Dynamic Pesticide Regulation under Resistance and Fiscal Constraints

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Abstract

Pesticide use generates dynamic externalities through resistance, health, and environmental channels, complicating the design of optimal regulation. We develop a dynamic framework in which pesticide use, resistance, and damages are jointly determined under a balanced-budget constraint. Resistance affects policy through two margins: it raises marginal external damages by amplifying effective exposure, but also reduces pesticide use, shrinking the fiscal base for intervention. This interaction creates a state-dependent gap between the *Pigouvian* benchmark and the constrained-efficient policy, which we term *fiscal attenuation*. We characterize the optimal tax-subsidy system and show that resistance both strengthens the case for taxation and shifts implementation toward non-chemical control. Simulations quantify the nonlinear interaction between resistance dynamics and fiscal capacity, highlighting the joint role of evolving damages and fiscal constraints in optimal environmental policy.

Keywords: pesticide regulation; resistance dynamics; environmental externalities; fiscal constraints; second-best policy; dynamic optimization

JEL Codes: Q12, Q18, Q28, D62, C61

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1 Introduction

Pesticides are a central input in modern agricultural production, yet their use generates a set of interrelated externalities that evolve over time. Chemical applications affect not only contemporaneous crop yields but also the accumulation of pest resistance, the exposure of workers and consumers to toxic residues, and the degradation of environmental quality. A key feature of these processes is their dynamic interaction. Current pesticide use alters both the future effectiveness of chemical control and the magnitude of associated external damages. As a result, the design of optimal pesticide regulation is inherently dynamic. A large literature studies the external costs of pesticide use and the role of corrective policy instruments such as taxes and input regulations (Lence and Hayes, 1994; Sunding and Zivin, 2000; Goodhue et al., 2010). A parallel strand examines the economics of resistance, emphasizing how repeated chemical applications select for resistant pest populations and reduce long-run control effectiveness (Gould, 1998; Alston et al., 1997). While these contributions highlight important mechanisms, most analyses either treat resistance as exogenous or abstract from the fiscal and institutional constraints that shape policy implementation. This creates a gap between the biological dynamics of pesticide use and the economic environment in which policy is implemented.

This paper develops a dynamic framework in which pesticide use, resistance accumulation, and health and environmental damages are jointly determined, and in which policy is subject to a balanced-budget constraint. The key observation is that resistance affects both the marginal external damage from pesticide use and the feasibility of corrective intervention (Varah et al., 2020). On the one hand, higher resistance amplifies effective chemical exposure through an endogenous scaling mechanism, increasing marginal social damages and strengthening the *Pigouvian* case for taxation. On the other hand, resistance induces substitution away from chemical inputs, shrinking the tax base that finances corrective policy and thereby limiting the regulator's ability to implement first-best instruments (Gould et al., 2018).

This interaction gives rise to a central mechanism that we term *fiscal attenuation*. As resistance accumulates, the corrective motive for pesticide taxation becomes stronger, while the fiscal capacity to implement it becomes weaker. The resulting divergence between the *Pigouvian* benchmark and the constrained-efficient policy generates a state-dependent policy wedge that evolves over the resistance cycle. Efficient regulation therefore requires a coordinated and dynamically adjusted policy mix in which the relative roles of taxes and subsidies respond endogenously to the biological state (Dahlby, 1998). We formalize this mechanism in a dynamic model of agricultural production with chemical and non-chemical pest control. Resistance evolves according to a biological law of motion driven by effective pesticide exposure, while health and environmental damages depend on the same exposure channel. The regulator chooses a tax on chemical inputs and a subsidy for non-chemical control subject to a balanced-budget constraint that incorporates administrative costs. We characterize both the *Pigouvian* benchmark and the second-best policy rules and show how resistance alters their relationship through both damage amplification and fiscal effects.

The analysis delivers three main results. First, resistance amplifies effective exposure and raises marginal external damages, increasing the *Pigouvian* benchmark tax. Second, it reduces equilibrium chemical use, shrinking the fiscal base and raising the marginal cost of public funds. Third, these effects jointly widen the gap between *Pigouvian* and second-best policies, shifting implementation toward non-chemical control. These results highlight that the effectiveness of corrective policy depends not only on the magnitude of external damages, but also on the endogenous response of the tax base and the fiscal structure of policy implementation. To quantify these mechanisms, we complement the analytical results with a simulation-based approach that constructs a global mapping from policy instruments and biological parameters to steady-state outcomes. Using a structural steady-state representation of the model, we solve for decentralized equilibria across a wide range of policy and biological configurations and approximate the resulting equilibrium correspondence with a metamodel (surrogate model), following the statistical emulation literature (Kennedy and O'Hagan, 2001; Conti and O'Hagan, 2010). This approach allows us to characterize the global properties of the model without repeatedly solving the full nonlinear equilibrium system and to evaluate how optimal policy varies across the resistance cycle and across alternative biological environments.

The paper contributes to three strands of the literature. First, it extends the economics of pesticide regulation by integrating resistance dynamics directly into the design of policy under fiscal constraints. Second, it contributes to the broader literature on dynamic externalities by introducing a mechanism through which evolving biological states affect not only the magnitude of external damages but also the implementability of corrective policy. Third, it relates to the literature on second-best environmental regulation by showing how fiscal and administrative constraints shape the composition of policy instruments in dynamic settings. This contribution is also connected to the literature on environmental regulation with stock externalities, where current actions affect future outcomes through evolving state variables.

The remainder of the paper is organized as follows. Section 2 introduces the production environment and characterizes the decentralized equilibrium. Section 3 derives the Pigouvian benchmark and the second-best policy rules and establishes the role of resistance in shaping optimal regulation. Section 4 discusses dynamic consistency and commitment. Section 5 presents the simulation-based policy analysis.

2 Chemical Pesticide Use in a Dynamic Modelling Framework

2.1 Production in the Decentralized Economy

We consider a closed economy populated by identical agents who consume and produce a single agricultural commodity, y, in the absence of population growth. The labor force equals the population, and labor is supplied inelastically. Production takes place in continuous time by a representative farm that uses effective labor as the sole productive input. Output at time t is given by

$$y_t = f\left(\ell_t^e\right)\Big(1 - g(b_t)\Big), \tag{1}$$

where ℓ_t^e denotes effective labor, b_t is the stock of pest infestation, and $g(\cdot) \in [0, 1)$ captures output losses due to pest damage. The production function $f(\cdot)$ is strictly increasing and concave, while the damage function satisfies $\partial g(\cdot)/\partial b_t > 0$ and $\lim_{b_t \to \infty} g(\cdot) < 1$, ensuring that pest damage reduces output but does not eliminate production (Lichtenberg and Zilberman, 1986; Chambers and Tzouvelekas, 2013).

