disentangled the forces that could lead the subsidy to increase or decrease over time. We investigate which forces dominate in the case of the CSI.

We calibrate the regulator's benefit to the social value of solar energy (including emission displacement) from Baker et al. (2013), with the concavity of the regulator's benefit reflecting how the intermittent nature of solar energy reduces its marginal value

43. For otherwise identical households, the difference in price sensitivity between the highest and lowest education groups is $-0.0300 \cdot 6 = -0.1800$, whereas the difference for the highest and lowest home value groups is $-0.1105 \cdot (\log(1) - \log(0.2)) = -0.1778$.

once there is a lot of solar on the electric grid (from Gowrisankaran et al. 2016). We require the regulator to achieve a target of 0.68% adoption in 41 months, which is consistent with the actual policy. Appendix C details the calibration and solution method. It also shows that results are qualitatively unchanged for an alternative target of 1.5% adoption.

In order to understand why a regulator might choose a particular subsidy trajectory, we focus on two key drivers of the efficient subsidy schedule: whether consumers are forward looking and whether technology is improving at the level observed in the data or held constant at its initial level. Figure 2 plots the efficient subsidy (fig. 2*A*) and expected monthly subsidy spending (fig. 2*B*) for the different combinations of assumptions about household foresight and technical change. Table 3 reports the present value of subsidy spending and the initial and terminal subsidy. It also reports the expected present discounted consumer surplus obtained by households in the absence of any subsidy and under the efficient subsidy.[44] Figure 3 depicts monthly adoption along the efficient subsidy trajectory for forward-looking (solid) and myopic (dotted) households as well as adoption by forward-looking households when they are offered the subsidy that would be efficient for myopic households (dashed).

The first main result is that both the subsidy level and total expected spending are substantially greater when technology is fixed rather than improving over time. If technology is fixed, then there are only two things that could convince initially reluctant consumers to adopt the technology: either the regulator offers them a larger subsidy or they happen to receive a set of stochastic draws that makes adoption especially attractive in some future period.[45] The second effect alone is not strong enough to achieve the targeted level of adoption in expectation. When technology is progressing, two forces work to reduce the regulator's spending. First, more and more consumers would adopt the technology even if the subsidy and preferences were fixed over time. The regulator can therefore use a smaller subsidy to achieve a given level of adoption in each period. Second, the regulator changes the timing of adoption along the efficient trajectory so as to substitute technological progress for subsidy spending. Comparing the left and right panels of figure 3, we see that introducing technological progress leads the regulator to delay adoption until later periods, when she does not need as high a subsidy to obtain adoption.

The second main result is somewhat less intuitive: it is more expensive to obtain adoption from forward-looking households than it is to obtain adoption from myopic households, especially when technology is improving. This is because forward-looking households account for future changes in the subsidy and in technology and for the

44. Appendix C.2 explains how we calculate consumer surplus for forward-looking and myopic households.

45. For instance, the household undertakes a home renovation project that reduces the disruption from installing solar.

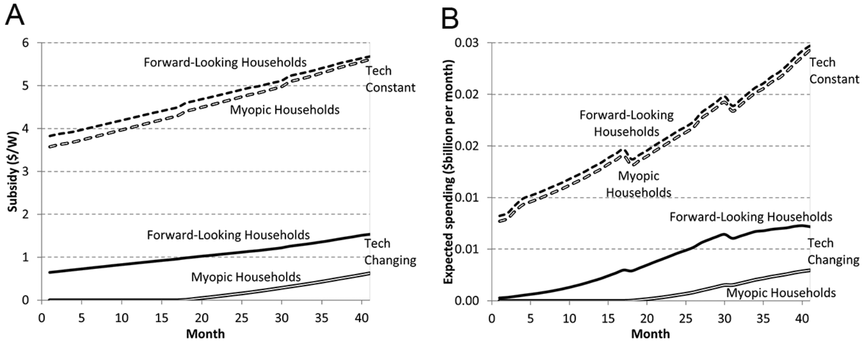

Figure 2. The efficient subsidy (*A*) and expected monthly spending (*B*) over time when households are forward looking (*solid*) and myopic (*hollow*). Connected lines allow for exogenous technical change at the level observed in the data, and dashed lines hold technology constant over time at its original level in the data. The jumps in spending correspond to the jumps in PG&E electricity prices seen in fig. 1.

