Additionality from Payments for Environmental Services with Technology Diffusion

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Abstract

Because payments for environmental services (PES) often subsidize practices that offer latent private benefits, there are concerns that PES programs may provide little additional environmental benefits. Previous literature has framed the problem of non-additionality as an adverse selection problem. We develop a model where moral hazard can also arise because some agents delay adoption due to the incentive of potentially receiving a payment in the future. Moral hazard arises when agents have expectations of potential future subsidies, the technology naturally diffuses without a policy, and a subsidy is only available if the agent has not previously adopted the technology. We develop a conceptual model to illustrate the moral hazard incentive and conduct numerical simulations to understand the impact of policy parameters on aggregate outcomes. Numerical simulations illustrate that moral hazard creates a non-monotonic relationship between policy parameters—such as the subsidy and budget levels—and the net change in adoption induced by the program because some agents delay adoption. We also find that the cost-effectiveness of the policy is smaller when the policy is introduced during periods of rapid technology adoption.

Keywords: Payments for environmental services, technology diffusion, additionality.
JEL codes: Q55, Q57, O33.

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1 Introduction

Additionality is an important metric when evaluating the effectiveness of incentive programs. Additionality refers to the benefits induced by the policy that would not have occurred without the policy. In other words, additionality represents the benefits caused by the policy. The presence of asymmetric information between the government and participants and dynamic policy expectations further complicate additionality studies. Using dynamic simulations, we seek to understand the sometimes perverse incentives that can arise when programs subsidize the adoption of already diffusing technologies. While we do not attempt to model the optimal policy formulation, our study reveals the non-monotonic relationships between policy parameters and policy efficacy.

Studying the additionality of payments for environmental service (PES) subsidies is important for two reasons. First, PES policies are becoming a more popular means of achieving environmental goals (Pattanayak, Wunder, and Ferraro, 2010). Second, there are concerns of non-additionality in many PES policies. These policies often subsidize the adoption of technologies that produce private benefits for the adopter along with public environmental benefits. For example, payments for soil carbon sequestration have been promoted in both developed and developing countries (Lal, 2004), but carbon sequestration provides substantial private benefits in agriculture (Graff-Zivin and Lipper, 2008; Knowler and Bradshaw, 2007).

Most additionality literature has focused on adverse selection problems (Ferraro, 2008; Mason and Plantinga, 2013; Horowitz and Just, 2013; Claassen, Duquette, and Smith, 2018). Adverse selection arises from imperfect information regarding private benefits of the subsidized behavior. Without perfect knowledge of these private benefits, the government may subsidize individuals for practices that they would have adopted independently. Ignoring transaction costs of applying for a subsidy, profit maximizing farmers that would adopt a practice without a subsidy would surely take one if it were offered. Funds spent to needlessly subsidize these applicants constitute waste and the resulting benefits of this adoption are said to be non-additional to the program.

Non-additionality can also occur due to moral hazard. Moral hazard arises in subsidy programs when an applicant that is denied a subsidy delays adoption to maintain eligibility to receive one in the future. Assuming forward-looking, profit maximizing agents have expectations of potential future subsidies, moral hazard can arise when the technology naturally diffuses without a policy and a subsidy is only available if the agent has not previously adopted the technology. A naturally diffusing technology implies that there are private benefits of adopting the technology that are increasing over time. Policies that do not pay for past practices introduce an opportunity cost of adopting the technology without receiving a subsidy.

Many agri-environmental subsidy programs provide payments for practices that are well into their diffusion process. The Environmental Quality Incentives Program (EQIP) provides payments for US farmers to adopt residue and tillage management—often a no-till practice—but adoption of no-till has been steadily increasing over time (Horowitz, Ebel, and Ueda, 2010). The diffusion of microirrigation systems, another practice that EQIP subsidizes, is largely driven by economic reasons such as water extraction costs and has been occurring naturally since the 1970s (Taylor and Zilberman, 2017). EQIP also pays farmers to implement nutrient management practices—which may include implementing precision agriculture technologies—but farmers are likely to continue adopting precision agriculture in the future without any incentive from the government. Between 2009 and 2013, EQIP only funded about 36% of the applications it received due to budgetary limitations. Furthermore, farmers are only eligible to receive a subsidy from these programs conditional on having not previously adopted the practice (Natural Resources Conservation Service, 2014).

Our primary contribution is to provide new insights to how policy parameters affect the efficacy of PES policies in a dynamic model of technology diffusion that accounts for both adverse selection and moral hazard. We develop a dynamic simulation model using the technological diffusion framework of Jaffe and Stavins (1995). In these simulations, we track the adoption decisions of a heterogeneous group of agents facing declining adoption costs over time. We compare the adoption decisions of this group of agents under a variety of policies with their respective free-market adoption decision. While several authors have estimated how policies influence technology diffusion (see Jaffe and Stavins (1995) and Milliman and Prince (1989)), there are no previous studies that we are aware of that analyze the effect of a subsidy when the program has a moral hazard incentive.

Our numerical simulations reveal three novel results. First, moral hazard creates a non-monotonic relationship between additionality and the budget level. Holding the subsidy level fixed, policies with larger budgets can award more subsidies in a given period and increase additionality. However, once the budget becomes sufficiently large, the probability of receiving a payment increases. This increases the opportunity cost of adopting without a subsidy, leading more agents to delay adoption. When the applicant pool has more delayed adopters, the policy induces less additional adoption. Second, there is also a non-monotonic relationship between additionality and the subsidy level. Policies with too small of a subsidy may not be attractive enough for agents to deviate from their free market decisions. Holding the budget fixed, policies with too large of a subsidy can pay fewer applicants in a given period and increase the number applicants that are delaying adoption due to the potential of receiving a large subsidy—both of these effects decrease additionality. Third, we show that the period the policy becomes active within the technology diffusion process has a non-monotonic relationship with the cost-effectiveness of the policy. Policies starting during periods of rapid free-market adoption result in larger incentives to delay adoption and are less cost-effective (i.e., change in adoption per dollar of expenditure) than if the policy starts early or late in the diffusion process. Importantly, we demonstrate that all of these non-monotonic relationships only hold when the model incorporates the moral hazard incentive.

Accounting for moral hazard also has important implications for econometric studies of additionality. Several authors have empirically estimated the additionality of PES policies using quasi-experimental designs (Claassen et al., 2014; Mezzatesta, Newburn, and Woodward, 2013; Claassen, Duquette, and Smith, 2018; Woodward, Newburn, and Mezzatesta, 2016; Chabé-Ferret and Subervie, 2013; Alix-Garcia, Shapiro, and Sims, 2012; Arriagada et al., 2012). Matching estimators and difference-in-differences assume agents, even those that were denied a subsidy due to budget limitations are a valid counterfactual when evaluating the policy's impact (i.e., the Stable Unit Treatment Value Assumption). However, in the case of diffusing technologies, control groups are comprised of agents that are delaying adoption for the potential of receiving a subsidy in the future. This results in an overestimation of additionality in the quasi-experimental design.

2 Conceptual Model

In this section, we introduce our conceptual model of a single agent deciding when to adopt a green technology under free-market and PES program scenarios. The conceptual model is useful for building intuition of delay incentives onset by moral hazard and provides an analytical foundation for the numerical simulations in the later sections. Our model is influenced by the technology diffusion literature. In particular, we use what is known as a threshold model, a standard among economists analyzing diffusion (Sunding and Zilberman, 2001). For simplicity, we assume agents are expected profit maximizers and are therefore risk neutral.

Some agent (i) using conventional technology in time period τ decides the optimal time to adopt a green technology according to a time horizon T. The agent earns $\pi_{i,CNV}$ each period she uses the conventional technology and $\pi_{i,GRN}$ each period she uses the green technology. The agent incurs a one-time installation cost of c_τ when adopting in period τ. This installation cost is assumed to decline over time as the technology becomes cheaper and easier to install $\frac{\partial c_\tau}{\partial \tau} < 0$. Declining adoption costs could represent a learning effect, actual decreases in the investment cost, or a combination of both. Diffusion of the technology occurs over time since the profit of the technology differs across agents and the cost of adoption declines over time. Since per period profits do not change and the cost of adopting the green technology declines over time, the agent never finds it optimal to switch back to the conventional technology after adopting the green technology.

Depending on the policy scenario, she may receive a one-time subsidy (s) for adopting the technology. The ι_τ term indicates whether the agent was offered a subsidy in period τ, equaling one if she is awarded a payment in period τ and zero otherwise. Furthermore, she may have expectations of future subsidies where $\phi_{\tau+1}$ is the expected probability of being offered a subsidy in period $\tau+1$. Formally, $\phi_{\tau+1} = \mathbb{E}_\tau\left[\iota_{\tau+1} = 1\right]$. If the agent is making the decision in period τ, she will know whether she received the subsidy or not and therefore the expected returns from adopting in period τ will be known. Our general framework captures three different scenarios: (i) the "free market" ($s = 0$) (ii) when there is a subsidy policy and a subsidy is offered to the agent in τ ($\iota_\tau = 1$), and (iii) when there is a subsidy policy but a subsidy is not offered to the agent in τ ($\iota_\tau = 0$). The total return for adopting in period τ for the forward looking agent i is:

$$(1)\quad \Pi\left(\tau\right) = \sum_{t=1}^{\tau-1} \beta^t \pi_{i,CNV} + \sum_{t=\tau}^{T} \beta^t \pi_{i,GRN} - \beta^\tau c_\tau + s\beta^\tau\left(\iota_\tau\right)$$

where $\beta < 1$ is the discount factor.

The profits from adopting in period τ exceed the profits of adopting in some future period $\tau + x$ when

$$(2)\quad \Pi\left(\tau\right) - \Pi\left(\tau + x\right) = \sum_{t=\tau}^{\tau+x-1} \beta^t \Delta_i - \beta^\tau c_\tau + \beta^{\tau+x} c_{\tau+x} + s\beta^\tau\left(\iota_\tau - \beta^x \phi_{\tau+x}\right) > 0 \text{ for } x \geqslant 1,$$

where $\Delta_i = \pi_{i,GRN} - \pi_{i,CNV}$ is the difference between the profit of the green technology and the conventional technology for agent i. Without loss of generality, we assume that Δ_i is positive for all agents. Note that we seek to find some x that makes equation 2 true. That is, we assume that the adoption of the technology will, at some point be profitable to the agent. While in reality, universal adoption of a given technology may never transpire, we seek to understand additionality in the added context of a diffusing technology and therefore focus our conceptual model across farmers on the diffusion continuum. Since, in this example, adoption costs monotonically decline over time and the green technology offers improved returns over the conventional technology, the green technology should universally diffuse over some time horizon. Rearranging (2) gives

$$(3) \quad \psi\left(\tau, x\right) = \frac{c_{\tau} - \beta^{x} c_{\tau+x} - s\left(\iota_{\tau} - \beta^{x} \phi_{\tau+x}\right)}{\sum_{t=0}^{x-1} \beta^{t} \Delta_{i}} < 1.$$

The condition in equation (3) can be interpreted within the context of purchasing an annuity, an investment with periodic payments that remain constant over time. The "purchase price" of this annuity is the additional cost of adopting in period τ over the lower adoption cost in period $\tau + x$ net of the expected benefit from a potential subsidy, and is represented in the numerator. The annuity's "payment value" is Δ_i, paid out over the intervening x periods between τ and $\tau + x$. When ψ is less than one it is more profitable for the agent to adopt in period τ relative to $\tau + x$ because the cost of the annuity is less than its discounted stream of payments.

2.1 A Two Period Comparison of Adoption Decisions

The decision to adopt in period τ can be characterized using pair-wise comparisons of the profit from adopting in period τ and the profit from waiting for at least another period. In practice, the agent will compare the profit from adoption in τ with the profit from adopting in the future period that offers the highest expected profit. This comparison period may or may not be $\tau + 1$.[1] Since using the profits from $\tau + 1$ is more notationally compact, we use

[1]See the supplementary appendix for details.

it to illustrate the adoption incentives in the conceptual model.

Equation (4) shows the condition to adopt—rearranging equation (2)—when the agent compares to the profit from adoption in $\tau + 1$.

$$\Delta_i > c_\tau - \beta c_{\tau+1} - s\left(\iota_\tau - \beta\phi_{\tau+1}\right) \tag{4}$$

Equation (4) has three critical values. Under the first critical value, it is profitable to adopt in period τ when there is no subsidy program, which we call the "free market" case ($s = 0$). In the second critical value, it is profitable to adopt in period τ under a policy and a subsidy is offered in τ (when $\iota_\tau = 1$). Under the third critical value, it is profitable to adopt in period τ under a policy and a subsidy is *not* offered in τ (when $\iota_\tau = 0$).

2.2 Graphical Illustration and Discussion

Figure 1 illustrates the conceptual model. The two curves show how profits of the green and conventional technologies vary across agents, where the vertical distance between these curves represents Δ_i. Different groups of agents are defined by the magnitude Δ_i from the three critical values in equation (4). Note that $0 < \beta\phi_{\tau+1} < 1$ so the critical value for those that receive the subsidy (when $\iota_\tau = 1$) is always smaller than the free-market critical value (when $s = 0$). Therefore, individuals that would adopt under free-market conditions would also accept a subsidy payment if it were offered.

The first few columns in table (1) summarize the adoption decision for the different groups illustrated in figure 1. In the free market, groups A and B adopt in period τ and groups C and D wait to adopt in a later period. Agents in groups A, B, and C that receive a subsidy will adopt in period τ. Between groups A, B, and C, only agents in group A would adopt in period τ if they were denied a subsidy.

The last columns in table (1) describe the effect of the subsidy program on each group of agents. For those that receive a subsidy, adoption in groups A and B are non-additional—they would have adopted in period τ absent the policy. Non-additionality occurs due to asymmetric information, where the government cannot observe the private adoption incentive of the agents. The policy only generates additional benefits from applicants in group C since these agents would not have adopted in the absence of the policy. Among those that receive the subsidy, there is an increase in adoption compared to the free market as long as $\beta\phi_{\tau+1} < 1$. However, it is also important to recognize that these agents may have adopted in the absence of the policy at some period later than τ so the subsidy only provides additional periods of adoption. In some cases, agents may have never adopted the technology without a subsidy so that adoption is fully additional.

For those that are denied a subsidy, agents in group B actually delay adoption compared to the free-market scenario because of the prospect of a future subsidy. Agents in this group that are denied a subsidy on or after their free-market adoption period cause environmental damages compared to the counterfactual scenario of no subsidy program. Delayed adoption occurs due to moral hazard, where agents have an incentive to alter their adoption decision in order to capture a subsidy from the program. Agents in groups A, C, and D make the same decisions when they are denied a subsidy as they would have made if there was no subsidy program.[2]

We conclude this section by discussing the effects of changing the characteristics of the policy. First, consider the effect of changing the payment amount. Ceteris paribus, increasing the subsidy increases the sizes of both group B and group C. For those agents that are offered a subsidy, increasing the subsidy amount will increase additionality and hasten adoption (i.e., the critical value decreases for equation (4) when $s > 0$ and $\iota_\tau = 1$). But for those denied a subsidy, larger subsidies will increase delayed adoption because a larger subsidy amount increases the opportunity cost of adopting without one (i.e., the critical value decreases for equation (4) when $s > 0$ and $\iota_\tau = 0$).

[2] Agents in group A adopt even without a subsidy and agents in groups C and D wait to adopt just as they did in the free market.

