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ABSTRACT

We analyze the efficient subsidy for durable good technologies. We theoretically demonstrate that a policymaker 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 new empirical estimates of household preferences for residential solar in California, we show that the efficient subsidy increases strongly over time if households are myopic and is much flatter if households have rational expectations. The regulator's spending increases by 70% when households anticipate future technological progress and future subsidies.

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1 Introduction

Policymakers commonly subsidize adoption of new durable good technologies. The U.S. government pays hospitals to adopt electronic medical record systems and car buyers to choose electric vehicles. The U.S. and other countries have paid farmers to install more efficient irrigation systems, firms to build renewable energy projects, and households to replace their aging appliances. And many U.S. states pay homeowners to install solar panels. These subsidies often change over time according to an announced schedule. Policymakers may employ 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. Yet the design of an efficient subsidy schedule has thus far remained an open policy question.[1]

We investigate how an efficient durable good subsidy evolves over time when the regulator wants to achieve a target level of adoption by a certain date.[2] To do this, we formally analyze the dynamically efficient subsidy schedule when potential adopters have heterogeneous, private values for the technology and the regulator can commit to the subsidy policy, values cumulative adoption, and dislikes spending public funds. We show that the regulator's efficient subsidy schedule depends on the anticipated pace of technical change and on whether agents consider future changes in the technology's cost and in the subsidy level when they decide whether to adopt the technology. To assess the relative magnitude of these forces in practice, we combine our theoretical analysis with a dynamic discrete choice estimation of households' preferences for residential solar systems in California. Beyond simulating the efficient trajectory to learn whether it 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 a given shape.

We demonstrate two particularly important results. First, the efficient subsidy will often increase over time, even though this type of subsidy is rarely enacted or discussed. An

[1] Throughout, we take the regulator's desire to achieve a target level of adoption as given, so that we remain agnostic about the welfare implications of the regulator's target. In practice, regulators often want to achieve suboptimal targets, whether for political or budgetary reasons. It is important to use economic analysis to understand how best to do so. We generally refer to our derived subsidy trajectories as "efficient": we avoid "optimal" because the policy may not maximize welfare, and we avoid "cost-effective" because the regulator's objective is not merely to minimize spending conditional on the target.

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

increasing subsidy allows the regulator both to delay spending and to "price discriminate" by offering a low initial subsidy to consumers with a high valuation of the technology 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. In our empirical application, the combination of our calibrated regulator objective, estimated consumer preferences, and observed technological change cannot generate an efficient subsidy that resembles the sharply declining subsidy used by California and many other states to speed adoption of solar power.

Second, we show that consumer foresight 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 8% 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 70% greater when households have rational expectations of technological progress in the market for solar as opposed to a world in which technological progress happens but households are myopic. We find that forward-looking households capture much of the surplus created by technological change whereas myopic households do not capture any of it. Rational expectations constrain the regulator's ability to substitute later technological progress for early subsidy spending.

To build intuition for these results, first imagine that consumers are myopic and do not anticipate future changes in either the technology's cost or the level of the subsidy when they decide whether to adopt the technology. In this case, the theoretical analysis shows that the regulator wants to offer a low initial subsidy to induce adoption by consumers with a particularly high willingness-to-pay for the technology and wants to increase the subsidy over time so as to then obtain adoption from consumers with lower willingnesses-to-pay. 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 when consumers are myopic. By using a low subsidy early and a high subsidy later, the regulator avoids "over-subsidizing" 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 are on the margin.[3]

The story changes if consumers anticipate future subsidies. In that case, if the regulator commits to offering a higher subsidy tomorrow, then some consumers will simply wait to take advantage of the higher subsidy.[4] Consumers' expectations constrain the regulator's ability to intertemporally price discriminate.[5] The theoretical analysis shows that the regulator commits to offering a relatively low subsidy in later periods in order to stimulate adoption in early periods, even though the regulator would prefer to offer a higher subsidy once later periods actually arrive. The combination of consumer expectations and the ability to commit to a subsidy schedule thus favors using lower subsidies in later periods.

Finally, consider how improving technology (i.e., declining private costs of adoption) affects the efficient subsidy schedule. 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, a regulator with a convex cost of public funds prefers to smooth spending over time. The regulator accomplishes this by decreasing the subsidy in later periods relative to early periods. Technological progress therefore generally favors a subsidy that decreases over time.[6]

[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. 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; De Groote and Verboven, 2016).

[5]Relatedly, Conlon (2010) emphasizes that firms want to lower the price of a durable good over time in order to intertemporally price discriminate, but consumers' willingness to wait for lower prices limits the rate at which firms can reduce prices.

[6]Further, we show that endogenizing technological progress amplifies the regulator's desire to use a

We use our empirical estimation to understand the relative importance of these different forces in a real-world setting. The California Solar Initiative (CSI) included a substantial subsidy for residential photovoltaic (rooftop solar) adoption between 2007 and 2014. This program spent nearly $2.2 billion to obtain 1,940 MW of residential solar capacity. The residential solar subsidy declined step-wise over time from $2.50/Watt to zero, with pre-subsidy installation costs over this period declining from around $9/Watt to around $4/Watt. We combine data on household-level installations with a dynamic discrete choice model to estimate the distribution of households' benefit of installing solar conditional on household demographics.[7] The estimation assumes that households know the full time-path of subsidies but allows solar system prices to evolve stochastically. The results show substantial heterogeneity in the private benefit of residential solar systems.

Our results highlight how the interaction between households' rational expectations and technological change is critical for the design and cost of the efficient policy. For myopic consumers in a world with no technological change, the efficient subsidy schedule is sharply increasing. Allowing for either forward-looking households or technological change flattens the efficient subsidy schedule somewhat, but allowing consumers to have rational expectations *and* allowing technology to advance generates a very different policy: the efficient subsidy schedule becomes nearly constant. Further, the present cost of the policy is nearly 70% greater and the efficient initial subsidy is over twice as large when households have rational expectations and technology is changing as opposed to when households are myopic and technology is changing. In this case, households who adopt the technology today lose the option to adopt the technology tomorrow. In order to induce adoption today, the regulator must compensate households for giving up that option by offering them a larger subsidy that will not increase sharply over time.

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 can take advantage of its understanding of technological progress to reduce spending by around 70%. Myopic

declining subsidy: 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.

[7] Because consumers are forward-looking, we cannot 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).

households actually obtain slightly more surplus in the absence of technological change because the regulator does not delay their adoption as strongly. However, when households are aware of the possibility of technological progress, the regulator can reduce its spending by only around 50% as technological change increases households' surplus by $650 million (84%). Expectations of technological progress increase households' incentives to wait until later periods to adopt the technology. Technological progress therefore increases the opportunity cost of adopting the technology today, which requires the regulator to offer households a larger subsidy than would be necessary in a world in which households were ignorant of technological progress.

Finally, whether or not we allow for technological change or household foresight, we never obtain an efficient subsidy that declines as strongly as did the one enacted in California. Either making the regulator much more patient or giving the regulator a much more convex cost of funds does generate a subsidy that declines over time, but in neither case does it decline anywhere near as sharply as did the actual subsidy. We can, however, generate the type of sharply declining subsidy seen in California if we substantially increase the regulator's marginal value for solar electricity. In particular, our policymaker would need to value solar electricity at a level that is substantially more than an order of magnitude greater than the estimates of the social value of solar electricity in Baker et al. (2013). In that case, the regulator does not want to defer the benefits of solar electricity and thus designs a subsidy schedule that prioritizes obtaining adoption quickly.

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) study the efficient subsidy trajectory in the presence of learning and of word-of-mouth diffusion. They argue that both channels call for a subsidy that declines over time.[8] In their conclusion, they mention that a desire to avoid subsidizing high-value consumers could argue for an increasing subsidy schedule. Meyer et al. (1993) discuss how to design investment tax credits in order to obtain the "biggest bang for the buck." They note that the investment incentive is determined by the credit offered to the marginal investor, whereas the regulator's spending depends on the average credit offered to investors. Policymakers should aim to combine a high marginal

[8]Kalish and Lilien (1983) implicitly assume myopic consumers. Our analysis of technological change suggests that both the cost and the trajectory of the efficient subsidy will be sensitive to households' expectations about their future preferences for solar.

credit with a low average credit. These papers' informal observations illustrate the logic underpinning our intertemporal price discrimination channel. We formally demonstrate this channel, show how it depends on private actors' expectations, and introduce new channels.[9]

A larger literature has analyzed how monopolists should set prices for durable goods over time. In particular, several papers have explored the conditions under which a monopolist finds intertemporal price discrimination to be optimal. When production is costless, a monopolist should commit to offering a constant price over time as long as all customers use the same discount rate, their valuations are constant over time, and the monopolist is at least as impatient as its customers (Stokey, 1979; Landsberger and Meilijson, 1985). In that case, all sales happen in the first instant. However, intertemporal price discrimination can be optimal when production costs are convex (Salant, 1989) or declining over time (Stokey, 1979). Our setting follows these in assuming that the regulator can commit to a subsidy schedule and in analyzing the implications of rational expectations. We avoid a corner solution (i.e., a constant subsidy) because our regulator has a concave benefit function and a convex distaste for spending in each instant. Further, we reserve the label of "price discrimination" for forces that arise only because of adopters' equilibrium decisions, so that we disentangle other dynamic forces from intertemporal price discrimination motives.[10]

[9] Three recent papers are also relevant. First, Kremer and Willis (2016) study the efficient subsidy trajectory in the presence of spillovers. They assume homogeneous private values for the technology and constant costs, whereas we emphasize the implications of heterogeneous private values and of (both exogenously and endogenously) declining costs. Second, Newell et al. (2017) informally discuss how to structure subsidy payments to a given project. They argue that upfront payments make sense when the government can borrow more cheaply than the private sector. We here formally analyze how to structure the upfront subsidies offered to different possible projects. We do allow the regulator's discount rate to differ from private sector discount rates. Third, Dupas (2014) considers how learning and reference-dependence interact with subsidy policies when consumers who have already adopted the technology must choose whether to adopt it again. In her application, insecticide-treated bed nets last only a few years and a single household can use multiple bed nets. In our application, solar panels can last more than twenty years and a single household has only a single roof.

[10] 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; Conlisk et al., 1984; Gul et al., 1986; Kahn, 1986; Besanko and Winston, 1990; Sobel, 1991). 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 policymakers appear to successfully commit to a subsidy schedule. Our theoretical analysis focuses on this environment with commitment. In this sense, our environment relates more closely to the optimal taxation literature, which analyzes the regulator's choice of, for instance, the trajectory of capital taxes under commitment (e.g., Judd, 1985; Chamley, 1986; Chari and Kehoe, 1999). In our empirical application, we consider policies over relatively short timescales (<10 years) that were authorized by legislation, not just by executive action.

The next section describes the model. Section 3 theoretically analyzes the efficient subsidy trajectory. Section 4 introduces the empirical application, including the setting and the data. Section 5 describes the dynamic structural model for estimating the distribution of household values for solar photovoltaics. Section 6 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 7 explores what assumptions might lead the efficient subsidy trajectory to resemble the actual CSI subsidy trajectory. The final section concludes. The appendix contains formal derivations, provides evidence that California households were forward-looking, outlines data details, reports sensitivity tests, describes the numerical calibration, and extends the theoretical analysis to the case of a fixed budget rather than a fixed adoption target.

2 Model

Our model of technology adoption includes households who are deciding whether to adopt a new 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.

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 the 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 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

Regulators have followed through on legislated subsidy schedules for residential solar in many states. Because these schedules are simple functions of time or of adoption rather than functions of uncertain factors (such as system cost) that would justify changes in policy, this follow-through is more suggestive of commitment than of equilibrium play.

the technology in a period, then it receives a 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: $C_1(t, Q_t, \omega_t) \leq 0$, with the subscript indicating a partial derivative with respect to the indicated argument. Second, the technology's cost may also decline as a result of technological change induced by cumulative adoption ($C_2(t, Q_t, \omega_t) \leq 0$), which is often referred to as "induced technological change" and may include "learning-by-doing." Finally, cost also depends on the stochastic shocks captured by ω_t.

Forward-looking households form rational 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.[11] The household's value of choosing whether to adopt the technology at time t is:

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

where β is the per-period discount factor and $\mathbb{E}$ is the expectation operator.[12] Forward-looking households have $\beta > 0$ and myopic households have $\beta = 0$. Myopic households therefore do not consider future changes in the technology's cost, in the subsidy, or in the characteristics of their household.

The regulator commits to a subsidy schedule that will, in expectation, achieve a predetermined level of adoption $\hat{Q}$ after some given time $T > 0$.[13] She knows the true distribution

[11] Note that 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.

[12] 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 (2016) do estimate the discount rate in an empirical model of solar installation).

[13] The assumptions of a fixed terminal time T and of a fixed adoption target $\hat{Q}$ will not be critical to the theoretical analysis. These assumptions will affect the transversality conditions for the regulator's problem, but they will not affect the necessary conditions that are the focus of the theoretical analysis. The appendix

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 $G(\cdot)$ could reflect political constraints or could reflect that the deadweight loss of taxation increases nonlinearly in revenue requirements. The regulator also receives instantaneous benefit $B(Q_t) > 0$ from cumulative adoption, with $B(\cdot)$ strictly increasing and strictly 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 $G''(\cdot)$ become small, the regulator's problem becomes one of minimizing the discounted cost of subsidy spending.

