Additionality from Payments for Environmental Services with Technology Diffusion

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March 2018

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 show that moral hazard can also arise where some agents delay adoption due to the incentive of potentially receiving a payment in the future. Three conditions for moral hazard to arise are that (i) technology adoption is diffusing over time, (ii) the program has a binding budget constraint so not all applicants receive a subsidy, and (iii) the program does not subsidize practices adopted previously. 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 introducing policies earlier in the diffusion process tends to induce greater additionality and delay is largest when introducing the policy 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 incentives programs. Additionality refers to the benefits induced by the policy that would not have occurred without the policy. In other words, additionality are 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, this study highlights ways in which poor green technology subsidy design can contribute to harm and 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 also added concerns of non-additionality in many PES policies. In particular, 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. 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. 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. In this paper, we focus on another source of non-additionality, 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, there are three necessary conditions for moral hazard: the technology naturally diffuses without a policy, the policy does not pay for past actions, and the policy has binding budget constraints. A naturally diffusing technology means that there is some period in the future where agents would adopt the technology in the absence of a subsidy. This also implies that there are private benefits of adopting the technology. Policies with binding budget constraints that do not pay for past practices open the possibility that an applicant will be denied a subsidy and that denied subsidies introduce opportunity costs for independent adoption.

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 naturally occurring since the 1970s (Taylor and Zilberman, 2017). EQIP also provides payments for farmers that 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).

Like adverse selection, moral hazard also stems from information asymmetry but has an added component of hidden action. In this case, moral hazard is a dynamic concept and the hidden action occurs when applicants delay their adoption relative to their free-market decision in the event they are denied a subsidy. While moral hazard could contribute to non-additional payments and increase the expected program costs, it can also reduce the environmental benefits achieved by the program. If a producer that, without the aid of a subsidy, would adopt a green technology in a particular period is denied a subsidy due to budgetary limitations, the policy creates an opportunity cost of adopting independently. If this opportunity cost is large enough, the producer may find it optimal to delay adopting the technology after the point they would have adopted in the free market. This constitutes environment damage since these individuals would provide more periods of green technology use if the policy had not been in place. We contribute to the literature on additionality by incorporating moral hazard using a dynamic framework and evaluating additionality over a series of policies varied by their subsidy and budget levels. Using this dynamic framework, we also study an often overlooked aspect of policymaking, the optimal time in the diffusion process to launch a policy.

Using the technological diffusion framework of Jaffe and Stavins (1995), we simulate the impact of a variety of PES policies. 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 allocated with a limited budget on technology diffusion. When we account for moral hazard, we find that delay can reduce additionality and in extreme cases lead to net environmental damage relative to the free-market counterfactual case. More importantly, simulating policy outcomes without moral hazard could lead modelers to incorrect generalizations, such as raising budgets always leads to increased additionality.

Moral hazard in our context is a dynamic problem and therefore brings unique consequences. To attract applicants, the expected benefits of the subsidy must be sufficiently large. However, benefits to adopters receiving a subsidy are opportunity costs to adopters that do not receive a subsidy. We show through numerical simulations that this creates non-monotonic relationships between additionality and key policy parameters such as the subsidy and the budget levels. For instance, policies with small subsidies may not be attractive enough for agents to deviate from their free market decisions. Holding the budget fixed, policies with larger subsidies can pay fewer applicants in a given period, attract more applicants, and burden denied applicants with higher opportunity costs for independent adoption. This results in larger applicant pools and a higher potential for further delays and non-additionality. Similarly, budgets are also non-monotonically related to additionality and delay. Holding subsidies fixed, policies with larger budgets provide a larger probability of being subsidized and, consequentially, higher opportunity cost for non-additional adoption. However, the likelihood of being denied in the first place is lower in policies with sufficiently large budgets.

Several authors have empirically estimated the additionality of PES policies, many using quasi-experimental designs. Claassen et al. (2014), Mezzatesta, Newburn, and Woodward (2013), and Claassen, Duquette, and Smith (2018) used propensity score matching methods to estimate the additional adoption of conservation practices in the U.S. due to EQIP. Woodward, Newburn, and Mezzatesta (2016) used matching methods to evaluate additionality in a U.S. water quality trading program and Chabé-Ferret and Subervie (2013) estimated additionality using difference-in-differences for environmental programs in France. Examples of impact evaluation in developing countries include Alix-Garcia, Shapiro, and Sims (2012) and Arriagada et al. (2012). Other papers estimate the probability of adopting a technology or land use and then simulate the additionality of a program (Wu et al., 2004; Kurkalova, Kling, and Zhao, 2006; Lubowski, Plantinga, and Stavins, 2008).

While these approaches are useful when studying additionality under one-time payments, they may not be well suited to study additionality in dynamic environments. 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, in these studies are likely comprised of agents that would simply wait another period to receive a subsidy in the future. This results in an overestimation of additionality.

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 period 0 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. If the government does not subsidize adoption in any future period, the problem for the forward-looking agent i is:

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

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

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

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. Rearranging (2) gives

$$(3) \quad \psi(\tau, x) = \frac{c_\tau - \beta^x c_{\tau+x}}{\sum_{t=0}^{x-1} \beta^t \Delta_i} < 1.$$

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 $\tau + x$, 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 represented in a two-period comparison, comparing 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 it to illustrate the adoption incentives in the conceptual model.

Equation (4) shows the condition to adopt when there is a potential subsidy for adopting in period τ. Here s represents the subsidy level, ι_τ is an indicator function equal to one if the agent applied for and was awarded a subsidy in period τ and zero otherwise, and $\phi_{\tau+1}$ is the probability of receiving a subsidy in period $\tau + 1$.

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

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

[1] See appendix for details.

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 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. For those that receive a subsidy, agents in groups A, B, and C adopt in period τ. For those that are denied a subsidy, only agents in group A adopt in period τ.

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 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 changes to the policy characteristics. First, consider the effect of changing the amount of the subsidy. 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 $\iota_\tau = 0$).

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 subsidy 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

[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.

[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.

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 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 follows 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

[4] See appendix.

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 are more likely to adopt earlier as they have a relatively larger increase in profit from adopting the green technology. 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, absent a policy, the technology fully diffuses 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 fully diffuses. Details of these functions can be found in the 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.

Computing all simulations is computationally burdensome and makes a concise summary of the 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, so 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 policy parameters considered allow us to show the effects over a broad range of policy parameters on two dimensional graphs.

In order 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 a 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 known as 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 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[6] (Bellman, 1958). 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 the 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

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

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

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 no-policy 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 $\phi_t = 0$ are zero for all $t < \tau$, $\phi_\tau \in \{1, 0\}$ if the individual recieves or does not recieve a subsidy respectively, and ϕ_t is between zero and one and is estimated probability of recieving 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).

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 adopt before the policy is disclosed and are ineligible for a subsidy because the subsidy 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 the remaining agents in which the one period prior to the activity period has no subsidy and the remaining periods have the *expected* subsidy. 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 are 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 maintaining the potential subsidies 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 for 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 simple four-period illustration of our simulation algorithm and 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

[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 appendix.

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 in policy outcomes. 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. The true counterfactual of in our study is the actions made by agents unperturbed by any influence from a PES *policy*.