One important feature of our model is that not every applicant necessarily receives a payment. A higher probability of receiving a subsidy slows adoption for those that are denied a subsidy since it increases the opportunity cost of adopting in period τ. It is useful to consider the case where the subsidy is offered to everyone that applies (i.e., $\phi_t = 1$ for all t). No one is denied the subsidy so only equation (4) where $s > 0$ and $\iota_\tau = 1$ is relevant for adoption. In this case, the subsidy only has an impact on adoption due to the discounting of future subsidy amounts. When discounting is negligible (i.e., $\beta \to 1$), the impact of the subsidy on adoption disappears. Intuitively, this result occurs because the agent is choosing the optimal time to adopt and can receive the same payment in any period so the subsidy has no effect on the optimal timing. In contrast, if the subsidy is provided in every period that the agents use the green technology—rather than a one-time subsidy—then a subsidy that is awarded with 100% probability does increase adoption because adopting in an earlier period provides a longer stream of subsidy payments.[3]

The discussion in the previous two paragraphs is useful for building intuition but fails to account for the effect of the budget and subsidy has on the probability of receiving a subsidy. For example, fixed-budget policies with larger subsidies cannot pay as many agents as those with smaller subsidies. Decreasing the number of agents receiving a subsidy slows adoption while decreasing the probability of receiving a future subsidy hastens adoption by decreasing the incentive to delay. Therefore, the net impact on adoption from changing a subsidy is ambiguous. Furthermore, the conceptual model only considers a single adoption decision. To consider the impact of decisions collectively, it is necessary to model the decisions of many profit maximizing agents, influenced by one another through the probability of receiving a subsidy. We do this by using discrete dynamic simulations. These simulations allow us to understand the impact of policy parameters on aggregate diffusion of the technology.

[3] Assume that a subsidy denoted σ is provided in each period an agent uses the green technology. Under the same assumptions of this section, the agent adopts in period τ if

$$\Delta_i > c_\tau - \beta c_{\tau+1} - \sigma.$$

Therefore, a larger σ implies more agents adopt in period τ or before.

3 Numerical Simulation

We use discrete-choice-discrete-time numerical simulations to better understand the impact of changing policy parameters on overall diffusion of the green technology. Numerical simulations allow us to aggregate the responses across heterogeneous agents and to model the interaction between different policy parameters and the probability of receiving a subsidy. The numerical simulation also relaxes the assumption that the relevant comparison period is the most imminent period, allowing it to be any future period.[4]

3.1 Parameters

Simulations for each individual closely follow equation (1) from the conceptual section. We consider the decisions of 1,000 profit-maximizing agents over the course of 50 periods $(N = 1000,\ T = 50)$. For all of these agents, we assume that the green technology is more profitable than the conventional technology but that the relative profit from switching to green technology per year varies over the agents $(\Delta_i > 0\ \forall i)$. This variation is captured by the heterogeneity factor (θ) such that $\Delta_i = \Delta(\theta_i)$. Without loss of generality, we assume $\frac{\partial \Delta}{\partial \theta} < 0$ so agents with smaller θ values are more likely to adopt earlier since they have a higher green technology profit premium. Over the population, the heterogeneity factor θ is distributed logistically. Since the logistic distribution is unimodal and costs decline over time, diffusion under free-market conditions follows the typical S-shaped diffusion curve (Sunding and Zilberman, 2001).

We do not attempt to model a specific technology (e.g., no-till or precision agriculture) as it would be difficult to construct profits as a function of some heterogeneity factor or to know the distribution of such a factor. Though it may be possible to estimate such a factor by taking soil and weather variation into account, diffusion likely depends largely on other unobservable variables such as the farmer's ability to learn a new technology. Instead we represent hypothetical profits and costs as linear functions and tailor them to ensure that,

[4]See the supplementary appendix.

absent a policy, the technology essentially diffuses completely over our 50 periods and that approximately 50% of adoption occurs by period 25. These functions could be represented as any function so long as costs monotonically decline over time and the profit premium from green technology declines with the heterogeneity factor. We normalize the cost of installation for the green technology so that it is equal to \$100 in $t = 25$. We define a linear function for costs over time where costs are declining and where the cost is \$164 in $t = 1$ and \$34 in $t = 50$ to ensure technology reaches near full adoption by the time horizon. Details of these functions can be found in the supplementary appendix.

We consider various policies, differing by their subsidy level, budget level, and the first period that agents can receive a subsidy (which we call the active period). Under every policy, we assume that farmers are given a single period of notice before the policy becomes active. Because discrete-choice-discrete-time simulations are computationally intensive, we chose specific combinations of these policy parameters to simulate. In particular the budget (B) varies from \$600 to \$6,000 in increments of \$600, subsidies (s) range from \$12 to \$120 in \$12 increments, and active periods vary from period 5 to period 50 in increments of 5 periods. Like our profit and cost terms, these parameter combinations were not chosen to represent a specific policy but to consider a variety of reasonable policy scenarios. For instance, the median subsidy (\$60) would, in the median active period (25), constitute a 60% cost share, equal to the cost share of the EQIP program (Natural Resources Conservation Service, 2014).

We do not attempt to parameterize our numerical model to replicate EQIP. For example, we assume a one-time subsidy while EQIP often provides subsidies over a 3-5 year period. However, the qualitative results are relevant for understanding the impacts of EQIP. The key feature of the EQIP subsidy is that it only provides payments for a limited time when the practice is first adopted rather than providing payments for every year the practice is implemented.

Simulating every policy combination is computationally burdensome and would make summarizing results challenging. We would need to run 1,000 simulations to consider every budget, subsidy, and active period combination for each expectation framework. Instead, we run 280 simulations, varying two of the three features of the policy while keeping the third policy parameter at the median value. For instance, we varied subsidies from \$12 to \$120 and the active period from 5 to 50 while keeping the budget fixed at \$3,000. As we will show in the results section, the time at which the policy becomes active is important. To ensure that our results are robust across start times, we also ran simulations varying both the subsidy level and budget when the active period is 10 in addition to the median value of 25. The budget-subsidy combinations capture policies that are able to provide a subsidy for between 0.5% and 50% of the total agents in a single year and are able to provide a subsidy for as little as 1% to as much as 100% of the total applicants in the initial active period. Therefore, the parameter values we considered allow us to compare the benefits of a wide range of polices on two dimensional graphs.

To understand the impact of forward looking expectations of subsidies on our results, we simulated the same polices but removed subsidy expectations. That is, we consider the same policy parameters where only a portion of applications actually receive a subsidy, but we assume that agents do not consider the potential of receiving a subsidy in the future when deciding whether or not to adopt the technology. Comparing our main results to the results with no expectations of future subsidies highlights the impact of moral hazard on the outcomes of different policies.

3.2 Solution Algorithm

Agents are forward-looking and maximize profits over periods 0 to T. To solve the optimal timing of adoption, we model the problem in terms of a longest path problem using a directional network graph, also called a diagraph. Figure 2 shows a 4-period version of the diagraph.[5] Agents start at node 0 and solve for a path to node T that maximizes the sum of the path's arc weights which represent periodic profits. The blue nodes indicate periods

[5]The discount factors are omitted for the sake of readability.

where the agent uses the conventional technology and the green nodes indicate periods where the agent uses the green technology.

To solve the problem for each agent, we use Dijkstra's algorithm–a shortest path algorithm–that is used commonly in operations research (Dijkstra, 1959). Although shortest-path algorithms are not as popular as other dynamic programming techniques such as the Bellman equation, they are conceptually related. Shortest-path algorithms can be viewed as efficient methods for solving dynamic programming problems by exhaustion and are particularly useful when there are a limited number of solution paths (Bellman, 1958).[6] This certainly holds in our application because, by the assumption of constant, positive green technology premiums, once a producer adopts the green technology, she uses it for the remaining periods.

A careful examination of figure 2 shows that all of the possible path combinations from equation (1) are embedded in the graph with a terminal time period $T = 4$ with the addition of an expected subsidy. Starting at node 0, the agent can move along the blue dots to traverse the graph to node T. In this case, the agent never switches from the conventional technology to the green technology over the time horizon. If the agent adopts the green technology in period 1, she will move from node 0 to the leftmost green dot. Doing so will restrict the agent to using only the green technology for the remaining periods. To find the profits along this path, we simply sum over the arc weights, earning the agent $\sum_{t=1}^{4} \beta^t \pi_{GRN} - \beta c_1 + \beta \phi_1 s$ in expected profits, paying c_1 for the original adoption and receiving subsidy of $\phi_1 s$. Considering different payment schemes is as simple as adjusting the transition arc weights. In the free-market case, the transition arc weights in between the green and blue nodes would simply be the green profit minus the cost of adopting for the respective period. In other words, we set the expectation coefficients equal to zero ($\phi_t = 0 \ \forall t$). To incorporate a subsidy, we simply adjust the expectation coefficients accordingly. Let τ be the contemporaneous period. The ϕ_t terms are zero for all $t < \tau$, $\phi_\tau \in \{1, 0\}$ if the individual receives or does not receive a subsidy respectively, and ϕ_t is between zero and one and is the estimated probability of

[6]Bellman (1958) showed this using the Bellman-Ford algorithm, but the same idea applies for Dijkstra's algorithm.

receiving a subsidy in period t for $t > \tau$.

Dijkstra's algorithm is appealing as it is the least time-complex algorithm to solve a shortest path problem in dense networks provided there are no negative arc weights and therefore tends to perform faster than other algorithms. We can use Dijkstra's algorithm to solve for the longest path by simply redefining the arc weights to represent the same problem as a shortest path. We redefine the arc weights (periodic profits) by multiplying each weight by -1 and then adding the absolute value of the smallest (most negative) arc weight to all arcs (Ahuja, Magnanti, and Orlin, 1993). A simple illustration of Dijkstra's algorithm is provided in the supplementary appendix.

Initially, for all agents, we run our adjusted Dijkstra's algorithm on their respective graphs with free-market conditions, where $s = 0$. Any agent that adopts (chooses a transition arc) between the first period and the announcement period under free-market conditions would not be eligible for a subsidy and is taken out of the pool of agents in further simulations. These agents are not eligible to receive a subsidy because eligibility is conditional on having not previously adopted the technology.

We continue by simulating decisions between the announcement period and the active period. During this intervening time, agents are exposed to expectations of future subsidies but the government does not yet award subsidies. In our simulations, the policy is disclosed one period before the active period. For this period, a single simulation is made on eligible agents in which agents have expected subsidy terms in every policy period but not in the announcement period itself. The method of calculating the probability of receiving a subsidy in future periods is described in the next section. Like those that adopt before the announcement period, any agent that adopts between the announcement period and the active period will not be eligible for payments and is removed from further simulations.

In the final simulation, illustrated in figure 3, we model the decisions of agents after the policy becomes active. This simulation runs two routines for each of the remaining agents. The first routine examines whether or not agents would adopt in the current period if given a subsidy.[7] Remaining agents that would chose to adopt the technology in the current period with a subsidy are considered "applicants" for the period. The government provides a subsidy to a random sample of size $\left(\frac{B}{s}\right)$ to the applicants and these agents are removed from the pool of agents in further simulations. The remaining unsubsidized applicants then enter the second routine of the simulation. The diagraphs for these agents are adjusted with no subsidy in the current period while retaining subsidy expectations in future periods. Agents that choose to adopt without the subsidy but with the expectation of future subsidies are removed from the pool of eligible agents in further simulations. The simulation then steps forward one period and the two routines are repeated for the remaining agents that have not yet adopted. In the supplementary appendix, we provide a more detailed description of the simulation algorithm and a simple four-period illustration of the respective digraphs used for the simulations.

Our diffusion framework makes several important contributions to this literature. First, it acknowledges the importance of temporal additionality. We emphasize that the timing of adoption matters when measuring the effectiveness of environmental incentives programs. We point out that additionality is only relevant between the time the technology is adopted with the payment to the period when the agent would have adopted in the absence of the PES policy.[8] This is an important distinction for diffusing technologies since, non-additionality as it is generally understood occurs when a technology would have been adopted without a subsidy, even if at some date in the future. Under this definition, if a practice would fully diffuse over time, then none of the payments go toward "additional" adoption even though the subsidy may provide environmental benefits that would not have occurred in the free market by speeding up the time to adoption. Second, it acknowledges the importance of expectations

[7]That is, we set the probability of receiving a subsidy to 1 in the current period and adjust the expected probability of receiving a subsidy for all future periods (transition arcs) as described in the supplementary appendix.

[8]Since our analysis considers a dynamic environment, additionality is not defined on the basis of what agents would do if they receive a payment or not because expectations about future payments also influence behavior. Rather, the true counterfactual in our analysis is the actions made by agents unperturbed by any influence from a PES policy.

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3.3 The Probability of Receiving a Subsidy

Modeling the probability of receiving a subsidy over time (ϕ) is a challenging aspect of the numerical simulations. We avoided this complication in the conceptual model by simply assuming some exogenous ϕ. To analyze aggregate adoption we must recognize that ϕ depends on the budget and subsidy levels and changes over time as more agents adopt the technology.

We calculate the expected probability of receiving a future subsidy based on four assumptions. First, the policy characteristics are all public knowledge—this includes knowledge of the budget and subsidy levels and, consequently, the number of subsidies that can be awarded in each period. Second, agents know how many agents would adopt the green technology for a given subsidy amount in the absence of potential future subsidies.[9] Third, agents know how many agents have adopted the technology up to the current period. Fourth, agents assume that in the future, only agents that receive a subsidy adopt the green technology.

For a simulation in period τ, we calculate the expected probability of receiving a subsidy in all future periods as:

$$(5) \quad \phi_{\tau+z} = \min\left\{\frac{\frac{B}{s}}{A^S_{\tau+z} - A_\tau - z\frac{B}{s}}, 1\right\},$$

[9]Our assumption is consistent with asymmetric information because we assume agents know how many agents would adopt the green technology if offered a subsidy but they do not know the individual agents that would adopt if given a subsidy. This assumption implies that agents know the distribution of the heterogeneity factor even though they may not know the θ value for a particular agent. For example, we assume that agents know that if a subsidy of $x is offered to adopt a practice that z% of agents would adopt. Even if program managers had this same information, it would not violate asymmetric information because the program managers could still not target the subsidies.

where z is the number of periods in the future from period τ, $A^S_{\tau+z}$ is the number of agents that would adopt the technology if given a subsidy payment in $\tau+z$, and A_τ is the number of agents that have adopted prior to period τ.[10] The numerator in equation (5) represents the number of agents the government can subsidize in a period and the denominator represents the expected number of agents that would apply for a subsidy in period $\tau + z$. The term $\left(z\frac{B}{S}\right)$ represents the number of agents that adopt between periods t and $t+z$ if only agents that receive a subsidy adopt the technology. For simulations in each period after the policy is announced, we estimate a new series of expectation terms to represent updated information about the number of agents that have adopted the technology. The min operator restricts the expected probability to 100% or below.

The calculated expectation terms do not correspond with the actual probabilities of receiving a subsidy due to independent adoption without subsidies and adoption delay. Knowing these latent outcomes would require agents to know the counterfactual decisions of the applicant pool which would contradict the asymmetric information assumption. While this difference could become large for distant periods (i.e., large z), expectations of these distant subsidies have a relatively smaller impact on the adoption decision due to discounting.

An alternative method of modeling ϕ is through naive expectations. Naive expectations imply that the expected ϕ stays constant over time.[11] Naive expectations ignore the fact that the number of agents willing to adopt with a subsidy changes over time and that some agents adopt in the future and become ineligible for the subsidy.

Another alternative method is to assume rational expectations. Rational expectations assume that agents' expected probability of receiving a subsidy corresponds with the actual probability. The challenge with modeling rational expectations is that realized probabilities of receiving a subsidy in the future depend on past actions of agents, which depend on

[10] $A^S_{\tau+z}$ and $A_{\tau+1}$ include agents that have already adopted the technology in the free market.