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

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

for given discount rate $r > 0$, for given initial adoption Q_0, and subject to the constraint that expected terminal adoption $\mathbb{E}_0[Q_{T+1}]$ equal $\hat{Q} > Q_0$. Potential adopters' decisions determine how the announced subsidy trajectory affects Q_t. Households expect the subsidy to drop to 0 after time T.

shows that the theoretical analysis is also robust to giving the regulator a fixed budget instead of a fixed adoption target. Intuitively, if the budget constraint does not bind, then that 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 here fix $\hat{Q}$ at the value that results from solving the problem with a budget constraint. All of the channels remain, with the only adjustment being that the marginal cost of public funds would be amplified by the shadow cost of the budget constraint.

3 Theoretical Analysis

We now theoretically analyze the subsidy trajectory that efficiently incentivizes actors 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 households' 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 households 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 δ and the regulator discounting at rate r. All other definitions and notation extend in the natural way. We now have $Q_0 \in [0, 1)$ and $\hat{Q} \in (Q_0, 1]$. Note that $\dot{Q}(t)$ gives adoption at time t, where a dot indicates a derivative with respect to time.

3.1 Myopic Adopters

When potential adopters are myopic, they adopt the technology as soon as their net benefit of adoption is positive. Therefore, at time t, all actors with $v_i \geq C(t, Q(t)) - s(t)$ who have not yet adopted should adopt the technology. Define $Y(t)$ as the value at which actors are just indifferent to adopting or not: $Y(t) \triangleq C(t, Q(t)) - s(t)$. The number of actors who have adopted the technology by t is $Q(t) = 1 - F(Y(t))$, which implies $\dot{Q}(t) = -f(Y(t))\,\dot{Y}(t)$. Note that $\dot{Y}(t) \leq 0$ along any efficient path: there is no reason for the regulator to adopt a subsidy that makes net costs strictly increase.

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 actors' equilibrium conditions. Writing $y(t) \triangleq \dot{Y}(t)$ and substituting for $s(t) = C(t, 1 - F(Y(t))) -$

$Y(t)$, the regulator's problem becomes:

$$\begin{aligned}\max_{y(t)} \int_0^T & e^{-rt}\left[B\Big(1-F(Y(t))\Big)-G\Big(-\left[C(t,1-F(Y(t)))-Y(t)\right]f(Y(t))\,y(t)\Big)\right]\,\mathrm{d}t\\ \text{s.t. } \dot{Y}(t) =& y(t)\\ Y(0) =& F^{-1}(1-Q_0),\ Y(T)=F^{-1}(1-\hat{Q}).\end{aligned}$$

The appendix shows that the efficient subsidy evolves as:

$$\dot{s}(t) = \frac{-r\,\lambda(t) - B'\,f(Y(t)) - G'\,y(t)\,f(Y(t)) - [s(t)]^2\;G''\,f(Y(t))\ddot{Q}(t) - G'\,[f(Y(t))]^2\,y(t)\,C_2(t,Q(t))}{G'\,f(Y(t)) - s(t)\,f(Y(t))\,G''\,y(t)\,f(Y(t))}, \tag{1}$$

where $\lambda(t) \leq 0$ is the shadow value of the state variable $Y(t)$ (the negative sign means that the shadow benefit of adoption is positive). This differential equation tells us how the subsidy changes along an efficient trajectory.

The shape of the subsidy's trajectory is determined by the five terms in the numerator, with the denominator positive (recalling $y(t) \leq 0$). First, the $-r\lambda(t) \geq 0$ reflects the regulator's impatience. The analysis in the appendix shows that the shadow benefit of adoption must equal the social cost of each moment's spending on marginal adopters. For now, ignore complications introduced by other channels. In order for the regulator to be indifferent to small deviations in her policy trajectory, the shadow benefit of adoption must grow at the discount rate r, which keeps its present value constant over time.[14] The efficient subsidy schedule therefore tends to increase because the impatient regulator will tolerate a greater social cost of spending in later periods. We call this first force for an increasing subsidy a *Hotelling channel*, due to its similarity to the Hotelling (1931) analysis of exhaustible resource extraction.

Second, the $-B'\,f(Y(t)) < 0$ reflects that raising today's subsidy in exchange for lowering

[14] 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 of funds enters through other channels). The regulator's savings today are $\epsilon\, s(t)\, f(Y(t))$, which by equation (A-1) and $s(t) = C(t,Q(t)) - Y(t)$ equals $-\epsilon\,\lambda(t)$. The regulator invests this money and earns interest at rate r before spending $-\lambda(t+\Delta t)$ to obtain the later adoption. For the regulator to be indifferent to this deviation for Δt small, it must be true that $-\lambda(t+\Delta t)+\lambda(t) = -r\lambda(t)$. Letting Δt go to zero and using the derivative of equation (A-1) with respect to time, we have $\dot{s}(t) = -r\lambda(t)$.

tomorrow's subsidy not only shifts the shadow benefit of adoption forward in time but also provides benefits tomorrow by raising cumulative adoption.[15] 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 how waiting to spend money on the subsidy forgoes benefits in the interim.

Third, the $-G'\,y(t)\,f(Y(t)) \geq 0$ recognizes that the regulator cannot price discriminate within a period. Recall that $y(t) \triangleq \dot{Y}(t) \leq 0$ measures the maximum gap between the private values of households adopting at time t. If the regulator offers a marginally greater subsidy to some adopter at time t, then it 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 it avoids paying the extra money to the $-y(t)\,f(Y(t))$ inframarginal adopters at time t.[16] 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.

The fourth term, $-[s(t)]^2\; G''\,f(Y(t))\ddot{Q}(t)$, captures the regulator's preference for smooth spending over time, driven by the convexity of the cost of public funds. $\ddot{Q}(t)$ describes how instantaneous adoption changes as time advances. When instantaneous adoption is increasing over time ($\ddot{Q}(t) > 0$), this fourth 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 makes installation costs fall 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. Early adopters are in the tail of the distribution, so more adopters are on the margin in later periods. In this case, subsidy spending again tends to increase over time, which favors using a declining subsidy schedule. Putting these pieces together, this *smooth spending channel* favors a decreasing subsidy schedule in the plausible case with $\dot{y}(t) \leq 0$ and $f'(Y(t)) \leq 0$.

Before analyzing the fifth term in equation (1), consider how anticipated improvements

[15] In footnote 14, the cost of delaying adoption should include $B'\,f(Y(t))\,\Delta t$. The logic of the footnote would then imply that $\dot{s}(t) = -r\lambda(t) - B'\,f(Y(t))$.

[16] Recall that $\dot{Q}(t) = -y(t)\,f(Y(t))$.

in technology affect the efficient subsidy schedule. First, more strongly declining costs make $y(t)$ more negative for a given subsidy and cost. The more rapidly that costs are declining, the greater the number of inframarginal adopters at a given subsidy and the greater 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 shadow benefit $\lambda(t)$ of adoption by making it easier to obtain adoption in later periods. 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.[17]

The final, fifth term in the numerator of equation (1) adjusts the efficient subsidy for the possibility of induced technical change. When technical change is purely exogenous, this term vanishes because $C_2(t, Q(t)) = 0$. However, when increasing adoption reduces the private cost borne by later adopters, this term is negative because $C_2(t, Q(t)) \leq 0$. This *endogenous technology channel* favors a declining subsidy because using a higher subsidy in earlier instants now carries the additional benefit of reducing the private cost of adoption (and thus reducing the required subsidy) in later instants. Endogenizing technological change favors stimulating adoption through a large early subsidy and taking advantage of lowered costs through a small later subsidy.

3.2 Forward-Looking Adopters

We have thus far considered the efficient subsidy schedule when potential adopters are completely myopic. However, when potential adopters anticipate future subsidies, the regulator can no longer induce adoption just by offering a large subsidy today; instead, the regulator must offer both a large subsidy today and a sufficiently small subsidy in the future.

[17]Declining costs will also affect several channels by changing the level of the subsidy.

Instead of adopting the technology as soon as instantaneous net benefits are greater than zero, each actor i now chooses the optimal time Ψ_i to adopt the technology, for given subsidy and cost trajectories:

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

The first-order necessary condition is[18]

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

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 actor 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 actor can save money by adopting the technology later. The optimal time of adoption balances these costs and benefits. As the potential adopter becomes perfectly patient ($\delta \to 0$), the cost of waiting disappears and the agent delays adoption until net costs reach their minimum.

Potential adopters' stopping problems generate the equilibrium conditions that constrain the regulator's choice of subsidy trajectory. As before, let the regulator's control be which actors are marginal in each period, with $Y(t)$ denoting the marginal actors' private value for the technology. Then, rearranging equation (2), the subsidy must evolve as

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

In the myopic setting, equilibrium adoption constrained only the level of the subsidy, but now it also constrains the change in the subsidy. The regulator's time 0 choice of subsidy

[18] Define net costs as $z(t, Q(t)) \triangleq C(t, Q(t)) - s(t)$. These necessary conditions are sufficient if $\ddot{z}(\Psi_i, Q(\Psi_i)) > \delta^2\left[v_i - z(\Psi_i, Q(\Psi_i))\right] + 2\delta\dot{z}(\Psi_i, Q(\Psi_i))$, where dots indicate total derivatives with respect to time. Substituting both equation (3) (obtained below) and its derivative with respect to time, we find that the necessary conditions are sufficient if $-\dot{Y}(\Psi_i) > \delta\left[v_i - Y(\Psi_i)\right]$. The left-hand side is positive. The inequality is satisfied for any v_i that is not too much greater than $Y(\Psi_i)$. But by the definition of $Y(\Psi_i)$ as the private value of the marginal adopter at time Ψ_i, it cannot be true that v_i exceeds $Y(\Psi_i)$ by more than $-\dot{Y}(\Psi_i)$ for any actor i who had not adopted prior to time Ψ_i. Thus, if $\delta < 1$, then constraining the subsidy's evolution via equation (3) ensures that the necessary conditions are sufficient for any agent who chooses to adopt the technology. In the numerical simulations that use the theoretical analysis, we verify that the sufficient condition holds for adopters along the entire trajectory.

schedule will be dynamically inconsistent because the 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 thus irrelevant to a decision problem that starts from time t. However, we assume that the regulator is able to commit at time 0 to not revise its announced subsidy schedule. There is a long tradition in the optimal taxation literature of analyzing similar "dynamic Ramsey" problems under the assumption of full commitment (e.g., Judd, 1985; Chamley, 1986), and this assumption is particularly applicable in the case of subsidies for new technologies.[19]

Again using $y(t)$ for $\dot{Y}(t)$, the regulator solves

$$\begin{aligned}
\max_{y(t),s(0)} \int_0^T e^{-rt} & \left[B\Big(1 - F(Y(t))\Big) - G\Big(- s(t)\, f(Y(t))\, y(t)\Big)\right] \,\mathrm{d}t \\
\text{s.t. } \dot{Y}(t) =& y(t) \\
\dot{s}(t) =& \delta \left[Y(t) - C(t, 1 - F(Y(t))) + s(t)\right] + \dot{C}(t, 1 - F(Y(t))) \\
Y(0) =& F^{-1}(1 - Q_0),\ Y(T) = F^{-1}(1 - \hat{Q}) \\
s(T) =& C(T, \hat{Q}) - Y(T) + J(Y(T), C(T, \hat{Q})).
\end{aligned}$$

In the case with myopic agents, we did not need a terminal condition on the subsidy because agents did not care how the subsidy changed at T. However, in the present setting, time T adoption depends on how the subsidy is changing at T. $J(v_i, C(T, \hat{Q}))$ is the present value to actor i of having the option to adopt the technology at time T, once the subsidy disappears for good. This actor adopts the technology at time T if and only if $v_i - C(T, \hat{Q}) + s(T) \geq J(v_i, C(T, \hat{Q}))$.

[19] 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.

The appendix shows that the efficient subsidy evolves as:

$$\dot{s}(t) = \Bigg[- r\,\lambda(t) - B'\,f(Y(t)) \overbrace{-G'\,y(t)\,f(Y(t)) - \dot{\mu}(t) + r\,\mu(t)}^{\delta\mu(t)} \\ - [s(t)]^2 G''\,f(Y(t))\,\ddot{Q}(t) + [r\,\mu(t) - f(Y(t))\,y(t)\,G']\;C_2(t, Q(t))\,f(Y(t))\Bigg] \\ \Bigg[G'\,f(Y(t)) - s(t) f(Y(t)) G''\,y(t)\,f(Y(t))\Bigg]^{-1}, \tag{4}$$

where $\lambda(t) \leq 0$ is as in the myopic setting and the new 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 periods). $\mu(0) = 0$ because the regulator is not constrained by past promises in the first instant.

Equation (4) defines the dynamics of the efficient subsidy when potential adopters correctly anticipate future subsidies and costs. We see the same five channels as in the myopic case, with the same denominator. However, we also have two new terms on the first line and one new term on the second line. The new terms on the first line are $-\dot{\mu}(t) \leq 0$ and $r\,\mu(t) \geq 0$. When $\dot{\mu}(t) > 0$ (as must be true in early instants), the regulator's promises are accruing over time. The first new term then favors a decreasing subsidy, because the regulator promises low future subsidies to time t adopters. The $r\,\mu(t)$ term reflects how an impatient regulator is willing to promise a low time t subsidy in order to spur adoption at earlier times. These promises of a low time t subsidy favor a subsidy that increases from time t towards the ex post preferred level.