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, but 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

[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.

[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 a subsidy of x is offered to adopt a practice that z% of agents would adopt.

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:

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

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_t 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 agent's expectation of the 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 ϕ's 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 ϕ's do not correspond with the actual probabilities of receiving a subsidy to the extent that some agents adopt the technology even without a subsidy and some agents delay adoption for the potential to receive a future subsidy. 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

Even if program managers had this same information, it would not violate asymmetric information because the program managers could still not target the subsidies.

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

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 increases in the future 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 in the future 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 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 would be to iterate over potential values of ϕ's until the actual probability of receiving a subsidy in each period is sufficiently close to the initially assumed ϕ's. 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 becomes active. One policy becomes active in period 25 and the other becomes active in period 10.

[11] We could calculate naive expectations as

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

The policy's active period is quite important as it will determine 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 recieve 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.

Both policies create temporary delay in adoption 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 number of 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.

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 efficiently 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. 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 rise in the 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 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 few subsidies that are actually awarded go towards additional adoption (figure 6D). However, if the goal is to achieve the largest net increase in periods of use for a given budget, then there is often some intermediate subsidy level that is optimal (figure 6C).

Result 3. *Delay can significantly hinder overall policy effectiveness.*

Figure 6 also shows that the effect of delay can be large. In these simulations the delay significantly reduces the overall periods of green technology use. When both the policy's budget and subsidy are large, it can cause net delay constituting environmental damage relative to the free market (figure 6C). In general, periods of green technology use per dollar falls as the subsidy increases. Reversals in this trend are likely caused by delay. Comparing panels 6B and 6D, it is clear that trend reversals in delayed periods coincide with trend reversals in the net periodic change per dollar.

Result 4. *Policies that start earlier in the diffusion process have greater additionality.*

We now compare how policy outcomes change with the active period over different subsidy levels when we fix the budget at \$3,000. Figure 7A shows that additionality is largest when policies begin earlier in the diffusion process. 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. This means that in the initial active period there are fewer individuals that have the potential to delay adoption. Figure 7B shows that in general policies that begin early in the diffusion process tend to have less delay. This in turn means that more of the applicant pool is made up of additional adopters in a given period. Therefore, the policy more effectively removes non-additional adopters than policies that begin later in the diffusion process.

Result 5. *Policies that begin when the technology is diffusing faster produce more delay.*

The S-shape of the diffusion process implies that the rate of change will reach its maximum at the inflection point of the diffusion curve. Using the bisection extremum distance estimator, we estimate the inflection point of the free market diffusion curve to be between 25 and 26 (Christopoulos, 2012). Figure 7B shows that policies with smaller subsidies tend to cause the greatest delay when they start in the 25th period. Policies with larger subsidies tend to have the greatest delay when they become active around period 30. At the inflection point, the number of potential counterfactual adopters is at its maximum. However, 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, fewer total applicants receive a payment and more applicants apply. 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 increase delay since many of the individuals that adopted in the earlier, more popular free-market adoption periods will not be eligible for subsidies.

Figure 7C shows that starting a subsidy program when the technology is being adopted rapidly can cause a net reduction in adoption if the subsidy is sufficiently large. Beginning the policy early in the diffusion process is clearly most preferable in terms of both net periods of green technology change (figure 7C) and change per dollar (figure 7D). But this does not mean that an early active period is better in all respects. The policy that begins early better targets agents so the policy also tends to provide a subsidy to a greater proportion of the overall population. This means that policies that begin earlier in the diffusion process tend to have larger total costs. Figure 7D shows that the net change in technology use per dollar spent is not monotonically decreasing with the active period.

Because the timing of the policy is important, we include figures A10 and A11 in the supplementary appendix that vary the budget and vary the subsidy when the policy begins in period 10 rather than 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, again highlighting the importance of the initial active period.

4.2 Comparing Results with No Moral Hazard

The major contribution of our paper is incorporating moral hazard into simulations involving diffusion technology. To demonstrate the importance of moral hazard we remove delay incentives and compare the results. We achieve this by removing the expectations of future subsidies (setting $\phi_t = 0 \; \forall \; t \neq \tau$)[12]. This removes delay incentives when applicants are denied a subsidy since, in equation (4), the free market case $s = 0$ case is equivalent when $\phi = 0$ 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.

Figures 8, 9, and 10 are analogous to figures 5, 6, and 7 except we remove forward looking expectations of receiving a subsidy. As expected, there is no delay in figures 8, 9, and 10

[12] 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.

because there are no moral hazard incentives. More importantly, not accounting for the expectations of futures subsidies leads to oversimplified prescriptions for policy improvement. Under an assumption of no forward expectations, the net change in technology use monotonically increases as the budget increases regardless of the subsidy level (figure 8C). The net period change per dollar spent was also relatively flat for different budgets (figure 8D). Smaller subsidies also tended to uniformly perform better over a variety of budgets (figures 9C and 9D). Lastly, not considering expectations precludes the possibility of a policy causing net delay in technology adoption.

5 Conclusion

Our paper identifies a new form of 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 incentive for moral hazard. 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 those practices that have 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.[13] Over half of conservation expenditures in the

[13] 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

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.[14]

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 only 22% of acres that applied for a CRP contract were accepted in the 2016 sign-up (Farm Service Agency, 2016). Some 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, to the extent that the price of services are determined competitively and all agents receive a payment that

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.

[14]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."

are willing to accept the price for providing the service, then delayed adoption due to moral hazard is not a concern.[15]

The numerical simulations illustrate the complex impacts of policy parameters 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. In our simulations raising the periodic budget produces 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 so there can be intermediate subsidy level that induces the greatest net change in technology use. Policies beginning earlier in the diffusion process had higher total expenditures but were far better at targeting farms that adopt earlier than they would have in the free market. We also compare our results to a simulation that ignores forward looking expectations to demonstrate the contribution of 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, matching and difference-in-differences will tend to overestimate additionality. These estimators will also tend to overstate the amount of additionality because

[15]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).

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.

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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