[11] We could calculate naive expectations as

$$\phi_{t,naive} = \frac{\frac{B}{S}}{A^S_t - A_t}.$$

expected future probabilities. There is no closed form solution for this problem in our numerical simulations since the government randomly selects agents to subsidize. One option to incorporate rational expectations would be to iterate over potential values of the expectation terms (ϕ) until the actual probability of receiving a subsidy in each period is sufficiently close to the initially assumed ϕ values. This approach is computationally burdensome and it is not clear that an optimization routine would actually converge. It is also not clear that rational expectations correspond with agents' true expectations in the presence of imperfect information.

4 Simulation Results

We now present the results of the simulations. We start by illustrating how free-market diffusion differs from diffusion under a subsidy policy. Since the free-market case is the true counterfactual that underlies additionality, all of the simulations are compared to the free-market case. As an illustration, figure 4 shows diffusion under free-market conditions and under two policies. Free-market diffusion exhibits the familiar S-shaped curve. Both policies have the same budget and subsidy and give farmers one period of notice before they become active. One policy becomes active in period 25 and the other becomes active in period 10. The policy's active period is quite important as it will determine the state of diffusion that the green technology is in before the policy becomes active. This is relevant since it determines the total number of agents that will be eligible to receive a subsidy when the policy becomes active, the number of individuals that will apply for the subsidy in a given period, and the speed of natural diffusion the policy is being benchmarked against.

We need a counterfactual free-market adoption period to quantify and compare the additional benefits of subsidy programs that incent a diffusing technology. In the conceptual model, universal adoption will occur if we consider adoption over some infinite horizon since the delta term is above 0 for every agent and cost declines monotonically. In the numerical simulations we randomly sample farmers from a logistic distribution and have a fixed horizon of 50 periods. It is therefore possible to have a horizon that is too short for the technology to reach full adoption in the free market. This was the case in these simulations as shown by a small but abrupt uptick in adoption in period 50 shown in figure 4. In our models, over 98% of the sample adopts before period 50 in the free-market. To estimate the additional benefits of the technology we call agents that did not adopt by the end of the time horizon "period 50 adopters." While this results in a slight underestimation of the additional benefits to a policy, the number of non-adopters is relatively small and we used the same counterfactual adoption periods to compare policies. This therefore had a negligible effect on the results.[12]

Both policies create temporary adoption delay in the announcement period. Beginning the policy in period 10 results in faster adoption compared to the free market in every subsequent period. The policy that begins in period 25 has a smaller impact on adoption. Next, we examine how different policy parameters affect the outcomes and summarize our key results in result statements.

4.1 Main Results

Result 1. *Increasing the budget with a given subsidy has a non-monotonic effect on both additional periods and periods of delay caused by the policy.*

Figure 5 shows the policy outcomes when we vary the budget over different subsidy levels. Panels A and B of figure 5 show the number of additional periods of green technology use and the periods of delay (represented as a negative number) generated by the policies. All policies are initially active in period 25. Panel C shows the net change in the periods of green technology use which is simply the sum of panels A and B. Panel D divides the net change in periods of use from panel C by the total expenditures of the program to give a benefit-cost ratio.

[12] We obtained similar outcomes in simulations with more flexible quadratic specifications of the cost trend and relative profits in which 99.8% of the sample adopted before period 50 in the free market.

Figure 5B illustrates the non-monotonic relationship between the budget and delayed adoption. By holding the subsidy level fixed, policies with larger budgets can award more subsidies in a given period. As demonstrated in the conceptual model, policies that give agents a higher probability of receiving a subsidy drive up the opportunity cost of adopting when denied a subsidy. Therefore, increasing the budget can lead to increased delay. Because the opportunity cost is a product of this probability and the subsidy, increasing the budget generally produces a sharper increase in delay when the subsidy is larger. However, as the budget continues to increase, delayed adoption begins to decrease since fewer applicants will be denied in the first place.

Figure 5A illustrates the non-monotonic relationship between the budget and additional adoption. When there is little delayed adoption, additionality increases as the budget increases because more first-time applicants are able to receive a subsidy and adopt earlier than they would have in the free market. As delay increases, more of the applicant pool is made up of non-additional applicants and the probability that an applicant capable of producing additional benefits will receive a subsidy goes down. Increasing the budget past a certain point allows the policy to more effectively subsidize delaying adopters earlier. This mitigates longer-run problems with delay and more effectively targets additional applicants. These policies subsequently generate more additional periods of green technology use. The impact of delayers in the applicant pool is also evident by noting that there are more additional periods under policies with small subsidies and small budgets.

Delay incentives can be especially pervasive under policies with high budgets and high subsidies. In extreme cases, this delay can produce a net reduction in green technology use relative to the free-market case (figure 5C). While high-budget, moderate-subsidy policies produce more net periods of green technology use, they are more expensive and do not produce as many periods of green technology use per dollar spent (figure 5D).

Result 2. *Increasing the subsidy while holding the budget constant produces a non-monotonic effect on additional periods and periods of delay.*

Figure 6 shows the impact of changing the subsidy while holding the budget fixed. Increasing the subsidy has two main effects. First, it decreases the probability that a given applicant will receive a subsidy. This is done directly by reducing the number of subsidies that can be given out and indirectly by incentivizing more agents to apply. Second, increasing the subsidy raises the opportunity cost of adopting independently when denied a subsidy payment. The first effect decreases the incentive to delay and the second effect increases the incentive to delay.

Figure 6B shows that under smaller subsidies the second effect dominates until subsidies reach a certain size and then the first effect dominates under larger subsidies. This creates a non-monotonic relationship between delay and the size of the subsidy payment. Figure 6A shows that there is also a non-monotonic relationship with additionality. Increasing the subsidy level when it is initially small leads to an increase in additional periods. This shows that the policy needs to meet some threshold of attractiveness before it incents agents to change their behavior. Increasing the subsidy from moderate to higher levels, however, significantly reduces the number of subsidies that can be given out and increases the number of delayers in the pool of applicants, negatively affecting additionality.

Programs with the smallest subsidies have the largest change in adoption per dollar spent (figure 6D), but do not give the largest net change in adoption (figure 6C). If the goal is to obtain the highest benefit-cost ratio, then it is optimal to choose very small subsidies since the subsidies that are awarded go towards additional adoption (figure 6D). However, if the goal is to achieve the largest net increase in periods of technology use for a given budget, then there is often some intermediate subsidy level that is optimal (figure 6C).

Result 3. *The periods of delay and cost-effectiveness of a policy are non-monotonically related to its active period within the diffusion process.*

We now compare how policy outcomes change with the active period over different subsidy levels when we fix the budget at $3,000. Figure 7B illustrates the non-monotonic relationship between the active period (i.e., the year the policy begins) and the periods of delay. Delay is largest if the policy begins in periods with rapid free-market adoption. The S-shape of the diffusion process implies that the rate of change in adoption will reach its maximum at the inflection point. We estimate the inflection point of free market diffusion to be between periods 25 and 26 using the bisection extremum distance estimator (Christopoulos, 2012). Introducing the policy when adoption is occurring at the fastest rate means that a smaller proportion of applicants receives the subsidy and there is a stronger incentive to delay adoption to receive a subsidy in a future period. Beginning policies earlier in the diffusion process incentivizes adoption earlier in the diffusion process which is more likely to be additional. Better targeting payments to additional adopters also produces less delay.

Figure 7B shows that policies with smaller subsidies tend to cause the greatest delay when they start in the 25th period, but policies with larger subsidies tend to have the greatest delay when they become active around period 30. With smaller subsidies, the government can subsidize more applicants and there are fewer total applicants willing to counterfactually adopt earlier with smaller subsidies. This increases the probability of receiving a subsidy and therefore increases the opportunity cost of adopting independently. When the subsidy is large, more agents apply for subsidies and fewer applicants receive a payment. This drives down the probability of receiving a subsidy in the next period leading many of those that are denied a subsidy to adopt independently. In this case, starting the policy just after the inflection point will give the largest delay since many of the individuals that adopted in the earlier periods will not be eligible for subsidies.

Figure 7A shows that additionality is largest when policies begin earlier in the diffusion process. This occurs for two reasons. First, a policy that begins earlier affects adoption decisions over more periods. Second, policies with an earlier active period are better targeted because few individuals would adopt in the early periods of the program in the free market and the applicant pool has less delayed adopters (figure 7B). Unsurprisingly, policies that began earlier in the diffusion process resulted in faster overall diffusion of the technology. Program expenditures are also larger when policies begin early because the budget is spent over more periods.

Figure 7D illustrates that there is a non-monotonic relationship between the active period and the net change in adoption per dollar spent on the policy (i.e., cost-effectiveness). Policies are less cost-effective if they begin when adoption is occurring rapidly in the free market because the policy causes more delayed adoption. Starting the policy early in the diffusion process results in better targeting of the payments and generates more additional periods per dollar of program expenditure.

Result 3 is informative for program managers even though they can never know with certainty the future adoption curve of a technology. Program managers have an idea of which technologies are likely to diffuse over time (e.g., no-till or variable rate fertilizer application) versus those where there is little private incentive for farmers to adopt (e.g., buffer strips). Program managers also have a general idea—either from survey data or anecdotal evidence—of how many farmers have already adopted the technology and the rate of recent adoption.

Because the timing of the policy is important, we include figures A16 and A17 in the supplementary appendix which show the results of varying the budget and subsidy when the policy begins in period 10 instead of period 25. The general relationship of the parameters with the amount of delay are similar to those in figures 5 and 6. The level of delay however is much smaller when the policy begins earlier in the diffusion process. This again highlights the importance of the initial active period.

4.2 Comparing Results with No Moral Hazard

This paper provides a major contribution by incorporating moral hazard into simulations involving technology diffusion. To demonstrate the importance of moral hazard we remove delay incentives and compare the results. We accomplish this by removing the expectations of future subsidies (setting $\phi_t = 0 \; \forall \; t \neq \tau$).[13] This removes delay incentives when applicants are denied a subsidy since, in equation (4), the free market case ($s = 0$) is equivalent to

[13] Again we assume τ is the contemporary period and so we allow for the fact that $\phi_\tau = 1$ if the agent is awarded a subsidy.

removing expectations without subsidy awards ($\phi = 0$ and $\iota = 0$). Because agents do not expect future subsidies, they will not delay their adoption when they are denied one. Setting the expectation coefficients to zero effectively makes the model a series of single-period decisions. This is similar to the adverse selection studies currently in the literature where each decision is distinguished only by the cost change.

The panels in figure 8 are analogous to panels A and D of figures 5, 6, and 7 with the only difference that we remove forward looking expectations of receiving a subsidy. We do not show a plot of delayed periods because delay does not occur when moral hazard incentives are absent. Panel A in the top row of figure 8 shows that additionality increases monotonically as the budget increases when ignoring moral hazard. The cost-effectiveness is also relatively flat for different budgets (figure 8B). Panel C shows that smaller subsidies tend to provide greater additionality over a variety of budgets. Both of these results contrast with the non-monotonic relationship when accounting for moral hazard (figures 5 and 6). Panel F does not show the same decrease in cost-effectiveness when starting the policy near the period of most rapid technology adoption because it ignores the sharp increase in delayed adoption when starting at this time (figure 7B). Importantly, ignoring moral hazard incentives leads to oversimplified prescriptions for policy improvement by ignoring the non-monotonic relationships between policy parameters and outcomes.

5 Conclusion

Our paper develops a model that incorporates moral hazard in PES programs with a limited budget—some agents that are denied a subsidy may delay adoption to receive one in the future. Ironically, the stipulation that agents must not have previously adopted the technology—in order to increase additionality—is the source of the moral hazard incentive. We also emphasize that payments only provide additional benefits to the extent that technology adoption occurs prior to the period when the agent would have adopted absent the policy. In one sense, it seems cost-effective to provide incentives for agents to adopt practices that produce large private benefits but still generate public benefits. However, the adoption of technologies with large private benefits is likely increasing over time and PES programs can result in little additional environmental benefits, and even delayed adoption in some cases.

Our conceptual and numerical model formulations are motivated by EQIP, but the arguments also apply generally to the Conservation Stewardship Program (CSP) which provides payments to farmers who currently use a set of conservation practices and agree to adopt more practices during the contract period.[14] Over half of conservation expenditures in the 2014 Farm Bill are for EQIP and CSP (Economic Research Service, 2016)—a substantial shift away from land retirement through the Conservation Reserve Program (CRP) and towards working lands programs. Yet there have been significant concerns raised about the level of additionality provided by these programs (Lichtenberg, 2014). Our analysis informs researchers and government agencies about how to assess the benefits from these programs, which Natural Resources Conservation Service (NRCS) recognizes is a significant challenge.[15]

Even though we emphasize the case of a conventional and green technology where the green technology is diffusing over time, the same principles apply to the case of two land uses where the environmentally-friendly land use is increasing over time. For example, the moral hazard that we describe could apply to CRP. Crop prices decreased substantially in 2016, creating an incentive for farmers to transition some land out of crop production, but

[14]CSP explicitly provides payments for practices already adopted, but also requires that farmers adopt an additional set of practices in order to receive payments. Obviously, the payments for practices already adopted are non-additional. Our paper also highlights that the new practices adopted in the contract period are only additional from the time adopted to the time when they would have been adopted in the future without the payment. In other words, the common assumption that the payment provides benefits over the entire life of the adopted practice overstates the additional benefits.

[15]The Regulatory Impact Analysis for EQIP states (Natural Resources Conservation Service, 2014, p. 6), "Most of this rule's impacts consist of transfer payments from the Federal Government to producers. While those transfers create incentives that very likely cause changes in the way society uses its resources, we lack data with which to quantify the resulting social costs or benefits. Given the existing limitation and lack of data, NRCS will investigate ways to quantify the incremental benefits obtained from this program... NRCS seeks public comment on how the agency should estimate the public value of conservation resulting from assistance provided through EQIP."

only 22% of acres that applied for a CRP contract were accepted in the 2016 sign-up (Farm Service Agency, 2016). Farmers that want to transition land out of crop production due to private incentives may actually delay exiting crop production for potential future CRP payments.

Our arguments also apply to PES programs in developing countries to the extent that adoption of the environmentally-friendly practice is increasing over time through private incentives and the payments are distributed to a proportion of willing agents. For example, these programs may provide payments to farmers for adopting no-till, for which adoption is increasing over time. These programs only provide additional benefits during the periods prior to when adoption would have occurred without a payment. However, if the price of services are determined competitively and all agents receive a payment that are willing to accept the price for providing the service, then delayed adoption due to moral hazard is not a concern.[16]

The numerical simulations illustrate the complex impacts of policy parameters have on the overall change in adoption and benefit-cost ratio of the program. The way that policies are designed can help improve additional periods of green technology use that they generate. Raising the periodic budget produced a non-monotonic effect on the net change in technology use. For a given subsidy, increasing the budget too much creates strong incentives to delay and actually reduces the net change in technology use. We also find a non-monotonic relationship between net change in technology use and the subsidy level. Generally intermediate subsidy levels induced the greatest net change in technology use. Policies beginning earlier in the diffusion process had higher total expenditures but were better at targeting agents that would have adopted earlier in the free market and are therefore more cost-effective than policies that start during periods of rapid technology diffusion. We also compare our results to a simulation that ignores forward looking expectations to demonstrate the contribution of

[16]However, expectations of the implementation of the program could create moral hazard where agents strategically adjust their baseline in order to receive payments as described in previous literature (Wunder, Engel, and Pagiola, 2008; Pattanayak, Wunder, and Ferraro, 2010; Claassen et al., 2014; Ribaudo and Savage, 2014).

incorporating moral hazard into additionality studies. An important area for future research is to use a principle-agent framework to analyze the optimal PES policy with technology diffusion.