possibility of future preference shocks. Today's subsidy must compensate forward-looking households not just for losses from installing solar but also for forsaking the option to adopt solar in some later period. When technology is fixed, households' foresight increases the regulator's spending by $19 million (4%). The effect of foresight is even stronger in the presence of technological change because households' option

Table 3. The Present Value of Spending, Initial and Terminal Subsidies, and Consumer Surplus along the Efficient Subsidy Trajectory, along with the Consumer Surplus Obtained in the Absence of Subsidies

	Myopic		Forward Looking	
	Technology Constant	Technology Improving	Technology Constant	Technology Improving
Present value of spending ($ million)	495	24	514	120
Present value of spending ($/W)	3.7	.2	3.8	.9
Initial subsidy ($/W)	3.6	.0	3.8	.6
Terminal subsidy ($/W)	5.6	.6	5.7	1.5
Consumer surplus without any subsidy ($ million)	26	176	84	918
Consumer surplus with efficient subsidy ($ million)	202	194	304	1,013

Note. Results with technology increasing assume that technology improves at the rate at which prices decline in the data. Forward-looking consumers are assumed to discount the future at 1% per month.

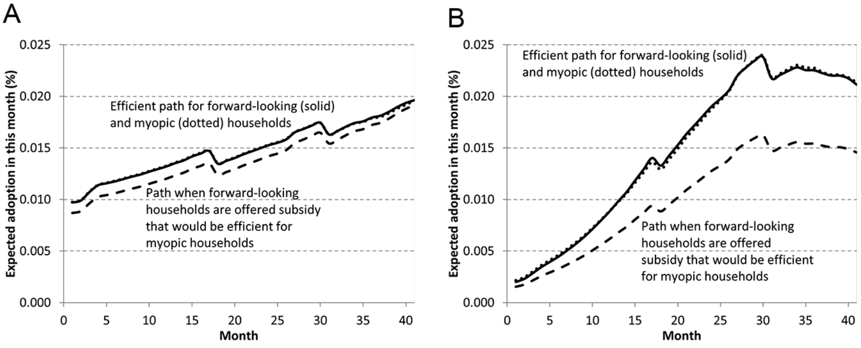

Figure 3. Expected adoption over time along the efficient subsidy schedule for forward-looking households (*solid*), along the efficient subsidy for myopic households (*dotted*), and for forward-looking households that are offered the subsidy that would be efficient for myopic households (*dashed*). *A*, Technology constant. *B*, Technology improving. The jumps in adoption correspond to the jumps in PG&E electricity prices seen in fig. 1.

to adopt in a later period becomes especially valuable: when technology is improving, households' foresight increases the regulator's spending by \$96 million (397%).[46]

However, households' foresight is good for households: the regulator's spending increases because households capture more surplus when they are forward looking. As we will see below, households' foresight constrains the regulator's ability to intertemporally price discriminate and thereby avoid "oversubsidizing" high-value households in early periods. As a result, the subsidy program increases myopic households' surplus by only \$175 million (\$18 million) when technology is constant (improving) but increases forward-looking households' surplus by \$219 million (\$95 million). In the absence of a subsidy, technological change increases forward-looking households' surplus by \$833 million, but technological change increases myopic households' surplus by only \$149 million because they do not optimize the timing of their adoption. With the efficient subsidy, the contrast is even starker: myopic households actually lose nearly \$8 million in surplus under technological change, whereas forward-looking households gain over \$700 million.[47] This difference arises because, when households are myopic,

46. The smaller option value in the case of constant technology also explains why myopia affects the subsidy trajectory in fig. 2 by less when technology is constant.

47. Comparisons of consumer surplus between myopic and forward-looking households must be undertaken with caution since the calculation is somewhat different for the two consumer types. Clearly, forward-looking consumers' ability to time adoption should weakly increase their welfare relative to a situation where they were forced to adopt solar in the first moment that their current benefits exceed their current costs. That is close to, but not exactly, the calculation that is presented here. See app. C.2 for details.

the forward-looking regulator can optimize the subsidy schedule to increase adoption in later periods when costs have fallen (see fig. 3) and can thereby capture more of the benefits of technological change. The delay in adoption reduces the present value of consumer surplus for myopic households below what it was with constant technology. In contrast, forward-looking households' awareness of future subsidies and technological improvements forces the regulator to share the cost reductions enabled by technological change.