The appendix shows that these first two new terms cancel the price discrimination channel and leave us with $\delta\mu(t) \geq 0$. We call this net effect of forward-looking agents a *promise-keeping channel*. In the myopic case, the price discrimination channel reflected the regulator's ability to intertemporally price discriminate by raising the subsidy once adopters with greater private values had already claimed their subsidy. But when adopters are forward-looking, they might wait for the higher subsidies, which limits the regulator's ability to price discriminate. Instead, the new term $\delta\mu(t)$ reflects the time t cost of keeping past promises. This promise-keeping cost is weakly positive, favoring an increasing subsidy schedule. All else equal, a regulator who obtained a lot of adoption prior to time t must have promised a low time t subsidy, which makes her want to raise the subsidy from that level as time passes. When adopters are perfectly patient ($\delta = 0$), the regulator must offer that low subsidy forever, but when adopters are impatient, the regulator can offer a higher subsidy in later periods without strongly disincentivizing adoption in early periods.[20] But the true importance of the promise-keeping channel derives from the difference between it and the price discrimination channel it replaced. Near the initial time, the promise-keeping channel is approximately zero. Recognizing that adopters anticipate future subsidies thus eliminates the price discrimination channel in early periods, which works to tilt the efficient subsidy trajectory downward over those early periods.

Finally, the new term on the second line of equation (4) is $r\,\mu(t)\,C_2(t, Q(t))\,f(Y(t)) \leq 0$. This new term is zero in the first instants but can be negative at later times. By favoring a declining subsidy in later instants, this new term amplifies the endogenous technology channel seen in the myopic case. Through induced technical change, adoption at time t lowers the next instant's private cost of adoption and thereby makes forward-looking agents want to wait until the next instant to adopt the technology. In order to obtain additional adoption at time t, the regulator must promise to reduce the subsidy before the next instant. $\mu(t)$ captures the scope of these promises. Large values of $\mu(t)$ favor a more strongly declining subsidy because the regulator has made promises to more past adopters.

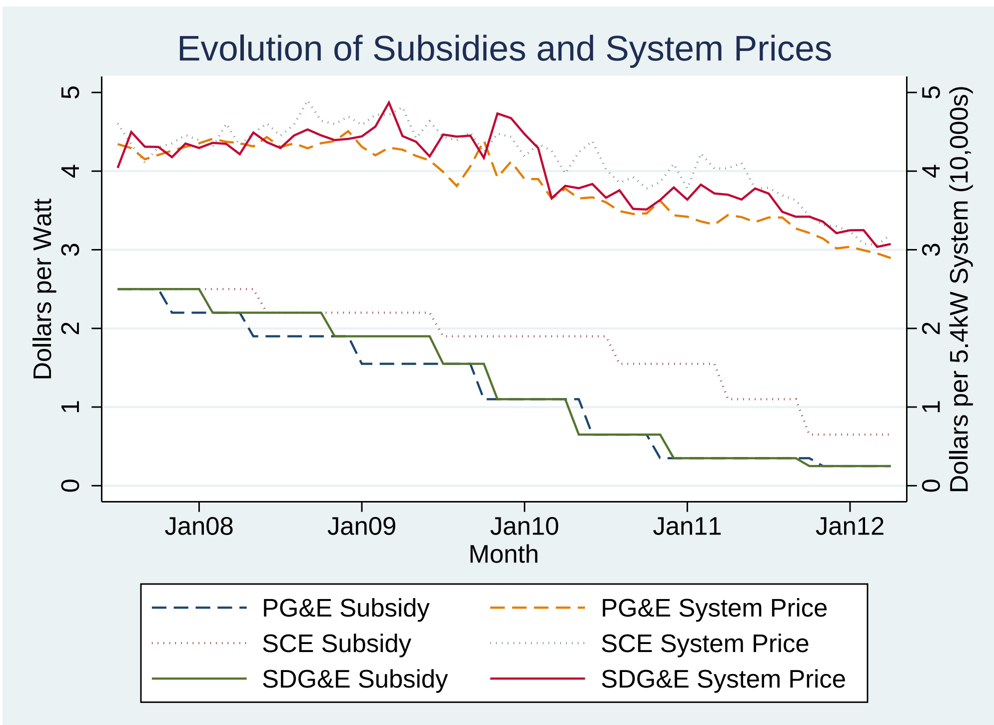
4 The California Solar Initiative

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 will pair our estimates with calibrations of the regulator's preferences to evaluate the efficient subsidy policy and to understand how households' technology adoption decisions would have changed under counterfactual subsidy policies.

[20]This desire to offer a higher subsidy in later periods can also be interpreted as a price discrimination channel that is constrained by consumers' willingness to wait, as determined by their discount rate δ. In particular, note that for $\delta = r$, $-G'\,y(t)\,f(Y(T)) = \dot{\mu}(t)$, so that the price discrimination channel is canceled exactly.

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 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)), the subsidy started at \$2.50/Watt installed and declined over time to \$0.

Figure 1: Monthly CSI Subsidy and Average System Cost by Utility



The CSI maintains data on all applications for residential solar subsidies under the program. The 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 shows the evolution of subsidies and pre-subsidy average system costs from July 2007 through May 2014.[21] While there are shocks to each

[21] The average system costs are based on the average cost per Watt in each month for each utility multiplied by the average 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 Figure 1.

utility's average system price, the general patterns are similar across the utilities. The cost of an average system is fairly flat in the initial periods when silicon costs are increasing and then declines over the majority of our estimation timeframe 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.

In addition to the information on solar system installations and costs, 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, we use data from the National Renewable Energy Laboratory (NREL) on the median solar direct normal irradiation at the zip code level to account for variation in the solar generation potential in different areas of California.[22]

Table 1 summarizes the demographic data. The first column presents the average demographics for owner-occupied housing in the three California utilities in our sample. The second column 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 are 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 are 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. Households that install solar live in zip codes with approximately the same education, household size, and number of mortgages as owner-occupied

[22]We remove from the sample any solar installations in zip codes served by more than one of the major utilities because we do not know what price and subsidy non-installers in those zip codes faced. For similar reasons, we also focus our analysis only on households in the territories of the three major utilities (PG&E, SCE, and SDG&E).

households overall.[23]

Table 1: Demographic Summary Statistics

	Average Owner-Occupied Household Demographics	
	Overall	Install Solar
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	0.59	0.55
Years of Schooling	13.6	13.8
Number of Mortgages (0/1/2+)	0.94	0.96
Number of Household Members	2.6	2.6
Count	4,104,377	49,765

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.

5 Econometrics

In order to understand how California households value residential solar and how different subsidy trajectories may change their installation decisions, we estimate a dynamic model of residential solar system demand and then pair the results with a calibrated version of the regulator's objective. 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 II, 2014; De Groote and Verboven, 2016). In Appendix B.1, we provide novel reduced-form evidence that households are indeed forward-looking when deciding whether to install solar systems.

5.1 Estimation framework

Our empirical estimation parameterizes the household technology demand model presented in Section 2, without the simplifications made in the theoretical analysis. Households are

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

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 upfront benefit from installing solar. The upfront 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 upfront nonmonetary cost of installing solar is likely to be large, which would make the upfront net benefit negative.

We parameterize the model in a few 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 differentiates our approach from Burr (2014) and is critical for understanding 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 system cost (net of subsidies) in a given period changes utility by $\alpha_i[(1-\phi)C(t, Q_t, \omega_{it}) - s_{it}]$, where α_i should be negative and costs and subsidies are allowed to vary by utility within a month.[24]

Third, we must specify how households form beliefs about the evolution of the states in Ω. We assume that each state evolves according to a first-order Markov process. In particular, we assume that technology costs evolve exogenously rather than depending upon the installed base of the technology: $C_{i(t+1)} = \gamma_0 + \gamma_1 C_{it} + \omega_{it}$, where ω_{it} is normally distributed and where we collapse the remaining cost function arguments into the subscript on C.

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, or shading are not conducive to solar. We therefore also include a variable Φ_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

[24]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 (2017).

household's preference for residential solar.[25]

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

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

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 Φ_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. The variation in the data is not sufficient to precisely estimate the percentage of households who consider installing solar. We therefore assume that 5% of the households who have not yet installed solar at the start of our time-frame are able to consider installing solar over our time-frame, and we assume that this consideration is independent of other household characteristics.[26]

At each step of the likelihood maximization, we solve for the fixed point of the value function when all CSI subsidies equal zero and are expected to equal zero in the future. We then solve recursively for the value function in all previous periods. 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 consistent with Busse et al. (2013) and De Groote and Verboven (2016)). Standard errors are calculated as the square root of the inverse of

[25] We discuss the role of the serial correlation that Φ_i introduces into the household's preference shocks in Appendix B.3.

[26] We did run the model where the share of households who consider installing solar, $\Phi = \sum_i \Phi_i / N_0$, is a parameter to be estimated. We obtained a point estimate of 0.0226, implying that 2.26% of households consider installing solar. Based on this point estimate, we make the more conservative assumption that 5% of households consider installing solar and estimate the model with the data limited to just those households. Appendix B.3 assess the sensitivity of the estimation to these assumptions and describes the implications for our simulations.

the outer product of the Jacobian.

5.2 Identification

The CSI provides data on the applications to install solar, which includes information on cost of the solar system and the household's zip code but not the household's demographics. In order to estimate how preferences vary with demographics, we simulate over the distribution of demographics within each zip code as given by the American Community Survey. This approach is similar to Nevo (2001) and Berry et al. (2004).[27] 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 are more likely to have higher rates of solar installation conditional on solar costs than are zip codes with low home prices.

Identification of the cost parameters and the demographic differences in the preference for solar systems and cost 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.[28] We therefore argue that we are estimating the causal effect of changes in system costs on adoption.[29] However, we do not 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

[27]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 draw from the unconditional distribution of each demographic characteristic 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.

[28]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.

[29]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 the subsidy rather than the installation date. The household could then delay installing solar. In our data, we observe average delays 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 (2017) 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 lower than 100%.

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.

5.3 Preference Estimates

The dynamic empirical model generates estimates of households' valuation of residential solar systems, which we will use to quantitatively evaluate the efficient subsidy trajectory. Table 2 presents the estimated coefficients, including the present value of the benefit of installing a solar system of the median size (and then that benefit interacted with household demographics) and the disutility of spending money (as well as how that disutility changes with demographics). The average household that considers installing solar has a negative valuation of solar, even after controlling for the fact that the overwhelming majority of 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 upfront cost of solar, and of going through the installation process. Many households will likely perceive this cost of considering solar to be substantial enough that they would require a considerable upfront payment to even evaluate whether solar is a reasonable option for them.

The benefit of installing solar is strongly increasing in the solar radiation in the household's zip code, which reflects that the quantity of radiation directly determines the quantity of electricity generated and thus the electricity savings from installing solar. Households with higher home values have a higher preference for solar, likely reflecting that these homes have more potential roof space for solar panels and that solar in California is particularly beneficial for homes that use a lot of electricity.[30] More educated households also have a higher

[30] Electricity prices in California are steeply tiered, such that installing solar has a much higher marginal benefit for households with higher monthly electricity demand than for those on lower tiers. See Borenstein

Table 2: Dynamic Demand Estimates

Benefit of Solar	-10.0788***
	(0.5665)
* Median Radiation (kWh/m^2/day/10)	5.2444***
	(0.1173)
* log(Home Value ($millions))	0.2176
	(0.1651)
* Years of Schooling	0.1475***
	(0.0356)
* SCE	-0.4278***
	(0.0175)
* SDG&E	0.5940***
	(0.0246)
* Time Trend	0.1260***
	(0.0022)
* Time Trend^2	-0.0022***
	(0.0001)
Cost ($10,000s)	0.0393
	(0.2596)
*log(Home Value ($millions))	0.1763**
	(0.0751)
* Years of Schooling	-0.0512***
	(0.0167)
-Log-likelihood	182,097
Months	41

Standard errors in parentheses. SCE is an indicator variable for Southern California Edison and SDG&E is an indicator variable for San Diego Gas and Electric.

value for solar, perhaps reflecting differences in the cost of collecting information about the benefits of solar. In addition to being statistically insignificant, the magnitude of the effect of home size is substantially smaller than that of either radiation or education: the difference in preference for solar between households in the highest and lowest bins (quintiles) of radiation is only slightly greater than the difference in preference between households with the highest and lowest levels of schooling (more than college verus only a high school degree), but the difference in solar valuation between households in the most and least expensive homes

(2017).

(those valued over \$1 million versus those valued under \$200,000) is less than one-seventh the size of the effect of radiation.[31] Thus the amount of electricity generated and the ability to collect and analyze information about solar systems are the important drivers of solar adoption, conditional on system cost. The benefit of installing solar is strongly increasing in the solar radiation in the household's zip code, which reflects that the quantity of radiation directly determines the quantity of electricity generated and thus the electricity savings from installing solar. Households with higher home values have a higher preference for solar, likely reflecting that these homes have more potential roof space for solar panels and that solar in California is particularly beneficial for homes that use a lot of electricity.[32] More educated households also have a higher value for solar, perhaps reflecting differences in the cost of collecting information about the benefits of solar. In addition to being statistically insignificant, the magnitude of the effect of home size is substantially smaller than that of either radiation or education: the difference in preference for solar between households in the highest and lowest bins (quintiles) of radiation is only slightly greater than the difference in preference between households with the highest and lowest levels of schooling (more than college versus only a high school degree), but the difference in solar valuation between households in the most and least expensive homes (those valued over \$1 million versus those valued under \$200,000) is less than one-seventh the size of the effect of radiation.[33] Thus the amount of electricity generated and the ability to collect and analyze information about solar systems are the important drivers of solar adoption, conditional on system cost.

[31] The highest quintile of radiation receives 0.7240 tenths of a kilowatt hour per square meter per day of radiation, whereas the lowest quintile receives only 0.5012 tenths of a kilowatt hour per square meter per day. Multiplying this difference by the coefficient on solar radiation, households in the highest quintile value solar by $5.2444^*(0.7240 - 0.5012) = 1.1685$ more than households in the lowest quintile, all else equal. Similarly, the difference in valuation between a household with a more-than-college-educated head and one with a high school educated head is $0.1475^*(6) = 0.8850$. However, the difference in valuation between a household in a \$1 million home and one in a \$200,000 home is only $0.2176 * (\log(1) - \log(0.2)) = 0.1521$.