Our results have important implications for empirical impact evaluations of PES programs. Matching estimators (e.g. Claassen et al., 2014; Mezzatesta, Newburn, and Woodward, 2013) and difference-in-differences (e.g., Chabé-Ferret and Subervie, 2013) assume that the adoption (or change in adoption) of agents that do not receive a payment are a valid counterfactual for those that do receive a payment. If agents did not receive a payment due to a budget limitation, then our results illustrate how expectations of future payments impact behavior and may delay adoption relative to the true counterfactual scenario of no PES program. Therefore quasi-experimental methods like matching and difference-in-differences will tend to overestimate additionality. These estimators will also tend to overstate the amount of additionality because they only consider adoption at a single point in time and do not account for the fact that some practices may have been adopted at some point in the future even without a payment.

References

Ahuja, R.K., T.L. Magnanti, and J.B. Orlin. 1993. “Network Flows.”, pp. 108–122 and 133–157.

Alix-Garcia, J.M., E.N. Shapiro, and K.R.E. Sims. 2012. “Forest Conservation and Slippage: Evidence from Mexico’s National Payments for Ecosystem Services Program.” *Land Economics* 88:613–638.

Arriagada, R.a.R., P.P.J. Ferraro, E.E.O. Sills, S.K. Pattanayak, and S. Cordero-Sancho. 2012. “Do Payments for Environmental Services Affect Forest Cover? A Farm-Level Evaluation from Costa Rica.” *Land Economics* 88:382–399.

Bellman, R. 1958. “On a Routing Problem.” *Quarterly of Applied Mathematics* 16:87–90.

Chabé-Ferret, S., and J. Subervie. 2013. “How Much Green for the Buck? Estimating Additional and Windfall Effects of French Agro-Environmental Schemes by DID-Matching.” *Journal of Environmental Economics and Management* 65(1):12–27.

Christopoulos, D.T. 2012. “Developing Methods for Identifying the Inflection Point of a Convex/Concave Curve.” *arXiv preprint arXiv:1206.5478*, pp. .

Claassen, R., E.N. Duquette, and D.J. Smith. 2018. “Additionality in US Agricultural Conservation Programs.” *Land Economics* 94:19–35.

Claassen, R., J.K. Horowitz, E. Duquette, and K. Ueda. 2014. “Additionality in U.S. Agricultural Conservation and Regulation Offset Programs.” *Economic Research Report*, July, pp. 1–69.

Dijkstra, E.W. 1959. “A Note on Two Problems in Connexion with Graphs.” *Numerische Mathematik* 1:269–271.

Economic Research Service. 2016. “Agricultural Act of 2014: Highlights and Implications.” Available at http://www.ers.usda.gov/agricultural-act-of-2014-highlights-and-implications.aspx. Accessed September 30, 2016.

Farm Service Agency. 2016. “49th CRP Signup Results.” Conservation Reserve Program Statistics, Available at: https://www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index. Accessed September 29, 2016.

Ferraro, P.J. 2008. “Asymmetric Information and Contract Design for Payments for Environmental Services.” *Ecological Economics* 65:810–821.

Graff-Zivin, J., and J. Lipper. 2008. “Poverty, Risk, and the Supply of Soil Carbon Sequestration.” *Environment and Development Economics* 13:353–373.

Horowitz, J., R. Ebel, and K. Ueda. 2010. “‘No-Till’ Farming Is a Growing Practice.” Economic Information Bulletin No. 70, Economic Research Service, USDA.

Horowitz, J.K., and R.E. Just. 2013. “Economics of Additionality for Environmental Services from Agriculture.” *Journal of Environmental Economics and Management* 66(1):105–122.

Jaffe, A.B., and R.N. Stavins. 1995. “Dynamic Incentives of Environmental Regulations: The Effects of Alternative Policy Instruments on Technology Diffusion.” *Journal of Environmental Economics and Management* 29(3):S43–S63.

Knowler, D., and B. Bradshaw. 2007. “Farmers’ Adoption of Conservation Agriculture: A Review and Synthesis of Recent Research.” *Food Policy* 32:25–48.

Kurkalova, L., C. Kling, and J. Zhao. 2006. “Green Subsidies in Agriculture: Estimating the Adoption Costs of Conservation Tillage from Observed Behavior.” *Canadian Journal of Agricultural Economics/Revue Canadienne D’Agroeconomie* 54:247–267.

Lal, R. 2004. “Soil Carbon Sequestration Impacts on Global Climate Change and Food Security.” *Science* 304:1623–1627.

Lichtenberg, E. 2014. “Conservation, The Farm Bill, and US Agri-Environmental Policy.” *Choices* 29.

Lubowski, R.N., A.J. Plantinga, and R.N. Stavins. 2008. “What Drives Land-Use Change in the United States? A National Analysis of Landowner Decisions.” *Land Economics* 84:529–550.

Mason, C.F., and A.J. Plantinga. 2013. “The Additionality Problem with Offsets: Optimal Contracts for Carbon Sequestration in Forests.” *Journal of Environmental Economics and Management* 66(1):1–14.

Mezzatesta, M., D.a. Newburn, and R.T. Woodward. 2013. “Additionality and the Adoption of Farm Conservation Practices.” *Land Economics* 89:722–742.

Milliman, S.R., and R. Prince. 1989. “Firm Incentives to Promote Technological Change in Pollution Control.” *Journal of Environmental Economics and Management* 17(3):247 – 265.

Natural Resources Conservation Service. 2014. “Regulatory Impact Analysis (RIA) for the Environmental Quality Incentives Program (EQIP).” Available at: `http://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/programs/farmbill/?cid=stelprdb1242633`.

Pattanayak, S.K., S. Wunder, and P.J. Ferraro. 2010. “Show Me the Money: Do Payments Supply Environmental Services in Developing Countries?” *Review of Environmental Economics and Policy*, pp. req006.

Ribaudo, M., and J. Savage. 2014. “Controlling Non-Additional Credits from Nutrient Management in Water Quality Trading Programs through Eligibility Baseline Stringency." *Ecological Economics* 105:233–239.

Sunding, D., and D. Zilberman. 2001. "The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector." *Handbook of Agricultural Economics* 1:207–261.

Taylor, R., and D. Zilberman. 2017. "Diffusion of Drip Irrigation: The Case of California." *Applied Economic Perspectives and Policy* 39:16–40.

Woodward, R.T., D.A. Newburn, and M. Mezzatesta. 2016. "Additionality and Reverse Crowding Out for Pollution Offsets in Water Quality Trading." *Ecological Economics* 128:224–231.

Wu, J., R.M. Adams, C.L. Kling, and K. Tanaka. 2004. "From Microlevel Decisions to Landscape Changes: An Assessment of Agricultural Conservation Policies." *American Journal of Agricultural Economics* 86:26–41.

Wunder, S., S. Engel, and S. Pagiola. 2008. "Taking Stock: A Comparative Analysis of Payments for Environmental Services Programs in Developed and Developing Countries." *Ecological Economics* 65:834–852.

Tables

Table 1: Summary of the Effects of Subsidy Program on Adoption of Different Groups of Agents

	Adoption Decision in τ			Effect of Program	
Group	Free Market	Receive Subsidy	Denied Subsidy	Receive Subsidy	Denied Subsidy
A	Adopt	Adopt	Adopt	**Non-additional**	No effect
B	Adopt	Adopt	Wait	**Non-additional**	**Delay**
C	Wait	Adopt	Wait	**Additional**	No effect
D	Wait	Wait	Wait	No effect	No effect

Figures

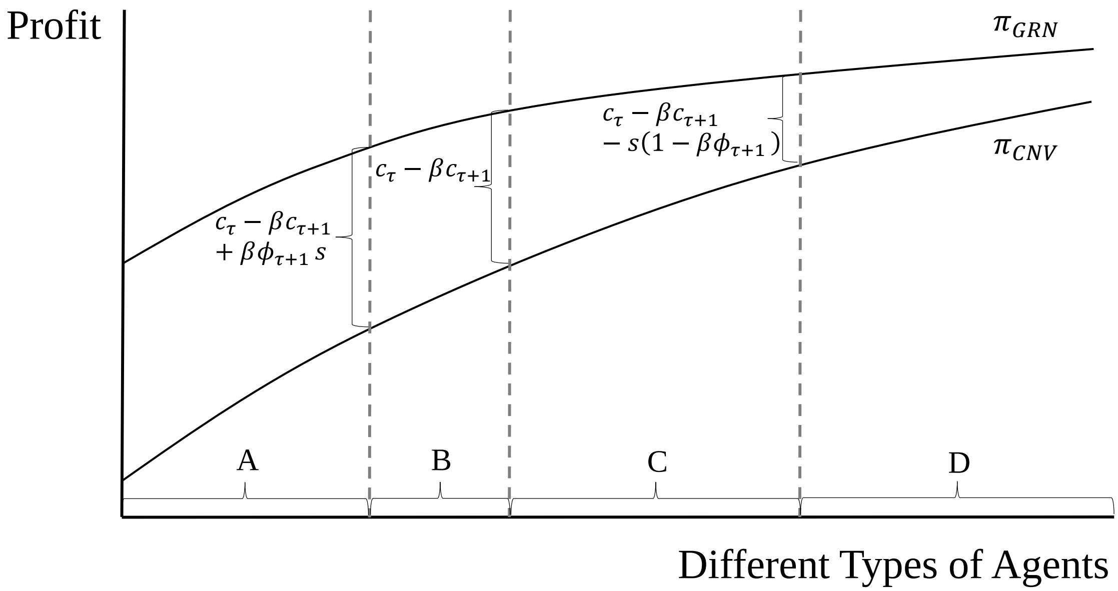

Figure 1: Illustration of Different Groups of Agents by the Impact of a Subsidy on the Adoption Decision in Period τ

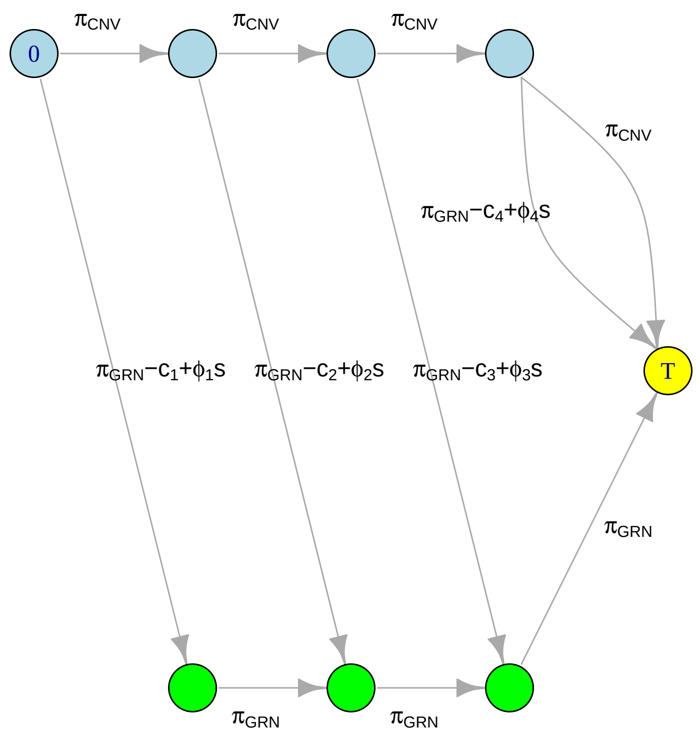

Figure 2: Discrete Dynamic Adoption Problem

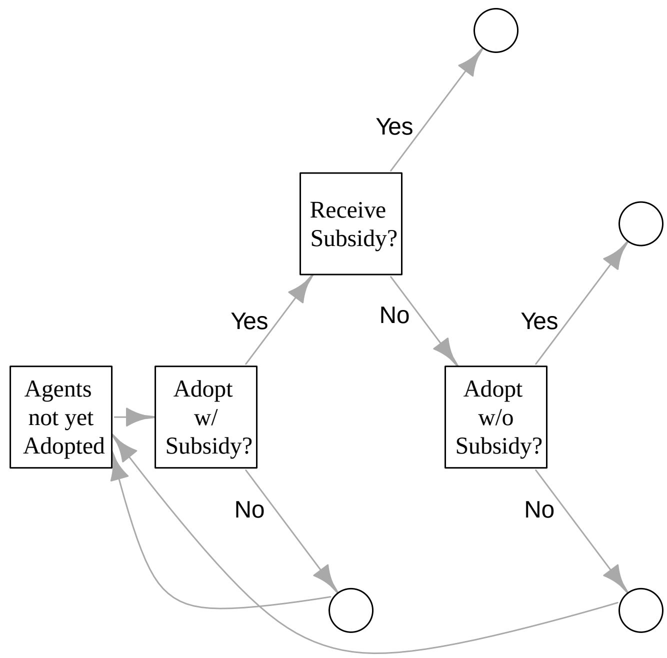

Figure 3: Post-Active-Period Simulation Schematic

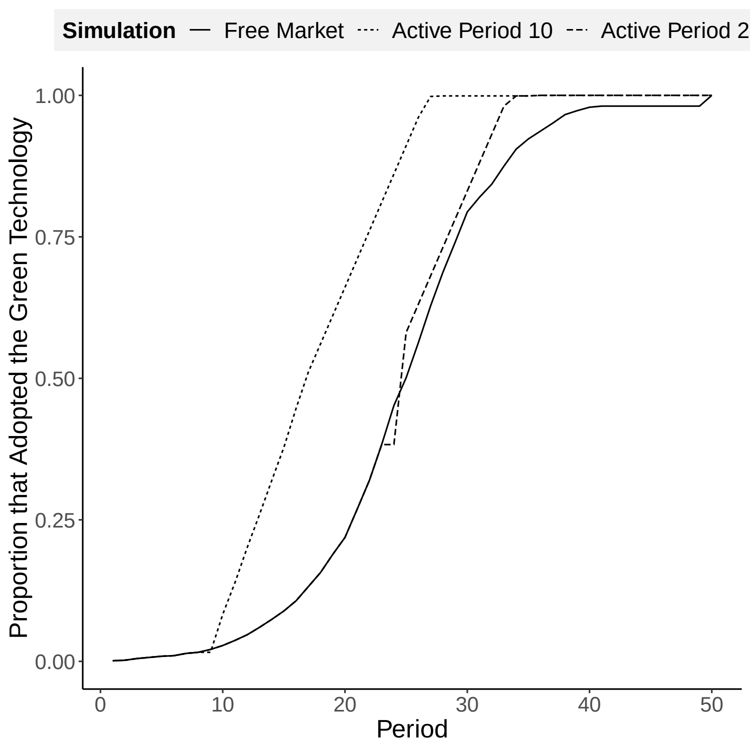

Figure 4: Diffusion Under Free Market and Two Potential Policies

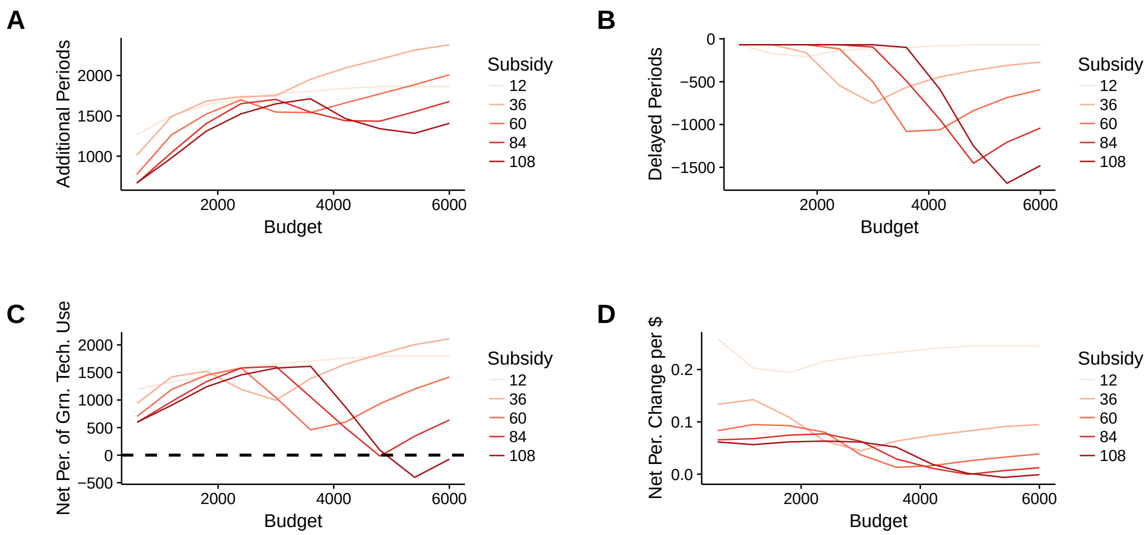

Figure 5: Policy Outcomes Varying the Budget by Subsidy Levels

Note: *Panel A shows the total additional periods of the policy. This is the sum total of periods of technology use that would not have occurred without the policy over the population of agents. Panel B shows the total periods of delay. This is the total number of periods lost due to delay from the policy over the population of agents and is expressed as a negative value. Panel C adds the values from panel A and panel B together to obtain the net change in periods of technological use from the policy. Panel D takes the values from panel C and divides them by the total policy cost to get the change in periods of green technology use per dollar spent. The initial active period is 25 and the budget is $3,000 unless otherwise stated.*