Following Strauss (1986) and Deolalikar (1988), effective labor depends on hours worked on the farm, ℓ_t, and workers' health status, h_t:

$$\ell_t^e = q(h_t)\,\ell_t, \tag{2}$$

where $q(\cdot) \in (0, 1]$ is continuous, twice differentiable, and concave, with $\partial q(\cdot)/\partial h_t > 0$ and $\partial^2 q(\cdot)/\partial h_t^2 < 0$, reflecting higher labor productivity when health improves.

We assume, for simplicity, that there are only two damage-control inputs available to the farmers: chemical pesticides, z, and an alternative, non-toxic damage control input, x (e.g. IPM, biocontrol or other agronomic and mechanical methods). The pest stock evolves according to

$$\dot{b}_t = \psi_b\left(b_t\right) - \Big[\psi_z\left(z_t^e\right) + \psi_x\left(x_t\right)\Big] b_t \tag{3}$$

where $\psi_b\left(\cdot\right)$ is the net natural increase in pest population due to natural growth and net migration, $\psi_z\left(\cdot\right)$ is the proportion of pests killed using chemical pesticides, and $\psi_x\left(\cdot\right)$ is the proportion of pests killed using non-chemical control. Effective pesticide application z_t^e is determined by actual pesticide use z_t and the potency/toxicity index of active ingredients, s_t, which depends on the stock of pest resistance d_t:

$$z_t^e = z_t s_t \quad \text{where} \quad s_t \;=\; \psi_s(d_t) \geq 1. \tag{4}$$

Thus, resistance reduces biological effectiveness but induces the use of more potent active ingredients, increasing toxicity per unit of application. We assume $\partial \psi_s(\cdot)/\partial d > 0$, so that higher resistance induces the use of more potent (and more toxic) active ingredients in order to maintain pest-control effectiveness. Intensive and repeated use of chemical pesticides generates strong selection pressure on pest populations, leading to the evolution of heritable resistance that reduces chemical efficacy over time (Hawkins et al., 2019). In the present formulation, resistance affects biological control only through the potency/toxicity scaler s_t, which maps physical application z_t into effective intensity z_t^e. Thus, resistance increases the toxicity-adjusted intensity of exposure for a given z_t, while the kill function remains increasing in effective intensity, $\partial \psi_z(\cdot)/\partial z_t^e > 0$. The non-chemical kill function satisfies $\partial \psi_x(\cdot)/\partial x_t > 0$. We further assume that the bracketed term in (3) is bounded above so that b_t does not explode along feasible paths.[1]

Resistance evolves according to

$$\dot{d}_t \;=\; \delta_z z_t \;-\; \delta_d d_t \tag{5}$$

with $\delta_z, \delta_d > 0$. Higher chemical use increases resistance accumulation, while resistance decays gradually at rate δ_d. This specification captures the intertemporal trade-off inherent in chemical control: current pesticide use improves pest suppression but increases future resistance pressure (Comont et al., 2020).

Pesticide use enhances agricultural production by reducing pest pressure, but it also adversely affects farmworkers' health, thereby lowering labor productivity (Antle and Pingali, 1994; Chatzimichael et al., 2022).[2] We assume that the stock of farmers' health evolves according to

$$\dot{h}_t = \delta_h \left(\bar{h} - h_t\right) - \psi_h(z_t^e, h_t) \tag{6}$$

where the first term captures baseline regeneration (medical recovery, rest, and replacement of health deficits) that mean-reverts health toward $\bar{h}$ with $\delta_h > 0$, while $\psi_h(\cdot)$ is twice continuously differentiable and convex in z_t^e, capturing the detrimental effect of pesticide exposure and aging. We assume $\partial \psi_h(\cdot)/\partial z_t^e > 0$ and $\partial \psi_h(\cdot)/\partial h_t \geq 0$. Thus, higher chemical intensity and/or greater toxicity (via resistance-induced escalation) reduce farm-worker health and hence productivity through (2).

The government imposes an *ad valorem* tax $\tau_t \geq 0$ on chemical pesticides, so the farm pays the tax-inclusive unit price $(1+\tau_t)c_z$ per unit of z_t where $c_z > 0$ is the unit cost of pesticides. To mitigate chemical pesticide application, it also provides a unit subsidy $\sigma_t \geq 0$ on non-chemical control, so that the unit price of x_t is $(c_x - \sigma_t)$, where $c_x > 0$ is the constant unit cost. Taking

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[1] Potency is an endogenous index determined by resistance, $s_t = \psi_s(\cdot)$; hence d_t is the only additional biological state variable besides b_t and h_t.

[2] Chronic occupational exposure to pesticides is associated with sustained liver, kidney, and neurological problems, reinforcing real biological pathways for chronic health damage from pesticide burdens (WHO, 2020).

prices and policies as given, the representative farm maximizes discounted profits:

$$\max_{\{\ell_t, z_t, x_t\}} \int_0^{\infty} e^{-rt} \Big[y_t - w\ell_t - (1+\tau_t)\, c_z z_t - (c_x - \sigma_t)\, x_t \Big]\, dt$$

subject to equations (1), (3), (5), and (6). Where $r > 0$ denotes the discount rate (equal to the real interest rate in equilibrium), w is the real wage rate determined in the labor market, while the price of y_t is normalized to one.

The current-value *Hamiltonian* is defined as:

$$\begin{aligned} \mathcal{H}_t^y = {} & f\Big(q\left(h_t\right)\ell_t\Big)\Big(1 - g\left(b_t\right)\Big) - w\ell_t - (1+\tau_t)\, c_z z_t - (c_x - \sigma_t)\, x_t + \lambda_d \Big[\delta_z z_t - \delta_d d_t\Big] \\ & + \lambda_b \Big[\psi_b(b_t) - \psi_z\left(z_t \psi_s\left(d_t\right)\right) b_t - \psi_x\left(x_t\right) b_t\Big] + \lambda_h \Big[\delta_h\left(\bar{h} - h_t\right) - \psi_h\left(z_t \psi_s\left(d_t\right), h_t\right)\Big] \end{aligned}$$

where λ_d, λ_b, and λ_h are the current-value costates associated with d_t, b_t and h_t. Assuming an interior solution, the first-order conditions determining the dynamics of the system are:

$$\frac{\partial \mathcal{H}_t^y(\cdot)}{\partial \ell_t} = 0 \quad \Rightarrow \quad w = \frac{\partial f(\cdot)}{\partial \ell_t^e} q\left(\cdot\right)\left[1 - g\left(\cdot\right)\right] \tag{7i}$$

$$\frac{\partial \mathcal{H}_t^y(\cdot)}{\partial z_t} = 0 \quad \Rightarrow \quad (1+\tau_t)\, c_z = \lambda_d \delta_z - \lambda_b \frac{\partial \psi_z(\cdot)}{\partial z_t^e} \psi_s(\cdot) b_t - \lambda_h \frac{\partial \psi_h(\cdot)}{\partial z_t^e} \psi_s(\cdot) \tag{7ii}$$

$$\frac{\partial \mathcal{H}_t^y(\cdot)}{\partial x_t} = 0 \quad \Rightarrow \quad (c_x - \sigma_t) = -\lambda_b \frac{\partial \psi_x(\cdot)}{\partial x_t} b_t \tag{7iii}$$