We now consider the slopes of the efficient subsidy trajectories in figure 2 in more detail. Critically, we do not need to speculate about why some subsidy trajectories increase strongly and some are flatter. Instead, we use the theoretical analysis from section 2 to disentangle the multiple forces that determine whether the efficient subsidy increases or decreases over time.[48]

In figure 4, the thick bold line gives the instantaneous change in the subsidy ($\dot{s}(t)$). The other lines are the components of that instantaneous change identified in the theoretical analysis, so that their vertical sum also equals $\dot{s}(t)$. When households are myopic and technology is constant (fig. 4*A*), the price discrimination channel is the most important channel over most of the policy horizon. By starting with a relatively small subsidy and raising it over time, the regulator avoids paying a large subsidy to households that would adopt even for a smaller subsidy. In the full model, the regulator reduces spending by 3.4% by using an increasing subsidy instead of the unique constant subsidy that achieves the adoption target. However, when households are forward looking (fig. 4*B*), their expectations and ability to time adoption constrain the regulator's ability to intertemporally price discriminate. The constrained price discrimination channel begins at zero and increases only slowly. The efficient subsidy therefore increases more slowly for forward-looking households.[49] In the full model, the efficient subsidy now reduces spending by only 2.9% relative to a constant subsidy.

48. The only approximations are that we impose the theoretical setting's restrictions that preferences are fixed over time and that technology evolves deterministically. We also fix electricity prices at their initial levels. Figure C3 plots the efficient subsidy and adoption trajectories under these restrictions. The efficient subsidy trajectories are qualitatively similar to the cases in fig. 2. The main differences are that these restrictions increase the level of the subsidy and that they change the subsidy trajectory in the case with forward-looking households and technological progress so that the subsidy's start is delayed and the subsidy declines over an initial interval once it does begin. Appendix C.3 explains these differences in more detail, emphasizing how they arise from eliminating stochasticity in households' preferences.

49. Using an increasing subsidy does not eliminate early adoption when households are forward looking and technology is constant because households that are not perfectly patient will adopt the technology as long as the subsidy is not increasing too fast. The more patient that households are, the less freedom the regulator has to use an increasing subsidy.