[32] Electricity prices in California are steeply tiered, such that installing solar has a much higher marginal benefit for households with higher monthly electricity demand than for those on lower tiers. See Borenstein (2017).

[33] The highest quintile of radiation receives 0.7240 tenths of a kilowatt hour per square meter per day of radiation, whereas the lowest quintile receives only 0.5012 tenths of a kilowatt hour per square meter per day. Multiplying this difference by the coefficient on solar radiation, households in the highest quintile value solar by $5.2444^*(0.7240 - 0.5012) = 1.1685$ more than households in the lowest quintile, all else equal. Similarly, the difference in valuation between a household with a more-than-college-educated head and one with a high school educated head is $0.1475^*(6) = 0.8850$. However, the difference in valuation between a household in a \$1 million home and one in a \$200,000 home is only $0.2176 * (\log(1) - \log(0.2)) = 0.1521$.

We find that households are sensitive to the net-of-subsidy cost of installing solar and that a household's cost sensitivity decreases with home value and increases in schooling.[34] This is what we would expect if households were largely using mortgages to finance solar purchases and if more educated households were more informed about potential future subsidy and cost declines. Although home value does have a statistically significant effect on price sensitivity, the magnitudes again suggest that education has a larger effect on preferences than home value: having more than a college degree increases price sensitivity relative to a high school degree over 2.5 times more than being in a \$200,000 home rather than a \$1 million home.[35] Solar radiation does not have either a large effect or a statistically significant effect on price sensitivity, which makes sense if radiation increases the long-run electricity generated by a solar system but has no impact on the upfront cost of the system. Whether a household voted Democratic, number of mortgages, and number of household members do not statistically significantly impact either households' preferences for solar or their sensitivity to system cost. Appendix B.3 discusses additional sensitivity checks of the model specification.

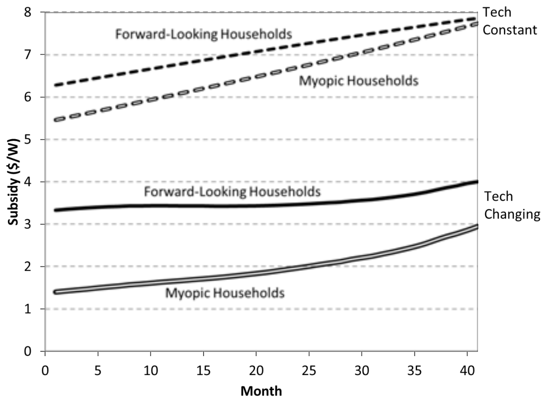
6 Results: The Efficient Subsidy for Rooftop Solar

We now use our structural estimates of household values for solar to simulate the efficient subsidy trajectory. We are agnostic as to the welfare implications of the regulator's adoption target and how the regulator selects it, but we use economic analysis to understand how best to achieve that target. 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 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 1.5% adoption in 41 months.[36] The appendix details the calibration and solution method.

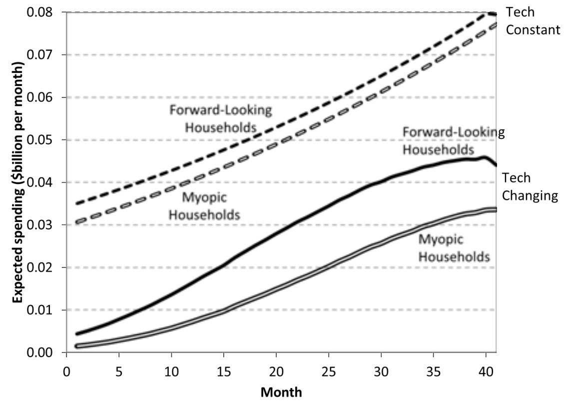
[34] The coefficient on system cost is slightly positive (and statistically insignificant), but all households have negative cost coefficients once cost is interacted with the demographics.

[35] The difference in the price sensitivity for schooling is $-0.0512{*}6 = -0.3072$ whereas the difference in the price sensitivity for home value is $0.1763{*}(log(0.2) - log(1)) = -0.1232$.

[36] Actual adoption in the CSI during our estimation window was closer to 0.68%, but in this case myopic households would not require any subsidy. Our goal is to understand the drivers of efficient policy, not to evaluate the particular policy implemented in the CSI. Therefore, we study a case with 1.5% adoption so that we can study how the regulator would subsidize myopic households. Our qualitative results are not sensitive to the choice of target. The time horizon of 41 months is consistent with the empirical setting.



(a) Efficient subsidy



(b) Subsidy spending

Figure 2: The efficient subsidy (left) and expected monthly spending (right) when households are forward-looking (solid) and myopic (hollow). Connected lines allow for exogenous technical change and dashed lines hold technology constant over time.

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. Figure 2 plots the efficient subsidy (left) and expected monthly subsidy spending (right) 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 consumer surplus obtained by households in the absence of any subsidy and under the efficient subsidy policy.[37] 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.[38] The second effect alone is not strong enough to achieve the targeted level of adoption.

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

[38]For instance, an installer approaches a household in a given period and provides an unsolicited quote for a solar system.

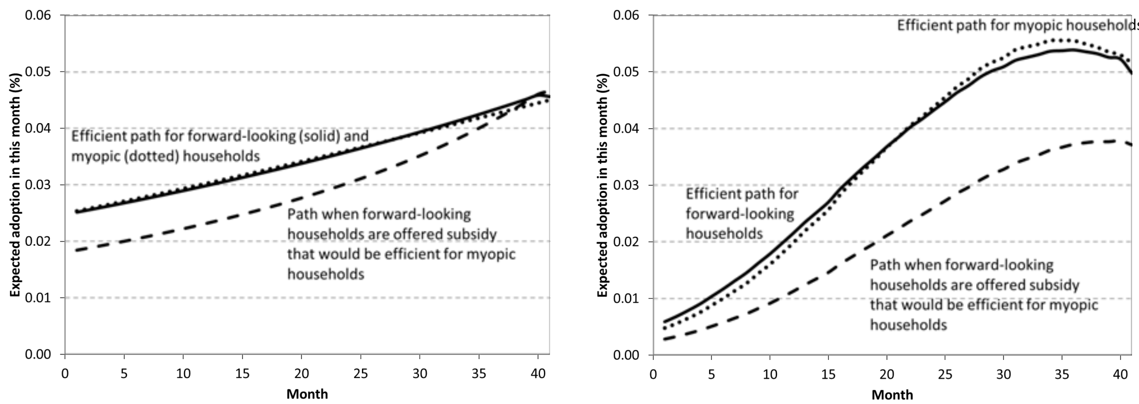
Table 3: The present value of spending, initial and terminal subsidies, and consumer surplus along the efficient subsidy trajectory, along with the consumer surplus obtained in the absence of subsidies.

	Myopic		Forward-Looking	
	Technology Constant	Technology Improving	Technology Constant	Technology Improving
Present value of spending ($billion)	1.7	0.5	1.8	0.9
Present value of spending ($/W)	5.3	1.6	5.7	2.8
Initial subsidy ($/W)	5.5	1.4	6.3	3.3
Terminal subsidy ($/W)	7.7	2.9	7.9	4.0
Consumer surplus without any subsidy ($billion)	0.03	0.20	0.12	0.94
Consumer surplus with efficient subsidy ($billion)	0.47	0.45	0.77	1.42

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 will change 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 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 $130 million (8%). The effect of foresight is even stronger in the presence of technological change because households' option to adopt in a later period becomes especially valuable: when technology is improving, households' foresight increases the regulator's spending by $350 million (70%).

Households' foresight is good for the households, however: the regulator's spending increases because households capture more surplus when they are forward-looking. As we will



(a) Technology Constant (b) Technology Improving

Figure 3: Monthly expected adoption along the efficient subsidy schedule for forward-looking households (solid), along the efficient subsidy for myopic households (dotted), and for forward-looking households who are offered the subsidy that would be efficient for myopic households (dashed).

see below, households' foresight constrains the regulator's ability to intertemporally price discriminate and thereby avoid "over-subsidizing" high-value households in early periods. As a result, the subsidy program increases myopic households' surplus by only around \$440 million (\$250 million) when technology is constant (improving) but increases forward-looking households' surplus by \$650 million (\$480 million). In the absence of a subsidy, technological change increases forward-looking households' surplus by \$820 million, but technological change increases myopic households' surplus by only \$170 million because they do not optimize the timing of their adoption. With the efficient subsidy, the contrast is even starker: myopic households actually *lose* \$20 million in surplus under technological change, whereas forward-looking households gain \$650 million.[39] This difference arises because, when households are myopic, the forward-looking regulator can optimize the subsidy schedule to increase adoption in later periods when costs have fallen (see Figure 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.

[39]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 Appendix C.2 for details.

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 3 to disentangle the multiple forces that determine whether the efficient subsidy increases or decreases over time.[40]

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 is also equal to $\dot{s}(t)$. When households are myopic and technology is constant over time (top left panel), the efficient subsidy increases strongly over time because the price discrimination channel is large. By starting with a relatively small subsidy and raising it over time, the regulator avoids paying a large subsidy to households who would adopt even for a smaller subsidy.[41] However, when households are forward-looking (top right panel), their expectations and ability to time adoption constrain the regulator's ability to intertemporally price discriminate. The large, positive price discrimination channel is replaced by a promise-keeping channel that begins at zero and increases only slowly. Therefore, when technology is constant, the efficient subsidy increases more slowly for forward-looking households.[42]

[40]The only approximations are that we impose the theoretical setting's restrictions that preferences are fixed over time and that technology evolves deterministically. The appendix plots the efficient subsidy and adoption trajectories under these restrictions. The efficient subsidy trajectories are qualitatively similar to the cases in Figure 2. The main differences are that these restrictions increase the level of the subsidy, make the efficient subsidy decline over an initial interval when households are forward-looking and there is technological progress, and delay the start of the subsidy when households are myopic and there is technological progress. The appendix explains these differences in more detail, emphasizing how they arise from eliminating stochasticity in households' preferences.

[41]The price discrimination channel is especially important in early periods because the marginal adopter is far in the tail of the distribution of households. In this case, most adopters tend to be inframarginal. The smooth spending channel also favors a more strongly increasing subsidy in the first instants. Spending tends to decline over the first instants as the weakening of the price discrimination channel slows the subsidy's initially rapid rate of increase. As a result, the measure of values that find adoption newly optimal falls over these instants ($\dot{y}(t) > 0$ in the notation of Section 3). The regulator smooths spending by not flattening the subsidy trajectory too quickly.

[42]Using an increasing subsidy does not eliminate early adoption when households are forward-looking and technology is constant because households who 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.

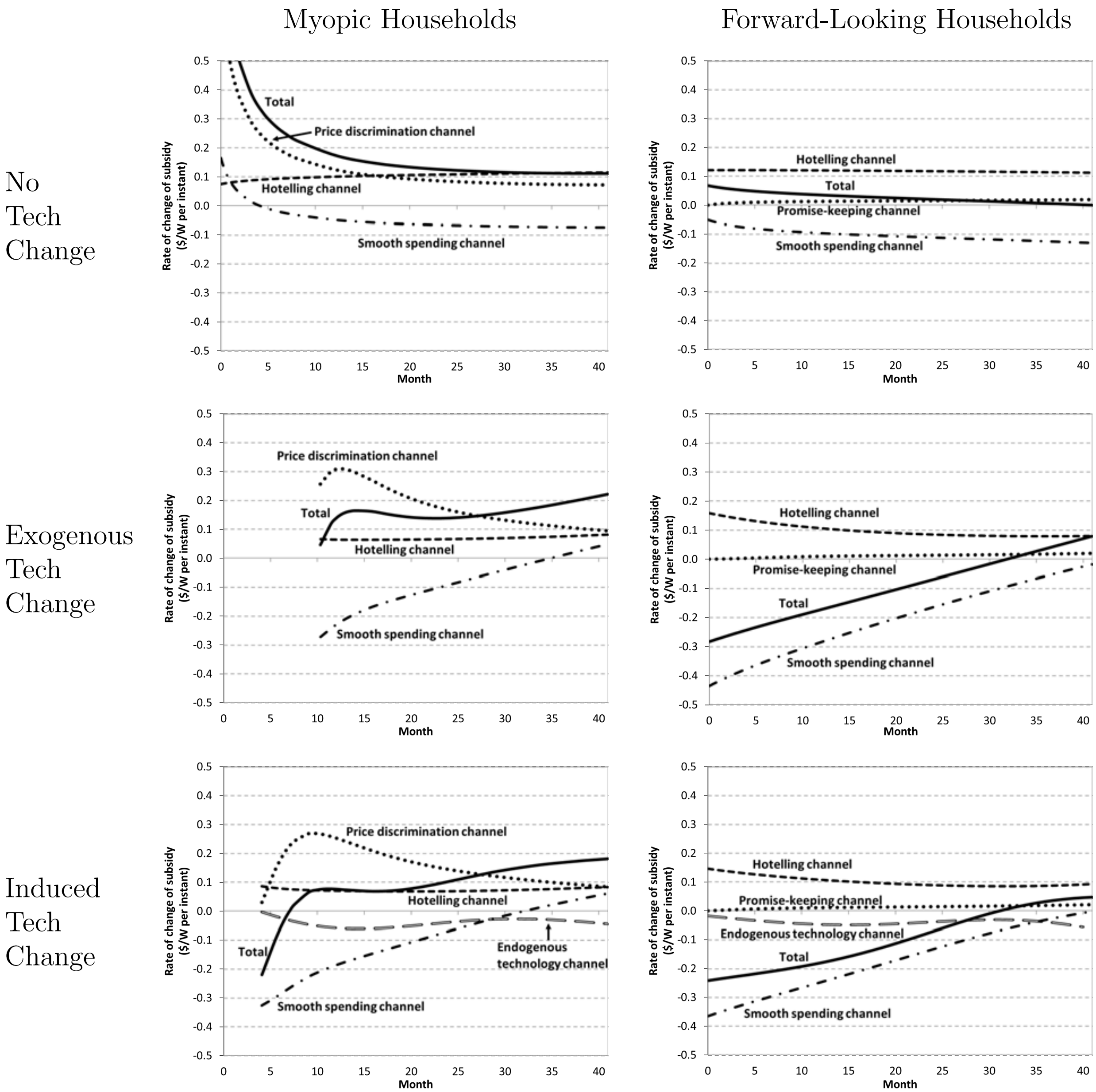


Figure 4: The change in the efficient subsidy at each instant ($\dot{s}(t)$, labeled "Total"), as well as each component from equations (1) and (4). The adoption benefit component (not plotted) is negative but very small in magnitude. When consumers are myopic and technology is changing, the regulator 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. Recall that 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. The left panel shows the case without technological change. Here, forward-looking households' incentives to delay adoption arise from the increasing subsidy schedule (seen in Figure 2). We see that the more sharply increasing subsidy offered to myopic households would significantly dampen adoption by forward-looking households in early periods.[43] Their willingness to wait for the high later subsidies limits the regulator's ability to price discriminate through an increasing subsidy schedule.