$$\frac{\partial \mathcal{H}_t^y(\cdot)}{\partial b_t} = -\dot{\lambda}_b + r\lambda_b \quad \Rightarrow \quad \dot{\lambda}_b = \lambda_b \left[r - \frac{\partial \psi_b(\cdot)}{\partial b_t} + \psi_z(\cdot) + \psi_x(\cdot) \right] + f(\cdot) \frac{\partial g(\cdot)}{\partial b_t} \tag{7iv}$$

$$\frac{\partial \mathcal{H}_t^y(\cdot)}{\partial d_t} = -\dot{\lambda}_d + r\lambda_d \quad \Rightarrow \quad \dot{\lambda}_d = \lambda_d \left(r + \delta_d\right) + \lambda_h \frac{\partial \psi_h(\cdot)}{\partial z_t^e} \frac{\partial \psi_s(\cdot)}{\partial d_t} z_t + \lambda_b \left[\frac{\partial \psi_z(\cdot)}{\partial z_t^e} \frac{\partial \psi_s(\cdot)}{\partial d_t} z_t \right] b_t \tag{7v}$$

$$\frac{\partial \mathcal{H}_t^y(\cdot)}{\partial h_t} = -\dot{\lambda}_h + r\lambda_h \quad \Rightarrow \quad \dot{\lambda}_h = \lambda_h \left[r + \delta_h + \frac{\partial \psi_h(\cdot)}{\partial h_t} \right] - \frac{\partial f(\cdot)}{\partial \ell_t^e} \frac{\partial q(\cdot)}{\partial h_t} \ell_t \left[1 - g\left(\cdot\right)\right] \tag{7vi}$$

with costate dynamics given by (7*iv*)–(7*vi*). A stationary decentralized equilibrium is defined by constant controls (ℓ, z, x) and constant states (b, d, h) together with the static first-order conditions (7*i*)–(7*iii*) and the associated costate equations (7*iv*)–(7*vi*) evaluated at the steady state. In steady state, $\lambda_h > 0$ since health raises effective labor productivity and increases output. The shadow value of resistance is negative, $\lambda_d < 0$, since higher resistance increases future effective toxicity and reduces the productivity of chemical control. The shadow price of the pests λ_b is negative since pest infestation reduces potential output (Clark, 2010).[3]

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[3] The transversality conditions rule out explosive paths for the biological state variables and ensure that the farmer does not accumulate pests, resistance, or health deficits in a manner that yields unbounded discounted shadow values. Given the boundedness of output and the assumed monotonicity properties of $\psi_b(\cdot)$, $\psi_z(\cdot)$, $\psi_x(\cdot)$ and $\psi_h(\cdot)$, together with $r > 0$, any optimal interior solution must satisfy $\lim_{t\to\infty} e^{-rt}\lambda_i(t)k_i(t) = 0$ for $k_i \in \{b, d, h\}$.

Before turning to policy design, it is useful to examine how changes in key parameters affect the steady-state equilibrium of the decentralized economy. Table 1 summarizes the local steady-state comparative statics of the decentralized economy obtained from the stationary system comprising the state equations, the farm's first-order conditions, and the associated costate equations.[4] These results should be interpreted as local responses around an interior steady state under the maintained assumptions of well-behaved pest-control technologies, gross substitutability between chemical and non-chemical controls, and local stability of the stationary equilibrium. Under these conditions, parameter changes affect the steady state through their impact on effective chemical intensity $z^e = z\psi_s(\cdot)$, pest pressure b, resistance accumulation d, and health-induced labor productivity.

Table 1: Decentralized local steady-state comparative statics

	ℓ	z	x	b	d	h	y	λ_b	λ_d	λ_h
Private cost and policy parameters										
c_z	$-$	$-$	$+$	$+$	$-$	$+$	$-$	$-$	$-$	$+$
c_x	$-$	$+$	$-$	$+$	$+$	$-$	$-$	$-$	$-$	$+$
w	$-$	$-$	$-$	$+$	$-$	$+$	$-$	$-$	$-$	$+$
τ	$-$	$-$	$+$	$+$	$-$	$+$	$-$	$-$	$-$	$+$
σ	$+$	$-$	$+$	$-$	$-$	$+$	$+$	$+$	$+$	$+$
Biological parameters										
δ_z	$+$	$-$	$+$	$+$	$-$	$+$	$-$	$-$	$-$	$+$
δ_d	$+$	$+$	$-$	$-$	$-$	$+$	$+$	$+$	$+$	$+$
δ_h	$+$	$+$	$-$	$-$	$+$	$+$	$+$	$+$	$+$	$-$
Intertemporal preferences										
r	$-$	$+$	$-$	$+$	$+$	$-$	$-$	$-$	$+$	$-$

Higher private chemical costs, either through a larger c_z or a higher tax τ, reduce chemical use and induce substitution toward non-chemical control (Goodhue et al., 2010). Because substitution is incomplete, overall pest suppression weakens and steady-state infestation rises. At the same time, lower chemical use reduces resistance accumulation and, through the exposure channel $z^e = z\psi_s(\cdot)$, improves worker health, although output declines as the productivity loss from higher pest pressure dominates the health gain. In contrast, a higher cost of non-chemical control c_x shifts production toward chemical inputs, increasing effective intensity, accelerating resistance accumulation, and worsening health through higher toxicity. Despite higher contemporaneous application, steady-state pest pressure rises because resistance erodes long-run control effectiveness, leading to lower output (Sunding and Zivin, 2000). Biological parameters generate analogous intertemporal responses. An

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[4] The signs in Table 1 are local and follow from the stationary system (state equations, first-order conditions, and costate equations) under standard regularity conditions ensuring an interior steady state and a nonsingular Jacobian. We assume: (i) well-behaved technologies, $f_{\ell_e} > 0$, $f_{\ell_e \ell_e} < 0$, $q' > 0$, $q'' < 0$, $g' > 0$, $\psi_{x,x} > 0$, $\psi_{z,z^e} > 0$, and $\psi_s'(\cdot) > 0$; (ii) health dynamics admit an interior stationary level, so that $\delta_h(\bar{h} - h) = \psi_h(\cdot)$ with $\delta_h > 0$, $\bar{h} > 0$, $\psi_{h,z^e} > 0$, and $\psi_{h,h}$ locally bounded, ensuring that h is pinned down smoothly by the steady-state condition; (iii) chemical and non-chemical controls are gross substitutes at the margin; and (iv) substitution responses do not overturn the direct biological effects on total pest pressure and resistance accumulation. Under these conditions, comparative statics follow from the implicit-function theorem.

increase in the resistance formation parameter δ_z raises the dynamic cost of chemical use and induces substitution toward non-chemical control; under the maintained conditions, the reduction in chemical use dominates the direct biological effect, so that steady-state resistance declines and health improves, albeit at the cost of weaker pest control and higher infestation.

