Innovation as a policy strategy for natural resource protection

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Abstract
Growing global food demands place major strains on water resources, including quality impairments and increased water scarcity. Drawing on the largely separate bodies of literature on externalities and technological innovation, this article develops a dynamic framework to explore the long-term impacts of alternative policy approaches to the agricultural impacts on water resources. Environmental policies, which focus on correcting environmental externalities, lead to an overall gain because costs to farmers are more than offset by reduced environmental damages. Technology policies, which direct public investments into agricultural eco-innovations, lead to benefits for farmers as well as the environment. Joint implementation of both types of policies leads to the largest overall gain. In principle, a technology policy alone could have greater environmental benefits than an environmental policy alone. This outcome is most likely in cases where the productivity effect of new technology is large and the cost of research is low.

Recommendations for research managers
• As an alternative to traditional environmental policy, investments in research can provide win–win solutions that benefit the environment and agricultural producers.
Conceivably, eco-innovations could lead to environmental conditions that are better than those achieved by environmental policy alone. Adding research investments to existing environmental policy would lead to further improvements in environmental quality while also benefitting farmers. Unlike environmental policies that are perceived to impose costs on agriculture, technology policies impart benefits to farmers and are less likely to face political opposition from industry. Technology policies are likely to be the most effective when eco-innovation leads to technologies that meaningfully reduce environmental impacts and also raise farm productivity.

**KEYWORDS**
agri-environmental policy, innovation, nutrient contamination, research and development, technical change

## 1 INTRODUCTION

Agriculture has widespread impacts on the environment globally, including long-term effects on water resources, biodiversity, and greenhouse gas concentrations. Driven by population growth, dramatic increases in agricultural output were associated with large increases in the use of nitrogen and phosphorous fertilizers and an expansion of irrigated cropland (Tilman, 1999). While nutrient use efficiencies increased during the same period, the losses of agricultural nitrogen and phosphorous into the environment are the largest source of nutrients in many of the world’s eutrophic marine and freshwater ecosystems (Howarth, 2008; Michalak et al., 2013; Vilmin, Mogollón, Beusen, & Bouwman, 2018). Similarly, despite improvements in water use efficiency, agriculture remains largest user of water worldwide and the volume of irrigation withdrawals continues to grow (Rosegrant, Ringler, & Zhu, 2009).

An extensive body of research has examined the environmental impacts from agriculture, modeling them as externalities of the production process. Nutrients and other by-products from crop production contaminate water supplies, leading to costly social damages in the form of increased health risks and reduced economic value of waterfront property, water-based recreation, fishery productivity, and other ecosystem services (Keeler et al., 2012, 2016; Rabotyagov, Kling, Gassman, Rabalais, & Turner, 2014; Sobota, Compton, McCrackin, & Singh, 2015). In water-scarce regions, water diverted for agricultural uses may reduce streamflow and impose damages on ecosystems, recreation, and navigation (Leones, Colby, Cory, & Ryan, 1997). Another form of externality arises in groundwater irrigated regions, where farmers impose costs on each other through the common-pool resource effect (Koundouri, 2004). Numerous studies have analyzed policy designs to address agricultural externalities and have quantified the resulting social gains (e.g., Garnache, Swinton, Herriges, Lupi, & Stevenson, 2016; Guilfoos, Khanna, & Peterson, 2016; Kling, 2011; Kuwayama & Brozović, 2013; Shortle & Horan, 2013).
A largely separate body of research has studied the innovation process driving technical change. Beginning with Arrow (1962), a longstanding rationale for innovation policies draws on market failure arguments. Due to the basic properties of information, new knowledge takes on public good properties (nonrival and nonexcludable), so that a private enterprise investing in research cannot prevent others from capturing the benefits of research results. These information spillovers undermine private incentives for research, resulting in an under-provision of innovation unless the government intervenes. More recent work on innovation introduced evolutionary arguments, emphasizing the process of information dissemination in the innovation process (Metcalfe, 1995; Pavitt, 1991; Rosenberg, 1990). Translating new knowledge into new technologies requires workers with specialized training to understand, interpret, and apply research findings. In the evolutionary view, the research enterprise is a broader set of activities that involves education and training, along with the creation of professional networks spanning basic researchers and technology developers. Evolutionary arguments also suggest that research, in this broader definition, will still be underprovided by private entities because they cannot capture all the gains from education and training of their current workers.

The case for public investments for innovation is been bolstered by a large body of empirical evidence. In the agriculture sector, research has led to improved crop varieties, mechanization of field operations, and more effective agronomic practices, all of which have combined to reduce the cost of food production. Typical estimates are that the social benefits from agricultural research have exceeded their costs by a factor of ten to one (Alston, Andersen, James, & Pardey, 2011; Hurley, Rao, & Pardey, 2014). Citing the compilation by Griliches (1995), Salter and Martin (2001) reported several empirical studies examining the social returns to innovation across multiple economic sectors, with estimated rates of return ranging from 10% to as high as 160%.

An emerging literature addresses the relationship between innovation and environmental externalities. Jaffe, Newell, and Stavins (2002) and Jaffe, Newell, and Stavins (2005) pointed out that technology policy and environmental policy can be viewed as corrections for two interacting market failures. The interactions imply that a policy in one of these domains may affect outcomes in the other. For example, eco-innovations are defined as novel methods that, once adopted by private entities, will reduce environmental damages, risk, or natural resource use (Kemp & Pearson, 2007). An attractive feature of policies promoting eco-innovation is the prospect of win–win outcomes. The public costs of those policies will be offset by the benefits of reduced environmental damage as well as the usual gains to industry from technological advances. Additional gains may accrue if the new technologies reduce the industry cost of complying with environmental regulation. The gains from eco-innovation are beginning to be explored in the energy sector. For example, Richels and Blanford (2008) find that new low-carbon emitting technologies would reduce the projected cost of meeting climate policy targets by nearly two-thirds.

This article contributes to the emerging literature by developing a dynamic framework drawing on concepts from both environmental policy and innovation research. The model is formulated to study the interactions between agricultural innovation and agricultural externalities. A production process generates environmental harm, but the process itself may change over time due to knowledge-driven technological change. For concreteness, the model is described for the case of water quality impairments from crop production. With small changes in interpretation of variables, however, the same model structure applies to the case of water depletion or other types of pollution problems from competitive industries.
The model examines two types of policies, in isolation and in combination. Environmental policy would impose limits on environmental harm each period. Technology policy invests in research to generate eco-innovations, which reduce environmental harm in future periods while also increasing farmers’ profits. Using this framework, technology policies are found to unambiguously benefit farmers while also reducing environmental damages, whether or not environmental policies exist. Environmental policy, in contrast, always reduces environmental damages while imposing costs on farmers. As expected in a market failure context, both policies impart overall gains to society, and gains are largest when both policies are implemented jointly. Conceptually, technology policy alone could reduce damages more than environmental policy alone, although the quantitative results depends on model parameters. While the model here is conceptual, it provides a framework for empirical analyses for quantitative comparisons.

The next section of this article provides additional context and a brief review of relevant literature on modeling agri-environmental and innovation policy. The third section introduces the model components including the processes governing agricultural production, environmental change, and innovation. Section 4 describes the policy scenarios to be analyzed, which are the different combinations of environmental and technology policy. Sections 5–8 then exercise the model for each of the scenarios in turn along with the relevant comparisons. Section 9 compares the social welfare across the four cases, and the final section provides discussion on the model assumptions and conclusions.