The middle row of Figure 4 explains why introducing technical change flattens the efficient subsidy trajectory, especially in early periods (seen in Figure 2). First, in the case with myopic households, the regulator here delays the start of the subsidy for several months in order to take advantage of technological progress. Once the subsidy does begin, it follows a flatter trajectory than in the case with constant technology because the smaller subsidy produces fewer inframarginal adopters and thus weakens the price discrimination channel. Second, and most importantly, the smooth spending channel is now strongly negative because technological progress increases adoption over time and thus tends to increase the regulator's spending over time for a given subsidy. A regulator with a convex cost of funds reduces the subsidy over time so as to achieve a smoother spending profile. The smooth spending channel weakens as the pace of technological progress slows, so that the efficient subsidy increases after a few periods. The bottom row of Figure 4 shows a third way in which technological change can favor a declining subsidy. These panels endogenize technological change by fitting the evolution of costs to the efficient adoption trajectory (see appendix), so that costs end up at the same place but the regulator can now choose to get there faster. Now an endogenous technology channel also favors a declining subsidy. All else equal, the regulator prefers to use a greater subsidy in early periods so as to stimulate early adoption that can reduce the technology's cost in later periods.

The right panel of Figure 3 shows how households' foresight flattens the efficient subsidy trajectory in the full model under (exogenous) technological change. We saw in Figure 2 that the efficient subsidy for forward-looking households is initially nearly constant. Because the

[43] As the terminal period approaches, forward-looking households' adoption rate increases when offered the subsidy that would be efficient for myopic households because they are aware that the subsidy will drop to zero after month 41.

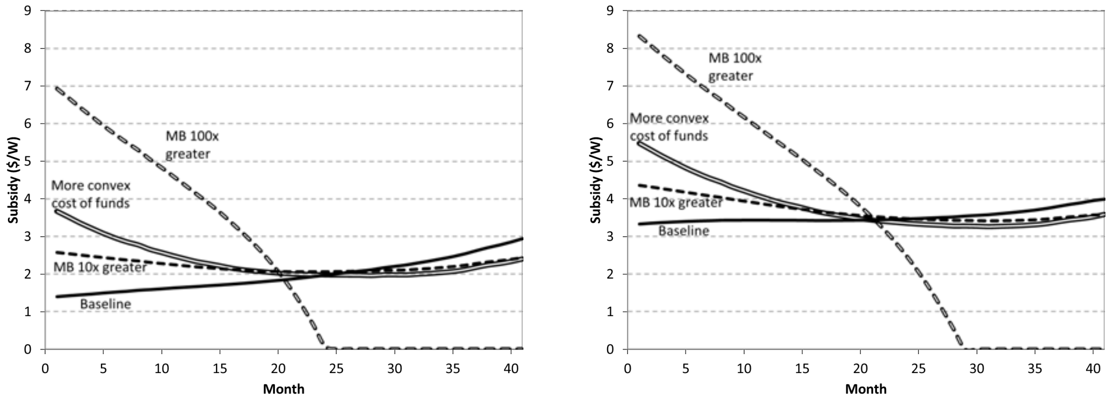
efficient subsidy at first increases only slowly for myopic households, offering that subsidy to forward-looking households does not substantially dampen adoption in early periods. However, the subsidy offered to myopic households increases more strongly in the middle periods. Forward-looking households would therefore delay adoption to a large degree in these middle periods if offered the subsidy designed for myopic households. In the presence of technological change, the efficient subsidy offered to forward-looking households must remain nearly constant for most of the policy horizon in order to convince enough forward-looking households not to postpone adopting the technology.

7 Comparison to Existing Subsidy Paths

We have seen that the combination of forward-looking households and technological progress can generate a nearly constant subsidy trajectory, but the California regulator used a strongly declining subsidy. What types of assumptions can generate that type of subsidy trajectory? Figure 5 shows that giving the regulator a much more convex cost of funds and increasing its marginal benefit of adoption tenfold can both make the subsidy decline over time. 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 half has nearly identical effects as increasing the regulator's marginal benefit tenfold. A more patient regulator is less inclined to defer spending to later periods. Yet even in these cases, the efficient subsidy still does not decline nearly as sharply as the actual subsidy.[44]

However, a final case is different: increasing the regulator's marginal benefit of adoption one hundredfold 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 here shows that a large adoption benefit channel drives the declining subsidy trajectory. 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 greater subsidy early on. These results are especially intriguing because it is entirely plausible that

[44] Endogenizing technological change as described for Figure 4 has a negligible effect on the subsidy trajectory.



(a) Myopic households (b) Forward-looking households

Figure 5: The effect on the efficient subsidy of reducing the spending level at which the cost of funds doubles to 0.1% of the original value, of increasing the regulator's marginal benefit of solar tenfold, and of increasing the regulator's marginal benefit of solar a hundredfold, for myopic households (left) and forward-looking households (right).

California regulators did value solar installations to a much greater degree than recommended by the economic analyses used in our calibrated objective. This disagreement about the marginal social value of solar would simultaneously explain why California regulators chose to use a subsidy to spur adoption at all and justify why California regulators designed such a sharply declining subsidy.

8 Conclusions

We have demonstrated the forces that determine how to design a subsidy to induce adoption of a new technology over time. In particular, we have shown that if consumers are myopic, then the regulator can reduce its overall spending by using an increasing subsidy schedule as a means of intertemporally price discriminating. However, if consumers have rational expectations over future subsidies, then their ability to wait for the higher subsidies constrains the regulator's ability to price discriminate. Quantitatively, these expectations increase the regulator's spending by 8% in the absence of technological change. Further, when consumers have rational expectations about technological progress, the regulator must offer them a relatively large subsidy in order to compensate them for forsaking their option to adopt the technology in a later period. Quantitatively, technological progress would reduce the regulator's spending by 70% if households were myopic, but technological progress reduces the regulator's spending by only 50% when households are forward-looking. Rational expectations thus increase the total cost of the policy program by nearly 70% in a world with technological progress.

Future work should 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. Future work should also consider when private decisions to wait are socially inefficient. For instance, our results suggest that a regulator could reduce spending if it could convince households to ignore the possibility of higher subsidies or better technology in the future. Additional theoretical analysis could consider when regulators may have an incentive to mislead households, and empirical work could test for such effects in actual policy environments.

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Appendix

The first section contains the formal derivations of the efficient subsidy trajectories. The second section provides empirical evidence that consumers are forward-looking in the California market for rooftop solar, which motivates why we estimate a dynamic choice model in order to study their adoption decisions. It also provides some additional detail on the data and reports sensitivity tests for the empirical model. The third section describes the numerical calibration of the policymaker's problem. It also describes the solution techniques and reports additional results. The final section demonstrates that analyzing a fixed budget does not substantially affect our theoretical analysis of the efficient subsidy trajectory.

A Formal Analysis

Begin with the setting in which potential adopters are myopic. The Hamiltonian is:

$$\begin{aligned} H(t, y(t), Y(t), \lambda(t)) =& e^{-rt}\left[B\Big(1-F(Y(t))\Big) - G\Big(-\left[C(t,1-F(Y(t)))-Y(t)\right] f(Y(t))\, y(t)\Big)\right] \\ &+ e^{-rt}\lambda(t)y(t). \end{aligned}$$

$\lambda(t)$ gives the (current) shadow value of $Y(t)$. The necessary conditions for a maximum are:

$$\lambda(t) = -\left[C(t,1-F(Y(t)))-Y(t)\right] f(Y(t))\, G'\Big(-\left[C(t,1-F(Y(t)))-Y(t)\right] f(Y(t))\, y(t)\Big), \tag{A-1}$$

$$\begin{aligned} -\dot{\lambda}(t) + r\lambda(t) =& -B'\Big(1-F(Y(t))\Big) f(Y(t)) \\ &- G'\Big(-\left[C(t,1-F(Y(t)))-Y(t)\right] f(Y(t))\, y(t)\Big) \\ &\quad \Big[f(Y(t))\, y(t) - \left[C(t,1-F(Y(t)))-Y(t)\right] f'(Y(t))\, y(t) \\ &\quad + [f(Y(t))]^2\, y(t)\, C_2(t,1-F(Y(t)))\Big], \end{aligned} \tag{A-2}$$

along with the transition equation, the initial condition, and the terminal condition. The first equation follows from the Maximum Principle and the second equation is the costate (or adjoint) equation for the state variable $Y(t)$. The first equation implies that $\lambda(t) \leq 0$: because lower $Y(t)$ corresponds to greater adoption $Q(t)$, this negative sign means that the shadow benefit of adoption is positive. Differentiate equation (A-1) with respect to time and suppress the argument of $G(\cdot)$:

$$\begin{aligned}\dot{\lambda}(t) = &- [\dot{C}(t,Q(t)) - y(t)]\, f(Y(t))\, G' - [C(t,Q(t)) - Y(t)]\, f'(Y(t))\, y(t)\, G' \\ &- [C(t,Q(t)) - Y(t)]\, f(Y(t))\, G'' \\ &\quad \Big[- [\dot{C}(t,Q(t)) - y(t)]\, f(Y(t))\, y(t) - [C(t,Q(t)) - Y(t)]\, f'(Y(t))\, y(t)^2 \\ &\qquad - [C(t,Q(t)) - Y(t)]\, f(Y(t))\, \dot{y}(t) \Big],\end{aligned}$$

where $\dot{C}(t,Q(t)) \triangleq \mathrm{d}C(t,Q(t))/\mathrm{d}t$. Substituting for $\dot{\lambda}(t)$ from the costate equation (A-2), using $\dot{s}(t) = \dot{C}(t,Q(t)) - y(t)$, and rearranging yields the expression for $\dot{s}(t)$ in the main text.

Now consider the setting in which potential adopters are forward-looking. The Hamiltonian is

$$\begin{aligned}H(t,y(t),Y(t),s(t),\lambda(t),\mu(t)) = &e^{-rt}\left[B\Big(1 - F(Y(t))\Big) - G\Big(- s(t)\, f(Y(t))\, y(t)\Big)\right] \\ &+ e^{-rt}\lambda(t) y(t) \\ &+ e^{-rt}\mu(t)\, \delta\, [Y(t) - C(t, 1 - F(Y(t))) + s(t)] \\ &+ e^{-rt}\mu(t)\, [C_1(t, 1 - F(Y(t))) - C_2(t, 1 - F(Y(t)))\, f(Y(t))\, y(t)]\,.\end{aligned}$$

The costate variable $\lambda(t)$ is the same as in the myopic setting. The new costate variable $\mu(t)$ measures the degree to which the regulator is constrained at each instant by private actors' equilibrium behavior and rational expectations: it measures the cost of keeping promises made to those who adopted the technology in past periods.

The necessary conditions for a maximum are:

$$
\begin{aligned}
\lambda(t) =& - s(t)\, f(Y(t))\, G'\Big(- s(t)\, f(Y(t))\, y(t)\Big) \\
&+ \mu(t)\, C_2(t, 1-F(Y(t)))\, f(Y(t)), \qquad \text{(A-3)} \\
-\dot{\lambda}(t) + r\lambda(t) =& - f(Y(t))\, B'\Big(1 - F(Y(t))\Big) \\
&+ s(t)\, f'(Y(t))\, y(t) G'\Big(- s(t)\, f(Y(t))\, y(t)\Big) + \delta\mu(t) \\
&+ \delta\, \mu(t)\, f(Y(t))\, C_2(t, 1-F(Y(t))) \\
&+ \mu(t)\Big[- C_{12}(t, 1-F(Y(t)))\, f(Y(t)) + C_{22}(t, 1-F(Y(t)))\, [f(Y(t))]^2\, y(t) \\
&\qquad - C_2(t, 1-F(Y(t)))\, f'(Y(t))\, y(t)\Big], \qquad \text{(A-4)} \\
-\dot{\mu}(t) + r\mu(t) =& f(Y(t))\, y(t)\, G'\Big(- s(t)\, f(Y(t))\, y(t)\Big) + \delta\mu(t), \qquad \text{(A-5)} \\
\mu(0) =& 0,
\end{aligned}
$$

along with the transition equations and the initial and terminal conditions. The first equation follows from the Maximum Principle, the next two equations are the costate (or adjoint) equations, and the final equation is the transversality condition corresponding to the choice of $s(0)$.