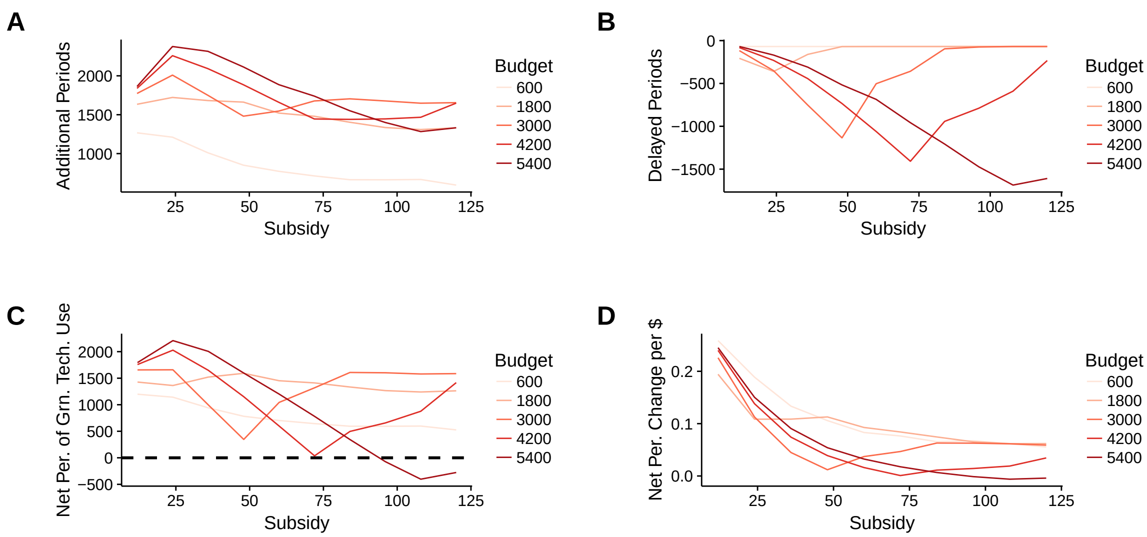

Figure 6: Policy Outcomes Varying the Subsidy by Budget Levels

Note: *Panel A shows the total additional periods of the policy. This is the sum total of periods of technology use that would not have occurred without the policy over the population of agents. Panel B shows the total periods of delay. This is the total number of periods lost due to delay from the policy over the population of agents and is expressed as a negative value. Panel C adds the values from panel A and panel B together to obtain the net change in periods of technological use from the policy. Panel D takes the values from panel C and divides them by the total policy cost to get the change in periods of green technology use per dollar spent. The initial active period is 25 and the budget is $3,000 unless otherwise stated.*

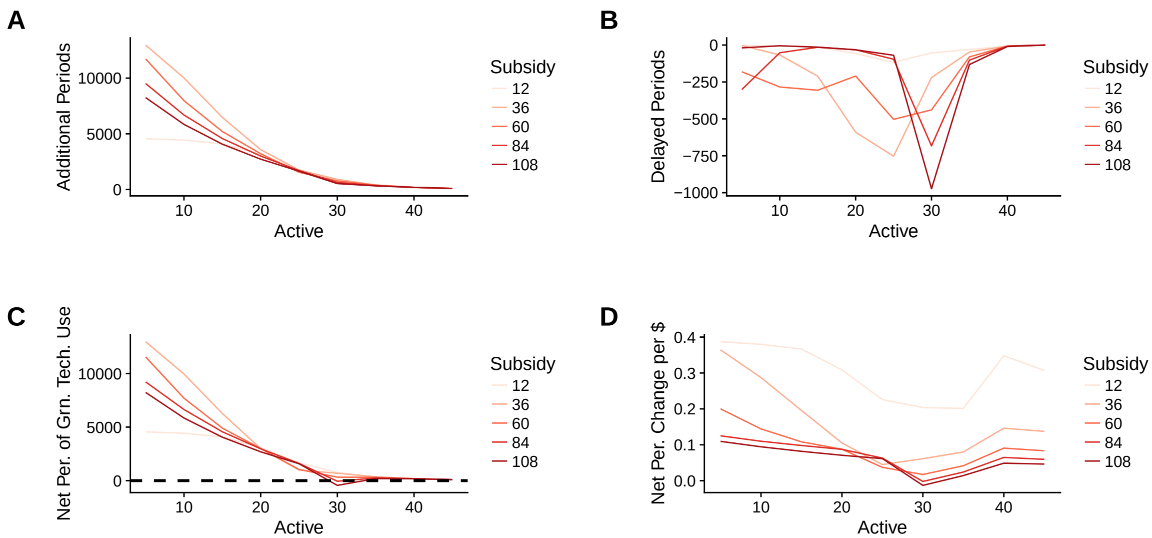

Figure 7: Policy Outcomes Varying the Active Period by Subsidy Levels

Note: *Panel A shows the total additional periods of the policy. This is the sum total of periods of technology use that would not have occurred without the policy over the population of agents. Panel B shows the total periods of delay. This is the total number of periods lost due to delay from the policy over the population of agents and is expressed as a negative value. Panel C adds the values from panel A and panel B together to obtain the net change in periods of technological use from the policy. Panel D takes the values from panel C and divides them by the total policy cost to get the change in periods of green technology use per dollar spent. The initial active period is 25 and the budget is $3,000 unless otherwise stated.*

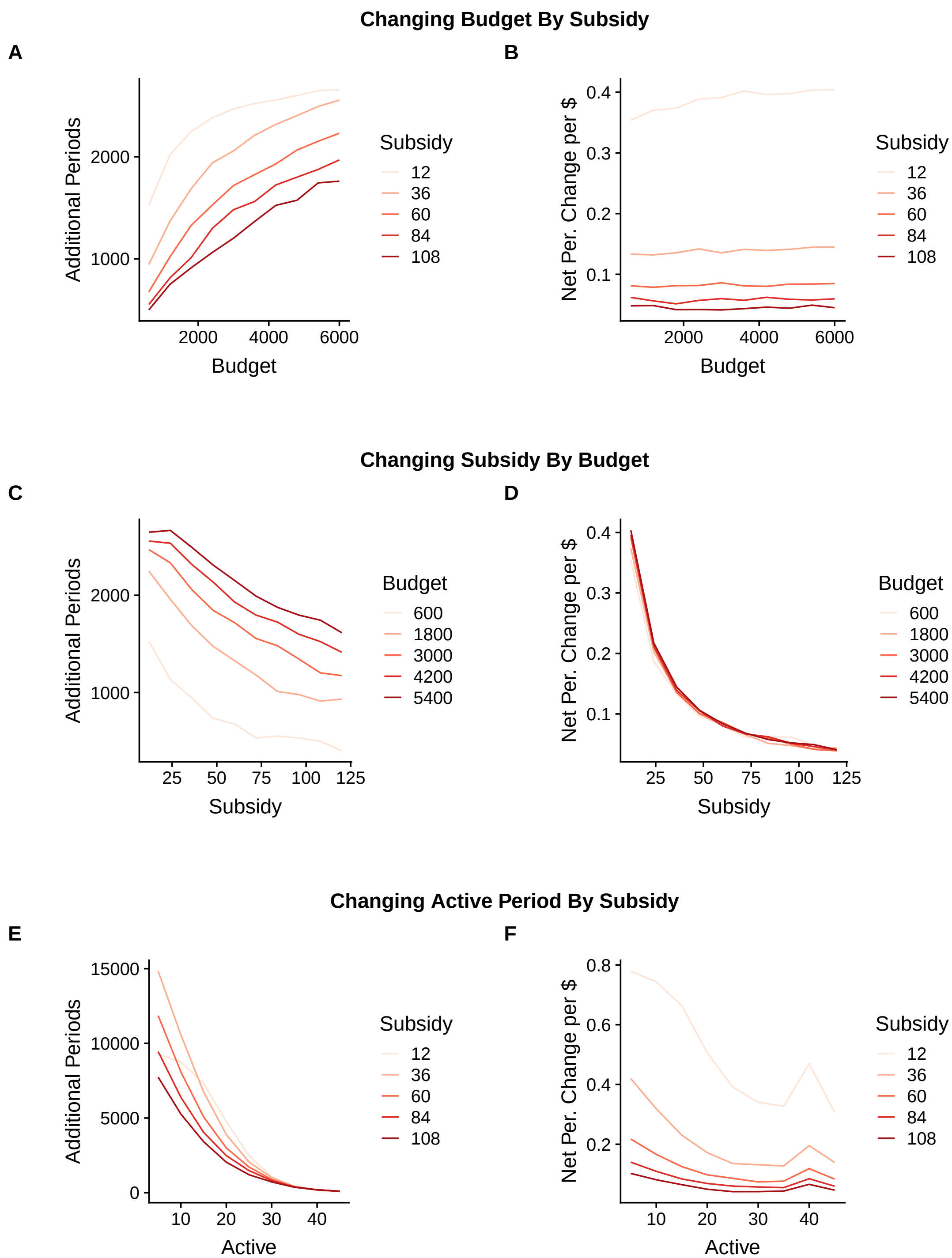

Figure 8: Assuming No Forward Expectations – Policy Outcomes Varying the Subsidy, Budget, and Active Period

Note: *Panels A, C, and E show the total additional periods of the policy. This is the sum total of periods of technology use that would not have occurred without the policy over the population of agents. Panels B, D, and F show the net periods of green technology use divided by the total policy cost to get the change in periods of green technology use per dollar spent. The initial active period is 25 and the budget is $3,000 unless otherwise stated. In every simulation with no expectations of future subsidies there were zero periods of delay.*

Supplementary Appendix

A1 Conceptual Model Assumptions

Properly characterizing the adoption decision requires analyzing equation (3) for all x which complicates the conceptual analysis. Here we examine the conditions where it is sufficient to compare profits between period τ and $\tau + 1$ to characterize the adoption decision. Here the agent considers adopting in period τ relative to $\tau + x$. Note that the condition in equation (3) is most binding for larger values of ψ. When ψ decreases with x, agents will use more imminent periods to inform their adoption decision. Therefore, agents use the earliest future period when

$$\text{(A6)}\quad \frac{\partial \psi}{\partial x} = -\frac{1}{\sum_{t=0}^{x-1} \beta^t \Delta_i}\left[\frac{\partial\left[\beta^x\left(c_{\tau+x} - s\phi_{\tau+x}\right)\right]}{\partial x} + \beta^x \Delta_i \psi\right] < 0$$

The sign of the condition in equation (A6) is determined by the sign of the term in brackets. The first term in brackets is negative when subsidies are equal to zero and ambiguous under positive subsidies. The second term is always positive. To understand the ambiguity of the sign, it is useful to think about the adoption decisions as purchasing annuities. The first term can be thought of as the change in the "purchase price" of the annuity. Since costs decline over time, agents consider paying a higher price for the annuity when they compare adoption in τ to a more distant period. In this framework, the future subsidy term acts as an additional cost of adopting in a given period. Generally the probability of receiving a subsidy increases over time $\left(\frac{\partial \phi_{\tau+x}}{\partial x} > 0\right)$. However, as a result of discounting, waiting an additional period will also reduce the benefits of potential future subsidies as well as the cost of adoption. This makes the sign of the first term ambiguous with positive subsidies. Longer lasting annuities generate more income through more annuity payments. This effectively dilutes the purchase price over more periods as represented in the second term. To see that the second term represents a dilution effect, we rewrite it as

$$\text{(A7)} \quad \beta^x \Delta_i \psi = \frac{c_\tau - \beta^x c_{\tau+x} - s\left(\iota_\tau - \beta^x \phi_{\tau+x}\right)}{\sum_{t=1}^{x} \beta^{-t}}.$$

When the dilution effect on the "purchase price" outweighs the increase in the purchase price, $\frac{\partial \psi}{\partial x} < 0$, agents look to more imminent periods when making their adoption decision. Based upon the first term in brackets in equation (A6), agents look to more imminent periods when costs are declining sufficiently slowly. In other words, as long as the cost of adoption is declining sufficiently slowly, the adoption decision depends on a comparison between profit from adopting in the current period and the profit from adopting in the next period. Alternatively, rapid increases in expected subsidies over time produce a similar effect.

A2 Simulation Details

Here we discuss how a full simulation operates as a series of five steps. These steps are: (1) Initialization and Parameterization, (2) Free Market Simulation, (3) Expectation Generation, (4) Disclosure Period Simulation, and (5) Policy Period Simulation.

Step #1: Initialization and Parameterization

We define the environment of the simulation in the first step. This includes the:

- Time horizon (how many periods in the simulation): (50 periods)
- Number of agents being simulated (1,000)
- The discount rate (14.5%)

- Production profit heterogeneity term (θ) for every agent and their distribution (Logistic($\mu =$ 0,β =6))
- Adoption costs as a function of time: $c\,(t) = c_0 - \delta_c t$
- Policy Parameters: (budget, subsidy, starting period, and disclosure periods)
- Policy timing: (the initial active period of the policy and the number of disclosure periods)

It is necessary to define these features for any simulation. We arrived on parameter values that provide a good demonstration of the conceptual problems in subsidy programs. Our time horizon (50 periods) and number of agents we considered (1,000) were chosen to be large enough to represent a typical diffusion curve while being small enough to ensure tractability in the simulation process. Specifically, 1,000 randomly simulated agents produces a smooth diffusion curve over the time frame with adoption occurring in nearly every time period under policy and no-policy scenarios. The time horizon of 50 periods was selected as a compromise between realism (i.e. representing a diffusion process that can potentially take decades) and the computational complexity of adding more iterations to the simulation.

A primary aim of this study is to analyze the additional benefits of subsidy policies with differing payment values, budgets, and initial active periods in the diffusion process. This is only possible when the additionality of a policy is measurable. Applicants that would not have adopted the green technology without the inducement of a subsidy would not have a counterfactual adoption period. This would make it impossible to quantify the additional periods of adoption caused by a policy. Producer heterogeneity, the profit functions, the discount factor, and the adoption costs were selected to produce a smooth diffusion curve in which nearly all producers had adopted the technology by the end of the time horizon (by period 50).

The periodic profit functions need to be constructed so that the green technology profits are higher than the conventional profits and that the difference between these profits monotonically increases or decreases with the heterogeneity term. This will ensure that reductions in adoption costs never disincent adoption. The only requirement of the cost trend is that the one-time adoption cost declines monotonically over time. In both cases we represent these functions as linear for the sake of parsimony, although we find that quadratic functional forms provide similar results. The logistic distribution was a similarly convenient functional form for the distribution of producer heterogeneity due to its analytical ease of use, its bell-shape, and its unimodality.