2 BACKGROUND ON AGRI-ENVIRONMENTAL AND TECHNOLOGY POLICIES

In response to environmental concerns, policy-makers have enacted various agri-environmental programs over the course of several decades. In the United States, for example, agricultural conservation program spending increased from under $1 billion to more than $5 billion annually from the mid-1980s to 2005 (Claassen, Cattaneo, & Johansson, 2008). These programs provide some combination of technical assistance and cost-share subsidies for farmers to adopt certain practices.

While agri-environmental policies may have multiple purposes including an equitable distribution of public expenditures, economists have found that they perform poorly in terms of cost-effectiveness. A key issue is that resource depletion effects from agriculture are localized and pollutants are generally nonuniformly mixed, implying that cost-effective polices require spatial targeting. Existing policies, however, favor uniform designs that do not always give farmers in environmentally vulnerable locations a higher incentive to participate. The result is that greater environmental gains would be possible from alternative designs with spatially varying incentives (Lichtenberg, 2004, 2014; Shortle & Horan, 2013). Political constraints appear to be a major barrier to enacting more efficient policy. Efficient policy designs typically concentrate costs on a subset of farmers, while spreading the environmental benefits over much larger segments of the public. Farmers then have an incentive to organize to oppose such a policy, but the large number of beneficiaries would have individually small incentives to support it.

Innovation and technology policies have been enacted with various justifications, including correction of market failures, development of a highly trained workforce, and promotion of overall economic growth (Salter & Martin, 2001). Policies have aimed to increase innovation through both private and public entities. Patents are a common device to provide incentives for
private innovators to develop new technologies, giving them the exclusive rights to sell a patented technology over a fixed period. Although existing patent systems provide incentives for base knowledge to be translated into usable technologies, they are not sufficient to generate the incentives for knowledge creation. Most governments directly invest in public research, through grants to universities and funding for government research institutes. These two approaches appear to be complementary, with many patent applications in the US citing findings from publicly funded research (Narin, Hamilton, & Olivastro, 1997).

Building on the early contributions of Griliches (1979), economists have modeled innovation as a dynamic process, where the flow of research expenditures increase the stock of knowledge, which in turn is translated into usable technologies (Jones & Williams, 1998; Goulder & Schneider, 1999; Popp, 2004; Romer, 1990). Knowledge may depreciate because of obsolescence of ideas and techniques, so a sufficiently large flow of research investment is needed to increase usable knowledge over time (Grimaud, Lafforgue, & Magné, 2011; Popp, 2006).

Eco-innovation in agriculture is a prime case study, not only because the environmental impacts and potential for reduced damages are large, but also because agriculture has a history of absorbing transformative technologies. Moreover, although the portfolio of eco-innovations is broad and new ones can be developed, several technologies are in some stage of development. Some specific examples spurred by public investment include: (a) the next generation of precision farming techniques with distributed sensor networks, which will allow for precise timing and rates of nutrient application that minimize losses to the environment, (b) varieties of new winter-hardy crops (e.g., winter camelina) that can be harvested to provide an economic return while also consuming excess water and nutrients that are vulnerable to environmental losses, and (c) drainage water recycling, which captures nutrient-rich drainage water in on-farm storage ponds and recycles it later in the season for supplemental irrigation water. Lewandowski et al. (2018) provide further descriptions and examples.

3 | MODEL FORMULATION

Consider a farming region where a large number of competitive, polluting farms use identical technology that advances over time. Throughout this article, time is represented by the continuous variable \( t \), and in general time-dependent variables are written as explicit functions of \( t \) only at their first mention. At instant \( t \), both aggregate output, \( y(t) \), and aggregate pollution, \( z(t) \), depend on aggregate input use, \( x(t) \), but both relationships are conditioned on the state of technology. For concreteness, \( y \) can be interpreted as grain production, \( x \) as fertilizer input, and \( z \) as nutrients leached into water supplies. However, the model applies more generally to other inputs, outputs, and environmental impacts. For example, in a region where irrigation-driven aquifer depletion is the resource concern, the relevant interpretation of \( y \) would be the production or the irrigated crop(s), while \( x \) would be water extracted and applied for irrigation, and \( z \) would be the net change in aquifer storage (extractions adjusted for recharge and return flows).

Another notational convention in this article is that lowercase symbols represent primal variables—that is, the value of variables before farmers have made a production decision—while uppercase symbols represent farmers’ chosen values of primal variables and quantities that are exogenous to farmers’ decisions. For example, \( x \) represents the possible value of input before farmers commit to production in a given period and \( X \) represent their chosen input level, after farmers observe the output price \( P_Y \) and input price \( P_x \). We also assume that the region in question, while having a large number of competitive farms, is still small enough relative to
world markets so that all prices are exogenous. Furthermore, to isolate the dynamic effects of technology and environmental impacts, we assume that prices are time-invariant.

3.1 Production

The state of technology can be indexed by the amount of usable knowledge, under the assumption that knowledge is instantaneously transferred into technological improvements. The innovation process that generates knowledge is described later. Here, it will be sufficient to define $S_0 \equiv S(0)$ as the stock of knowledge at $t = 0$ and $K(t) \equiv S(t) - S_0$ as the amount of knowledge added to the stock up until $t$. Consider the decisions of profit-maximizing farmers in the region at instant $t$. After observing $K$, farmers can determine their profit-maximizing actions in two steps. First, for any target value of leaching, $z$, farmers can identify an input plan that maximizes their profits. Their maximum profits are

$$
\Pi(z; K) = \max_x P_y f(x; K) - P_x x
$$

subject to: $g(x; K) \leq z$, \hspace{1cm} (1)

where $P_y$ and $P_x$ are the exogenous output and input prices, respectively, $f(x; K)$ is the knowledge-conditioned production function, and $g(x; K)$ is the knowledge-conditioned pollution function. $\Pi(\cdot)$ depends on the exogenous level of $K$ and the target level of leaching, $z$.

In the second step, the farmers can choose $z$ by maximizing $\Pi(z; K)$. Conveniently, this function takes on the same properties as a direct profit function where $z$ is treated as an input: $\Pi_z(z; K) \geq 0$ and $\Pi_{zz}(z; K) \leq 0$. If $z$ is unregulated (i.e., if farmers face no-policy restrictions on environmental harm), their profit maximization problem is $\max_z \Pi(z; K)$. The solution to this problem is where marginal profits are zero:

$$
\Pi_z(z; K) = 0.
$$

Unregulated pollution will depend on the value of $K$ because knowledge conditions the functions $\Pi(\cdot)$ and $\Pi_z(\cdot)$.

For the remainder of this article, profits are specified as a quadratic function of $z$ and $K$:

$$
\Pi(z; K) = \tilde{\eta}(K) + \tilde{\alpha}(K)z - \frac{\beta}{2}z^2,
$$

where the Greek letters are parameters, the first two of which are time-varying values that depend on the state of knowledge. Marginal profits are

$$
\Pi_z(z; K) = \tilde{\alpha} - \beta z.
$$

The time-varying parameters, $\tilde{\eta}$ and $\tilde{\alpha}$, are linked to innovation through two equations:

$$
\tilde{\eta}(K) = \eta K, \hspace{1cm} (5)
$$

$$
\tilde{\alpha}(K) = \alpha - \gamma K, \hspace{1cm} (6)
$$
where $\eta$, $\alpha$, and $\gamma$ are positive parameters. Equation (5) represents the productivity effect from innovation, capturing the increase in profits when $z$ is fixed. Equation (6) captures the efficiency effect through the effect of $K$ on marginal profits and, in turn, farmer-chosen pollution levels.