Conversely, faster resistance decay δ_d lowers the resistance stock, improves health, and restores the effectiveness of chemical control, reducing pest pressure and increasing output. The health recovery parameter δ_h operates differently: faster regeneration raises the steady-state health stock and effective labor productivity, thereby increasing output, but by relaxing the health constraint it also encourages greater chemical use and resistance accumulation. Higher wages reduce labor demand and overall control intensity, increasing pest pressure while improving health through lower exposure, whereas a higher discount rate r strengthens short-run orientation, increases reliance on chemical control, and raises both resistance and pest pressure, reducing health and output. Overall, the comparative statics reveal a common structure: parameters that increase chemical reliance amplify resistance accumulation and toxic exposure, whereas parameters that promote substitution mitigate resistance but may raise pest pressure when substitution is incomplete. The decentralized equilibrium therefore fails to internalize the dynamic interaction between chemical use, resistance, and health, motivating the welfare-based analysis that follows.

2.2 Consumption in the Decentralized Economy

On the consumption side of the economy, welfare depends on aggregate consumption, population health, and environmental quality. Although environmental quality does not enter the production technology directly, it affects welfare through household preferences, thereby generating a consumption-side externality. In addition, pesticide use in farm production creates chemical residues in food products that may have persistent adverse effects on consumers' health (Beyuo et al., 2024). Whereas farm-worker health is directly influenced by contemporaneous effective pesticide exposure, consumer health depends on the accumulated stock of food-borne residues, reflecting indirect and persistent exposure along the food chain.

Since the economy is closed and there is no capital accumulation, aggregate consumption equals residual output after pest-control expenditures. The representative infinitely lived household's lifetime welfare is therefore given by[5]

$$\int_0^\infty e^{-rt}\left[\frac{c_t^{1-\theta_c}}{1-\theta_c}+\beta_v\,\frac{v_t^{1-\theta_v}}{1-\theta_v}+\beta_e\,\frac{e_t^{1-\theta_e}}{1-\theta_e}\right]dt \quad \text{with} \quad r>0,\ \beta_v>0,\ \beta_e>0 \tag{8}$$

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[5] We assume a common discount rate r for households and firms, consistent with perfect capital markets and no intertemporal distortions.

where c_t denotes aggregate consumption, v_t is an index of chronic population health, e_t measures environmental quality, and $\theta_c, \theta_v, \theta_e > 0$ are the reciprocals of the intertemporal elasticities of substitution for the corresponding utility components. Utility is additively separable across arguments and isoelastic within each component.

Consumers' health status evolves according to

$$\dot{v}_t = \zeta_v(\bar{v} - v_t) - \psi_v(k_t, v_t) \tag{9}$$

where $\zeta_v > 0$ governs regeneration toward baseline health $\bar{v}$ in the absence of exposure, and $\psi_v(\cdot)$ is twice continuously differentiable and convex in the stock of pesticide residues k_t, with $\partial\psi_v(\cdot)/\partial k_t > 0$. This captures the detrimental effects of chronic exposure to pesticide residues (Godfray et al., 2010).

Food-borne pesticide residues accumulate according to

$$\dot{k}_t = \zeta_z z_t^e - \zeta_k k_t \tag{10}$$

where effective pesticide application is defined in (4). The parameter $\zeta_z > 0$ measures the contribution of effective chemical intensity to residual contamination, while $\zeta_k > 0$ captures the natural attenuation of residues through chemical degradation, environmental dispersion, and metabolic clearance. This specification guarantees bounded residue stocks along feasible paths and admits an interior stationary equilibrium.

Environmental quality evolves as

$$\dot{e}_t = \zeta_e(\bar{e} - e_t) - \psi_e\left(z_t^e\right) \tag{11}$$

where $\bar{e} > 0$ denotes the natural carrying capacity of the environment, $\zeta_e > 0$ is the regeneration rate, and $\psi_e(\cdot)$ is twice continuously differentiable and convex in effective pesticide intensity, with $\partial\psi_e(\cdot)/\partial z_t^e > 0$. Sustained chemical application therefore lowers the long-run environmental stock.

With no capital accumulation, aggregate consumption equals output net of pest-control costs. Thus, aggregate feasibility requires

$$c_t = y_t - c_z z_t - c_x x_t \tag{12}$$

where y_t denotes output and $(c_z z_t, c_x x_t)$ represent the real resource costs of chemical and non-chemical pest-control inputs.

In the decentralized equilibrium, households take pesticide use z_t and the associated evolution of effective pesticide intensity $z_t^e = z_t\psi_s(\cdot)$ as given, since chemical application is chosen by farms.

Through equations (9)-(11), effective pesticide use affects welfare through two dynamic channels. First, higher z_t^e increases the stock of food-borne residues k_t, which reduces chronic health v_t and lowers utility directly. Second, it degrades environmental quality e_t, which also enters preferences directly.

From (10), the steady-state stock of residues satisfies

$$k = \frac{\zeta_z}{\zeta_k} z^e$$

implying that sustained effective pesticide use permanently raises chronic exposure. Similarly, from (11), steady-state environmental quality is given by

$$e = \bar{e} - \frac{\psi_e(z^e)}{\zeta_e}$$

so that persistent chemical intensity leads to a permanently lower environmental stock. These relations highlight that pesticide use generates lasting welfare effects even when biological and environmental variables converge to stationary levels. In particular, any parameter change affecting the decentralized steady state through effective pesticide intensity also shifts the consumption-side steady state: increases in z^e raise the residue stock k and reduce environmental quality e, while decreases in z^e lower chronic exposure and improve environmental quality.

Because producers do not internalize the effects of pesticide use on residue accumulation and environmental degradation, and households take production decisions as given, the decentralized allocation fails to account for the dynamic interaction between pesticide intensity, residue accumulation, chronic health deterioration, and environmental degradation. This consumption-side externality, combined with the production-side feedbacks analyzed in Section 2.1, provides the foundation for corrective policy intervention and motivates the social planner's problem examined next.

2.3 The Social Planner's Problem

We now characterize the constrained-efficient allocation. A benevolent social planner allocates aggregate resources, internalizing all dynamic production- and consumption-side effects of chemical pesticide use. Labor supply is inelastic and normalized to $\bar{\ell} > 0$, so that $\ell_t = \bar{\ell}$ for all $t \geq 0$. Instantaneous welfare is given by the separable isoelastic aggregator in (8). The planner chooses paths $\{c_t, z_t, x_t\}$ to solve

$$\max_{\{c_t, z_t, x_t\}} \int_0^\infty e^{-rt} \left[\frac{c_t^{1-\theta_c}}{1-\theta_c} + \beta_v \frac{v_t^{1-\theta_v}}{1-\theta_v} + \beta_e \frac{e_t^{1-\theta_e}}{1-\theta_e} \right] dt \tag{13}$$

subject to the state dynamics (3)–(6) and (9)–(11), and the aggregate resource constraint

$$f\big(q(h_t)\bar{\ell}\big)\big(1-g(b_t)\big) = c_t + c_z z_t + c_x x_t, \tag{14}$$

with initial stocks $(b_0, d_0, h_0, k_0, v_0, e_0)$ given.