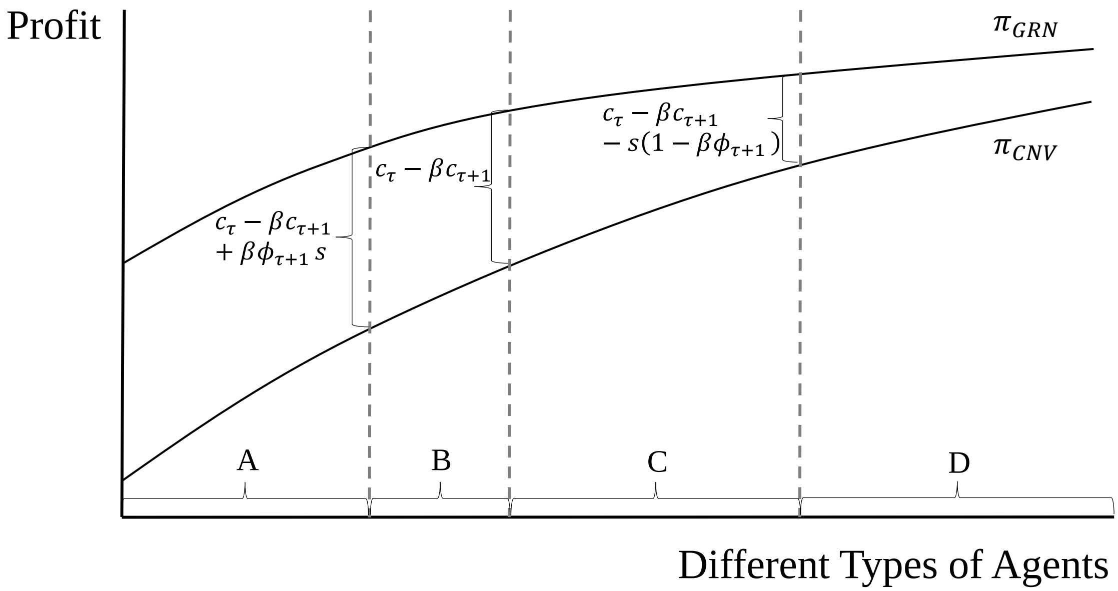

Figure 1: Illustration of Different Groups of Agents by the Impact of a Subsidy on the Adoption Decision in Period τ