### 3.2 The innovation process

The innovation process is modeled following the dynamic frameworks in the literature (Goulder & Schneider, 1999; Griliches, 1979; Grimaud et al., 2011; Popp, 2004, 2006). The stock of technology-enhancing knowledge grows over time if the rate of production of agri-environmental research, $R(t)$, is sufficient to offset knowledge depreciation. Recalling that $K(t) = S(t) - S_0$ is the amount of knowledge beyond the $t = 0$ baseline of $S_0$ (implying that $K(0) = 0$), the change in the stock of knowledge is modeled as

$$\dot{K} = R - \theta K,$$

where $\dot{K} \equiv dK/dt$ is the rate of change in knowledge and $\theta > 0$ is the knowledge depreciation rate.

The scalar $R$ is the amount of usability-adjusted research produced per period, reflecting the most recent addition to the stock of knowledge that is usable for technological advances. If research were absent, usable knowledge would depreciate over time because previous knowledge would become obsolete in the face of changing conditions (e.g., in regional climate) and advancing technology in companion sectors (e.g., in the sectors supplying the input, $X$, and processing the output, $Y$). Knowledge depreciation would be partially offset by the “shoulders of giants effect,” or the autonomous increase in scientists’ productivity from a larger knowledge pool. It is also partially offset by knowledge spillovers from research in other domains of expertise, including those obtained from privately funded agri-environmental research. However, these combined effects are assumed to be smaller than the inherent depreciation rate, so that $\theta > 0$ is the net rate of decline.

As noted, the private incentives to invest in agri-environmental research are undermined by knowledge spillovers because they prevent private researchers from capturing the benefits of new knowledge. These limited incentives support the assumption that private research (and the resulting spillovers) will be small and that the public sector will be the main provider of research. Public research expenditure is measured by the research cost function

$$C(R, K) = \frac{\epsilon}{2} R^2 + \frac{\omega}{2} K^2,$$

where $\epsilon$ and $\omega$ are positive parameters representing the slope of marginal cost functions with respect to each argument, that is, $C_R(\cdot) = \epsilon R$ and $C_K(\cdot) = \omega K$. Increasing marginal costs in this specification reflects the assumption of diminishing marginal returns of research expenditures. An incremental increase in research expenditures become less productive as research activity grows, due to increasing scarcity of scientist talent. Similarly, research expenditures are less productive when the stock of knowledge is already high, due to the idea-crowding effect.

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1For example, $R$ could be empirically measured as an index involving the number of articles published in a relevant subset of scientific journals.
3.3 | Environmental impacts

Environmental impacts are also modeled dynamically, where the state of water resources change as a result of production-induced harm but recover at some rate due to natural regeneration. The health of water resources in the region at instant $t$ is measured by $Q(t)$. For example, $Q$ can be interpreted as an index of water quality that depends on measured concentrations nutrients from agricultural fertilizer. Resource health evolves according to

$$
\dot{Q} = \begin{cases} 
\phi_0 - \phi_1 Q - Z & \text{if } Q > 0, \\
0 & \text{if } Q = 0,
\end{cases}
$$

(9)

where $\dot{Q}$ is the rate of change in environmental quality and $\phi_0 > 0$, $\phi_1 \geq 0$ are physical resource parameters. The first two terms, $\phi_0 - \phi_1 Q$, capture the assumption that the natural rate of resource regeneration diminishes with respect to $Q$, while the last term, $-Z$, represents the harm from current-period production. The declining regeneration assumption presumes that further improvements in water quality occur more slowly when current quality is high.

Low levels of environmental health can impart various damages to society. Quality impairments can lead to higher water treatment costs, elevated human health risks, altered aquatic ecosystems including reduced harvests of commercial and recreational fish species, and reduced demand for water-based recreation. Total social damages are assumed to be measurable in monetary units as

$$
D(Q) = \frac{\delta}{2} (\bar{Q} - Q)^2,
$$

(10)

where $\delta > 0$ is a marginal damage parameter and $\bar{Q} > 0$ is the threshold below which damages occur. $\bar{Q}$ is assumed to be a sufficiently large value so that $\bar{Q} - Q > 0$ for all $Q$ in the range of feasible outcomes. Marginal damages are

$$
D_Q(Q) = -\delta (\bar{Q} - Q) < 0.
$$

(11)

That is, damages increase as environmental health declines.

The model formulation is general enough to apply to water availability contexts as well. In the case of groundwater extraction for irrigation, $Z$ represents net extraction, $Q$ is the volume of groundwater in storage, and Equation (9) is the rate of aquifer recharge. $\phi_1 > 0$ ($\phi_1 = 0$) represents the case where recharge declines with (is independent of) the stored volume.

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2While environmental impacts from agriculture are sometimes modeled in static (single year) frameworks, a dynamic approach captures the possibility of longer term impacts. For example, in a river where loadings of nutrients from cropland have downstream impacts, a static model would capture the downstream impacts that occur in the same period (e.g., drinking water treatment costs to downstream communities). However, there are usually impacts on the receiving water body that are longer lasting, such as coastal hypoxia and eutrophication of inland lakes. Further, some of the nutrients applied to farmland in a watershed also will leach into aquifers, where the impacts can last for decades and may even contribute to future river loading through baseflow into aquifer-connected tributaries.

3This assumption avoids potential discontinuities or nondifferentiable points in the marginal damage function. For cases where damages are zero for a portion of the feasible range, this specification should be viewed as yielding smooth approximation.
POLICY SCENARIOS AND COMPARISONS

With the base elements defined, the model can be exercised to compare policy alternatives. Four scenarios will be considered as summarized in Table 1. This section provides a brief overview of the four scenarios and the detailed solutions for each case are derived in the following sections.

The first scenario serves as a baseline where there is no-policy intervention in either the environmental or technology domains. No public investments are made in research ($R = 0 \forall t$) and $z$ is left unregulated to be chosen by farmers. Given the initial value of $K(0) = 0$, Equation (7) implies that $\dot{K} = K = 0 \forall t$. The long-term equilibrium unregulated level of environmental harm per period, determined by farmers’ profit maximization, is denoted $Z^0$ and the associated level of environmental health is $Q^0$.

The second scenario is the case of environmental policy without any investment in research. This scenario corresponds with much of the analysis of agri-environmental policies in the literature, which assumes constant technology. As in the first scenario, $\forall R K_t = 0$. In this case, though, $Z$ is selected by forward-looking social planner who balances production profits against the social damages from environmental harm. The resulting long-term equilibrium is represented by $Z^E$ and $Q^E$.

The third scenario assumes that $Z$ is not regulated but that research investments lead to technical advances. Here, the government’s problem is one of optimally selecting research investments while incorporating farmers’ induced responses to changing technology. Under the assumption that the government seeks to maximize social welfare, the government’s objective balances the gains from production profits against the cost of research and environmental damages. The long-term equilibrium involves the government’s chosen level of research, $R_T$, the associated stock of knowledge, $K_T$, the induced level of environmental harm, $Z_T$, and the resulting level of environmental health, $Q_T$.