We now describe in more detail the parameterization of the heterogeneity distribution, the cost trend c_t, and profit functions $\pi_{CNV}(\theta)$ and $\pi_{GRN}(\theta)$. We draw 1,000 random values of θ from a $Logistic\,(0,6)$ to represent agent heterogeneity. The 1,000 values of θ we drew ranged from -43 to 55. Figure A1 shows the sample density of the heterogeneity factor. Because this density is unimodal, declining costs will create an S-shaped diffusion curve.

By adjusting the slope and intercept of the cost trend, we can reach approximate cost values that will bring free-market diffusion from approximately 0% in the early periods, approximately 50% at around period 25, and approximately 100% diffusion at period 50. In these simulations we set $c_1 = 164$, $c_{25} = 100$ and $c_{50} = 34$ generating a cost trend with the following form:

$$\text{(A8)}\quad c_t = 166.327 - 2.653t$$

The profit functions π_{CNV} and π_{GRN} are plotted in figure A3. In order to quantify the additionality of policies, we assume the technology reaches nearly full adoption by the end of the time horizon, so we require that $\pi_{GRN}(\theta) - \pi_{CNV}(\theta) > 0$ for every θ in our sample. We also assume this profit difference declines over θ. We choose to model both $\pi_{CNV}(\theta)$ and $\pi_{GRN}(\theta)$ as linear functions for the sake of parsimony. We also calibrated the slope and intercept parameters of each respective profit function to ensure that adoption starts from near zero in the initial period, reaches 50% by period 25 and 100% by period 50. We calibrated the functions by establishing a given function of π_{CNV} and then selecting π_{GRN} based upon the distribution of θ and the cost trend. We used the results from our conceptual model to make our calibrations. While these calibrations generate a diffusion curve that is close to our specifications, there were 19 out of the 1,000 agents that did not adopt by period 49 in the free-market simulation. For these agents, we considered period 50 to be their free market adoption period in order to quantify the additionality of the policies. We set our functions for $\pi_{GRN}(\theta)$ so that:

$$\text{(A9)}\quad \Delta(\theta_{min}) \approx \frac{c_1 - \beta^{50} c_{50}}{\sum_{t=1}^{50} \beta^t}$$

$$\text{(A10)}\quad \Delta\left(\bar{\theta}\right) \approx \frac{c_{25} - \beta^{25} c_{50}}{\sum_{t=1}^{25} \beta^t}$$

$$\text{(A11)}\quad \Delta(\theta_{max}) \approx c_{49} - \beta c_{50}.$$

Our final profit functions illustrated in figure A3 are:

$$\text{(A12)}\quad \pi_{Conv}(\theta) = 71.000 + 0.505\theta$$

$$\text{(A13)}\quad \pi_{Grn}(\theta) = 85.934 + 0.275\theta$$

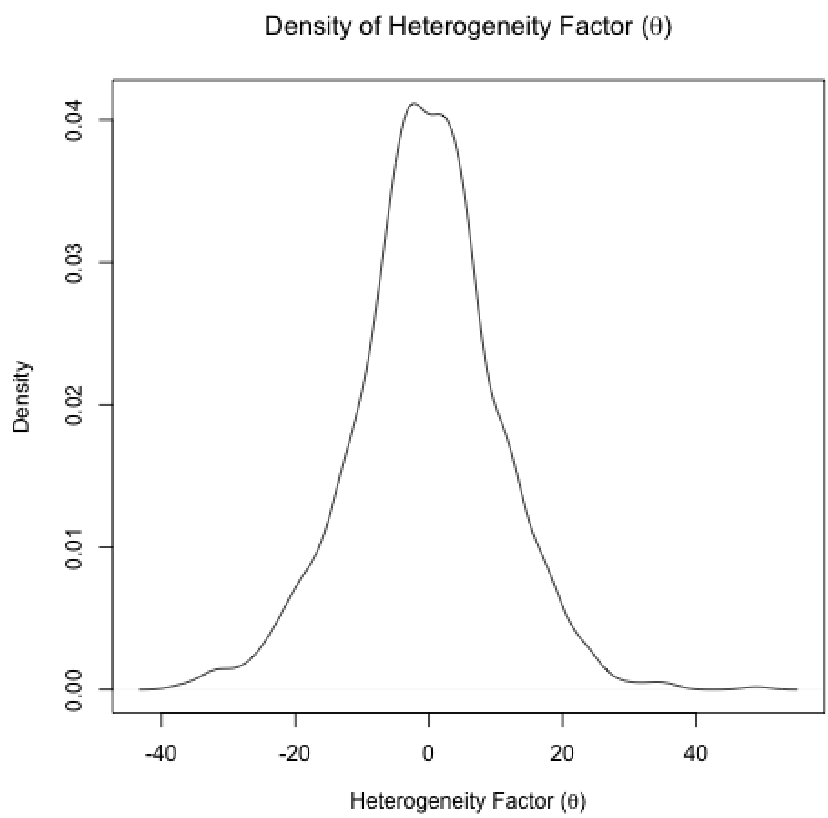

Figure A1: Heterogeneity Factor Density

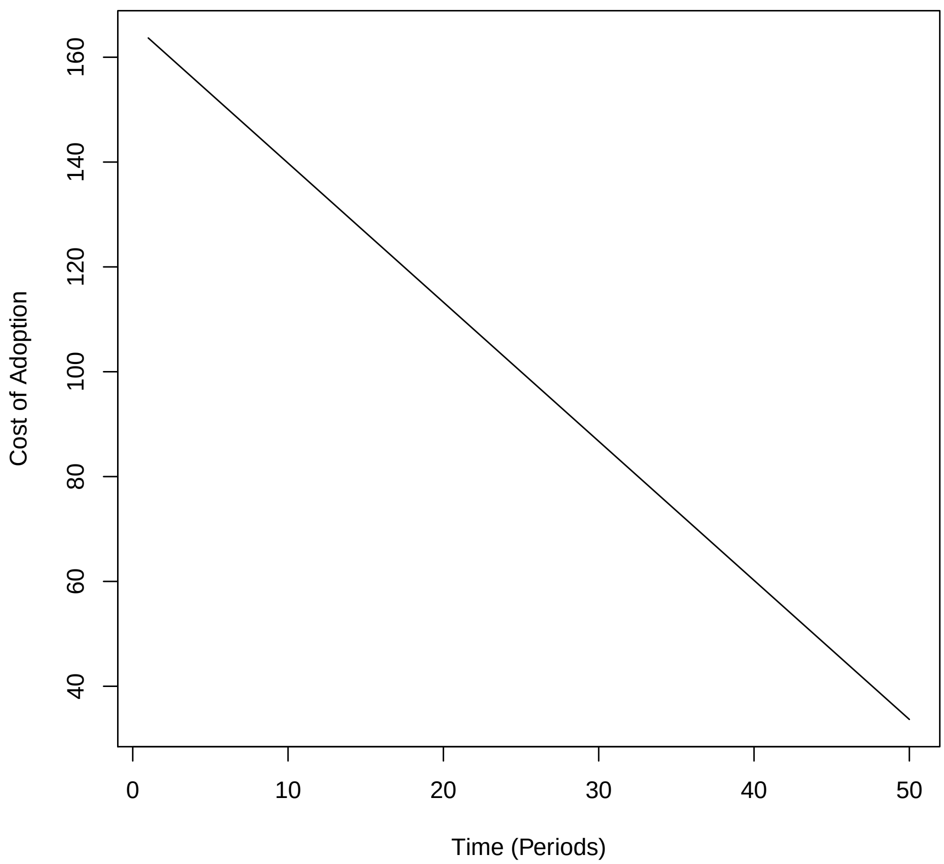

Figure A2: Cost of Adoption Over Time

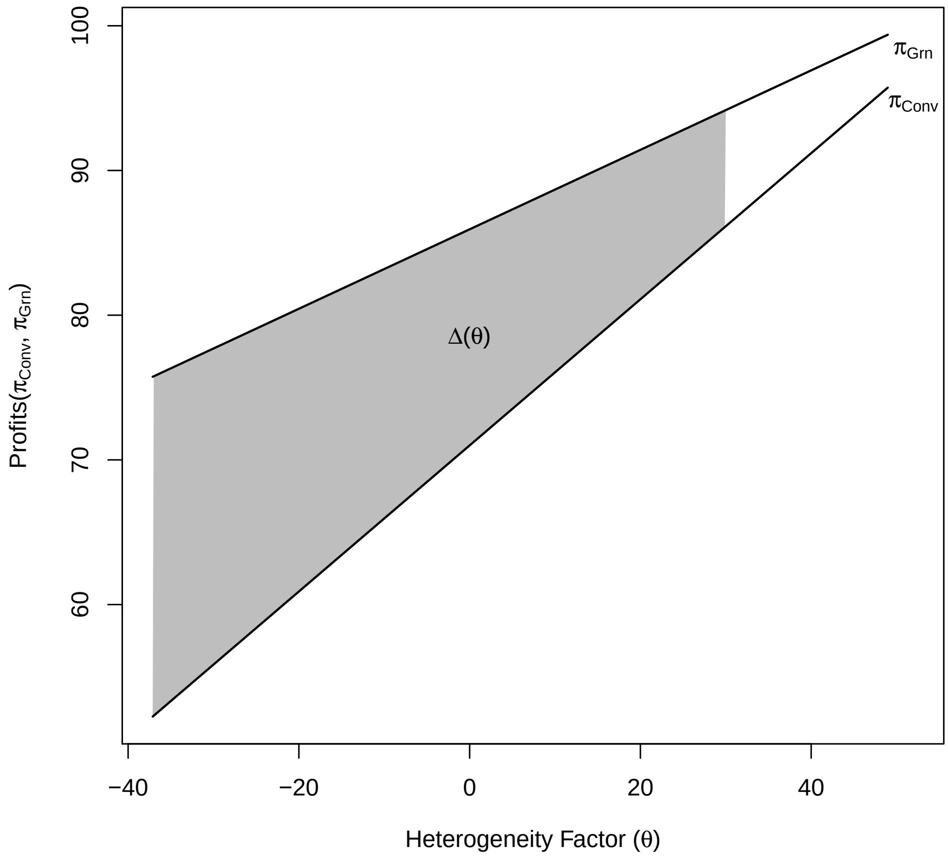

Figure A3: Profit Functions π_{CNV} and π_{GRN}

Step #2: Free-Market Simulation

To define additionality, we need to know what agents would do if the policy were not in place. In this next step, we simulate the adoption decisions of agents without the policy to obtain their free market adoption periods. Here agents do not receive or expect to receive subsidies for adopting the green technology. To accomplish this from a computational standpoint, we set the subsidy level to zero. The relevant variable we use to compute the additional benefits of policies is the number of free-market green technology use periods for each of the 1,000 agents. We use these values as a reference to determine if the policy sped up or slowed down the adoption of technology for each of the agents.

The outcomes from the free-market simulation also help identify agents that would have adopted before a policy was disclosed. Since only agents that had not previously adopted the technology are eligible to receive a subsidy, any agent that adopted before the policy's disclosure period was removed from further simulations. For example, if a policy were disclosed in period 24 and became active in period 25, agents adopting in periods 1, 2, 3, . . . 23 would not have been influenced by the policy and would be ineligible for subsidies and would therefore not enter the subsequent policy simulations.

Throughout the discussion here we use a simplified diagraph to illustrate how the simulation was carried out at each step. In these graphs, the subsidy policy is disclosed in period 2 and begins in period 3. Figure A4 shows the four-period version of the free-market diagraph simulation. Notice that none of the arc weights contain a subsidy or policy expectation term. Figure A4 shows the decision of an agent adopting before the policy's active and disclosure period. An agent with this adoption path would have adopted before she even knew about the subsidy and is therefore not considered in the subsequent steps of the simulation.

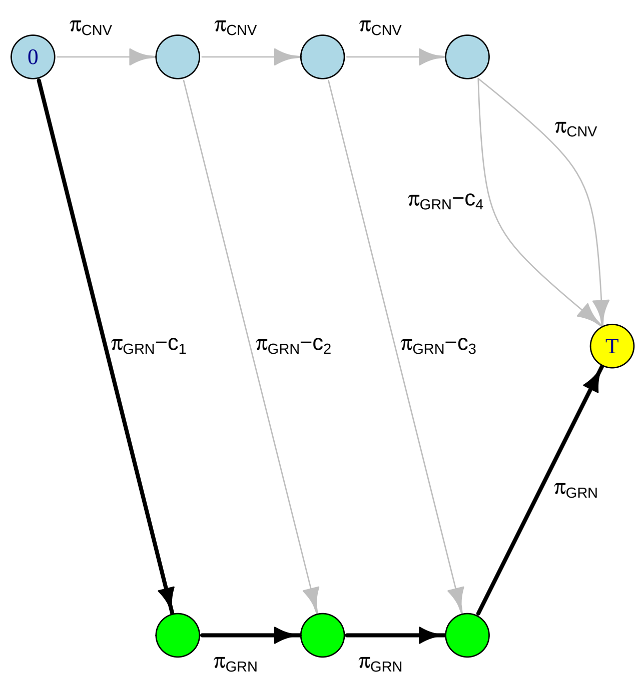

Figure A4: Free Market Adoption Path

Step #3: Expectation Generation

Expectations are an important driver of behavior in these simulations. To construct agent expectations, we assume that agents know the distribution of profits among agents, the cost trends, and the payment level for the policy. With this, they have all the required information to determine the highest number of agents that would accept a subsidy of a given size if it were offered in a given period. In other words, they have an idea of how popular a subsidy of a given size will be in each period but, like the government, do not know which farmers are adopting or have adopted in the past.

Subsidy expectations are based off of the highest number of potential applicants in each period. A series of simulations were run to estimate the highest number of applicants for a given subsidy in each policy period. In each simulation, agents are offered a subsidy with certainty in a given policy period. In these simulations, agents do not have expectations of receiving a subsidy in any other period other than the offer period. The lack of subsidy expectations in any other period means that there are no opportunity costs for accepting the offered subsidy other than the relative profits from adopting independently in the other periods. That is, only the farmer heterogeneity and the a priori known subsidy amount determines the adoption paths in these simulations. This is important since, in diffusion simulations, the policy issues payments at random to applicants. Depending on the policy and randomized payment outcomes, the applicant pool can be diverse with respect to the heterogeneity factor. The maximum number of potential applicants for each policy period therefore provides a measure of potential applicant competition with a given subsidy value and can be utilized iteratively to provide subsidy expectations when simulating adoption across policy periods.

To compute a policy's largest applicant pool in each period, simulations needed to be run for every agent across all policy periods. For example, if the policy begins in period 10, we carry out a series of 41 simulations. In the first of these simulations, every agent is offered a subsidy in period 10 with 100% probability and agents do not expect any subsidies in the other periods (past or future). Any agent adopting in period 10 under this simulation would be a possible applicant in period 10. The next simulation is identical to the period 10 simulation but the subsidy payment is now offered in period 11. In this simulation the number of period 11 adopters will represent the potential applicants in period 11. These simulations repeat across all policy periods (periods 10 to 50) to produce expectations for the maximum number of applicants in each policy period.

Figures A5 and A6 illustrate these simulations across two policy periods (periods 3 and 4) and show the adoption path for potential adopters in period 3 and 4 respectively. Notice that period 3 applicants are identified by providing a single subsidy in period 3 and that there are no other subsidy terms along the remaining arcs. Likewise the graph in figure A6 provides a subsidy to all agents in period 4 and does not contain a subsidy term across any other arc. Within these simulations agents that choose to adopt before or after the subsidized period would not be considered a potential applicant for that year's subsidy. By applying simulations across all of the agents in the study, the highest number of potential applicants for each period can be estimated.