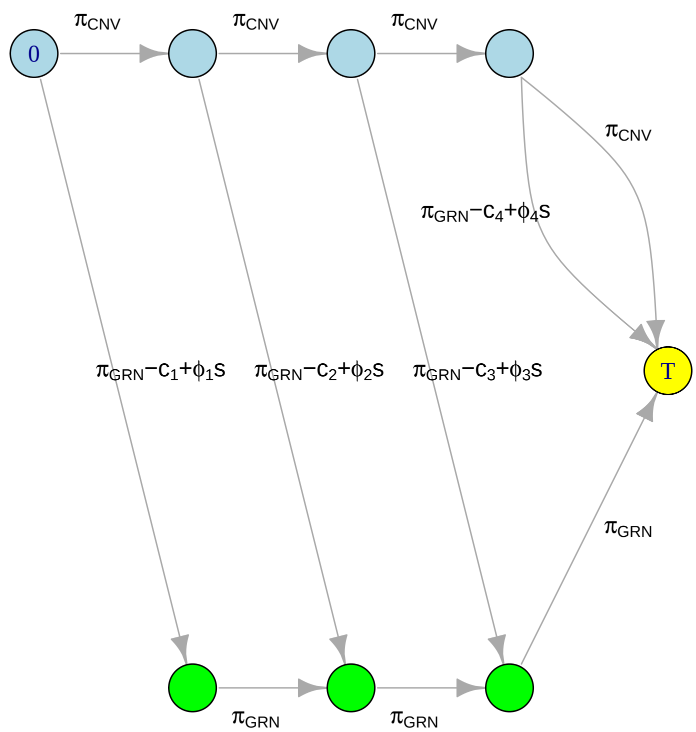

Figure 2: Discrete Dynamic Adoption Problem

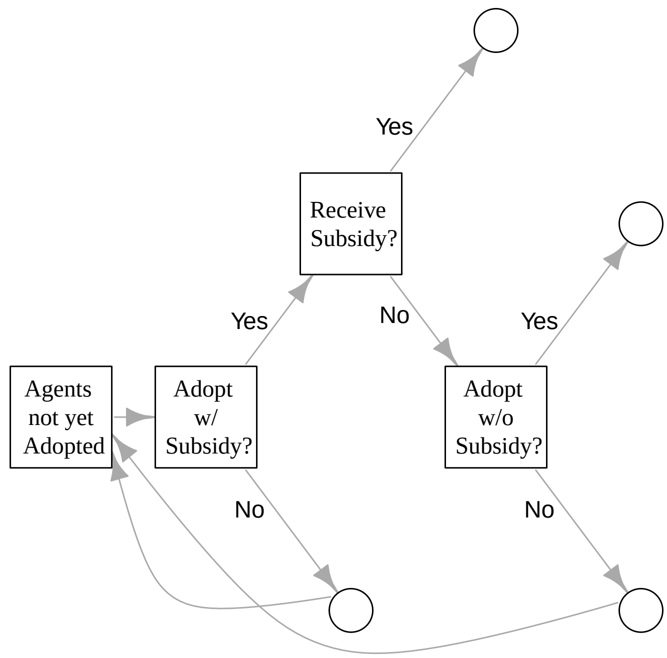

Figure 3: Post-Active-Period Simulation Schematic

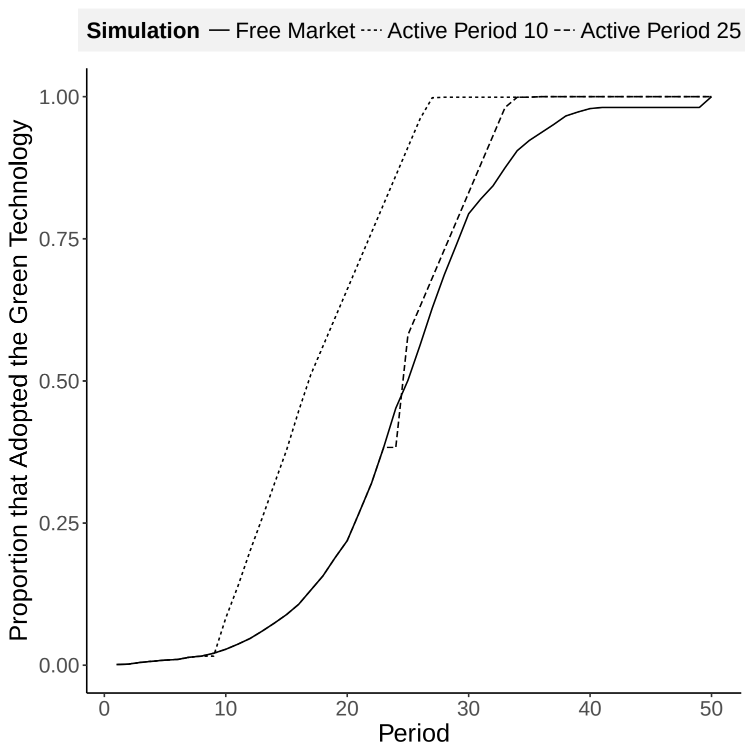

Figure 4: Diffusion Under Free Market and Two Potential Policies

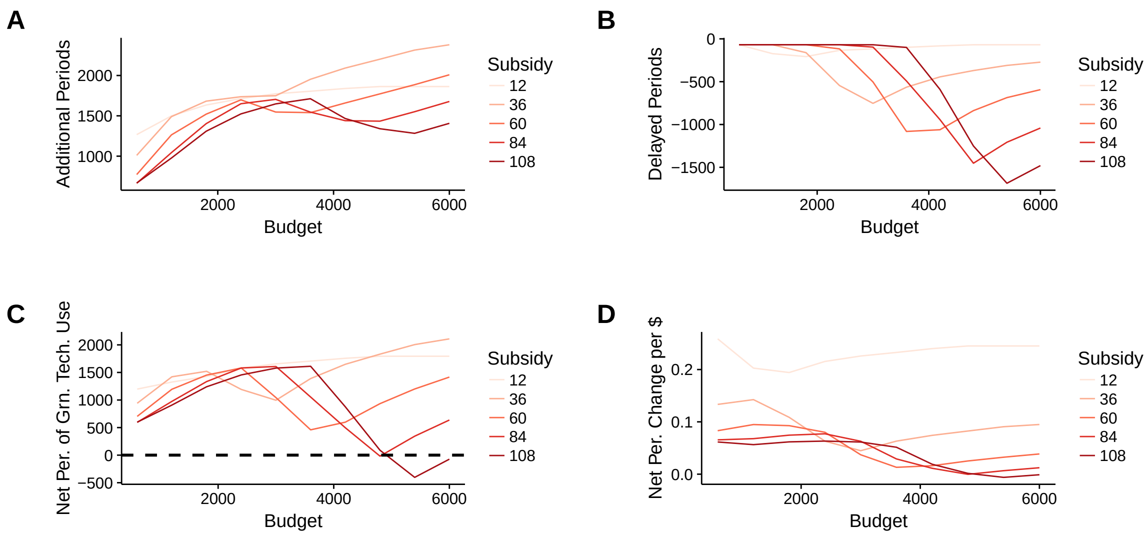

Figure 5: Policy Outcomes Varying the Budget by Subsidy Levels

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 statistics from panel C and divides it 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.*

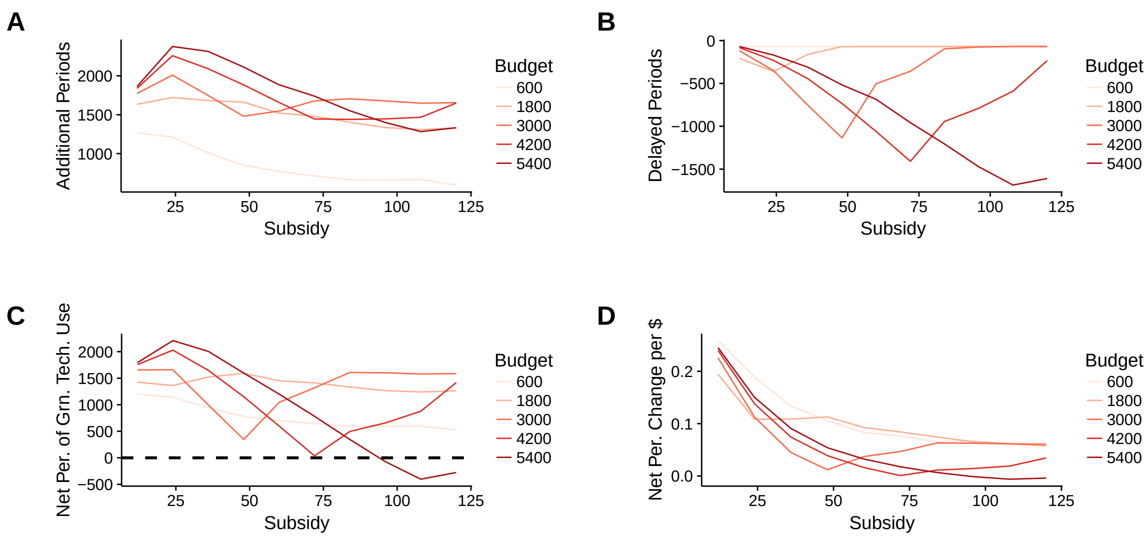

Figure 6: Policy Outcomes Varying the Subsidy by Budget Levels

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 statistics from panel C and divides it 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.*

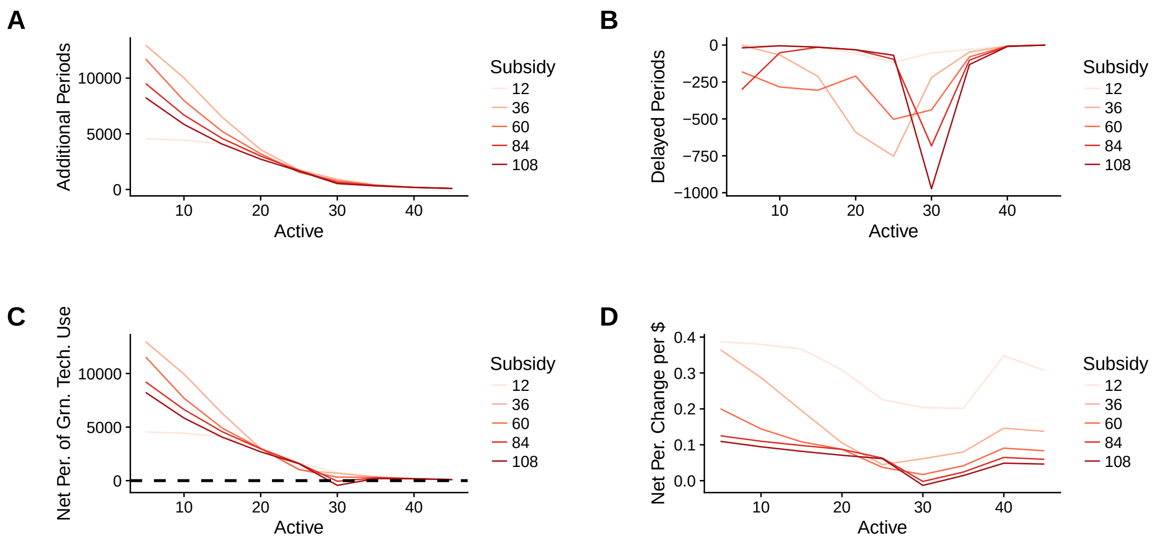

Figure 7: Policy Outcomes Varying the Active Period by Subsidy Levels

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 statistics from panel C and divides it 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.*

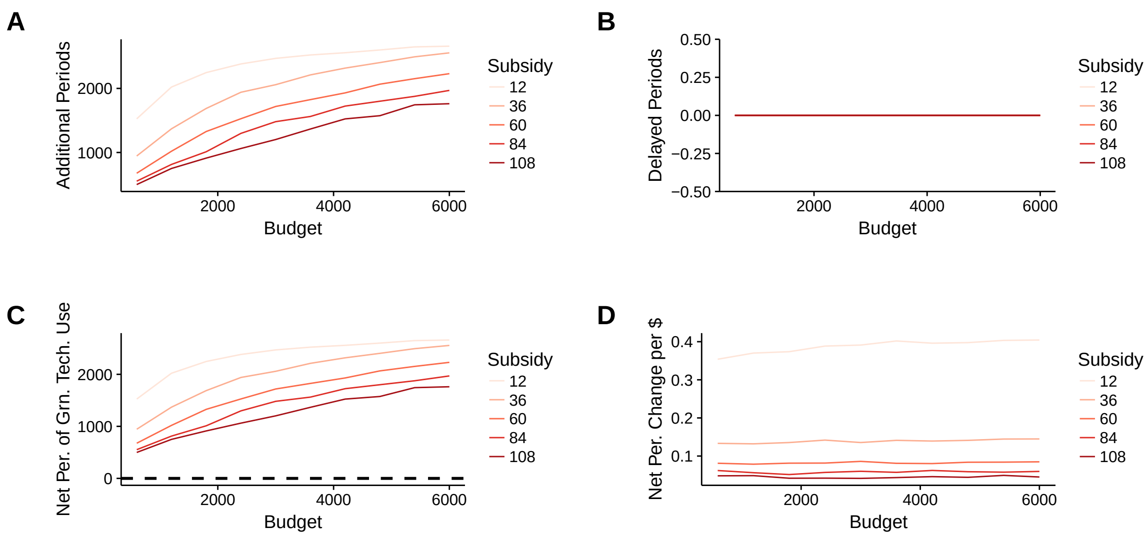

Figure 8: Assuming No Forward Expectations – Policy Outcomes Varying the Budget by Subsidy Levels