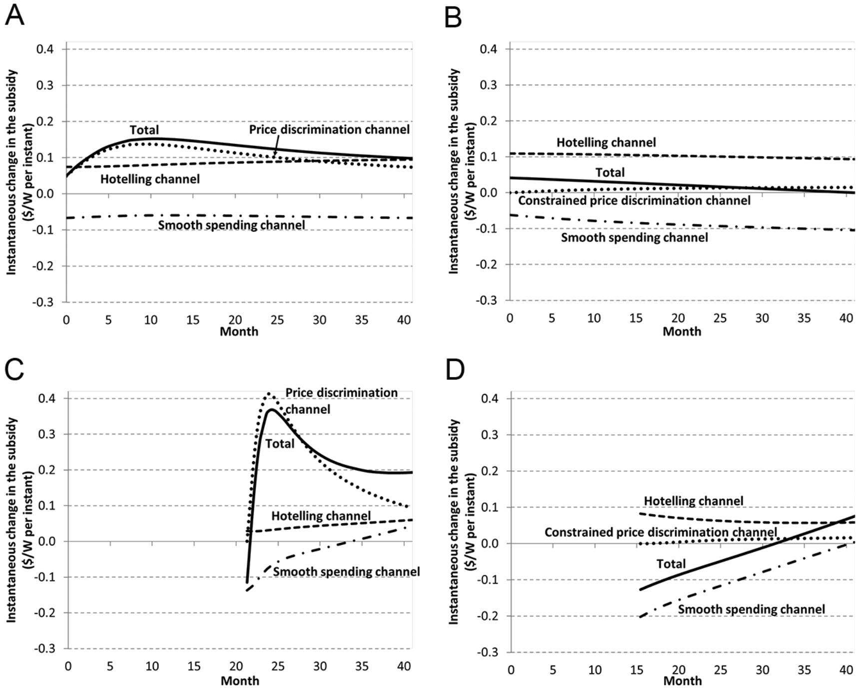

Figure 4. Decomposition of the efficient subsidy path over time for myopic (*A*, *C*) or forward-looking (*B*, *D*) households with (*A*, *B*) or without (*C*, *D*) technological change. The change in the efficient subsidy at each instant ($\dot{s}(t)$, labeled "Total"), as well as each component from equation (4). The adoption benefit component (not plotted) is negative but very small in magnitude. When technology is changing, the regulator chooses to start the subsidy after the initial period to take advantage of technological progress.

Figure 3 highlights forward-looking households' incentive to delay adopting the solar technology in the full model. The dashed lines give the adoption rate per month if the forward-looking households were offered the subsidy that would be efficient for myopic households. Figure 3*A* shows the case without technological change. Here, forward-looking households' incentives to delay adoption arise from the increasing subsidy schedule (seen in fig. 2). We see that the slightly more sharply increasing subsidy offered to myopic households would dampen adoption by forward-looking households in early periods. Their willingness to wait for the high later subsidies limits the regulator's ability to price discriminate through an increasing subsidy schedule.

Figure 4*C*, *D* explains why introducing technical change flattens the efficient subsidy trajectory. When households are myopic, the regulator delays the start of the subsidy for several months in order to take advantage of technological progress. Once the subsidy does begin, advancing technology amplifies the price discrimination channel by increasing the number of inframarginal households, but the smooth spending channel is now strongly negative. The net effect is to flatten the subsidy trajectory.[50] Technological change has an even stronger effect in the case of forward-looking households: the constrained price discrimination channel is unchanged in the first instants and only slightly altered in later instants even as the effect on the smooth spending channel is even greater. In the full model, the enhanced incentive to price discriminate when households are myopic and technology is changing allows the regulator to reduce spending by 7.8% relative to a case with a constant subsidy, but the regulator can reduce spending relative to a constant subsidy by only 1.9% when households are forward looking.

Figure 3*B* shows how households' foresight flattens the efficient subsidy trajectory in the full model with technological change. The efficient subsidy is initially fixed at zero for myopic households because the regulator waits to take advantage of technological improvements.[51] Offering that constant subsidy to forward-looking households does not substantially dampen adoption in early periods. However, forward-looking households would substantially delay adoption in the middle periods if offered the subsidy designed for myopic households because they are willing to wait for the subsidy to become nonzero. The efficient subsidy offered to forward-looking households changes more smoothly in order to convince enough forward-looking households not to postpone adopting the technology.

6. COMPARISON TO EXISTING SUBSIDY PATHS

We have seen that the efficient subsidy increases over time, but the California regulator used a strongly declining subsidy. The California regulator designed a decreasing subsidy schedule because it anticipated that, as time passed, improving technology and increasing electricity costs would combine to incentivize adoption at progressively smaller subsidies (CPUC 2009). Our analysis has incorporated both of these factors. We here explore whether reasonable variations in either the regulator's understanding of technological change or the regulator's objective could favor a sharply declining subsidy.

Two of the primary arguments for a declining subsidy are that the subsidy might endogenously increase the speed of cost declines (through induced technological change

50. The efficient subsidy declines in its very first instants because the price discrimination channel vanishes. Formally, eq. (4) shows that the price discrimination channel vanishes as $\dot{Q}(t) \rightarrow 0$, which is the condition that defines the delayed time at which the subsidy begins.

51. When households are myopic and technology is changing, expected adoption in the absence of a subsidy would reach 0.62% by the end of the 41-month interval, just shy of the target of 0.68%. The regulator therefore does not find it costly to concentrate the subsidy in later periods. In contrast, when households are forward looking, expected adoption would reach only 0.45% in the absence of a subsidy.