Solving for $\mu(t)$ in equation (A-5), we find

$$
\mu(t) = - \int_0^t e^{-(\delta - r)(t-i)} f(Y(i))\, y(i)\, G'\Big(- s(i)\, f(Y(i))\, y(i)\Big) \mathrm{d}i \geq 0. \qquad \text{(A-6)}
$$

Whereas costate variables in standard optimal control problems are forward-looking, here the costate variable $\mu(t)$ is backward-looking. The costate variable $\mu(t)$ is the discounted value of all past adoption. In the first instant, the regulator is not bound by past commitments, but over time the regulator becomes more bound by the commitments it has made in order to obtain past adoption. The regulator's promises accrue as past adoption accrues, and these promises decay at rate $\delta - r$. The more impatient that potential adopters are (the higher is δ), the faster that past commitments fade away and the smaller $\mu(t)$ is. The more impatient that the regulator is (the higher is r), the more commitments tend to accumulate and the larger $\mu(t)$ is: the regulator obtained early benefits by making promises about later dates' subsidies.

Differentiate equation (A-3) with respect to time to obtain

$$
\begin{aligned}
\dot{\lambda}(t) = &- \dot{s}(t)\, f(Y(t))\, G' - s(t)\, f'(Y(t))\, y(t)\, G' \\
&- s(t)\, f(Y(t))\, G'' \Big[- \dot{s}(t)\, f(Y(t))\, y(t) - s(t)\, f'(Y(t))\, [y(t)]^2 - s(t)\, f(Y(t))\, \dot{y}(t) \Big] \\
&+ \dot{\mu}(t)\, C_2(t, 1 - F(Y(t)))\, f(Y(t)) \\
&+ \mu(t)\, C_{12}(t, 1 - F(Y(t)))\, f(Y(t)) \\
&- \mu(t)\, C_{22}(t, 1 - F(Y(t)))\, [f(Y(t))]^2 y(t) \\
&+ \mu(t)\, C_2(t, 1 - F(Y(t)))\, f'(Y(t))\, y(t),
\end{aligned}
$$

where we suppress the argument of $G(\cdot)$. Substituting for $\dot{\lambda}(t)$ from the costate equation (A-4) and rearranging yields the equation for $\dot{s}(t)$ in the main text. To show that the price discrimination channel and $r\,\mu(t) - \dot{\mu}(t)$ combine to leave $\delta\,\mu(t)$, use the costate equation (A-5).

B Empirical Appendix

B.1 Evidence that Consumers are Forward-Looking

Before we estimate consumers' private values for residential solar, we must understand whether consumers actually do think about future solar costs and subsidies when they make their investment decisions. There are a few reasons why we might think that the dynamic trajectory of prices and subsidies would matter for households' solar installation decisions. First, there are examples in the literature on goods other than residential solar where consumers make decisions in expectation of future policy changes (e.g., Mian and Sufi, 2012). Second, it is not necessary that households themselves are informed about the future trajectory of solar subsides as long as solar installers are informed. If installers use the fact that subsidies will be changing to encourage households to install solar now, then households will act as if they were directly informed about the subsidy schedule.

To understand whether households in California behave as if they are forward-looking, we begin by looking at the monthly installations in each utility along with the dates on which subsidies change (recall that the subsidy levels are shown in Figure 1 in the text). Figure B1 shows that there are large increases in the number of permits filed to install solar in the last full month before a utility's subsidy declines.[1] This suggests that households are anticipating the subsidy decline.

While Figure B1 provides some basic evidence that consumers are forward-looking, it does not control for other factors that might affect households' decision to adopt. In order

[1] This effect has also been shown in Burr (2014) and Hughes and Podolefsky (2015).

Figure B1: Monthly Installations and Dates of Subsidy Declines by Utility

to better understand whether households are reacting to dynamic incentives, we regress the weekly counts of residential solar subsidy applications on measures of current and future solar system costs and controls. In particular, we focus on future drops in the CSI subsidy, changes in the prices of solar modules and of silicon, and changes in the US-China exchange rate. As we saw above, when the subsidy is about to decrease, more households will choose to install solar now if households are forward-looking. Similarly, for a given current cost of solar modules, high input (silicon) costs might suggest that the cost of solar modules is about to increase, so forward-looking households will want to install now. Since China produces a large number of solar panels, if the US-China exchange rate is increasing, then panels will be less expensive in the future and forward-looking households should wait to invest in solar.

In order to test whether household behavior responds to these measures of future costs, we combine the CSI application data with a solar module price index and a silicon price index from Bloomberg. We also include the realized 3-month change in the dollar-yuan exchange rate and a set of controls that includes the VIX (a measure of the expected volatility of U.S. equities), the current dollar-yuan exchange rate, the current Euro-yuan exchange rate, the 6-month Treasury bill interest rate, and the DOW real estate investment trust index. These controls aim to capture macroeconomic conditions that affect the incentive to invest in solar.[2]

Table B1: Evidence That Consumers are Forward-Looking

Dependent Variable: Log Weekly CSI Applications	
Within 2 months of subsidy drop	0.300***
	(0.055)
Solar Module Price Index	-2.701***
	(0.619)
Silicon Price Index	0.012**
	(0.006)
3 month change in Dollar-Yuan Exchange Rate	-2.045***
	(0.694)
VIX (Instrumented)	-0.032**
	(0.014)
Number of utility-weeks	650
R^2	0.6779

Standard errors clustered by week. Controls include the Dollar-Yuan exchange rate, the Euro-Yuan exchange rate, the 6 month T-bill interest rate, the DOW REIT index, utility fixed effects and utility-specific time trends. Instruments are month-over-month changes in 10 year bond yields for Greece, Italy, Russia, and Spain. F=482.55 Results are not substantially different if the VIX is not instrumented.

The regression results presented in Table B1 suggest that consumers are forward-looking in their decision to install solar (or at least that solar installers are forward-looking and convey this information to households). The coefficient estimates suggest that more households submit applications to install solar systems when subsidies are about to decline.[3] Higher solar module prices reduce installation, but conditional on solar module prices, higher silicon prices (which suggest that module prices will be higher in the future) increase installation. Similarly, if the US-China exchange rate is increasing (conditional on the current level of the exchange rate) then solar panels will likely be less expensive in the future. Indeed, our estimates suggest that an increasing US-China exchange rate reduces installations today.

[2] We instrument for the VIX with month-over-month changes in 10-year bond yields for several economically volatile developed countries (Greece, Italy, Russia, and Spain) in order to isolate sources of market uncertainty that should not directly affect California households through channels such as employment or income.

[3] Since the CSI subsidies were tied to cumulative installation in each utility, it is possible that higher adoption is causing subsidy declines. To test for this, we conducted a separate analysis restricted to media markets served by two utilities. If local conditions were leading households to install solar and thereby trigger declines in the subsidy, then we would see increased adoption in households in one utility when their neighboring utility was about to have a subsidy decline. We found no evidence that this was true, leading us to conclude that reverse-causality is not a major problem for this descriptive analysis.

Finally, it is interesting that economic uncertainty, as captured by the instrumented VIX, tends to decrease solar installations, as would be expected if households account for option value when timing their installation decision (which again implies that households are not fully myopic).

Given that households behave as if they are forward-looking, it is important to use a dynamic model of residential solar adoption in order to estimate the benefits of installing a solar system. If we used a static model of solar adoption, we would underestimate the benefits to households of adopting: some households that value solar above the current system cost will choose not to install for now as they wait for technology to advance and for costs to drop. Correctly accounting for the value of waiting for lower prices is critical to understanding the trade-offs regulators face in structuring solar subsidies.

B.2 Data Details

Sample

In order to estimate our dynamic solar adoption model, we limit our estimation sample in a few important ways to make sure that our model fits what actually happened in California during the CSI program. First, we limit the timeframe of our analysis. In the early months of the CSI, there was a 30% federal tax credit available for residential solar installation, represented by ϕ. However, the federal tax credit was initially capped at $2,000 (which was strictly binding for most systems in California), and this cap was only lifted on January 1, 2009. Because we do not know whether households anticipated this federal policy change, we limit our analysis to installations that occurred after the cap was lifted.

Additionally, because the CSI data only includes information on installations that applied for CSI subsidy funding, we need to end our analysis when the CSI data ends. There is some evidence that some installers were not submitting applications for CSI subsidies at the very end of the program when the subsidy was very low, so we end our estimation period in May of 2012 when all utilities still had a subsidy, but our results are fundamentally unchanged if we end the estimation window 3 periods earlier. These restrictions leave us with a 41-month time-frame for estimating households' preferences. We solve recursively for the value function by working backwards from the value function's fixed point in the first period in which all utilities' subsidies were zero, but we limit our maximum likelihood estimation window to only those periods where we were sure that all three utilities had positive subsidy levels and there were enough subsidy applications for the reported system costs to be reliable.

We geographically limit our estimation sample by only estimating preferences for households in those zip codes that are wholly part of one of the three major California utilities. We therefore exclude households in zip codes that are not serviced by PG&E, SCE, or SDG&E and households in zip codes that are serviced by more than one of those utilities. We found that households did not react to subsidy changes by utilities with customers in the household's media market but who were not actually serving that particular zip code, so we are not concerned about spillover effects from subsidy changes in nearby zip codes.

Finally, some households in our data actually "lease" residential solar systems rather than purchasing them outright, meaning that an outside firm pays the upfront cost of the system and then shares the benefits of the solar generation over time. Since the reported costs for these systems may differ from purchased systems (Podolefsky, 2013), we might be concerned about treating these leases as purchases if the rate of leasing varies systematically with subsidy changes. Third-party ownership is reported in our data, and while we did find some reduced-form evidence that leased systems report lower costs than purchased systems, we did not find a substantial systematic change in the leasing rate near subsidy changes and therefore treat both leased and purchased systems identically.

Cost evolution

We use the average per-Watt installed system price in each of the three utilities in each month to estimate the parameters of the AR1 model for system costs, assuming that all utilities have the same transition function. When expressed in tens of thousands of dollars for the average 5.4kW system, we estimated costs to evolve as $C_{i(t+1)} = 6.468 \times 10^{-4} + 0.9925 C_{it} + \omega_{it}$, where ω_{it} is mean-zero and has a standard deviation of 0.1611.

B.3 Sensitivity of Dynamic Estimation

Stochasticity

As explained in the text, we assume that 5% of households consider installing solar and estimate the model accordingly. This is primarily because we are concerned that if we were to estimate a model with i.i.d. draws and every household considering adopting solar, we would be obscuring a substantial amount of serial correlation in the residuals that actual households receive each month. Some homes are just not suited for solar systems, whether that is because of the age of the building or the orientation of the roof (if the majority of suitable roof space is north-facing, then a standard solar system will not generate much electricity and will not pay for itself in reduced electricity bills). By including a permanent, random shock to preferences in the form of the "considered" variable, we allow for a degree of serial correlation that is otherwise missing from the model. Indeed, when we estimate the percent considered as a variable, we find that 2.26% of households consider installing solar. All other coefficients in that estimation are nearly identical to the coefficients presented, but the standard errors are very large, reflecting the difficulty with estimating serial correlation in this type of model. We therefore assume that 5% of households consider adopting solar, limit our data to this subsample, and then estimate the preference coefficients. Coefficient estimates are similar if we instead assume that 2.26% or 10% of households consider adopting solar.

Understanding how this assumption affects the results of our paper also provides insight into the role of the stochastic errors in the design of the efficient subsidy schedule (discussed in Section C.3). If we had instead assumed that every household considered installing solar, then there would be 20x more households deciding whether to adopt solar in the initial period (and similar increases in other periods). Given that total adoption is unchanged, adoption becomes an extremely rare event that can occur only if a household gets a very uncommon draw of residuals in a period. Since there is no serial correlation in a household’s draws, forward-looking households will not expect to receive another draw of this magnitude within a reasonable time-frame. Because we are studying a similarly low adoption target, adoption will be driven by households who happen to receive extreme draws. Therefore, the model without serial correlation in the residuals leads the forward-looking households who are responding to the subsidy to behave very similarly to myopic households and adopt as soon as they receive a set of draws that makes adoption attractive, even if technology or subsidies are set to improve in the future. The efficient subsidy for forward-looking households will therefore converge to the efficient subsidy for myopic households. Given that we believe (both from introspection and estimation) that the percent of households who consider installing solar is low and that there is serial correlation in the stochastic errors, we base our simulations on the model where 5% of households consider adopting solar.

Variables and Timing

In addition to the empirical specification presented, we estimated models that included log income, an indicator for Democrat, the number of home mortgages, the number of people in the household, and, instead of median radiation in each zip code, mean radiation in each zip code. Income has a similar effect to home prices but has a larger standard error. Democrat, mortgages, and number of people in the household were not statistically significantly important in predicting installation decisions. Replacing median radiation with mean radiation produced very similar results.

In reality, the step-wise declines in the CSI subsidy were triggered once a utility achieved a predefined level of total solar adoption. Since it was broadly announced when the quantity targets were approaching, we make the assumption that the subsidies declined on set dates rather than at set installation quantities. In the theoretical setting, the regulator understands how the subsidy will determine expected adoption over time, so she could just as easily announce the subsidy as a function of time or of cumulative adoption. However, we could be concerned that households who were unsure when the subsidy would drop might adopt solar earlier to ensure that they receive the higher subsidy. Empirically, running the model with subsidy changes moved one period forward resulted in coefficients that were nearly identical to and statistically indistinguishable from the baseline coefficients, so we use the actual timing of the subsidy schedule in our baseline results.

Finally, there is some uncertainty as to when the subsidies officially ended in each utility’s service area. The lowest subsidy level was low enough that it appears that some installers found that the cost of submitting the paperwork for the subsidy did not justify the benefit to be received. In order to test whether the uncertainty surrounding the end date of the subsidy is affecting our results, we estimated a model where we assumed that the subsidies ended three periods earlier than they do in our baseline specification. Recall that this does not change our estimation window since we end our estimation before the actual end of the CSI. Our results are fundamentally unchanged.