The final scenario combines the previous two and assumes that a planning authority optimally chooses both $Z$ and $R$, again with the objective of balancing production gains against research costs and environmental damages. The optimized steady state in this scenario is denoted by the quadruplet $(Z^*, R^*, Q^*, K^*)$.

With the model components defined above, all policy scenarios can be solved with linear-quadratic optimal control problems—that is, problems with quadratic objectives and linear equations of motion. Provided that the quadratic objectives are concave functions, which is imposed with parameter restrictions, these problems are assured to converge to a unique, saddle-point stable steady state via a linear dynamical system. Although the speed of convergence may not be identical in all cases, this structure ensures that a unique steady state exists in every scenario. Steady states can be compared

| Policy scenario | Environmental regulation | Research expenditures | Symbols for endogenous variables in steady state |
|-----------------|--------------------------|----------------------|-----------------------------------------------|
| None (unregulated) | No | No | $Z^0$ | $R^0$ | $Q^0$ | 0 |
| Environmental | Yes | No | $Z^E$ | 0 | $Q^E$ | 0 |
| Technology | No | Yes | $Z^T$ | $R^T$ | $Q^T$ | $K^T$ |
| Jointly optimal | Yes | Yes | $Z^*$ | $R^*$ | $Q^*$ | $K^*$ |
for a sufficiently large $t_\infty$ in which all scenarios have converged. For example, a key policy question is whether one policy strategy leads to more environmental damage than another. The following proposition relates the comparisons of damage and environmental health to the underlying difference in steady-state environmental harm.

**Proposition 1.** Suppose that the steady-state level of periodic environmental harm in policy scenario $i$ is lower than in scenario $j$, $Z^i < Z^j$. Then scenario $i$ results in a greater level of environmental health, $Q^i > Q^j$, and a lower level of environmental damage, $D^i \equiv D(Q^i) < D(Q^j) \equiv D^j$.

Proofs of this and all other propositions are in the appendix.

## 5 | NO POLICY

As noted, zero investments in research implies that $R = K = 0 \forall t$. Substituting these results into Equations (3), (5), and (6) implies that profits in this case are

$$\Pi(z; 0) = \alpha - \frac{\beta}{2} z^2. \quad (12)$$

The first-order condition for a profit maximum, $\Pi_z(z; 0) = 0$, implies farmers’ chosen level of $Z$ each period will be

$$Z^0 = \alpha \frac{\beta}{\beta}. \quad (13)$$

Finally, substituting (13) into (12) yields maximized profits of

$$\Pi^0 = \frac{\alpha^2}{2\beta}. \quad (14)$$

As (13) and (14) are time-invariant, they identify the steady-state values of periodic environmental harm and profits.

The steady-state level of environmental health can be found by substituting (13) into (9) and imposing $\dot{Q} = 0$, which yields

$$Q^0 = \frac{\phi_0 - Z^0}{\phi_1} = \frac{\phi_0 \beta - \alpha}{\phi_1 \beta}. \quad (15)$$

Finally, steady-state damages are

$$D^0 = \frac{\delta}{2}(\bar{Q} - Q^0)^2. \quad (16)$$
6 | ENVIRONMENTAL POLICY

This and all remaining policy scenarios are modeled as sequential two-player games between farmers and the government. In the first stage the government sets the policy (an optimal trajectory from a control problem), and in the second stage farmers respond by maximizing profits at each $t$, subject to policy restrictions. Following the literature on stock externalities, farmers are assumed to be myopic and make their decision at each $t$ by only considering the current state of the system. This structure allows the game to be solved by backward recursion.

6.1 | Farmers’ best response

In the environmental policy scenario, at each $t$ farmers observe a regulatory limit on $z$ set by the government, under the maintained assumption that $R = K = 0 \forall t$. Farmers’ best response at each $t$ is to maximize constrained profits by solving

$$
\max_z \Pi(Z; 0)
\text{subject to: } z \leq Z,
$$

where the constraint reflects the regulatory limit on $z$. As $\Pi(\cdot)$ is an increasing function of $z$ in the relevant range, this solution to this problem is $z = Z$ and farmers optimized profits are $\Pi(Z; 0)$.

6.2 | The government’s problem

Recursing backward to the first stage, the government’s problem is to maximize the stream of discounted social welfare while incorporating farmers’ best response:

$$
\max_{Z,Q} \int_0^\infty [\Pi(Z; 0) - D(Q)]e^{-rt}dt,
$$

subject to (9), an initial state $Q(0) = Q_0 > 0$, and a nonnegativity constraint on the control, $Z(t) \geq 0 \forall t$, where $r > 0$ is the discount rate. The first term in the integrand represents farmers’ optimized profits, while the second term accounts for environmental damages. In contrast to the no-policy scenario, the optimization accounts for the future environmental damages from current harm, $Z$. The current-value Hamiltonian for this problem is

$$
\hat{H} = \alpha Z - \frac{\beta}{2}Z^2 - \frac{\delta}{2}(\bar{Q} - Q)^2 + \mu_Q(\phi_0 - \phi_1Q - Z),
$$

where $\mu_Q$ is the current-value costate variable associated with $Q$. The Maximum Principle conditions for an interior solution ($Z > 0, Q > 0$) include

$$
\alpha - \beta Z = \mu_Q,
$$

$$
\dot{\mu}_Q - r\mu_Q = -[\delta(\bar{Q} - Q) - \mu_Q\phi_1],
$$

4Nonnegativity also is presumed for the state, $Q$, which always holds by the structure of (9) if $Q_0 > 0$. 


along with the equation of motion (9). Imposing \( \dot{\mu}_Q = \dot{Q} = 0 \) and rearranging Equations (20), (21), and (9) yields the system of equations determining the steady-state optimal values, \( Z^E, Q^E, \) and \( \mu^E_Q. \)

\[
Z^E = \frac{\alpha - \mu^E_Q}{\beta}, 
\]

\[
\mu^E_Q = \frac{\delta (\dot{Q} - Q^E)}{r + \phi_1}, 
\]

\[
Q^E = \frac{\phi_0 - Z^E}{\phi_1}. 
\]

Equation (22) follows from the optimality condition (20). Compared to the equivalent condition from the no-policy case (equation (13)), (22) implies that \( Z^E \) will be smaller than \( Z^0 \) as long as \( \mu^E_Q \) is positive. This value is determined from (23), which implies that \( \mu^E_Q > 0 \) under the assumptions that all parameters are positive and \( (\dot{Q} - Q) > 0 \) for all \( Q. \) (24) is derived from the steady state of the equation of motion (9). A comparison of (24) to the equivalent condition from the no-policy case (equation (15) suggests that policy intervention improves environmental health, given the prior result that \( Z^E < Z^0. \) A rigorous comparison of the outcomes in the two cases is the subject of the next section.

### 6.3 Policy comparisons

Steady-state outcomes provide a basis on which to compare the environmental policy and no-policy scenarios. Consider some \( t_\infty \) when steady state would be reached in either scenario. The following proposition compares the steady-state values of \( Z, Q, D, \) and \( \Pi \) in the two cases.

**Proposition 2.** Compared to no policy, environmental policy leads to a steady state with a smaller level of periodic environmental harm (\( Z^E < Z^0 \)), greater environmental health (\( Q^E > Q^0 \)), smaller environmental damages (\( D^E < D^0 \)), and smaller production profits (\( \Pi^E < \Pi^0 \)).