The current value *Hamiltonian* is given by

$$\begin{aligned}
\mathcal{H}_t^p = &\left[\frac{c_t^{1-\theta_c}}{1-\theta_c} + \beta_v \frac{v_t^{1-\theta_v}}{1-\theta_v} + \beta_e \frac{e_t^{1-\theta_e}}{1-\theta_e}\right] + \lambda_y \Big[f\big(q\left(h_t\right)\bar{\ell}\big)\left(1-g\left(b_t\right)\right) - c_t - c_z z_t - c_x x_t\Big] \\
&+ \mu_b \Big[\psi_b(b_t) - \psi_z(z_t^e)\, b_t - \psi_x(x_t)\, b_t\Big] + \mu_d \Big[\delta_z z_t - \delta_d d_t\Big] + \mu_h \Big[\delta_h(\bar{h} - h_t) - \psi_h(z_t^e, h_t)\Big] \\
&+ \mu_v \Big[\zeta_v(\bar{v} - v_t) - \psi_v(k_t, v_t)\Big] + \mu_k \Big[\zeta_z z_t^e - \zeta_k k_t\Big] + \mu_e \Big[\zeta_e(\bar{e} - e_t) - \psi_e(z_t^e)\Big]
\end{aligned}$$

where λ_y is the shadow value of aggregate resources (the multiplier on the feasibility constraint), and $\mu_b, \mu_d, \mu_h, \mu_v, \mu_k$, and μ_e are the current-value costate variables associated with the corresponding state equations.

Under an interior solution, the necessary first-order conditions are:[6]

$$\frac{\partial \mathcal{H}_t^p(\cdot)}{\partial c_t} = 0 \Rightarrow c_t^{-\theta_c} = \lambda_y \tag{15i}$$

$$\frac{\partial \mathcal{H}_t^p(\cdot)}{\partial z_t} = 0 \Rightarrow \lambda_y c_z = \mu_d \delta_z - \left[\mu_b \frac{\partial \psi_z(\cdot)}{\partial z_t^e} b_t + \mu_h \frac{\partial \psi_h(\cdot)}{\partial z_t^e} - \mu_k \zeta_z + \mu_e \frac{\partial \psi_e(\cdot)}{\partial z_t^e}\right] \psi_s(\cdot) \tag{15ii}$$

$$\frac{\partial \mathcal{H}_t^p(\cdot)}{\partial x_t} = 0 \Rightarrow \lambda_y c_x = -\mu_b \frac{\partial \psi_x(\cdot)}{\partial x_t} b_t \tag{15iii}$$

$$\frac{\partial \mathcal{H}_t^p(\cdot)}{\partial b_t} = -\dot{\mu}_b + r\mu_b \Rightarrow \dot{\mu}_b = \mu_b \left[r - \frac{\partial \psi_b(\cdot)}{\partial b_t} + \psi_z(\cdot) + \psi_x(\cdot)\right] - \lambda_y f(\cdot) \frac{\partial g(\cdot)}{\partial b_t} \tag{15iv}$$

$$\begin{aligned}
\frac{\partial \mathcal{H}_t^p(\cdot)}{\partial d_t} = -\dot{\mu}_d + r\mu_d \Rightarrow \dot{\mu}_d = \mu_d \left(r + \delta_d\right) + \mu_b \frac{\partial \psi_z(\cdot)}{\partial z_t^e} \frac{\partial \psi_s(\cdot)}{\partial d_t} z_t b_t \\
+ \left[\mu_h \frac{\partial \psi_h(\cdot)}{\partial z_t^e} + \mu_e \frac{\partial \psi_e(\cdot)}{\partial z_t^e} - \mu_k \zeta_z\right] \frac{\partial \psi_s(\cdot)}{\partial d_t} z_t
\end{aligned} \tag{15v}$$

$$\frac{\partial \mathcal{H}_t^p(\cdot)}{\partial h_t} = -\dot{\mu}_h + r\mu_h \Rightarrow \dot{\mu}_h = \mu_h \left[r + \delta_h + \frac{\partial \psi_h(\cdot)}{\partial h_t}\right] - \lambda_y \frac{\partial f(\cdot)}{\partial \ell_t^e} \frac{\partial q(\cdot)}{\partial h_t} \bar{\ell}\Big(1 - g(\cdot)\Big) \tag{15vi}$$

$$\frac{\partial \mathcal{H}_t^p(\cdot)}{\partial v_t} = -\dot{\mu}_v + r\mu_v \Rightarrow \dot{\mu}_v = \mu_v \left[r + \zeta_v + \frac{\partial \psi_v(\cdot)}{\partial v_t}\right] - \beta_v\, v_t^{-\theta_v} \tag{15vii}$$

$$\frac{\partial \mathcal{H}_t^p(\cdot)}{\partial k_t} = -\dot{\mu}_k + r\mu_k \Rightarrow \dot{\mu}_k = \mu_k \left(r + \zeta_k\right) + \mu_v \frac{\partial \psi_v(\cdot)}{\partial k_t} \tag{15$viii$}$$

$$\frac{\partial \mathcal{H}_t^p(\cdot)}{\partial e_t} = -\dot{\mu}_e + r\mu_e \Rightarrow \dot{\mu}_e = \mu_e \left(r + \zeta_e\right) - \beta_e e_t^{-\theta_e} \tag{15ix}$$

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[6] Standard transversality conditions apply. Given $r > 0$, bounded utility, and the assumed regularity of the state dynamics, any optimal interior solution satisfies $\lim_{t\to\infty} e^{-rt}\mu_i(t)k_i(t) = 0$ for $k_i \in \{b, d, h, k, v, e\}$, ruling out explosive paths of the state variables.

A stationary constrained-efficient (planner) allocation is characterized by constant controls (c, z, x) and constant stocks (b, d, h, k, v, e) satisfying $\dot{b} = \dot{d} = \dot{h} = \dot{k} = \dot{v} = \dot{e} = 0$, together with the steady-state versions of (15i)–(15ix). The steady-state controls are determined by the planner's optimality conditions (15i)–(15iii), while the associated shadow values are given by the costate equations (15iv)–(15ix) evaluated at the steady state.

Condition (15i) equates the marginal utility of consumption to the shadow value of aggregate resources, λ_y, thereby expressing all resource costs in welfare units. Condition (15ii) shows that the planner chooses chemical use by equating its marginal resource cost, valued at λ_y, to the full shadow-value-weighted marginal impact of pesticide use on resistance accumulation, pest dynamics, farm-worker health, residue accumulation, and environmental quality. In contrast to decentralized producers, the planner internalizes both the intertemporal feedback from chemical use to resistance and toxicity, and the cross-sectoral spillovers operating through consumer health and environmental degradation (Sunding and Zivin, 2000). Condition (15iii) characterizes optimal non-chemical control, which affects welfare exclusively through its biological effect on pest pressure.