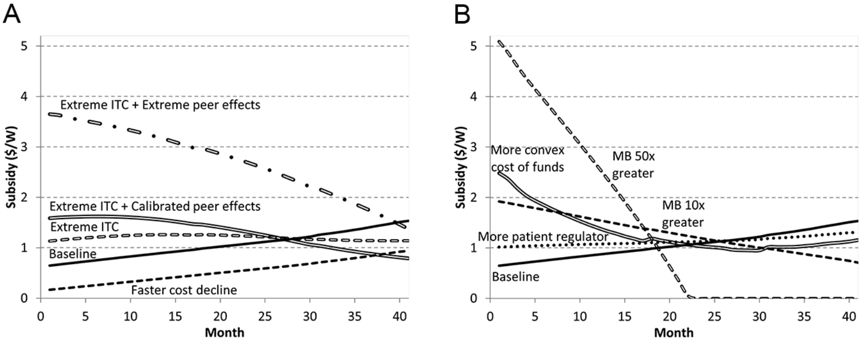

Figure 5. *A*, The effect on the efficient subsidy over time of varying assumptions about the pace and origin of technical progress, as described in the text. *B*, The effect on the efficient subsidy over time of varying parameters in the regulator's objective. All cases use forward-looking households and allow for technological change. ITC = induced technological change; MB = marginal benefit.

or learning by doing) or endogenously inculcate preferences for solar (through peer effects). These two forces are notoriously hard to identify empirically. To understand the maximal effect of induced technological change ("Extreme ITC"), we assume that, contrary to evidence in Gerarden (2018), all realized changes in cost were due to past adoption in California (see app. C.2). This extreme assumption rules out installations anywhere else in the world having an effect on solar costs, so it severely overstates—and therefore bounds—the potential size of the effect from induced technological change. Figure 5*A* shows that the efficient subsidy increases at first and then is basically constant. The case with "Extreme ITC + Calibrated peer effects" additionally calibrates peer effects to Bollinger and Gillingham (2012), as detailed in appendix C.2. The efficient subsidy again increases at first, before eventually declining only a bit faster than did the efficient subsidy in the "Extreme ITC" case.[52]

The case with "Extreme ITC + Extreme peer effects" is a bounding case that considers the strongest amount of ITC and peer effects consistent with our data: we have heretofore interpreted the estimated time trend in the preference for solar as reflecting exogenous improvements in the quality of solar technology, but we now assume that the entire time trend was due solely to peer effects within California. This extreme case implies that neither the cost nor the quality of solar technology would have changed at all in the absence of Californian solar installations. The efficient subsidy

52. The "Faster cost decline" case shows that the shape of the efficient subsidy trajectory is unchanged even if the regulator believes that costs will (exogenously) fall twice as fast as they did in reality.

does now decline over time, but it still declines much more slowly than did the actual subsidy.[53] While arguments about the true strength of ITC and peer effects are difficult to settle empirically, the global nature of the market for solar technology suggests that realistic assumptions are closer to our base case than to these extreme scenarios. This sensitivity analysis suggests that alternative interpretations of technological change and solar panel quality trends will not suffice to generate a subsidy that declines sharply.

Figure 5*B* varies parameters in the regulator's objective. A more patient regulator is less inclined to defer spending to later periods. The figure shows the effect of reducing the regulator's discount rate by half: the efficient subsidy still increases over time. Giving the regulator a much more convex cost of funds and increasing its marginal benefit of adoption 10-fold can both make the subsidy decline over time.[54] A more convex cost of funds makes the regulator use a declining subsidy in order to smooth spending over time, and a regulator with a greater marginal benefit of adoption is less inclined to defer adoption to later periods. Additional experiments showed that reducing the regulator's discount rate by 90% has similar effects as increasing the regulator's marginal benefit 10-fold. Yet even in these cases, the efficient subsidy still does not decline nearly as sharply as the actual subsidy.