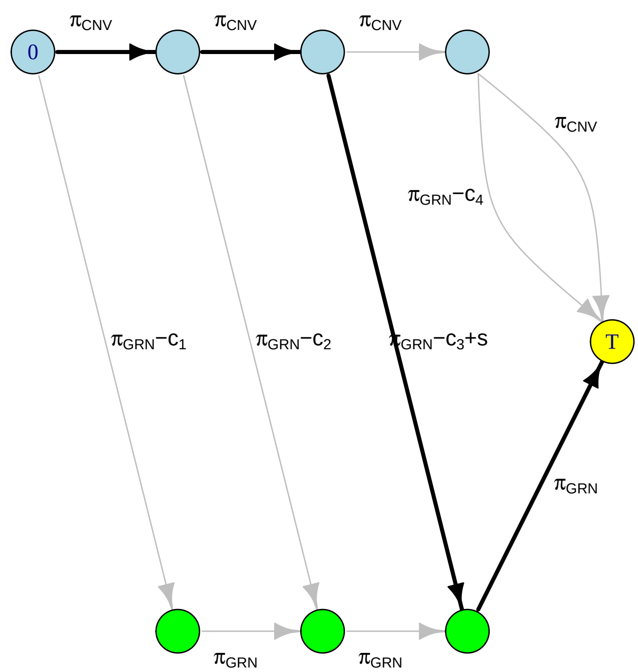

Figure A5: Adoption Path For a Period 3 Applicant

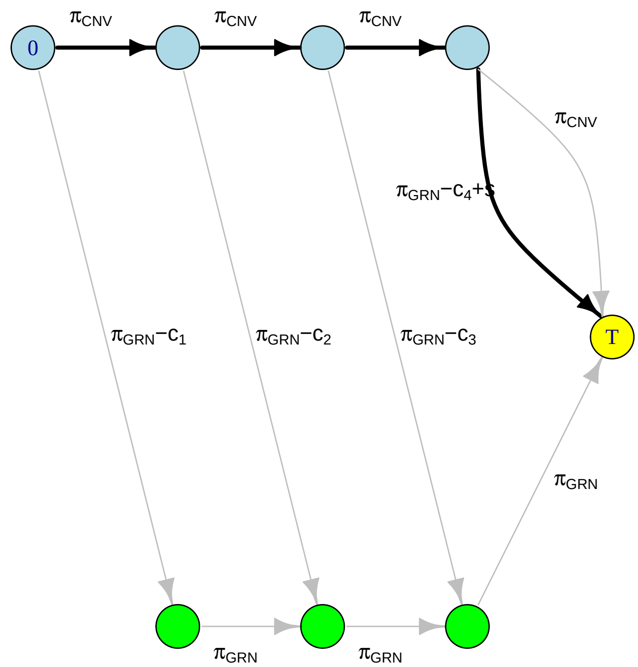

Figure A6: Adoption Path For a Period 4 Applicant

Using the highest number of potential applicants in each policy period, agents will determine the probability of receiving a subsidy in a given year. To generate the expected probability of receiving a subsidy in every subsequent year, the agent divides the number of agents that could be subsidized by the maximum number of potential applicants in the given period. To estimate the probability of being subsidized in iterative periods, they assume that those that applied for the subsidy and did not receive one would carry over to the next period and the process would continue. These expectations are represented analytically in equation A14, shown as equation 5 in the main text. Here $A^S_{\tau+z}$ is the maximum number of applicants in a given policy period $\tau + z$. The budget level is denoted with B, A_τ is the number of agents that have actually adopted by period τ, and s is the subsidy level. This expectation term assumes that, across each time period, the subsidy provides the maximum number of payments $\left(\frac{B}{s}\right)$ in each period. When adoption has reached the point where the maximum number of eligible applicants is less than the total subsidies that can be awarded in a given period, applicants can expect to receive a subsidy with certainty.

$$\text{(A14)}\quad \phi_{\tau+z} = \min\left\{\frac{\frac{B}{s}}{A^S_{\tau+z} - A_\tau - z\frac{B}{s}}, 1\right\}$$

Step #4: Disclosure Period Simulation

We incorporate pre-policy response by including a single "disclosure" period in the simulations. In this period, agents have been informed about the policy but the policy has not started issuing payments. Agents are informed about the policy's start date in the next period, the size of the subsidy, the size of the budget, and are aware of the number of agents that are eligible to receive a payment. During the disclosure period simulations agents are exposed to *expected* subsidies in the policy periods. In this way, agents that would have adopted in the disclosure period in the free-market scenario may instead delay their adoption to capture the potential future subsidy payments. Those that, even with the inducement of expected future subsidies, would adopt in the disclosure period are considered adopters and, just as agents that adopted before the policy was disclosed, are removed from further simulations.

To illustrate the steps of the disclosure period simulations, we show the simple four-period adoption scenarios which simulates a policy that is disclosed in period 2 and begins in period 3—in this scenario the two policy periods are 3 and 4. Figures A7 and A8 show two potential adoption curves when simulating in the disclosure period. Notice that the arc weights in these graphs are adjusted, adding expected subsidy terms to the post-policy transition arcs. Here the ϕ terms in the policy period transition arcs are assumed to be less than or equal to one. This means that these agents do not necessarily know with certainty whether they will receive a subsidy in a future period. Figure A7 shows the adoption path for an agent that adopts in the disclosure period even with the prospect of receiving future subsidies. Figure A8 shows the adoption path for an agent that defers adoption of the technology to the first of the policy periods. Notice that, unlike figure A4, applicants are aware of the incoming policy in period 3. The adoption path in deferred adoption is colored red to signify the potential for delayed adoption. If, after looking at the agent's free-market adoption curve, we find that the agent would have adopted in period 2 absent the policy, we can say that the policy delayed adoption for this agent.

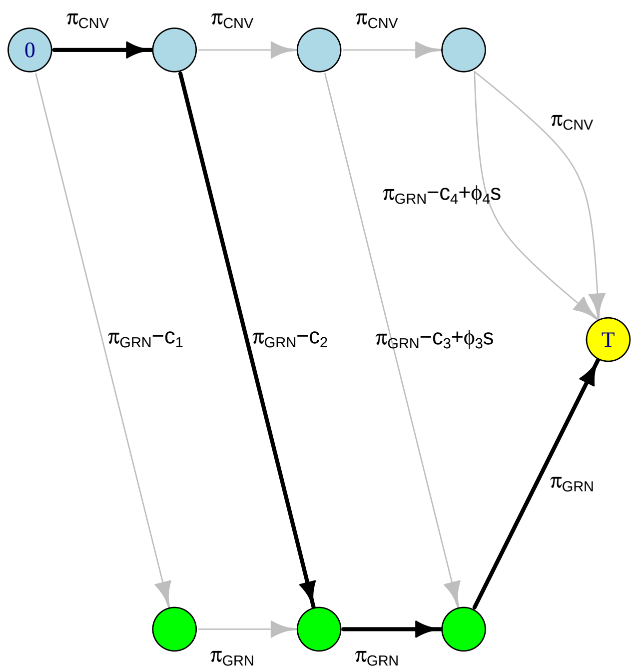

Figure A7: Adoption Path for Adopter in the Disclosure Period (Period 2)

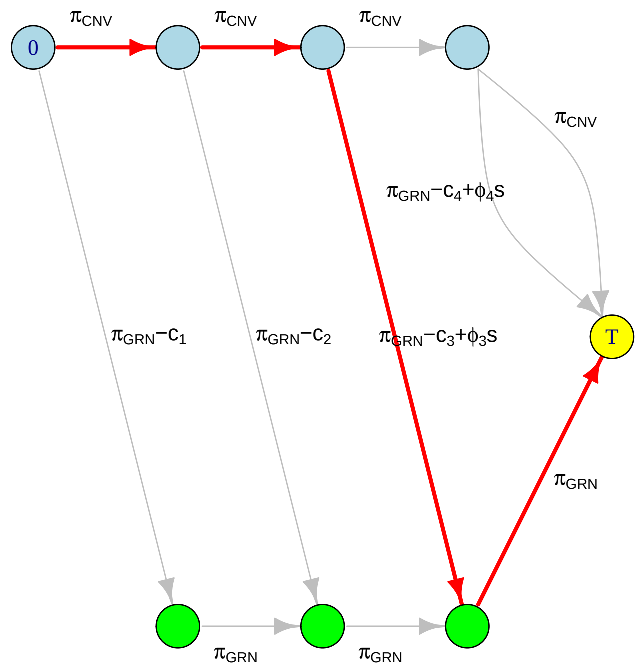

Figure A8: Deferred Adoption Path for the Disclosure Period (Period 2)

Step #5: Policy Period Simulation

After simulating free-market adoption, adoption in the disclosure period, and computing applicant expectations, we now simulate adoption in the policy periods. Simulating over the remaining policy periods can be broken down into four steps.

Substep #1: Update expectations of individuals according to equation 5 in the text.

Substep #2: Simulate realized applications and subsidized adoption.

After simulating free-market adoption, adoption in the disclosure period, and computing applicant expectations, we now simulate adoption in the policy periods. To determine the number of actual applicants in a given year, each producer not yet marked as "adopted" is awarded a subsidy with 100% probability and they continue expect potential future subsidies according to the previous step. Any agent that would adopt the technology if given a subsidy is considered an "applicant." All others are considered non-applicants and are carried over as potential adopters in the next period. Then a random sample of size $\frac{\text{Budget}}{\text{Subsidy}}$ is drawn from the set of applicants. Those that are selected are labeled as "adopted with subsidy" in that period and removed from further simulations. The adoption path of an applicant in period 3 is shown in figure A9.

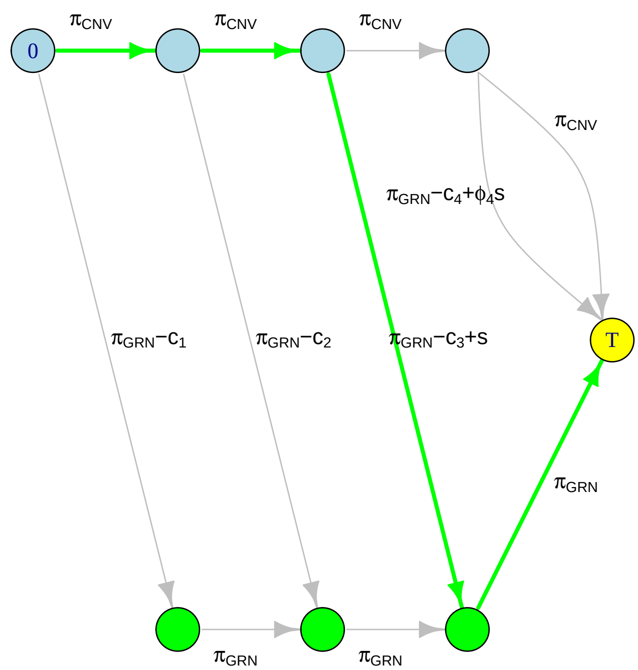

Figure A9: Adoption Path of a Period 3 Applicant

Substep #3: Simulate Adoption After Subsidy Denial

We then simulate the decisions of agents that would have adopted with a subsidy but did not receive one. Agents that are denied a subsidy may expect to receive one in a later period. We simulate the adoption profits where agents do *not* receive a subsidy in the given policy year but have expectations of receiving subsidies in future periods. Any agent that adopts in the given period without receiving a subsidy are marked as "adopted without subsidy" and removed from further simulations. Those that would not adopt are considered "non-adopters" and reconsidered in further simulations. Figures A10 and A11 show the adoption path for agents that are denied subsidies in period 3. Notice that the transition arc weight in period 3 now does not contain a subsidy term but the period 4 transition arc weight still contains an expected subsidy term. We therefore color the adoption arcs black to signify a lack of response from the denial and red to designate a potential delay response from the denial. Figure A10 shows an adoption path for an agent that chooses to adopt the green technology independently after being denied a subsidy in period 3. Figure A11 shows the adoption path for an agent that defers adoption after being denied a subsidy in period 3.

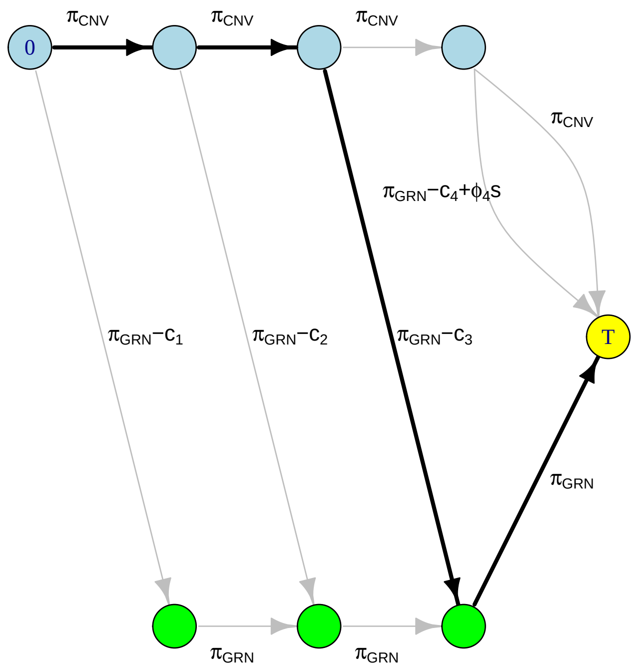

Figure A10: Independent Adoption After Subsidy Denial in Period 3

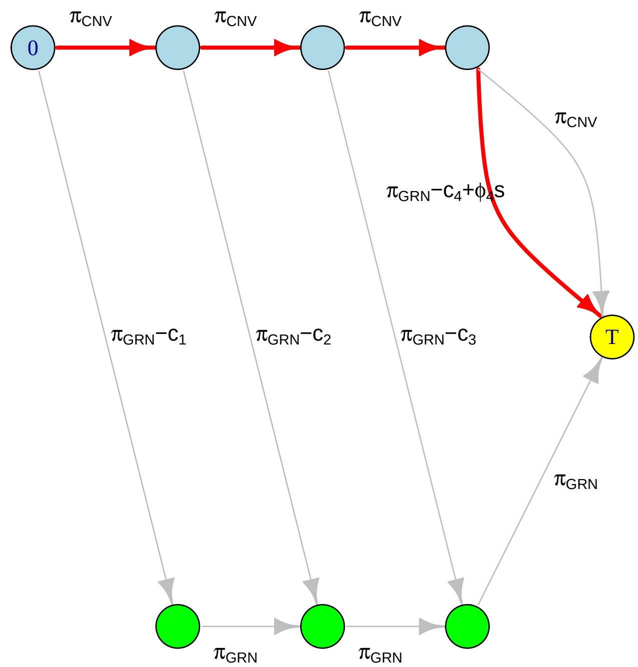

Figure A11: Deferred Adoption After Subsidy Denial in Period 3

Substep #4: Repeat Substeps 1-3 for each policy period until the terminal period is reached or every agent has adopted the technology.

A3 A Simple Demonstration of Dijkstra's Algorithm

Dijkstra's algorithm is used extensively throughout operations research. It is traditionally used to solve the shortest path problem where the goal of the problem is to find the shortest path from an initial node to a destination node. Dijkstra's algorithm is useful for its efficiency in solving shortest path problems but cannot be used on graphs that have negative arc weights. In this section, we present a simple five-period example of Dijkstra's algorithm from start to finish to demonstrate how the algorithm works and how graphs were adjusted to utilize the algorithm.