The costate equations (15iv)–(15ix) determine the shadow values of the biological and environmental stocks. Pest infestation and resistance carry negative shadow values, reflecting their adverse effects on current productivity and future control effectiveness. In contrast, farm-worker health, chronic population health, and environmental quality carry positive shadow values, as they enhance effective labor supply and enter preferences directly. The residue stock carries a negative shadow value because higher residues worsen chronic health through $\psi_v(\cdot)$. At the stationary constrained-efficient allocation, these shadow values summarize the discounted marginal welfare impact of changes in the underlying stocks. Taken together, the steady-state conditions define an allocation in which pesticide use balances contemporaneous production gains against dynamic biological and environmental costs. The divergence between this allocation and the decentralized equilibrium arises because private agents fail to internalize these shadow-value effects, thereby motivating the optimal regulatory framework developed in the next section.

3 Optimal Regulation and Welfare

3.1 Optimal Pigouvian Regulation

The model delivers three central policy implications. First, chemical pesticide use generates a dynamic externality: it increases food-borne residues and environmental degradation, while resistance amplifies effective exposure. These effects are not internalized by farms, creating a wedge between private and social marginal costs. Second, the constrained-efficient allocation can be decentralized using a two-instrument policy consisting of a tax on chemical pesticides and a subsidy to non-chemical control. Third, when policy is implemented under a cyclical balanced-budget rule with administrative costs, the first-best *Pigouvian* instruments are fiscally attenuated. Because resistance affects both external damages and the fiscal tax base, optimal regulation is inherently state-dependent, reflecting broader second-best considerations where the availability of tax bases constrains corrective policy (Bovenberg and De Mooij, 1994; Parry, 1995). The key mechanisms are summarized in Figure 1, which decomposes the effects of resistance on corrective taxation and on the optimal policy mix.

To characterize corrective taxation, it is useful to define the marginal external welfare damage generated by pesticide use. Using the planner's shadow value of resources and the costate variables associated with the environmental state variables, this damage can be written as follows.[7]

Lemma 1 (External marginal damage from pesticide use) *At the constrained-efficient allocation, the marginal welfare damage generated by an increase in pesticide use z_t is*

$$MD_t = \left[-\mu_k \zeta_z + \mu_e \frac{\partial \psi_e(z_t^e)}{\partial z_t^e}\right] \psi_s(d_t) \qquad \text{and} \qquad z_t^e = z_t \psi_s(d_t) \tag{16}$$

The term MD_t captures the consumption-side externality from pesticide use through residues and environmental degradation. The residue channel enters through $\mu_k < 0$, since a higher residue stock worsens chronic health through $\psi_v(k_t, v_t)$, while the environmental channel enters through $\mu_e > 0$, since environmental quality raises welfare directly. Hence both channels increase the marginal external damage of pesticide use, consistent with the broader literature linking chemical use to environmental and health externalities (Lichtenberg, 2010; Antle and Pingali, 1994).

The representative farm internalizes only private production and farm-worker health effects and ignores the consumption-side spillovers operating through residue accumulation and environmental degradation. The corrective pesticide tax must therefore price the marginal external damage in (16). Since MD_t is measured in welfare units, while private decisions are taken in resource units, the tax must be scaled by the planner's shadow value of aggregate resources, $\lambda_y = u_c(c_t)$. In the absence of fiscal or administrative frictions, the *Pigouvian* pesticide tax is therefore

$$\tau_t^p = \frac{MD_t}{\lambda_y c_z} \tag{17}$$

Comparing the farm's first-order condition for chemical use in ($7ii$) with the planner's condition in ($15ii$), both evaluated at the constrained-efficient allocation, shows that the wedge between them is exactly MD_t. This wedge corresponds to the standard *Pigouvian* correction in the presence of unpriced externalities (Sandmo, 1975).

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[7] All results follow directly from the planner's and decentralized first-order conditions together with standard envelope arguments; detailed algebra is available upon request.

A symmetric argument applies to non-chemical control. Comparing the farm's condition for x_t

$$(c_x - \sigma_t) = -\lambda_b \frac{\partial \psi_x(\cdot)}{\partial x_t} b_t \tag{18}$$

with the planner's condition,

$$\lambda_y c_x = -\mu_b \frac{\partial \psi_x(\cdot)}{\partial x_t} b_t \tag{19}$$

yields the *Pigouvian* unit subsidy

$$\sigma_t^p = \frac{[\mu_b - \lambda_y \lambda_b] \frac{\partial \psi_x(\cdot)}{\partial x_t} b_t}{\lambda_y} \tag{20}$$

This subsidy corrects the divergence between the social and private valuation of pest suppression embodied in the shadow values μ_b and λ_b. This mechanism is consistent with the role of input subsidies in correcting under-provision of environmentally beneficial practices (Wu, 2000).

Proposition 1 (Pigouvian decentralization) *In the absence of fiscal or administrative frictions, the constrained-efficient allocation can be decentralized through a* Pigouvian *pesticide tax and a subsidy to non-chemical pest control satisfying*

$$\tau_t^p = \frac{MD_t}{\lambda_y c_z} \qquad \textit{and} \qquad \sigma_t^p = \frac{[\mu_b - \lambda_y \lambda_b] \frac{\partial \psi_x(\cdot)}{\partial x_t} b_t}{\lambda_y} \tag{21}$$

The tax internalizes the marginal external damage from chemical pesticide use, while the subsidy corrects the wedge between the social and private value of non-chemical pest suppression.

Hence, the *Pigouvian* tax internalizes the marginal external damage from pesticide use that arises through residues and environmental degradation and is not perceived by individual producers. In contrast, the subsidy corrects the private undervaluation of non-chemical control, as farms account only for its direct effect on pest suppression but not for its full social value. Together, the two instruments align private input choices with the social optimum by correcting distinct wedges on the chemical and non-chemical margins.

We now introduce the fiscal environment in which policy is implemented. We impose a cyclical balanced budget that holds period by period, with no exogenous purchases and no transfers:

$$\tau_t c_z z_t = \sigma_t x_t + c_\tau(\tau_t, \sigma_t) \tag{22}$$

where $c_\tau(\tau_t, \sigma_t) \geq 0$ is a convex resource cost of tax collection and subsidy administration. Let equilibrium input demands be denoted by $z_t = z(\tau_t, \sigma_t; \omega_t)$ and $x_t = x(\tau_t, \sigma_t; \omega_t)$, where ω_t collects the underlying state variables. Net public revenue is then

$$R(\tau_t, \sigma_t; \omega_t) \equiv \tau_t c_z z(\tau_t, \sigma_t; \omega_t) - \sigma_t x(\tau_t, \sigma_t; \omega_t) - c_\tau(\tau_t, \sigma_t) \tag{23}$$

so that the balanced-budget condition is $R(\tau_t, \sigma_t; \omega_t) = 0$.