C Numerical Calibration, Solution Method, and Additional Results

We begin by describing the calibration. We then describe how we solve the stochastic and deterministic models. We conclude this section with additional results.

C.1 Calibration

We here describe the calibration of the regulator’s benefit from cumulative adoption and the cost of public funds. Assume that the regulator’s benefit function is quadratic:

$$B(Q_t) = \gamma_1 Q_t + \gamma_2 Q_t^2.$$

We calibrate γ_1 as the marginal social benefit of solar from Baker et al. (2013). They simulate a 5 kW array, whereas we use a 5.4 kW array. They report a south-facing array in San Francisco as generating 7,220 kWh (AC) per year. Assume that this energy production is evenly distributed across months. They report the value of solar to the electric grid (“weighted average λ”) as \$0.055/kWh. They report the emission displacement rate as 1.11 pounds of carbon dioxide (CO_2) per kWh. Using the U.S. government’s year 2015 social cost of carbon (with a 3% discount rate) of \$36/tCO_2, we have the emission benefit of a 5 kW array as \$0.0181/kWh. Over the course of a month, the combined grid and emission benefit of a 5.4 kW array is

$$(5.4/5)(7220/12)(0.0181 + 0.055)/10^4 = 0.0048$$

in tens of thousands of dollars, which we use as the marginal social benefit of the first array to be adopted (i.e., the first 5.4 kW array to be adopted generates \$48 per month of social value). In the simulations, Q_t measures the fraction of the population that has adopted solar. The parameter γ_1 must adjust for the size N of the population:

$$\gamma_1 = 0.0048N.$$

Assume that the marginal social value of an installed solar array falls by x% by the time we reach z% adoption (e.g., because of concerns about intermittency). Then

$$\gamma_1 + 2\gamma_2 z/100 = (1 - x/100)\gamma_1,$$

which implies

$$\gamma_2 = -\frac{1}{2}\frac{x}{z}\gamma_1 \leq 0.$$

Gowrisankaran et al. (2016) estimate that the intermittency of solar electricity would impose costs of \$46/MWh if solar photovoltaics provided 20% of electricity in Arizona.[4] For our 5.4 kW array, this works out to a cost of

$$(5.4/5) * (7220/12) * (46/1e3)/1e4 = 0.0030$$

in tens of thousands of dollars, which means that our marginal benefit of solar would decline by 62.5% (yielding $x = 62.5$) if solar photovoltaics provided 20% of electricity in California. Using California's 2014 electricity consumption of 296,843 GWh,[5] providing 20% of electricity means providing 59,369 GWh. To generate this much electricity, we require $59369e6/[(5.4/5) * 7220]$ arrays (or nearly 8 million arrays). We therefore have $z = 100 * 59369e6/[(5.4/5) * 7220]/N$, or an adoption rate of 185%.

Assume that the regulator's cost of funds is quadratic:

$$G(z) = g_1 z + g_2 z^2,$$

where z is subsidy spending in tens of thousands of dollars. The argument of $G(\cdot)$ in the main text is $s_t[Q_{t+1} - Q_t]$, which is total subsidy spending. When Q is normalized to be the fraction of the population (as in the simulations), we have $z = s_t[Q_{t+1} - Q_t]N$. Barrage (2016) collects estimates of the marginal cost of public funds from the literature. Averaging the estimates for the U.S. yields \$1.35 for the marginal cost of the first dollar of spending. We therefore have:

$$g_1 = 1.35.$$

Let the marginal cost of funds double when spending reaches x dollars. So the cost of funds doubles when we have $z = x/10^4$. Thus, we have

$$g_1 + 2g_2\frac{x}{10^4} = 2g_1,$$

which implies

$$g_2 = \frac{1}{2}\frac{g_1}{x}10^4.$$

[4]This scenario assumes that conventional sources of electricity are reoptimized around the 20% solar penetration rate. This number does not account for how the marginal value of electricity may decline in solar penetration.

[5]`http://energyalmanac.ca.gov/electricity/total_system_power.html`

There is not much literature on the curvature of the cost of public funds. The traditional marginal cost of public funds is likely to be linear over the sums of interest, but our cost of funds is meant to be a broad measure whose curvature captures the regulator's distaste for disbursing a lot of money all at one time. This distaste could be driven by political constraints that are beyond traditional economic estimates of the marginal cost of public funds. We assume that this distaste is such that the marginal cost of public funds would double if the regulator were to allocate its entire actual cumulative spending to a single instant. This assumption yields x equal to \$148 million.

The regulator's horizon is 41 months. As in the empirical model, we assume that households use a monthly discount rate of 1% and we measure time in months. We assume that the regulator uses the same discount rate as its households. We begin with 0.071% of households having adopted solar ($Q_0 = 0.00071$).

C.2 Solving the stochastic setting

We now describe how we solve the setting in which each household can receive a new draw of each ε_i in each period and in which installation costs may evolve stochastically. For any candidate subsidy trajectory, we simulate the empirical model over 100 draws of the stochastic component of the system cost evolution in order to obtain adoption in each period.[6] This simulation gives expected adoption at the end of the horizon and gives the regulator's expected value from committing to the candidate subsidy trajectory. We use the Knitro solver in Matlab to search for the 41-element trajectory of per-month subsidies that maximizes the regulator's expected value while matching expected adoption at the end of the horizon to $\hat{Q}$.

We estimate our model assuming that households are forward-looking, based on the evidence provided in Appendix B.1. In order to calculate the expected consumer surplus of having the choice to install solar for forward-looking households under the counterfactual of no subsidy or the efficient subsidy, we use the standard expected consumer surplus equation:

$$E[CS_{foresight}] = \sum_{i=1}^{N_1} \Phi_i log\left[exp(X'_{i1}\gamma + \alpha_i \tilde{C}_1) + exp(\beta E[V(\Omega_2|\Omega_1)])\right] + S,$$

where S is a constant and $\tilde{C}_1$ is the average net-of-subsidy system cost in the initial period. We calculate the consumer surplus for myopic households by calculating expected utility in each period and discounting it back to the initial period:

$$E[CS_{myopic}] = \sum_{i=1}^{N_1} \Phi_i \sum_{1}^{T} \beta^{t-1}\left[Pr_{it}(X'_{it}\gamma + \alpha_i \tilde{C}_t - log(Pr_{it})) + (1 - Pr_{it})(-log(1 - Pr_{it}))\right] + S,$$

where Pr_{it} is the probability that household i adopts solar in period t. This formulation subtracts γ, Euler's constant, from the standard formulation of a household's expected utility

[6] Experiments with more draws did not yield substantially different results.

of choosing to adopt and from the household's utility of choosing to wait. Because households do not make a choice after they adopt, including the expectation of the EV1 draw would lead to higher expected consumer surplus estimates in situations where adoption by myopic households happens later in the policy window. As a result, expected consumer surplus is not directly comparable between myopic and forward-looking households, but the differences between the myopic households' expected consumer surpluses under different subsidy policies should be comparable to the differences for forward-looking households.

C.3 Solving the deterministic setting

We now describe how we use the theoretical analysis to solve the setting in which each household receives only a single draw of each $\vec{\varepsilon}_i$ for all time and in which the evolution of installation costs is deterministic.

To start, consider how the structural empirical model provides the desired distribution over private values v_i from the theoretical setting. The household's private value from adopting solar is equal to the price at which the household would be indifferent between adopting solar and not adopting solar if adoption were a now-or-never decision. From equation (1) and the definition of h_{it}, household i is indifferent to adopting solar at time t when

$$X_{it}'\gamma + \alpha_i \tilde{C}_{it} + \varepsilon_{i1t} = \varepsilon_{i0t} + \beta \mathbb{E}[V(\Omega_{t+1}|\Omega_t)],$$

which we can write as

$$b_i + \alpha_i \tilde{C}_{it} + \varepsilon_{i1t} - \varepsilon_{i0t} = \beta \mathbb{E}[V(\Omega'|\Omega)], \tag{C-7}$$

with

$$b_i = X_{it}'\gamma.$$

When adoption is a now-or-never decision, the expectation on the right-hand side of equation (C-7) is zero. Household i's private value for solar is then

$$v_i = -\frac{1}{\alpha_i}\left(b_i + \varepsilon_{i1t} - \varepsilon_{i0t}\right),$$

where each ε_{i*t} is a draw from a type I generalized extreme value distribution with location parameter 0 and scale parameter 1 and where each estimated α_i is negative. Rewrite as

$$\varepsilon_{i1t} - \varepsilon_{i0t} = -\alpha_i v_i - b_i.$$

The difference of two type I generalized extreme value random variables is itself a random variable following a logistic distribution with location parameter 0 and scale parameter 1. The cumulative distribution function $P(\cdot)$ of v_i is:

$$P(v_i) = \frac{1}{1 + e^{\alpha_i v_i + b_i}}.$$

The number of households with the same demographic characteristics as household i is N_i. Aggregate across demographic groups to obtain the cumulative distribution function for private values v across all demographic groups:

$$F(v) = \frac{\sum_i N_i \frac{1}{1+e^{\alpha_i v + b_i}}}{\sum_i N_i}.$$

Differentiating yields the density function of private values:

$$f(v) = \frac{-\sum_i N_i \frac{\alpha_i e^{\alpha_i v + b_i}}{\left(1+e^{\alpha_i v + b_i}\right)^2}}{\sum_i N_i}.$$

Differentiating a second time yields:

$$f'(v) = \frac{-\sum_i N_i \frac{\alpha_i^2 e^{\alpha_i v + b_i}\left(1-e^{\alpha_i v + b_i}\right)}{\left(1+e^{\alpha_i v + b_i}\right)^3}}{\sum_i N_i}.$$

Now consider the evolution of the private cost of installing solar. The empirical estimates account for changes in both the monetary cost of installing solar panels and the preference for solar, which we interpret as changes in the quality of solar panels. We take $C(t, Q(t)) = \xi(t, Q(t)) - \chi(t)$ to measure the quality-adjusted cost, with $\xi(t, Q(t))$ the direct monetary cost and $\chi(t)$ a discount to reflect quality improvements since time 0. As described above for b_i, the trend in quality will be valued by demographic groups differentially via α_i. We abstract from the time trend's demographic dependence by using a population-weighted average of α_i when calibrating $\chi(t)$ to the empirical estimates. The empirical estimates yield $\chi(t) = \chi_0\, t + \chi_1\, t^2$, with $\chi_0 > 0$ and $\chi_1 < 0$.

In the cases without induced technical change, we regress the cost of installation (beginning with the elimination of the federal subsidy cap) against a constant and its lagged value (as explained in Appendix B.2):

$$\xi_{t+1} = \theta_0 + \theta_1 \xi_t,$$

where t is measured with 1 as the first month of the estimation window and costs are measured in tens of thousands of dollars per 5.4 kW system. The initial cost of installing is assumed to be $\xi(0) = 4.4$, with the initial period serving as the reference for quality ($\chi(0) = 0$). Subtracting ξ_t from each side and passing to the continuum, we have

$$\dot{\xi}(t) = \theta_0 + [\theta_1 - 1]\xi(t),$$

where we ignore the potential dependence of ξ on $Q(t)$ because we are here focusing on the case with exogenous technical change. Solve the differential equation:

$$\begin{aligned}
&\dot{\xi}(t) + [1-\theta_1]\xi(t) = \theta_0 \\
\Leftrightarrow & e^{[1-\theta_1]t}\left\{\dot{\xi}(t) + [1-\theta_1]\xi(t)\right\} = e^{[1-\theta_1]t}\theta_0 \\
\Leftrightarrow & \int_0^t e^{[1-\theta_1]s}\left\{\dot{\xi}(s) + [1-\theta_1]\xi(s)\right\} \mathrm{d}s = \int_0^t e^{[1-\theta_1]s}\theta_0 \,\mathrm{d}s \\
\Leftrightarrow & \xi(t) = \frac{\theta_0}{1-\theta_1}\left[1 - e^{-[1-\theta_1]t}\right] + e^{-[1-\theta_1]t}\xi(0).
\end{aligned} \tag{C-8}$$

Substituting into $\dot{\xi}(t)$, we have

$$\dot{\xi}(t) = \theta_0 e^{-[1-\theta_1]t} - [1-\theta_1]e^{-[1-\theta_1]t}C(0).$$

Differentiating with respect to time, we have:

$$\ddot{\xi}(t) = -\theta_0(1-\theta_1)e^{-[1-\theta_1]t} + [1-\theta_1]^2 e^{-[1-\theta_1]t}\xi(0).$$

In the cases with induced technical change, we calibrate the pace of technical change to the efficient adoption pathway (from the full, stochastic model) in the presence of exogenous technical change. This calibration ensures that the efficient subsidies in the case with induced technical change differ due to the endogeneity of technology, not due to differences in eventual costs. Regressing log costs on cumulative adoption yields the following cost function:

$$\xi(t, Q(t)) = e^{\hat{\theta}_0 + \hat{\theta}_1 Q(t) + \hat{\theta}_2 Q(t)^2 + \hat{\theta}_3 Q(t)^3},$$

with $\hat{\theta}_0 = 1.50$, $\hat{\theta}_1 = -51$, $\hat{\theta}_2 = 3989$, and $\hat{\theta}_3 = -135443$. The fit to the exogenous cost trajectory (along that scenario's efficient adoption trajectory) is quite good, with an R^2 of 0.999.