To start, consider a simple five-period version of the problem with arc weights in figure A12. The structure of the diagraph is similar to the earlier illustrations with the blue nodes representing conventional technological use and green nodes representing green technology use. Demonstrating the algorithm by hand requires keeping track of the distance that each node is away from the initial node. For this reason, the nodes on the example graph are labeled using capital letters. The purpose of this example is to illustrate how the algorithm works. For this reason, we use whole number arc weights and only include five periods for simplicity. Without loss of generality, the values of these arc weights are relative to a single period of the conventional technology returns.

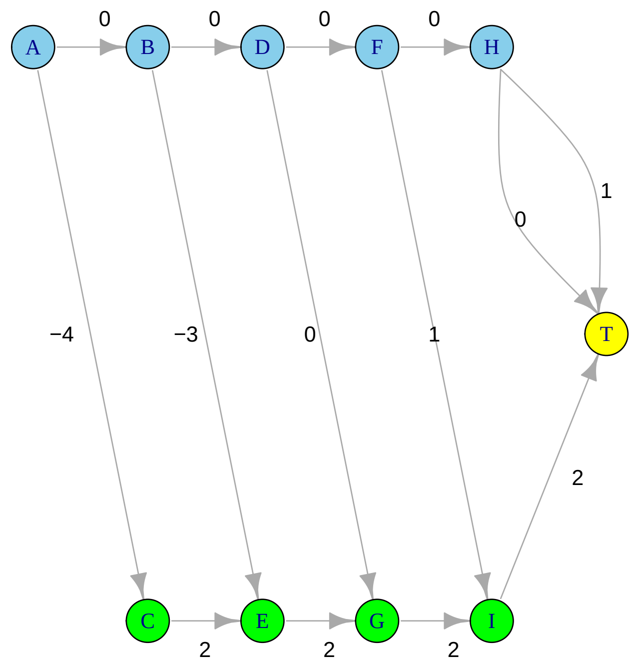

Figure A12: Five Period Graph Example

The objective here is to find the most profitable adoption path among all of the agent's potential paths. In the context of the graph, this means solving for the longest path from nodes A to T. Because Dijkstra's algorithm is used to solve the shortest path problem and cannot facilitate negative weights, adjustments to the arc weights need to be performed to orient the problem into a shortest path problem and eliminate the negative arc weights. To do this, we first multiply all of the arc weights by negative one, shown in figure A13. This reverses the relative positions of each arc, turning the longest path problem into a shortest path problem.

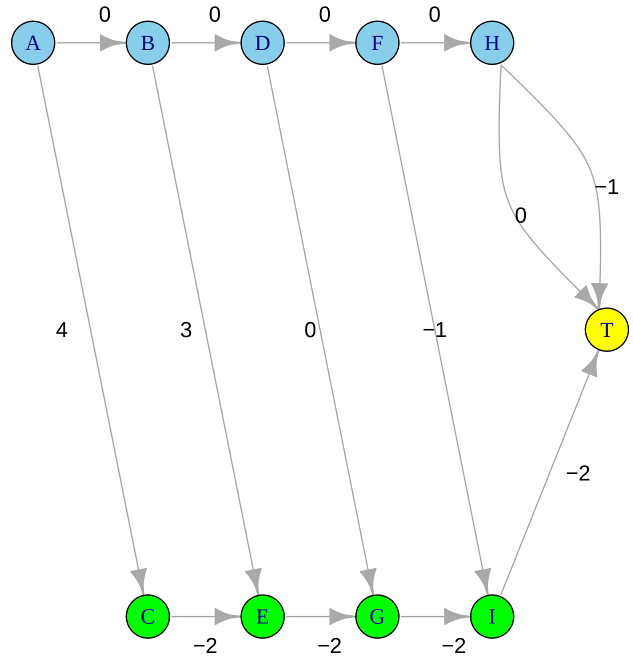

Figure A13: Five Period Graph With Neg. Arc Weights

To remove the negative arc weights and preserve the relative positions of the arc weights, we add the absolute value of the most negative number plus one. Here the most negative arc weight is -2. We therefore add $|-2| + 1 = 3$ to every arc, shown in figure A14. This is the graph that we actually use to carry out Dijkstra's algorithm. Dijkstra's algorithm solves the shortest path problem by moving out from the initial node (in this case node "A") along the path that is shortest path from "A" at every step in the algorithm.

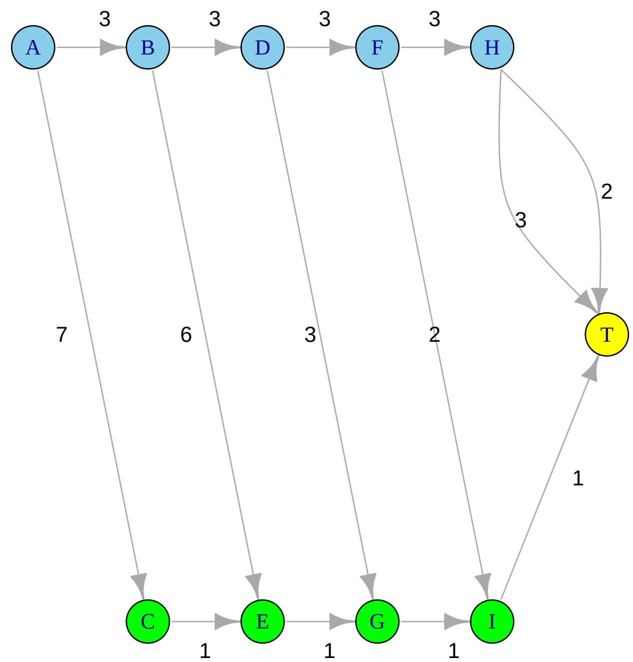

Figure A14: Five Period Graph After Shortest-Path Adjustment

The steps of the algorithm are illustrated in table A1. In the initialization step, a set of terminal nodes are established. The initial node “A” is the starting place which has a distance from itself of zero. At the initialization step (here step 0 in table A1), all other nodes are considered infinitely far from node “A”. Any node that is not adjacent to previously-visited nodes remain infinitely far from “A” until the algorithm updates them. At each step, the algorithm updates the distance from each node adjacent to the previously visited nodes. For instance, in step 1, we find that both “B” and “C” are adjacent to node A and have a distance of less than infinity from “A”. At each step the smallest value has a star over it indicating where the next node the algorithm should proceed from and shortest distance to “A”. Once the node has been “starred” we can establish that the corresponding value equals the closest distance from that node to “A”. The reason for this is there are no negative arc weights, meaning that reaching the node via another route would be as long or longer than the starred value.

After initialization, we consider all other nodes that are adjacent to “A” and note “B” is 3 units away and “C” is 7 units away from “A”. Since “B” is the closest node to “A” with a distance of 3, the algorithm then proceeds from “B”. The algorithm now considers nodes adjacent to “B” and finds that “D” is the next closest node to “A.” Notice that nodes “D” and “E” are now adjacent to “B” and are found to be reachable from “A” at a length less than infinity. The path lengths are then updated to reflect the current shorter paths. Although node “E” can be reached by “B”, we proceed from “D” since it is the closest node to “A” that is yet unconsidered. In step 3, we can now reach “F” and “G” but at this step “C” has the shortest path from “A” and therefore we proceed from “C” in the next step.

At step 4, we discover that “E” can be reached at a lower distance by traveling from “C” rather than “B”. Its distance is therefore updated from 9 to 8. Since the path ending in “E” has the shortest path from “A” we proceed from “E” in the next step. At step 5, while “G” can be reached from “E” at a distance of 9, it is no better than a previous path from “D” and is therefore not updated. There is a distance tie at step 5. We therefore proceed from the node arbitrarily in the alphabetical order from “F”. In step 6 “G” remains the closest previously unconsidered node and we proceed from “G” in the step 7. In step 7 we again discover that a node (in this case “I”) is closer to “A” when proceeding from the shortest path to “G” its distance is therefore updated from 11 to 10. In the final step of the algorithm, we proceed from node “I” since it is the closest unconsidered node to “A”. At this step we can reach the goal node “T” from a distance of 11. This is closer to “A” from any other node we previously proceeded from and this terminates the algorithm. This is indicated by the double star. Notice that we did not need to consider the paths from “H” because, as the algorithm demonstrates, “H” is farther away than the terminal node. Since the graph is free from negative weights, we can conclude that traveling to “H” will do no better than our current shortest and skip “H” as a result. We can also conclude that a shortest path from “A” to “T” has a length of 11 and follows: “A” → “B” → “D” → “G” → “I” → “T”.

Step #	Min Dist Node:	Terminal Node									
		A	B	C	D	E	F	G	H	I	T
0	A	$0^{\star}_{A}$	∞_A	∞_A	∞_A	∞_A	∞_A	∞_A	∞_A	∞_A	∞_A
1	A	$\downarrow$	$3^{\star}_{A}$	7_A	∞_A	∞_A	∞_A	∞_A	∞_A	∞_A	∞_A
2	B	$\downarrow$	$\downarrow$	7_A	$6^{\star}_{B}$	9_B	∞_A	∞_A	∞_A	∞_A	∞_A
3	D	$\downarrow$	$\downarrow$	$7^{\star}_{A}$	$\downarrow$	9_B	9_D	9_D	∞_A	∞_A	∞_A
4	C	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$8^{\star}_{C}$	9_D	9_D	∞_A	∞_A	∞_A
5	E	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$9^{\star}_{D}$	9_D	∞_A	∞_A	∞_A
6	F	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$9^{\star}_{D}$	12_F	11_F	∞_A
7	G	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	12_F	$10^{\star}_{G}$	∞_A
8	I	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	12_F	$\downarrow$	$11^{\star\star}_{I}$

Table A1: Dijkstra's Algorithm Iterations

We now relate this solution back to the original profit-maximization problem in figure A12, we find that it is optimal to adopt the technology in period 3 which yields a profit of 0+0+0+2+2=4. Note, adopting in period 1 also yields a profit of 4 which demonstrates that solutions to discrete-time-discrete choice problems can not, in general be characterized by a solution rule between two consecutive periods. As a note, this problem is quite simple since only whole numbers were used in the arc weights. Ties were not a serious issue in the policy simulations in this paper since the solution space was larger (with 50 periods relative to 5 periods) and arc weights were not restricted to whole numbers. Figure A15 shows the solution to the problem on the original diagraph.

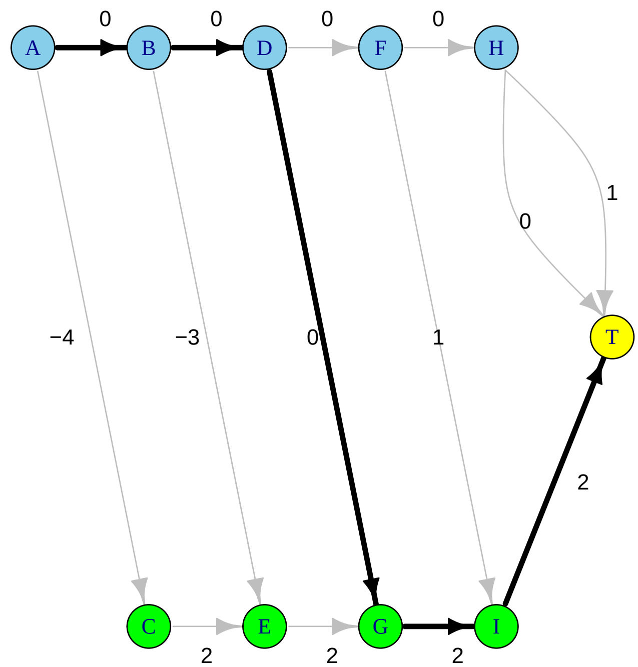

Figure A15: Dijkstra's Algorithm Solution

1081 ## A4 Plots with Active Period 10

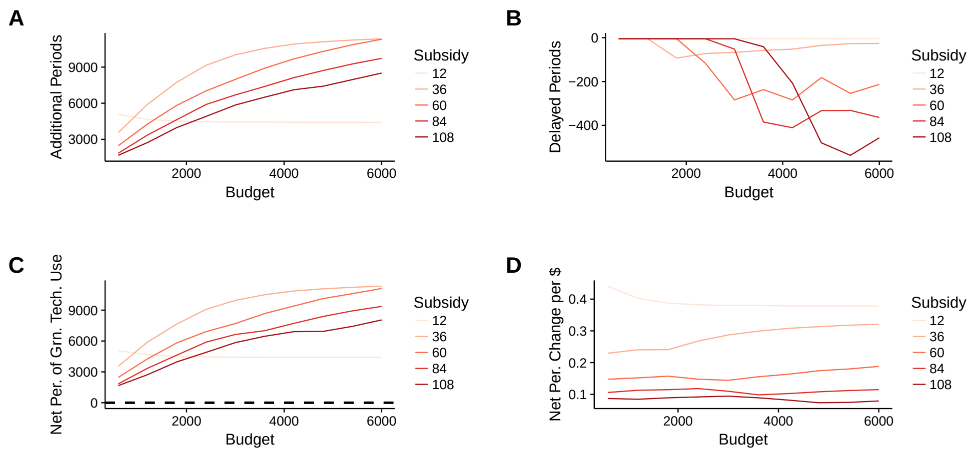

Figure A16: Policy Outcomes Varying the Budget by Subsidy Levels (Active Period 10)

Note: *Panel A shows the total additional periods of the policy. This is the sum total of periods of technology use that would not have occurred without the policy over the population of agents. Panel B shows the total periods of delay. This is the total number of periods lost due to delay from the policy over the population of agents and is expressed as a negative value. Panel C adds the values from panel A and panel B together to obtain the net change in periods of technological use from the policy. Panel D takes the values from panel C and divides them by the total policy cost to get the change in periods of green technology use per dollar spent. The initial active period is 25 and the budget is $3,000 unless otherwise stated.*

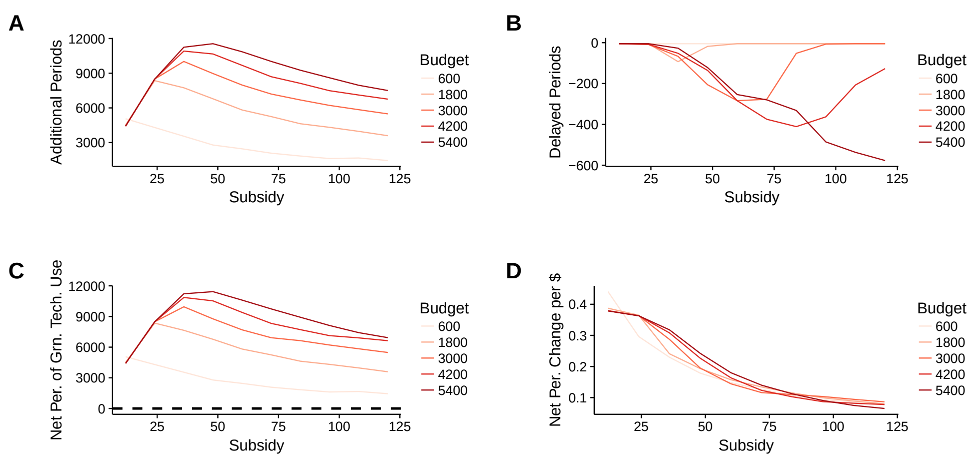

Figure A17: Policy Outcomes Varying the Subsidy by Budget Levels (Active Period 10)

Note: *Panel A shows the total additional periods of the policy. This is the sum total of periods of technology use that would not have occurred without the policy over the population of agents. Panel B shows the total periods of delay. This is the total number of periods lost due to delay from the policy over the population of agents and is expressed as a negative value. Panel C adds the values from panel A and panel B together to obtain the net change in periods of technological use from the policy. Panel D takes the values from panel C and divides them by the total policy cost to get the change in periods of green technology use per dollar spent. The initial active period is 25 and the budget is $3,000 unless otherwise stated.*