For each instrument $j \in \{\tau, \sigma\}$, define the marginal value of public funds as

$$MVF_t^j \equiv \frac{\partial W / \partial j_t}{\partial R / \partial j_t} \tag{24}$$

Using the envelope property of the planner's problem, marginal changes in fiscal instruments affect welfare only through the resource constraint. Hence

$$MVF_t^j = \frac{\lambda_y}{\partial R / \partial j_t} \quad \text{and} \quad MCF_t^j \equiv \frac{1}{MVF_t^j} = \frac{\partial R / \partial j_t}{\lambda_y} \tag{25}$$

The marginal value and cost of public funds follow the standard public finance formulation used to evaluate distortionary taxation in second-best settings.

The marginal revenue effects are

$$\frac{\partial R(\cdot)}{\partial \tau_t} = c_z z_t + \tau_t c_z \frac{\partial z(\cdot)}{\partial \tau_t} - \sigma_t \frac{\partial x(\cdot)}{\partial \tau_t} - \frac{\partial c_\tau(\cdot)}{\partial \tau_t} \tag{26a}$$

$$\frac{\partial R(\cdot)}{\partial \sigma_t} = \tau_t c_z \frac{\partial z(\cdot)}{\partial \sigma_t} - \left[x_t + \sigma_t \frac{\partial x(\cdot)}{\partial \sigma_t} \right] - \frac{\partial c_\tau(\cdot)}{\partial \sigma_t} \tag{26b}$$

Under a local approximation in which behavioral responses are second order and administrative costs are small relative to contemporaneous tax and subsidy bases,

$$\frac{\partial R(\cdot)}{\partial \tau_t} \approx c_z z_t - \frac{\partial c_\tau(\cdot)}{\partial \tau_t} \qquad \text{and} \qquad \frac{\partial R(\cdot)}{\partial \sigma_t} \approx -x_t - \frac{\partial c_\tau(\cdot)}{\partial \sigma_t} \tag{27}$$

Accordingly,

$$MVF_t^\tau \approx \frac{\lambda_y}{c_z z_t - \frac{\partial c_\tau(\cdot)}{\partial \tau_t}} \tag{28a}$$

$$MVF_t^\sigma \approx \frac{\lambda_y}{x_t + \frac{\partial c_\tau(\cdot)}{\partial \sigma_t}} \tag{28b}$$

The subsidy-side expression is written in terms of the absolute marginal fiscal cost of expanding the subsidy, so that $MVF_t^\sigma > 0$ captures the welfare value of relaxing the subsidy-side financing constraint.

Under the cyclical balanced-budget rule, the optimal second-best instruments are

$$\tau_t^{sb} = \tau_t^p MVF_t^{\tau} \tag{29}$$

and

$$\sigma_t^{sb} = \sigma_t^p MVF_t^{\sigma} \tag{30}$$

Together with the period-by-period constraint $R(\tau_t, \sigma_t; \omega_t) = 0$, these expressions characterize the second-best tax–subsidy system.

Proposition 2 (Second-best fiscal implementation) *Under the cyclical balanced-budget requirement with administrative costs, the optimal pesticide tax and subsidy are given by*

$$\tau_t^{sb} = \tau_t^p MVF_t^{\tau} \qquad \textit{and} \qquad \sigma_t^{sb} = \sigma_t^p MVF_t^{\sigma}$$

Hence fiscal frictions scale the first-best Pigouvian instruments through the instrument-specific marginal value of public funds. Because these fiscal wedges depend on equilibrium input demands, the second-best policy instruments are state-dependent.

The balanced-budget rule links the two instruments through endogenous fiscal capacity. When chemical use is high, the pesticide tax base is broad and the marginal fiscal cost of taxation is low, allowing the tax to track closely its *Pigouvian* benchmark. As resistance accumulates, chemical use declines, the tax base contracts, and fiscal attenuation strengthens. At the same time, expanding non-chemical control must be financed from a shrinking tax base, raising the marginal fiscal cost of the subsidy. Because both z_t and x_t are jointly determined by the biological state, fiscal capacity is inherently state-dependent.

As a result, the optimal policy mix reflects both the magnitude of external damages and the endogenous evolution of the tax and subsidy bases. This interaction between biological dynamics and fiscal constraints underlies the state dependence of second-best regulation and is illustrated in Figure 1. Panel (a) shows that the *Pigouvian* benchmark rises with resistance, while the second-best tax remains below it due to fiscal attenuation. Panel (b) illustrates the corresponding rebalancing of the policy mix toward non-chemical control as resistance increases.[8] Taken together, these results imply that optimal pesticide regulation requires a jointly determined tax–subsidy system whose intensity and composition adjust endogenously to both the biological state of resistance and the evolving fiscal capacity of the economy.

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[8] The policy rules in (29) and (30) characterize interior solutions. If policy instruments are constrained, such as $\sigma_t \geq 0$ or upper bounds on tax rates, the corresponding *Kuhn–Tucker* conditions apply.

3.2 State Dependence and Fiscal Attenuation

Optimal regulation is state-dependent because resistance affects both the marginal external damage from pesticide use and the fiscal capacity of corrective intervention. The first channel operates through the exposure scaler $\psi_s(d_t)$. Since $\psi_s'(d_t) > 0$, higher resistance increases effective pesticide intensity for a given z_t, thereby amplifying the external damage term in (16) and raising the associated *Pigouvian* tax in (17). The second channel operates through equilibrium input demands. As resistance accumulates, farms substitute away from chemical control, reducing pesticide use and thereby shrinking the tax base that finances corrective policy under the balanced-budget rule.

These two forces generate a fundamental trade-off between corrective efficiency and fiscal feasibility. On the one hand, resistance strengthens the corrective motive by increasing the marginal damage from pesticide use. On the other hand, it weakens fiscal capacity by contracting the tax base that supports corrective taxation. As a result, the gap between the first-best *Pigouvian* tax and its second-best implementation expands with resistance, even as the benchmark corrective motive becomes stronger.