We also must solve for $J(Y(T), C(T, Q(T)))$ in the setting with forward-looking households. Recall that $J(v_i, C(T, \hat{Q}))$ is the present value to household i of having the option to adopt the technology at time T, once the subsidy disappears for good. At time T, a household that has yet to adopt the technology solves:

$$J(v_i, C(T, Q(T))) = \max_{\Psi_i} e^{-\delta(\Psi_i - T)}\left[v_i - C(\Psi_i, Q(\Psi_i))\right],$$

for $\Psi_i > T$. In our application, it is always true that $v_i \leq 0$ for households who have yet to adopt solar at time T. Such households will never adopt the technology at a later time Ψ_i, once the subsidy is gone. We can therefore fix $J(v_i, C(T, Q(T))) = 0$, which yields the terminal subsidy $s(T)$ as described in the main text.

To solve the setting with myopic households, note that equation (A-1) implicitly defines $y(t)$ as a function of $\lambda(t)$ and $Y(t)$. We then have two differential equations ($\dot{Y}(t) = y(t)$ and the costate equation) in two variables. We know $Y(0)$ and $Y(T)$. For any guess for $\lambda(T)$, we solve the system backwards from time T to time 0 and compare the obtained $Y(0)$ to the desired $Y(0)$. We use the Matlab fzero root-finding function to search for the $\lambda(T)$ that yields trajectories that satisfy the initial conditions. We use Matlab's ode15s solver with an analytic Jacobian to solve the system of differential equations for any guess of $\lambda(T)$.

To solve the setting with forward-looking households, note that equation (A-3) implicitly defines $y(t)$ as a function of $\lambda(t)$, $s(t)$, $\mu(t)$, and $Y(t)$. We then have four differential equations (the transition and costate equations) in the same four variables. We know $Y(0)$, $\mu(0)$, $Y(T)$, and $s(T)$. For any guess for $\lambda(T)$ and $\mu(T)$, we solve the system backwards from time T to time 0 and compare the obtained $Y(0)$ and $\mu(0)$ to the desired $Y(0)$ and $\mu(0)$. We use the Knitro solver in Matlab to search for the terminal conditions that yield trajectories that satisfy the initial conditions. We use Matlab's ode15s solver with an analytic Jacobian to solve the system of differential equations for any guess of terminal conditions.[7]

Figure C2 plots the resulting efficient subsidy and cumulative adoption. The subsidy trajectories are qualitatively similar to those in the full model analyzed in the main text, except for three differences that are all related to the stochastic preference draws contained in the full model but not in the present model. First, the level of the subsidy is here greater because the regulator cannot expect some households to receive favorable draws in later periods (which makes the adoption target more difficult to achieve). Second, the efficient subsidy here decreases over an initial interval when households are forward-looking and technology is changing, whereas in the main text it was approximately constant over this same interval. In the full model, households that receive a favorable draw act somewhat myopically because they expect to have a lower value for solar in the future, which means that they may adopt the technology even without being promised a lower future subsidy. In contrast, here preferences are fixed over time, so many households will adopt the technology only if the subsidy declines sufficiently rapidly to offset the lure of waiting for technological change. Third, in the cases with myopic households and technological change, the efficient subsidy here does not start incentivizing adoption until several periods in. The regulator waits until technology becomes cheaper to start incentivizing the first myopic households to adopt. The full model does not display this effect for the analyzed target because the regulator wants to take advantage of the fact that some households will receive favorable preference draws in these early periods even while the technology is still expensive.

D Analyzing a Fixed Budget

We now consider a setting in which the regulator has a fixed budget but is free to choose cumulative adoption. Let $Z(t)$ denote cumulative spending, with $\hat{Z} > 0$ the fixed budget.

[7] In the case of forward-looking households with endogenous technical change, we use ode45 because the Knitro solver had problems converging with ode15s.

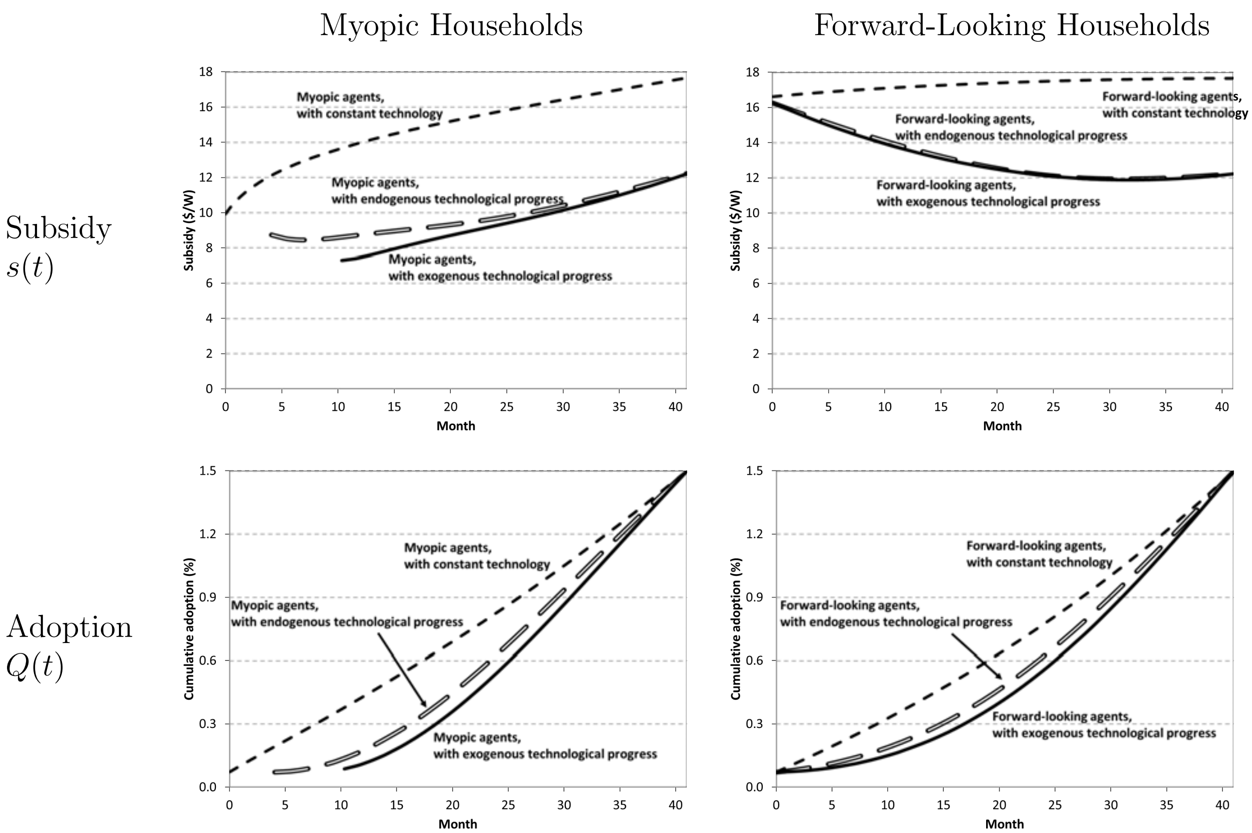

Figure C2: The efficient subsidy and corresponding adoption trajectories in the model from the theory section.

We assume that the budget is small enough that the regulator wants to exhaust it. We analyze the case with myopic consumers. The regulator solves:

$$\begin{aligned}
\max_{y(t),Y(T)} \int_0^T e^{-rt} &\left[B\Big(1-F(Y(t))\Big) - G\Big(-\left[C(t,1-F(Y(t))) - Y(t)\right] f(Y(t))\, y(t)\Big)\right] \mathrm{d}t\\
\text{s.t. } \dot{Y}(t) =& y(t)\\
\dot{Z}(t) =& -\left[C(t,1-F(Y(t))) - Y(t)\right] f(Y(t))\, y(t)\\
Y(0) =& F^{-1}(1-Q_0)\\
Z(0) =& 0,\ Z(T) = \hat{Z}.
\end{aligned}$$

The Hamiltonian is:

$$\begin{aligned}
H(t,y(t),Y(t),Z(t),\lambda_Y(t),\lambda_Z(t)) =& e^{-rt}\Bigg[B\Big(1-F(Y(t))\Big)\\
&- G\Big(-\left[C(t,1-F(Y(t))) - Y(t)\right] f(Y(t))\, y(t)\Big)\Bigg]\\
&+ e^{-rt}\lambda_Y(t) y(t) - e^{-rt}\lambda_Z(t)[C(t,1-F(Y(t))) - Y(t)]\, f(Y(t))\, y(t).
\end{aligned}$$

$\lambda_Y(t)$ gives the (current) shadow value of $Y(t)$, and $\lambda_Z(t)$ gives the (current) shadow value of $Z(t)$. The necessary conditions for a maximum are:

$$\begin{aligned}
\lambda_Y(t) =& [C(t,1-F(Y(t))) - Y(t)]\, f(Y(t))\\
&\left[\lambda_Z(t) - G'\Big(-\left[C(t,1-F(Y(t))) - Y(t)\right] f(Y(t))\, y(t)\Big)\right], \quad \text{(D-9)}\\
-\dot{\lambda}_Y(t) + r\lambda_Y(t) =& -B'\Big(1-F(Y(t))\Big)\, f(Y(t))\\
&+ \left[\lambda_Z(t) - G'\Big(-\left[C(t,1-F(Y(t))) - Y(t)\right] f(Y(t))\, y(t)\Big)\right]\\
&\Big[f(Y(t))\, y(t) - [C(t,1-F(Y(t))) - Y(t)]\, f'(Y(t))\, y(t)\\
&+ C_2(t,1-F(Y(t)))\, [f(Y(t))]^2\, y(t)\Big],\\
-\dot{\lambda}_Z(t) + r\lambda_Z(t) =& 0,\\
\lambda_Y(T) =& 0,
\end{aligned}$$

along with the transition equations, the initial conditions, and the terminal condition on $Z(\cdot)$. Extending the problem to allow the regulator to obtain benefits after time T would only change the final, transversality condition, which does not affect our analysis of $\dot{s}(t)$.

Differentiate equation (D-9) with respect to time and suppress the argument of $G(\cdot)$:

$$\begin{aligned}\dot{\lambda}_Y(t) =& [\dot{C}(t,Q(t)) - y(t)]\, f(Y(t))\; [\lambda_Z(t) - G'] + [C(t,Q(t)) - Y(t)]\, f'(Y(t))\, y(t)\; [\lambda_Z(t) - G'] \\ &- [C(t,Q(t)) - Y(t)]\, f(Y(t))\, G'' \\ &\qquad \Big[- [\dot{C}(t,Q(t)) - y(t)]\, f(Y(t))\, y(t) - [C(t,Q(t)) - Y(t)]\, \big[f'(Y(t))\, y(t)^2 + f(Y(t))\, \dot{y}(t)\big] \Big] \\ &+ [C(t,Q(t)) - Y(t)]\, f(Y(t))\, \dot{\lambda}_Z(t),\end{aligned}$$

where $\dot{C}(t,Q(t)) \triangleq \mathrm{d}C(t,Q(t))/\mathrm{d}t$. Substitute for $\dot{\lambda}_Y(t)$ and $\dot{\lambda}_Z(t)$ from the costate equations and rearrange to obtain:

$$\begin{aligned}\dot{s}(t) =& \Bigg\{ - r\,\lambda_Y(t) + \overbrace{r\,\lambda_Z(t)\, s(t)\, f(Y(t))}^{\text{new channel}} - B'\, f(Y(t)) \\ &\qquad - [G' - \lambda_Z(t)]\, \big[y(t)\, f(Y(t)) + C_2(t,Q(t))[f(Y(t))]^2 y(t)\big] - [s(t)]^2\; G''\, f(Y(t))\, \ddot{Q}(t) \Bigg\} \\ &\Big\{ [G' - \lambda_Z(t)] f(Y(t)) - s(t)\, f(Y(t))\, G''\, y(t)\, f(Y(t)) \Big\}^{-1},\end{aligned}$$

where we use $\dot{s}(t) = \dot{C}(t,Q(t)) - y(t)$ from the definition of $Y(t)$ and suppress the argument of $B(\cdot)$. We see the same effects as in the main text's setting with a fixed adoption target $\hat{Q}$, plus an additional effect. $\lambda_Z(t) < 0$ is the shadow value of additional spending, so that $-\lambda_Z(t)\, s(t)$ is the shadow cost of time t spending. This shadow cost is driven by the scarcity of funds. We see the price discrimination channel and the endogenous technology channel become amplified by this additional cost of funds. We also see a new channel that works to make the efficient subsidy decline over time. The regulator has a fixed budget, and all else equal, an impatient regulator chooses to consume more of this budget earlier.

Combine this new channel with the first (Hotelling) channel and substitute for $\lambda_Y(t)$ from equation (D-9) to obtain:

$$\begin{aligned}\dot{s}(t) =& \Bigg\{ r\, s(t)\, G'\, f(Y(t)) - B'\, f(Y(t)) \\ &\qquad - [G' - \lambda_Z(t)]\, \big[y(t)\, f(Y(t)) + C_2(t,Q(t))[f(Y(t))]^2 y(t)\big] - [s(t)]^2\; G''\, f(Y(t))\, \ddot{Q}(t) \Bigg\} \\ &\Big\{ [G' - \lambda_Z(t)] f(Y(t)) - s(t)\, f(Y(t))\, G''\, y(t)\, f(Y(t)) \Big\}^{-1}.\end{aligned}$$

We have replaced the Hotelling channel and the new channel with $r\, s(t)\, G'\, f(Y(t))$. This remaining term is the exact same term as the Hotelling channel in the main text, once we substitute for $\lambda(t)$ in equation (1) from equation (A-1). Thus, the main text's analysis of

$\dot{s}(t)$ also applies to a setting with a fixed budget instead of a fixed adoption target (only replacing G' with $[G' - \lambda_Z(t)]$). The analysis for the case with forward-looking households is similar.

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