Proposition 2 is illustrated in Figure 1, which depicts the no-policy and environmental policy scenarios at a typical \( t_\infty \) in steady state. In the no-policy case, \( Z^0 \) is the point where marginal profits, \( \Pi_Z = \alpha - \beta Z, \) are equal to zero (equation (13)). Under environmental policy, \( Z^E \) is the point where \( \Pi_Z = \mu^E_Q. \) Environmental policy causes farmers to lose profits equal to area \( B. \) However, environmental damages are reduced by at least area \( A + B = \mu^E_Q (Z^0 - Z^E). \)

Combining the welfare losses from reduced profits with the gains from reduced damages implies a welfare gain of at least area \( A. \)

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5The precise reduction in damages is \( \Delta D = \int_{Z^E}^{Z^0} \mu_Q(Z)dZ, \) where \( \mu_Q(Z) \) captures the nonconstant relationship between \( \mu_Q \) and the steady-state level of \( Z. \) \( \mu_Q \) increases with \( Z \) because higher levels of \( Z \) are associated with lower levels of environmental health equation (A1), and lower levels of health result in a larger costate value (equation (23)).
TECHNOLOGY POLICY

With technology policy, the government first invests in research that changes technology, to which farmers respond by choosing a level of environmental harm at each \( t \). Here, the backward recursion is more complex because farmers chose \( Z \) and treat the government’s chosen level of \( K \) as a parameter.

7.1 Farmers’ best response

At instant \( t \), previous investments in research have accumulated the stock of knowledge to \( K \), so that farmers’ profits are \( \Pi(z; K) \) as specified in equation (3). Substituting the \( K \)-dependent parameters from (5) and (6) into (3) yields the reduced-form profit function:

\[
\Pi(z; K) = \eta K + \alpha z - \frac{\beta}{2} z^2 - \gamma K z. \tag{25}
\]

Farmers’ best response at \( t \) is to maximize profits conditional on \( K \). The first-order condition for a maximum is \( \Pi_z(z; K) = 0 \), which has the solution

\[
Z = \frac{\alpha - \gamma K}{\beta}. \tag{26}
\]

Substituting (26) into (25) yields optimized profits as a function of \( K \):

\[
\Pi(K) = a + bK + \frac{c}{2} K^2, \tag{27}
\]

where

\[
a = \frac{\alpha^2}{2\beta}, \quad b = \eta - \frac{\gamma \alpha}{\beta}, \quad c = \frac{\gamma^2}{\beta}. \tag{28}
\]
Equation (26) also can be substituted into (9) to obtain an equation of motion for \( Q \) that depends on \( K \):

\[
\dot{Q} = \begin{cases} 
\phi_0 - \phi_1 Q - \frac{\alpha - \gamma K}{\beta} & \text{if } Q > 0, \\
0 & \text{if } Q = 0.
\end{cases}
\] (29)

Equations (27), (28), and (29) characterize farmers’ best response to a given \( K \).

### 7.2 The government’s problem

The government’s problem is again to maximize the discounted stream of social welfare, incorporating farmers’ best response. The control problem becomes

\[
\max_{R,K,Q} \int_0^\infty [\Pi(K) - C(R, K) - D(Q)]e^{-\nu t}dt,
\] (30)

subject to (7), (29), the initial values \( K(0) = 0 \) and \( Q(0) = Q_0 > 0 \), and nonnegativity of the control, \( R(t) \geq 0 \) \( \forall \ t \).\(^6\) Concavity of the objective function requires the parameter restriction \( \omega - c = \omega - \gamma^2/\beta > 0 \), implying that the effect of knowledge of the marginal costs of research must be sufficiently large in comparison to the efficiency effect on profits. The current-value Hamiltonian for this problem is

\[
\bar{H} = a + bK + \frac{c}{2}K^2 - \frac{\varepsilon}{2}R^2 - \frac{\omega}{2}K^2 - \frac{\delta}{2}(\bar{Q} - Q)^2 + \mu_Q\left(\phi_0 - \phi_1 Q - \frac{\alpha - \gamma K}{\beta}\right) + \mu_K(R - \partial K),
\] (31)

where \( \mu_K \) is the current-value costate variable associated with \( K \). For an interior solution \( R > 0, K > 0, Q > 0 \), the Maximum Principle conditions include

\[
\mu_K = \varepsilon R,
\] (32)

\[
\dot{\mu}_K - r\mu_K = -\left[b + cK - \omega K + \mu_Q\frac{\gamma}{\beta} - \mu_K \theta\right],
\] (33)

\[
\dot{\mu}_Q - r\mu_Q = -[\delta(\bar{Q} - Q) - \mu_Q \phi_1],
\] (34)

along with the equations of motion (7) and (29). After invoking \( \dot{\mu}_K = \dot{\mu}_Q = \dot{K} = \dot{Q} = 0 \) and some manipulation, the five-equation system characterizing the optimal steady state can be written as

\[
R^T = \partial K^T,
\] (35)

\(^6\)As above, nonnegativity of \( Q \) follows from (29) and \( Q_0 > 0 \). Additionally, nonnegativity of \( K \) follows from (7) when \( K_0 = 0 \) and \( R \geq 0 \).
Additionally, from (26), steady-state rate of environmental harm is

$$Z^T = \frac{\alpha}{\beta} - \frac{\gamma K^T}{\beta},$$  \hspace{1cm} (40)$$

Equation (40) is comparable to equation (13) from the no-policy scenario and (22) from the environmental policy scenario. Assuming that $K^T > 0$, these comparisons imply that technology policy reduces environmental harm ($Z^T < Z^0$). This result, along with (37) and its no-policy equivalent (equation (15)), imply that technology policy also will improve environmental health. How the technology-induced level of harm ($Z^T$) compares to that from environmental policy ($Z^E$), however, is ambiguous and depends on the long-run value of $K^T$, which in turn is determined by the complex expression in (36). While the sign of $Z^T - Z^E$ is ambiguous, model parameters influence the likely sign of this difference. All these comparisons are explored more rigorously in what follows.

### 7.3 Policy comparisons

To compare these results to other scenarios, consider a $t_\infty$ when this and all other scenarios have converged to their respective steady states. The following proposition compares the technology policy to the no-policy baseline.

**Proposition 3.** Consider an interior steady state in the technology policy scenario where $R^T > 0$, $K^T > 0$, and $Q^T > 0$. Compared to no policy, technology policy results in a steady state with a smaller periodic environmental harm ($Z^T < Z^0$), greater environmental health ($Q^T > Q^0$), and smaller environmental damages ($D^T < D^0$). Farm profits will be larger with technology policy ($\Pi^T > \Pi^0$) if $\eta > \gamma\alpha/\beta$.

Proposition 3 is illustrated in Figure 2, which represents a typical $t_\infty$ after convergence to steady state. Comparing to the no-policy baseline of $K = 0$, a technology policy with $K^T > 0$ would shift the marginal profit function, $\Pi_z(Z; K)$, downward and would induce farmers to select a lower level of environmental harm, $Z^T < Z^0$. The associated environmental gain is at least as large as area $A + B = \mu_Q^T (Z^0 - Z^T)$. Farmer’s steady-state profits increase due to the productivity effect, represented by area $E$, the box in the upper right of the figure. The productivity gains are offset by the efficiency effect, area $B + C + D$, so that the net change in
steady-state profits is $E - B - C - D$. This value is positive if $\eta > \gamma \alpha / \beta$. The third and final component of welfare is research costs, represented by the box $F$. The net gain in steady-state welfare is at least $A + E - D - C - F$. In Section 9, this will be shown to be a positive value. Intuitively, the government would not choose to invest in any research if there were no gains from doing so, so any solution with a positive $R$ implies a welfare gain.