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 statistics from panel C and divides it 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.*

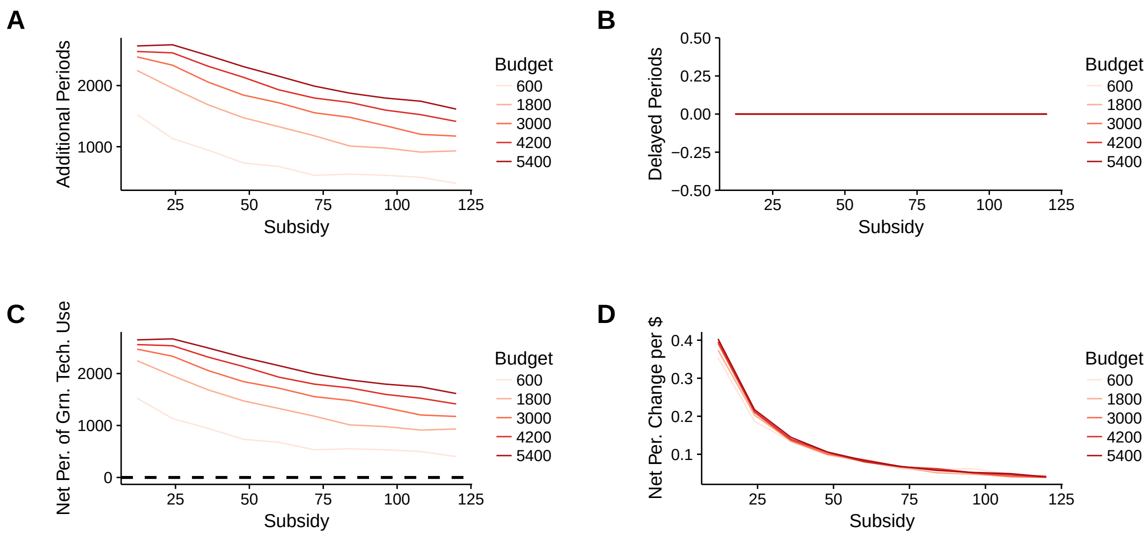

Figure 9: Assuming No Forward Expectations – Policy Outcomes Varying the Subsidy by Budget Levels

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 statistics from panel C and divides it 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.*

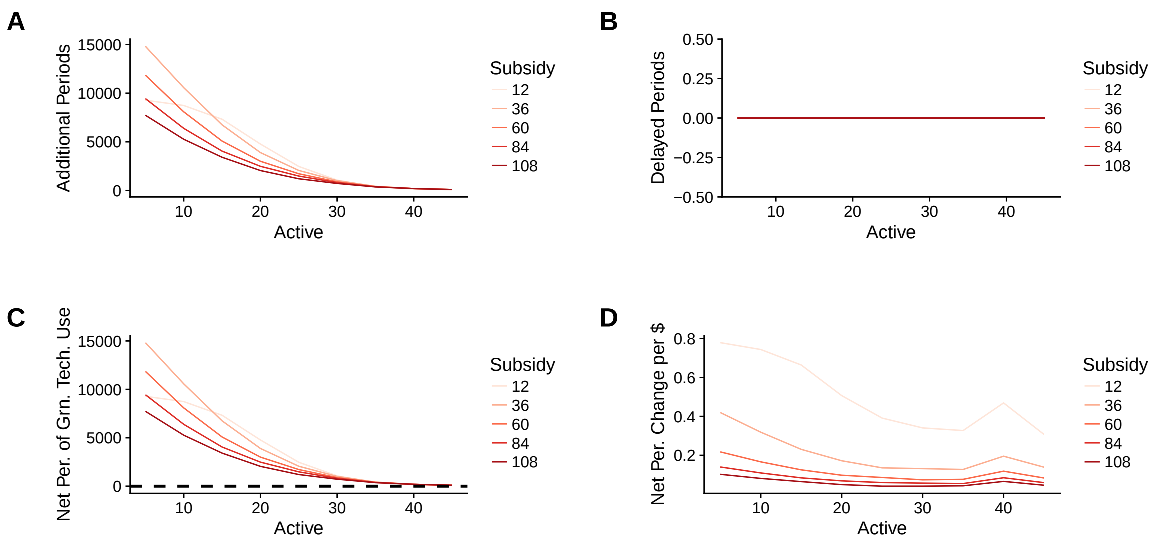

Figure 10: Assuming No Forward Expectations – Policy Outcomes Varying the Active Period by Subsidy Levels

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 statistics from panel C and divides it 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.*

Supplementary Appendix

A1 Conceptual Model Assumptions

In general, to analyze 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 analyze the adoption decision. 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

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

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 and the second term is positive. To understand the ambiguity of the sign, it is useful to think about the adoption decisions as the purchase of an annuity. 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. However, 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

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

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.

A2 Simulation Parameters

We now describe in more detail the parameterization of the heterogeneity distribution, the cost function 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.

Solving a system of equations, we generated a cost function that reached certain values over key time periods and also induced full diffusion over the course of the time horizon. We set $c_1 = 164$, $c_{25} = 100$ and $c_{50} = 34$ generating a cost function with the following form:

(A8) $c_t = 166.327 - 2.653t$

The profit functions π_{CNV} and π_{GRN} are plotted in figure A3. We assume the technology reaches 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 and for the sake of parsimony. We calibrate the parameter values of the profit functions in order to satisfy certain restrictions. We assume 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 function. We used the results from our conceptual model to make our calibrations. 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:

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

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

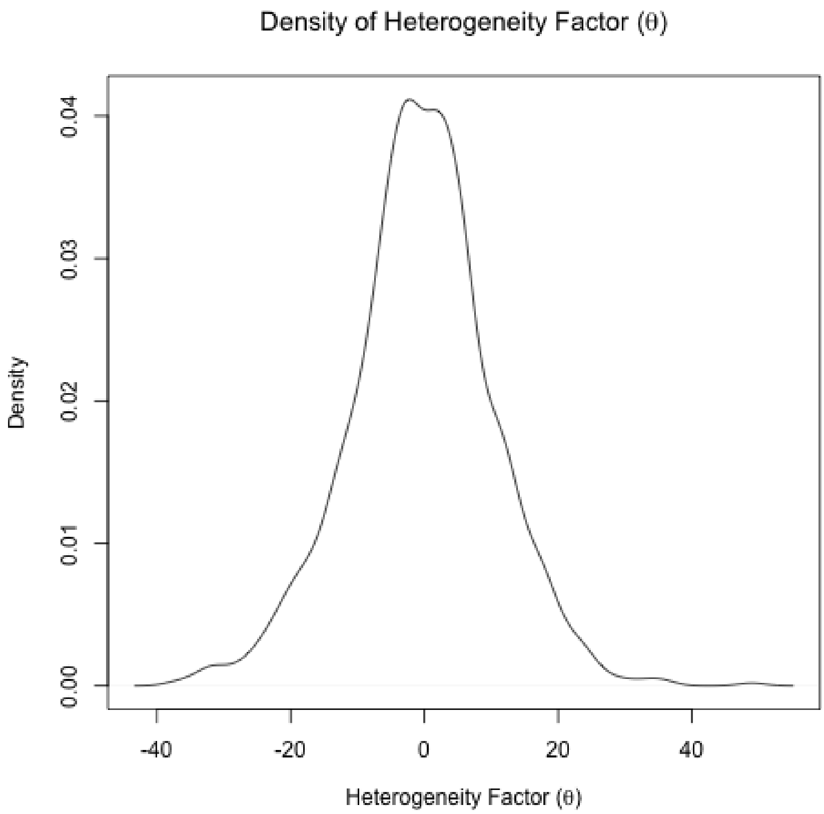

Figure A1: Heterogeneity Factor Density

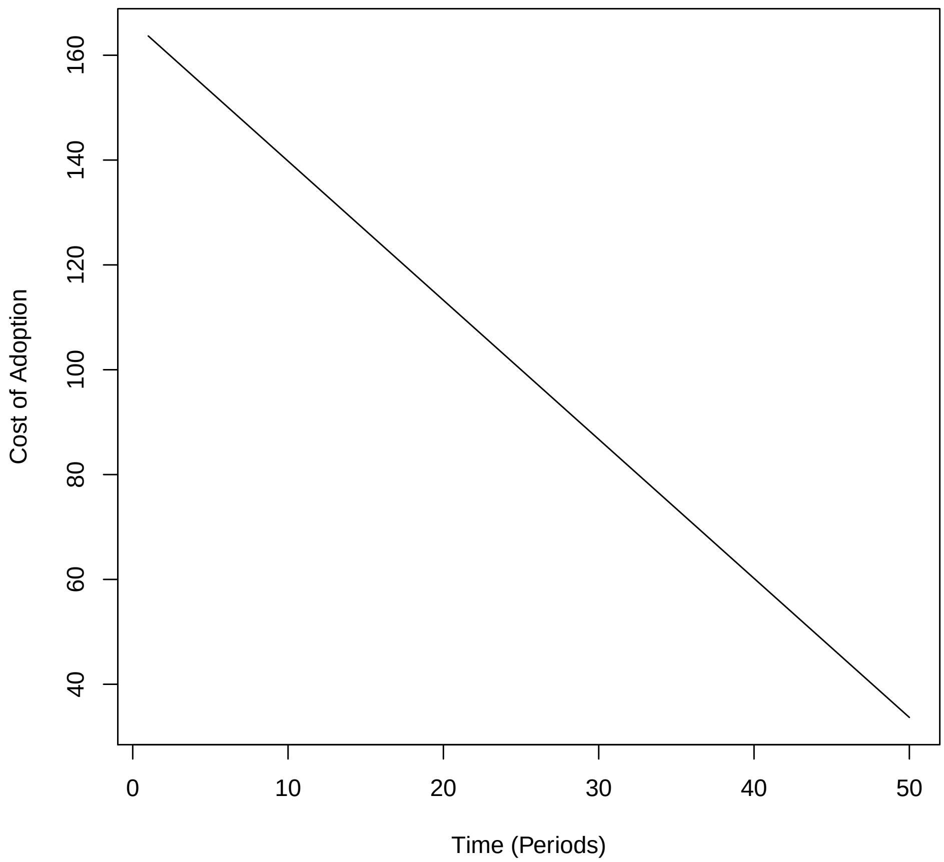

Figure A2: Cost of Adoption Over Time

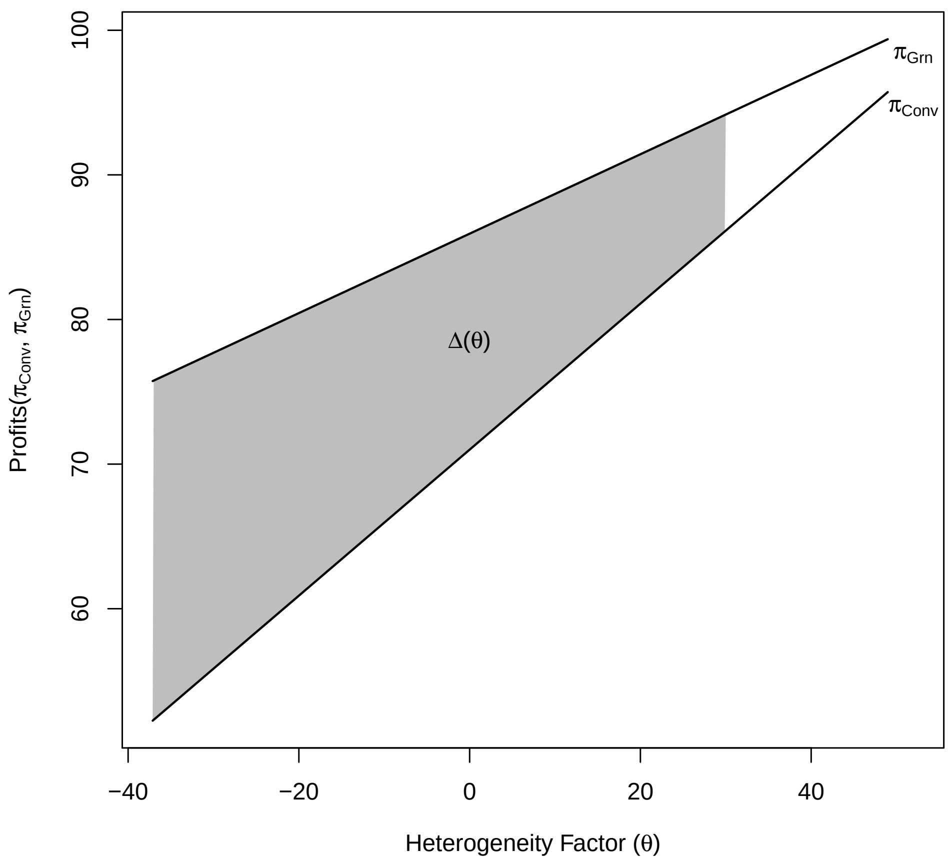

Figure A3: Profit Functions π_{CNV} and π_{GRN}

A3 Small Simulation Example

Here we go through a simple example of the algorithm. Suppose we have the simple four-period digraph we showed in the paper and we are testing a policy. Suppose this policy is announced in period 1 and become active in period 2. Figure A4 shows the expected payoffs for agents when the policy is announced. Notice that the first period transition arc is known not to be subsidized while in the remaining periods there is some probability that a subsidy can be issued. Running our group of agents through this graph with their respective profit terms in on the arcs, we remove any agent that adopts before the policy begins, traversing the path shown in figure A5. These agents will not be offered a subsidy since past adopters are not eligible for a subsidy.