However, a final case is different: increasing the regulator's marginal benefit of adoption 50-fold can generate the type of sharply declining subsidy trajectory seen in practice. In our baseline calibration, the adoption benefit channel was trivial, but the same theoretical decomposition shows that a large adoption benefit channel drives this new declining subsidy trajectory. In this scenario, the regulator values solar so much that it wants to speed up adoption in order to obtain the benefits of solar electricity sooner, even at the cost of having to offer a larger subsidy early on. These results are especially intriguing because it is plausible that California regulators did value solar installations to a much greater degree than recommended by the economic analyses to which we calibrated the regulator's objective. This higher valuation could be due to placing a higher value on emission reductions or to believing that additional adoption would kick-start the wider industry. This disagreement about the marginal social value of solar would simultaneously explain why California regulators chose to spur substantial adoption

53. It is also worth noting that peer effects (or network effects or social learning) substantially increase the initial subsidy and the total cost of the subsidy program, since households need to be incentivized to purchase early rather than waiting for others to adopt first.

54. The case with more convex funds reduces the spending level at which the cost of funds doubles to 0.1% of the original value, and the case with a greater marginal benefit of adoption increases the marginal benefit of the first unit of adoption by the stated amount. In additional simulations, we found that making the cost of funds linear does not substantially alter the subsidy trajectory from the base case.

and justify their decision to achieve that adoption through such a sharply declining subsidy.[55]

7. CONCLUSIONS

This paper analytically decomposes how to efficiently structure a subsidy to induce adoption of a new technology over time. A regulator's desire to save money motivates a subsidy that increases over time in order to intertemporally price discriminate among potential adopters, but a regulator's desire to begin benefiting from technology adoption and to smooth spending in the face of technological progress motivates a subsidy that decreases over time. Different forces might dominate in different applications. Although most actual subsidies decrease over time, we might expect the efficient subsidy to increase over time when early adopters have especially high values for the technology, as is the case for consumer energy technologies such as solar panels, house-scale batteries, and electric cars.

We evaluate the efficient subsidy for residential solar adoption in California in order to understand the net effect of these forces in an important empirical application. We show that the efficient subsidy would increase over time to avoid overpaying early adopters. We also show that households' anticipation of technological progress and of future subsidies forces the regulator to spend more on subsidies. Consumer foresight quintuples the regulator's subsidy spending by preventing the regulator from capturing all the benefits of cheaper technology and by constraining the regulator's ability to intertemporally price discriminate.

Our results have several implications for regulatory subsidy design. First, they demonstrate that regulators need information not only on current prices and on past adoption of the technology but also on the distribution of consumers' values for the technology and on consumers' expectations of future cost and quality. Second, regulators have an incentive to undersell the scope for future technological progress in order to encourage consumers to adopt new technologies sooner and to reduce total subsidy spending. Third, we show that conventional declining subsidy schedules potentially induce much less adoption per dollar than increasing subsidy schedules. Regulators should make sure they consider a broad variety of subsidy schedules.

One limitation of our analysis is that we estimate our dynamic model of households' preferences assuming that there are no peer effects or induced technological change. Either type of feedback from households' decisions is notoriously difficult to estimate credibly and is beyond the scope of this paper. Instead, we estimate transitions for costs that may incorporate the realized effects of induced technical change, and we estimate a

55. The cases with a greater marginal benefit of solar are also the only cases in which the regulator's maximized value is positive. These results explain the claim in n. 17 that the welfare-maximizing regulator would target a much lower level of adoption under the baseline calibration.

time trend in households' preferences that may incorporate realized peer effects. We simulate how coarsely breaking out these factors might affect the efficient subsidy schedule. Future work could consider more refined versions of these effects.

Future work should also explore the implications of rational expectations and technological dynamics in other policy environments. For instance, economists commonly recommend emission taxes that increase over time and subsidies for research that would improve future technology. Yet many economic models abstract from consumer and firm expectations of policy and of technology, which could change the efficiency of these policies.

Finally, future work should study the implications of political economy considerations for the design of dynamic subsidy instruments. For instance, future analysis could consider why decreasing subsidy schedules are so dominant in practice when our analysis suggests that increasing subsidy schedules may reduce public spending per unit of adoption. In addition, our regulator promises not to raise future subsidies by too much so as not to defer early adoption, but the regulator would subsequently be tempted to renege by offering higher subsidies once early adoption has already occurred. Political economy considerations could generate further types of credibility problems. For instance, the regulator may be subject to future elections or to future lobbying by interest groups that gained clout as a result of the subsidies. Future work should consider how such considerations might constrain the set of feasible subsidy policies.

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