An attractive feature of technology policy is the potential for a win–win outcome. Compared to no policy, the long-run equilibrium with research investments will feature lower environmental damage and, for a certain region of the parameter space, larger farm profits. However, the cases with smaller profits in steady state are implausible. If technology adoption is assumed to be voluntary, then farmers would likely decline to adopt new technologies that are profit-reducing. In what follows, the parameter restriction $\eta > \gamma \alpha / \beta$ is assumed to hold.

While technology policy compares favorably against the no-policy baseline, it is less obvious how it compares to environmental policy. Figure 3 illustrates the intriguing case where technology policy leads to a lower level of environmental harm, that is, $Z^T < Z^E$. In that case, Proposition 1 implies that technology policy would also yield lower costs from environmental damage ($D^T < D^E$). If, in addition, farmers’ profits are larger ($\Pi^T > \Pi^E$), then both farmers and

**FIGURE 2** Steady-state welfare in technology versus no-policy scenarios

**FIGURE 3** Environmental harm in technology versus environmental policy scenarios
the environment would gain from replacing environmental policy with investments in research. Naturally, this case is more likely to obtain if $Z^T$ is small. The proposition below identifies the parameters that raise the likelihood of this outcome.

**Proposition 4.** Suppose that the technology policy scenario has converged to its steady state with environmental harm of $Z^T$. Consider a collection of alternative scenarios, identical to the technology policy scenario except for small perturbations to the parameters $\eta$ and $\omega$. Comparing steady states across a continuum of these scenarios, $Z^T$ declines with respect to $\eta$ and increases with respect to $\omega$, that is, $\frac{\partial Z^T}{\partial \eta} < 0$ and $\frac{\partial Z^T}{\partial \omega} > 0$.

Proposition 4 reveals the rather intuitive results that greater innovation arises in cases where the productivity impact of research ($\eta$) is large and the congestion effects in the research enterprise have little effect on research cost (small $\omega$). In these cases, large investments in research will benefit society in the form of increased productivity as well as reduced environmental damage. If these benefits are large enough, and if overall research costs are sufficiently low, the overall welfare gain from technology policy could exceed that of environmental policy.

## 8 | JOINT POLICIES

In this scenario, the government jointly chooses a path of upper limits on $Z$ along with a stream of investments in $R$. As in the environmental policy scenario, farmers respond at each $t$ by choosing a level of $Z$ that is restricted by the first-stage policy choice.

### 8.1 | Farmers’ best response

At each $t$, the value of $K$ will be known to farmers because of the government’s previous choices of $R$. As in the environmental policy case, farmers also will observe the government’s allowable level of $Z$. Farmers’ best response is to maximize constrained profits by solving

$$\max_z \Pi(z; K) \quad \text{subject to: } z \leq Z. \quad (41)$$

As above, the assumed properties of $\Pi(\cdot)$ imply that the solution is $z = Z$, with optimized profits equal to $\Pi(Z; K)$.

### 8.2 | The government’s problem

The government’s problem in the joint policy case has two controls and two states:

$$\max_{Z,R,Q,K} \int_0^\infty [\Pi(Z; K) - C(R, K) - D(Q)]e^{-rt}dt, \quad (42)$$
subject to (9), (7), \( K(0) = 0, Q(0) = Q_0, Z \geq 0, \) and \( R \geq 0. \) The current-value Hamiltonian is

\[
\tilde{H} = \eta K + \alpha Z - \frac{\beta}{2} Z^2 - \gamma K Z - \frac{\epsilon}{2} R^2 - \frac{\omega}{2} K^2 - \frac{\delta}{2} (\bar{Q} - Q)^2 + \mu_Q (\phi_0 - \phi_1 Q - Z) \\
+ \mu_K (R - \bar{Q} K).
\] (43)

For an interior solution \((R > 0, Z > 0, K > 0, Q > 0)\), the Maximum Principle conditions include

\[
\mu_Q = \alpha - \beta Z - \gamma K, \tag{44}
\]

\[
\mu_K = \epsilon R, \tag{45}
\]

\[
\dot{\mu}_Q - r \mu_Q = -[\delta (\bar{Q} - Q) - \mu_Q \phi_1], \tag{46}
\]

\[
\dot{\mu}_K - r \mu_K = -[\eta - \gamma Z - \omega K - \mu_K \theta], \tag{47}
\]

along with the equations of motion (9) and (7). After invoking \( \dot{\mu}_K = \dot{\mu}_Q = \dot{K} = \dot{Q} = 0 \) and some manipulation, the six-equation system characterizing the optimal steady state can be written as

\[
Z^* = \frac{\alpha - \gamma K^* - \mu_Q^*}{\beta}, \tag{48}
\]

\[
R^* = \bar{Q} K^*, \tag{49}
\]

\[
Q^* = \frac{\phi_0 - Z^*}{\phi_1}, \tag{50}
\]

\[
K^* = \frac{\eta - \gamma Z^* - (r + \theta) \mu_K^*}{\omega}, \tag{51}
\]

\[
\mu_Q^* = \frac{\delta (\bar{Q} - Q^*)}{r + \phi_1}, \tag{52}
\]

\[
\mu_K^* = \epsilon R^*. \tag{53}
\]

Similar to previous scenarios, Equation (48) follows directly from the optimality condition (44). Comparing (48) to its no-policy equivalent, (13), immediately reveals that environmental harm will be reduced from joint policies \((Z^* < Z^0)\). This result and a comparison of (50) to (15) imply that environmental health will be improved \((Q^* > Q^0)\). Comparisons to the environmental and technology policy scenarios are less obvious. For example, comparing (48) to (40) suggests that \(Z^*\) will be smaller than \(Z^T\) if \(\gamma K^T < \gamma K^* - \mu_Q^*\). The latter inequality, however, depends on the complex expressions in
The analysis in next section reveals that the model can resolve at least some of these questions.

8.3 | Policy comparisons

The steady-state outcomes in the joint policy scenario can be compared with the other policy scenarios to assess the impact of combining policies. The next proposition compares the environmental outcomes in the joint policy to those of the environmental policy only, revealing the environmental impact of technology policies when environmental outcomes are already regulated.

**Proposition 5.** Suppose that all scenarios have converged to interior steady states. Compared to the environmental policy scenario, the steady state in the joint policy scenario has lower environmental harm \((Z^* < Z^E)\), greater environmental health \((Q^* > Q^E)\), and lower damages \((D^* < D^E)\).

Proposition 5 means that there is an environmental benefit from research investments, even if environmental policies already exist. This result is the counterpart to Proposition 3, which showed that introducing technology policies benefits the environment in the absence of regulation. Technology policy has a positive impact on environmental outcomes, regardless of the status of environmental regulation.

Figure 4 illustrates the results from Proposition 5 by comparing the steady states of joint policies and environmental policy. Compared to environmental policy, a joint policy approach would add research investments leading to a steady-state stock of knowledge equal to \(K^*\). This knowledge would spur innovations that shift the marginal profit function downward, reducing the regulated level of environmental harm from \(Z^E\) to \(Z^*\). The reduced harm would improve environmental health and reduce damages by at least area \(A + C = \mu Q^*(Z^E - Z^*)\). Farmers’ profits would change by \(E - (B + C + D)\), reflecting the gains from the productivity effect offset by the losses from the efficiency effect. Adding research investments leads to a net change in steady-state welfare of \(A + E - D - B - F\). In the next section, the change in welfare will be shown to be positive.