After the removal of these agents, the graph transition arcs are adjusted again (figure A6). Over this graph we test whether some of the remaining agents would adopt in the first active period if given a subsidy, traversing over the path shown in figure A7. Any agent that chooses this path would also apply for a given subsidy. Since, with a periodic budget, if the applicant pool is larger than $\frac{B}{s}$, the highest number of individuals the policy can subsidize, payments are given out randomly over the applicants.

Applicants that receive a subsidy are removed from further simulations because they adopted with the subsidy when it was given to them. The remaining applicants are asked to choose the optimal path when they know that, in period 2, they were denied the subsidy. The agents that choose to adopt in period 2 without the subsidy (shown in figure A8) are removed from further simulations. Those that wait in the hopes of receiving a subsidy later on (shown in figure A9) reenter the simulations in the graph figure A6, this time "asking" whether the remaining agents would adopt with a subsidy in period 3 ($\phi_3 = 1,\ \phi_2 = 0$).

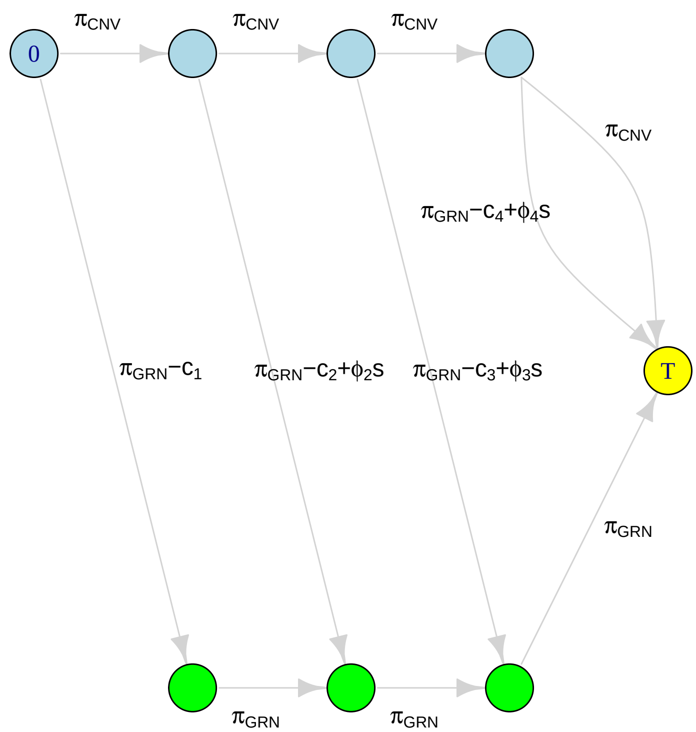

Figure A4: Expectations at Announcement

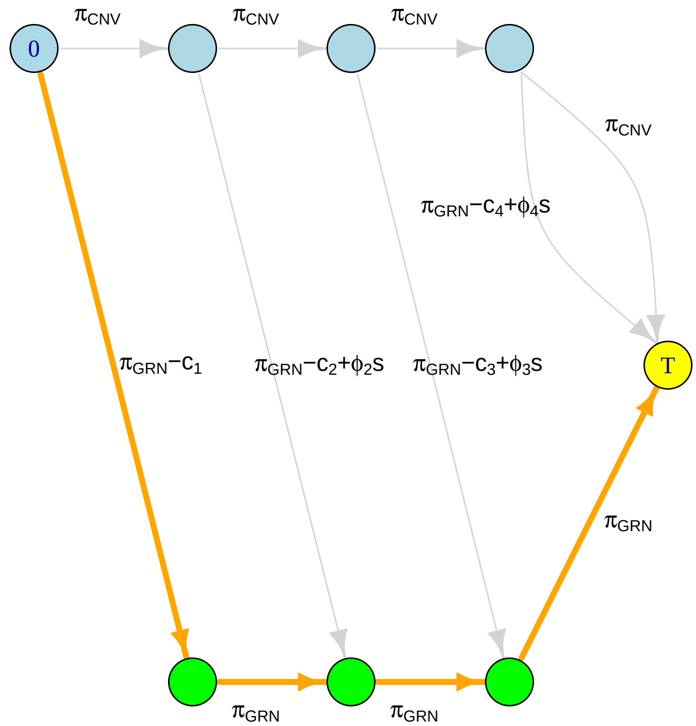

Figure A5: Adopters Before Subsidy Begins

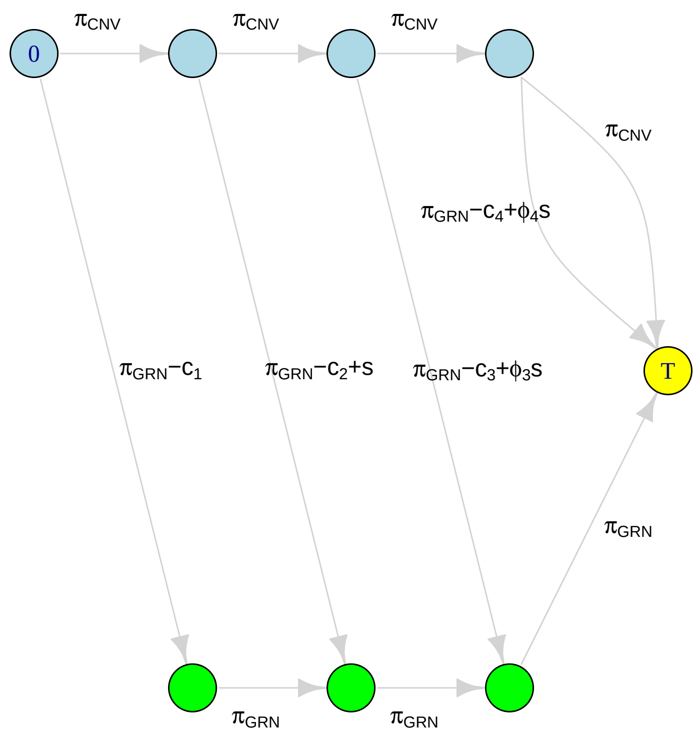

Figure A6: Simulating a Subsidy in Period 2

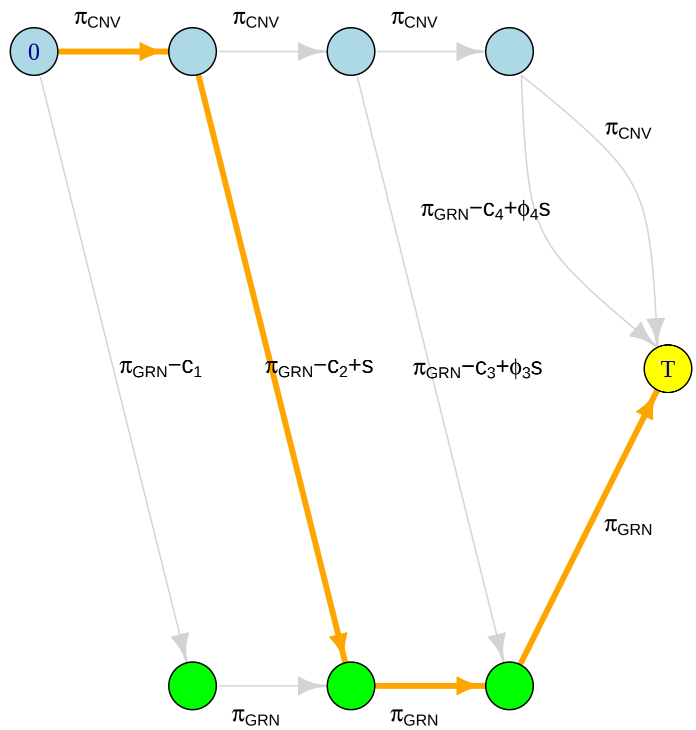

Figure A7: Applicant Path for Period 2 Subsidy

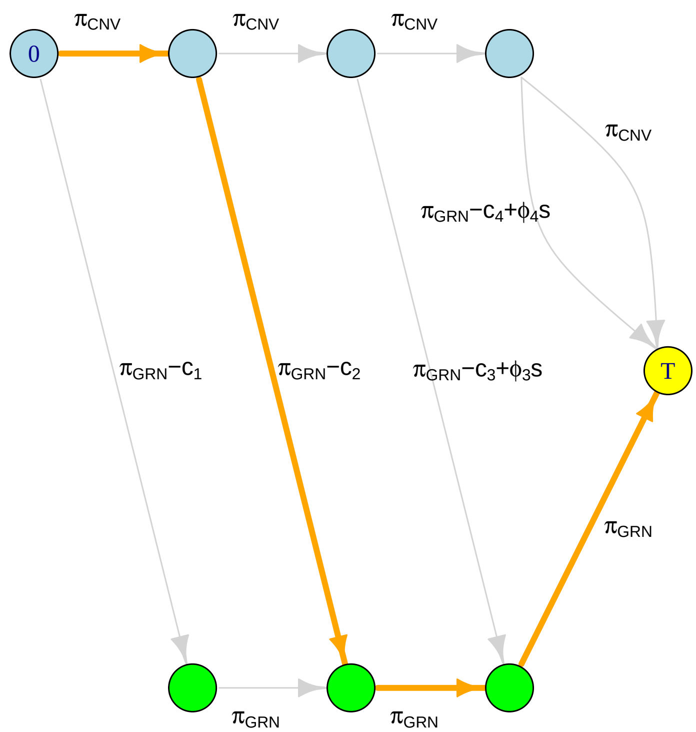

Figure A8: Independent Period 2 Adoption

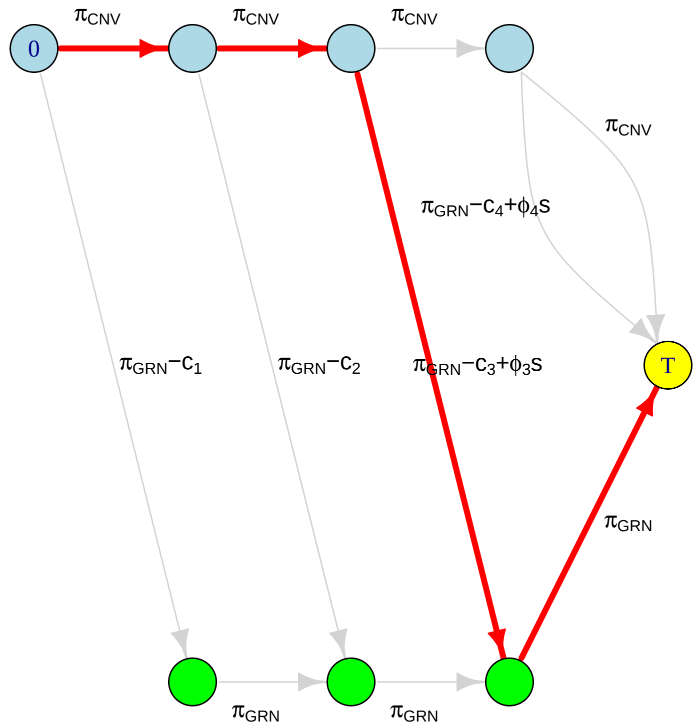

Figure A9: Deferred Adoption

A4 Plots with Active Period 10

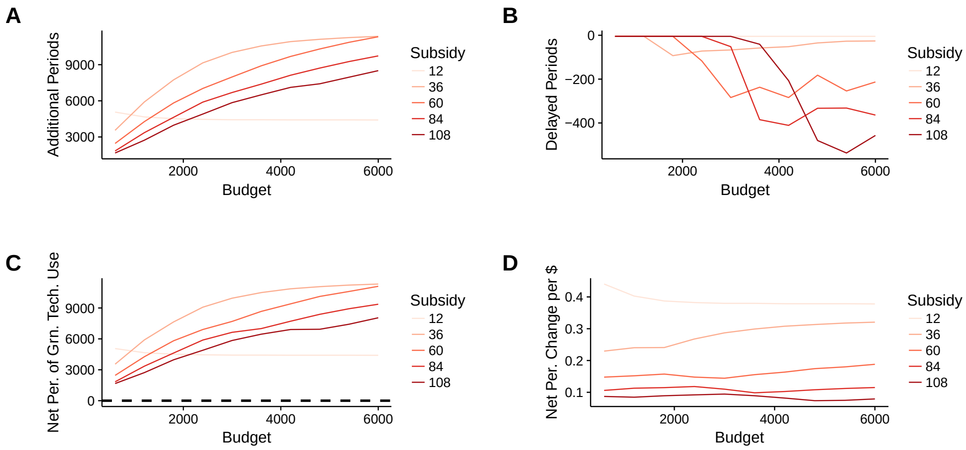

Figure A10: Policy Outcomes Varying the Budget by Subsidy Levels (Active Period 10)

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 statistics from panel C and divides it 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.*

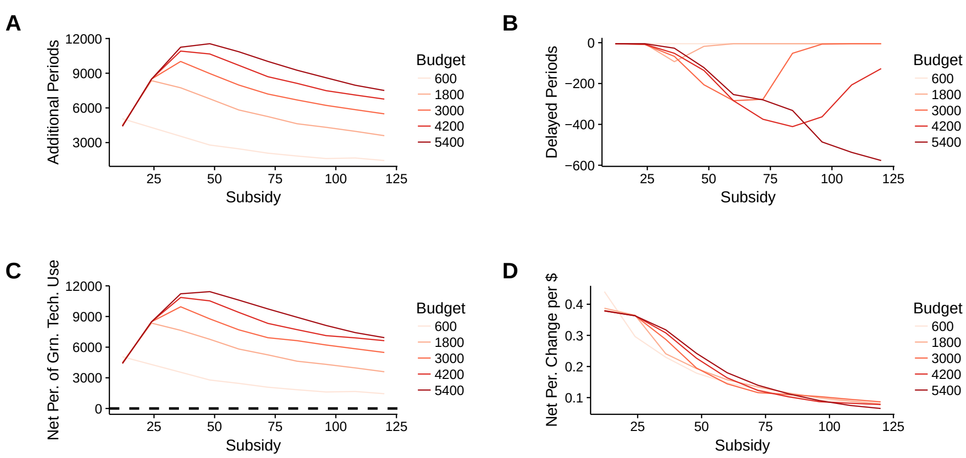

Figure A11: Policy Outcomes Varying the Subsidy by Budget Levels (Active Period 10)

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 statistics from panel C and divides it 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.*