![FIGURE 4](image_url)  
*Steady-state welfare in joint versus environmental policy scenarios*
9 | SOCIAL WELFARE ANALYSIS

While previous sections have provided graphical analyses of welfare in steady states, this section provides a more general, analytical comparison of welfare accounting for the transition period. In particular, the discounted stream of welfare is compared across scenarios. Let

\[ W^0 = \int_0^\infty [\Pi(\bar{Z}_0(t); 0) - D(\bar{Q}_0(t))]e^{-\alpha t}dt \]  

(54)
denote the discounted stream of social welfare in the no-policy scenario. By (13) and (14), \( \bar{Z}_0(t) = \alpha/\beta \) and \( \Pi(\bar{Z}_0(t)) = \alpha^2/(2\beta) \) for all \( t \). By (9), \( \bar{Q}_0(t) \) is then the particular solution to the differential equation, \( \dot{Q} = \phi_0 - \phi_1 Q - \alpha/\beta \), given the initial value \( Q_0 \). Let this solution be denoted \( Q(t; \alpha, \beta, Q_0) \). Combining these results yields a simplified expression for prepolicy welfare:

\[ W^0 = \int_0^\infty \left[ \frac{\alpha}{2\beta} - D(Q(t; \alpha, \beta, Q_0)) \right]e^{-\alpha t}dt. \]  

(55)

To compare this value to the policy scenarios, define

\[ W^E = \int_0^\infty [\Pi(\bar{Z}_E(t); 0) - D(\bar{Q}_E(t))]e^{-\alpha t}dt \]  

(56)
as the optimized value of social welfare with environmental policy, where \( \bar{Z}_E(t) \) and \( \bar{Q}_E(t) \) are the optimal trajectories solving (18). Similarly, the optimized present value of social welfare with technology policy is

\[ W^T = \int_0^\infty [\Pi(\bar{K}_T(t)) - C(\bar{R}_T(t), \bar{K}_T(t)) - D(\bar{Q}_T(t))]e^{-\alpha t}dt, \]  

(57)

where the trajectories \( \bar{R}_T(t), \bar{K}_T(t), \) and \( \bar{Q}_T(t) \) are the solutions to (30). Finally, the optimized joint policy welfare is

\[ W^* = \int_0^\infty [\Pi(\bar{Z}(t); \bar{K}(t)) - C(\bar{R}(t), \bar{K}(t)) - D(\bar{Q}(t))]e^{-\alpha t}dt, \]  

(58)

where \( \bar{Z}(t), \bar{R}(t), \bar{Q}(t), \) and \( \bar{K}(t) \) are the optimal trajectories for (42).

The following proposition shows how the welfare measures compare.

**Proposition 6.** Among the four scenarios, the largest value of discounted welfare is obtained by joint policies while the lowest value results from the no-policy case. Discounted welfare in the environmental and technology policy scenarios lie within this closed range. In particular, the following inequalities hold: (a) \( W^* \geq W^E \geq W^0 \) and (b) \( W^* \geq W^T \geq W^0 \).

Proposition 6 verifies that model yields expected results consistent with previous work. \( W^E \geq W^0 \) is the expected finding that environmental policy is welfare improving. This and all remaining results follow from the nested structure of the scenarios and the properties
of constrained optimization. Intuitively, technology policy is preferred to no policy, because both can obtained by the same optimization problem except that the no-policy case imposes more constraints. By similar reasoning, the joint policy case is preferred to single policies, because the individual cases impose restrictions on otherwise equivalent optimization problems.

10 | DISCUSSION AND CONCLUSIONS

This paper developed a model to assess the agri-environmental policies and technology policies in a dynamic setting. The linear-quadratic specification here assures the existence of saddle-point stable steady states in all scenarios so that long-run equilibria can be compared. This formulation also cleanly distinguishes the productivity and efficiency effects of technological change, revealing, for example, that productivity improvements must overcome efficiency effects in order for technical change to be profit-improving for farmers.

Relaxing some of the restrictive assumptions in the model may affect the results. The dynamics of environmental damage and knowledge accumulation are both assumed to follow linear first-order differential equations without time lags. Payoff functions were assumed to be quadratic. While this specification allowed for tractable analysis, new analysis would be needed to evaluate whether the main results are robust across functional forms.

Additional analysis also would be needed to assess the impact of time lags, which are plausible in agricultural settings. For example, inventors require time to transfer new knowledge into patented, commercializable technologies, and even profitable technologies are not adopted by all farmers immediately. In deeply buried aquifers, years or decades can pass from the time nutrients are applied to the surface until they reach the groundwater resource. While the presence of time lags would not affect steady states in the model, they may have an impact on the transition dynamics and discounted welfare. Technology policies are less likely to be advantageous in discounted welfare terms if the innovation process is subject to long time lags. On the other hand, if the lags in environmental impacts are even longer, environmental policies may be at a disadvantage because they would impose costs on farmers over the entire planning horizon, while technology policies will begin to generate gains.

This model was constructed to be a scaffold to support further analytical or empirical research. A numerical implementation of the model with empirically grounded parameters could resolve a number of important questions. Foremost among these is a quantitative comparison of the welfare gains from technology and environmental policy, when implemented separately and jointly. In addition, nonlinear forms or time lags could be incorporated in either an analytical or numerical version of the model. Yet another avenue would be to consider multiple stocks of related knowledge to explicitly account for spillover effects. In climate models with induced technical change, for example, specialized knowledge domains generate technologies with different types of impacts (e.g., improving energy efficiency vs. developing clean energy sources). In an agri-environmental setting, an analogous approach would model the productivity and efficiency effects as derived from distinct knowledge pools with bidirectional spillovers.

As a framework for further analysis, the model has been shown to produce results consistent with previous work. Environmental policies generate an overall welfare gain because the costs to farmers is more than offset by reduced environmental damages. Policies to encourage innovation benefit farmers, and also will benefit the environment assuming that new
technologies have the appropriate efficiency effects. Joint implementation of environmental and technology policy raises social welfare by more than either policy in isolation.

The model also revealed new insights about the interactions between environmental and innovation externalities. Assuming technologies have improve both productivity and environmental efficiency, they unambiguously benefit the environment, whether or not environmental policies are present. Farmers also gain from these policies in both cases. In principle, a technology policy alone could have greater environmental benefits than an environmental policy alone. This outcome is most likely in cases where the productivity effect of new technology is large and the cost of research is low.

While an analytical approach cannot quantify the difference between social welfare in the technology and environmental policy scenarios, it sheds light on the welfare impacts to different groups. Environmental policy in isolation will always be opposed by farmers because they bear the costs. Technology policy will very likely gain farmers’ support due to its profit-increasing effects. Jointly implemented policies may not yield benefits to farmers compared to no policy, but it is unambiguously preferable to environmental policy alone. All three of these policy scenarios yield positive environmental benefits. Taken together, these results suggest the possibility of space for mutually beneficial and mutually supported policies.

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APPENDIX A

Proofs of the Propositions

Proof of Proposition 1. Setting $\dot{Q} = 0$ and rearranging (9) yields the relationship between steady-state levels $Q$ and $Z$ as

$$ Q = \frac{\phi_0 - Z}{\phi_1}. \tag{A1} $$

As $\frac{\partial Q}{\partial Z} = -1/\phi_1 < 0$, $Z^i < Z^j$ implies that $Q^i > Q^j$. By Equation (11), damages are a declining function of $Q$, which implies that $D^i < D^j$. □

Proof of Proposition 2. From Equations (13), (22), and (23),

$$ Z^E - Z^0 = -\frac{\mu^E_Q}{\beta} = -\frac{\delta(\bar{Q} - Q^E)}{\bar{\beta}(r + \phi_1)} < 0, \tag{A2} $$

where the inequality follows from the assumptions that all model parameters are positive and that $(\bar{Q} - Q) > 0$ for all $Q$ in the relevant range. Simple rearrangement of terms in (A2) yields the first result that $Z^E < Z^0$. Proposition 1 then implies that $Q^E > Q^0$ and $D^E < D^0$. Finally, the facts that $\Pi^0 \equiv \Pi(Z^0; 0) = \max_Z \Pi(Z; 0)$ and $Z^E < Z^0$ imply that $\Pi^E \equiv \Pi(Z^E; 0) < \Pi^0$. □

Proof of Proposition 3. Comparing (40) and (13) under the assumption that $K^T > 0$ implies that $Z^T < Z^0$. This result and Proposition 1 imply that $Q^T > Q^0$ and $D^T < D^0$. □

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Regarding profits, (28) implies that \( b > 0 \) when \( \eta > \gamma \alpha / \beta \). In that case, \( \Pi(K) \) in (27) is a strictly increasing function, so that \( \Pi(K^T) > \Pi(0) = \alpha^2 / (2\beta) = \Pi^0 \).

**Proof of Proposition 4.** First, note that (40) implies \( Z^T \) is determined by \( K^T \), with \( \partial Z^T / \partial K^T = -\gamma / \beta < 0 \). Therefore, the claimed result will hold iff (a) \( \partial K^T / \partial \eta > 0 \) and (b) \( \partial K^T / \partial \omega < 0 \). The value of \( K^T \) is determined by the system of Equations (35), (36), (37), (38), and (39). Through substitution, this system can be expressed as a single equation involving \( K^T \) and model parameters. Substituting (35) into (38) yields

\[
\mu_K^T(K^T) = \varepsilon \partial K^T,
\]

and substituting (37) into (39) yields

\[
\mu_Q^T(K^T) = \Theta - \frac{\delta \gamma}{\phi_1 \beta} K^T,
\]

where \( \Theta \) is an expression of fixed parameters that does not affect subsequent results. Incorporating these expressions into (36) and rearranging yields

\[
\left( \omega - \frac{\gamma^2}{\beta} \right) K^T - \eta + (r + \theta) \mu_K^T(K^T) - \left( \frac{\gamma}{\beta} \right) \mu_Q^T(K^T) = \frac{\alpha \gamma}{\beta},
\]

which can be written more compactly as

\[
\Phi(K^T, \eta, \omega) = v,
\]

where \( v = \alpha \gamma / \beta \). By the Implicit Function Theorem, (A6) implicitly defines the function \( K^T(\eta, \omega) \), with derivatives

\[
\frac{\partial K^T}{\partial \eta} = -\frac{\partial \Phi / \partial \eta}{\partial \Phi / \partial K^T} \quad \text{and} \quad \frac{\partial K^T}{\partial \omega} = -\frac{\partial \Phi / \partial \omega}{\partial \Phi / \partial K^T}.
\]

The derivatives needed to evaluate (A7) are as follows:

\[
\frac{\partial \Phi}{\partial \eta} = -1 < 0,
\]

\[
\frac{\partial \Phi}{\partial \omega} = K^T > 0,
\]

\[
\frac{\partial \Phi}{\partial K^T} = \left( \omega - \frac{\gamma^2}{\beta} \right) + (r + \theta) \varepsilon \theta - \left( \frac{\gamma}{\beta} \right) \left( -\frac{\delta \gamma}{\phi_1 \beta} \right) > 0.
\]

In (A10), the first term is positive because of the parameter restriction noted for concavity in (30), while the last two terms follow from (A3) and (A4). As all model
parameters are defined to be positive values, the overall result is that $\frac{\partial \Phi}{\partial K T} > 0$. Substituting (A8) and (A10) into (A7) implies that $\frac{\partial K T}{\partial \eta} > 0$. Substituting (A9) and (A10) into (A7) implies that $\frac{\partial K T}{\partial \omega} < 0$. □

**Proof of Proposition 5.** Suppose the opposite were true—that is, $Z^* > Z^E$, $Q^* < Q^E$, and $D^* > D^E$. From (22) and (48), $Z^* > Z^E$ implies $\mu^*_Q - \mu^E_Q < -\gamma K^* \leq 0$, which in turn implies that $\mu^*_Q \leq \mu^E_Q$. From (23) and (52), this inequality implies $\delta (\bar{Q} - Q^*) \leq \delta (\bar{Q} - Q^E)$, which in turn implies that $Q^E \leq Q^*$, contradicting the supposition. □

**Proof of Proposition 6.** The first inequality in (a), $W^* \geq W^E$, follows from the fact that the environmental policy scenario is an amended version of (42) with an additional constraint. In particular, the constraint $R(t) = 0 \forall t$ along with an initial value of $K(0) = 0$ implies that $K(t) = 0$ for all $t$, which further implies that $C(R, K) = 0$ for all $t$. Substituting $R = K = 0$ into (42) yields a problem identical to (18). Therefore, $W^* \geq W^E$ because the former is an optimum after the removal of a constraint from otherwise identical problems. The second inequality in (a), $W^E \geq W^0$, similarly follows from nested optimization problems. Social welfare in the no-policy scenario can be obtained by solving an amended version of (18) with the additional constraint that $\frac{\partial}{\partial t}(\bar{Q}) = 0$ for all $t$. The resulting solution will yield a constrained optimal welfare identical to that in (55). The original version of (18) without the constraint leads to an optimized welfare of $W^E$. By the definition of constrained optimization, the optimum with an extra constraint will be no larger than that obtained without the constraint, that is, $W^E \geq W^0$.

Proving (b) relies on parallel arguments. The first inequality results from the fact that the technology scenario is a version of (42) with the added constraint, $Z = (\alpha - \gamma K)/\beta$. Substituting that constraint into (42) and into the equation of motion (9) produces a problem identical to that in (30). Therefore, $W^* \geq W^T$, due to the optimality of the former after the constraint is removed. For the last inequality, the no-policy level of welfare can be obtained by solving an amended version of (30) with the additional constraint that $R = 0$, which in turn implies that $K = 0$. Substituting these constraints into (27) yields $\Pi = \alpha = \alpha^2/(2\beta)$. Similarly, a value of $K = 0$ in (29) means that $Q(t)$ is the particular solution to $Q = \phi_0 - \phi_1 Q - \alpha/\beta$, with an initial value of $Q_0$, or $Q(t; \alpha, \beta, Q_0)$ as defined in (30). Substituting these results into the objective functional in (30) yields an identical expression to the definition of $W^0$ in (55). As $W^T$ represents the optimized value from (30) in the original version of the problem with no constraint, the definitions of constrained optimization imply that $W^T \geq W^0$. □