Proposition 3 (Resistance, fiscal attenuation, and policy rebalancing) *Suppose* $\psi_s'(d_t) > 0$*,* $\partial z_t/\partial d_t < 0$*, and* $\partial x_t/\partial d_t > 0$*. Under the local approximation in* (27)*, if the resistance-induced increase in effective exposure dominates any offsetting change in the shadow values entering* MD_t*, then*

$$\frac{\partial MD_t}{\partial d_t} > 0 \qquad \textit{and} \qquad \frac{\partial \tau_t^p}{\partial d_t} > 0$$

Moreover, if the contraction of the pesticide tax base reduces the marginal fiscal value of taxation sufficiently strongly, then the implementation wedge is increasing in resistance:

$$\frac{\partial}{\partial d_t}\left(\tau_t^p - \tau_t^{sb}\right) > 0$$

Finally, if this fiscal attenuation effect dominates the corresponding subsidy-side adjustment, the optimal second-best policy mix shifts toward relatively greater reliance on non-chemical control:

$$\frac{\partial}{\partial d_t}\left(\frac{\tau_t^{sb}}{\sigma_t^{sb}}\right) < 0$$

Hence, higher resistance strengthens the benchmark case for corrective taxation while simultaneously widening the gap between the Pigouvian *and second-best policies and reallocating intervention toward the subsidy instrument.*

The proposition summarizes the central mechanism of the paper. Resistance affects regulation through two opposing margins: it raises marginal external damage by amplifying effective exposure, while simultaneously eroding the fiscal capacity required to implement corrective taxation. When resistance is low, chemical use remains widespread, the pesticide tax base is broad, and the second-best tax can closely track its *Pigouvian* benchmark. As resistance accumulates, the corrective motive strengthens because effective exposure and marginal damages increase, while fiscal implementation becomes increasingly constrained due to the erosion of the tax base. This divergence between rising external damages and declining fiscal capacity generates a systematic widening of the gap between first-best and second-best policy.[9] Efficient regulation therefore requires a coordinated and state-contingent tax–subsidy system in which the relative intensity of instruments adjusts endogenously over the resistance cycle, with increasing reliance on non-chemical control as resistance builds. Figure 1a illustrates the widening gap between $\tau^{p}(d)$ and $\tau^{sb}(d)$ as resistance rises, while Figure 1b illustrates the associated rebalancing of the second-best policy mix toward relatively greater reliance on the subsidy instrument at higher resistance levels.

4 Dynamic Consistency and Long-Run Regulation

Section 3 characterizes optimal regulation as a function of the contemporaneous biological state. In a dynamic environment, however, current pesticide use affects the future evolution of resistance according to (5),

$$\dot{d}_t = \delta_z z_t - \delta_d d_t$$

and therefore alters the future policy environment itself. This creates an intertemporal policy problem: current chemical use not only affects contemporaneous external damages, but also influences future effective toxicity, future equilibrium input demands, and hence the future fiscal capacity of the regulator under the balanced-budget rule.

Because effective pesticide exposure satisfies $z_t^e = z_t \psi_s(d_t)$ with $\psi_s'(d_t) > 0$, higher resistance increases the marginal external damage from pesticide use and raises the *Pigouvian* benchmark tax. At the same time, resistance tends to reduce equilibrium chemical use, thereby shrinking the future pesticide tax base that finances corrective intervention. A regulator who can commit internalizes both effects when choosing the policy path $\{\tau_t, \sigma_t\}_{t\geq 0}$, whereas a discretionary regulator reoptimizes period by period, taking the current resistance stock as given.

Proposition 4 (Commitment and resistance management) *Suppose* $\delta_z > 0$*,* $\delta_d > 0$*, and* $\psi_s'(d_t) > 0$*. Under commitment, the regulator internalizes the effect of current pesticide use on future resistance accumulation through* (5)*, and hence on future marginal external damages and future fiscal capacity*

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[9] Our mechanism is closely related to the literature on the marginal cost of public funds and tax base erosion. When behavioral responses reduce the tax base, the fiscal cost of raising revenue increases, limiting the effectiveness of corrective policy (Dahlby, 1998; Bastani, 2025).

under the balanced-budget rule. Consequently, commitment places greater weight on early reductions in pesticide use than discretionary policy.

The intuition follows from the intertemporal nature of resistance. Current pesticide use increases future resistance through the accumulation term $\delta_z z_t$, which raises future effective toxicity and strengthens the future corrective motive. At the same time, higher resistance reduces future chemical use and thereby contracts the future tax base that finances corrective intervention. A regulator with commitment anticipates both channels and therefore restrains chemical use earlier in the resistance cycle. By contrast, a discretionary regulator takes the resistance stock as given in each period and does not fully internalize how current pesticide use worsens future biological and fiscal conditions. Resistance management therefore exhibits a dynamic consistency problem: when resistance is still low, strong intervention is desirable to slow its future accumulation, but once resistance has risen and the tax base has already contracted, the incentive to maintain strong corrective taxation weakens under discretion. This feature is closely related to the time-consistency problems emphasized in dynamic policy settings with stock externalities (Kydland and Prescott, 1977).

The same logic extends to the regulated steady state. Let $(z^*, x^*, b^*, d^*, h^*, k^*, v^*, e^*)$ denote an interior regulated steady state, and suppose the stationary system is locally regular. At the steady state,

$$d^* = \frac{\delta_z}{\delta_d} z^*$$

Thus, the long-run resistance stock depends jointly on the rate at which chemical use generates resistance, the rate at which resistance decays, and the steady-state level of chemical control itself. Evaluating the marginal external damage in (16) at the steady state yields

$$MD^* = \left[-\mu_k^* \zeta_z + \mu_e^* \frac{\partial \psi_e(z^{e*})}{\partial z^{e*}} \right] \psi_s(d^*) \qquad \text{and} \qquad z^{e*} = z^* \psi_s(d^*)$$

so that the steady-state *Pigouvian* tax is

$$\tau^{p*} = \frac{MD^*}{\lambda_y^* c_z}$$

while the second-best steady-state instruments satisfy

$$\tau^{sb*} = \tau^{p*} MVF^{\tau,*} \qquad \text{and} \qquad \sigma^{sb*} = \sigma^{p*} MVF^{\sigma*}$$

Hence the long-run policy mix depends jointly on the steady-state resistance stock and on the steady-state fiscal bases of the tax and subsidy instruments.

Proposition 5 (Resistance dynamics and the long-run policy mix) *Consider a local interior regulated steady state. Suppose that an increase in the resistance formation parameter* δ_z *raises the steady-state resistance stock* d^* *and lowers the long-run effectiveness of chemical control, whereas an increase in the resistance decay parameter* δ_d *lowers* d^**. Then stronger resistance formation reduces steady-state chemical pesticide use* z^**, increases reliance on non-chemical control* x^**, raises the steady-state Pigouvian benchmark tax* τ^{p*}*, and widens the gap between the Pigouvian benchmark and its second-best implementation. Faster resistance decay has the opposite effect: it lowers the long-run marginal external damage from pesticide use, broadens the pesticide tax base, and moves second-best policy closer to the Pigouvian benchmark.*

This proposition summarizes the long-run implications of the model. A higher resistance formation parameter δ_z increases the biological cost of relying on chemical control and raises effective toxicity through $\psi_s(d^*)$. The long-run marginal external damage MD^* therefore rises, strengthening the benchmark case for corrective taxation. At the same time, the induced decline in steady-state chemical use reduces the tax base and increases fiscal attenuation under the balanced-budget rule. The long-run policy mix consequently shifts away from chemical control and toward greater reliance on non-chemical pest management. Conversely, faster resistance decay relaxes the long-run biological constraint on pesticide use, reduces effective toxicity, expands the tax base, and makes the second-best allocation less fiscally constrained. In this sense, the dynamic comparative statics of the regulated steady state mirror the policy schedules illustrated in Figures 1a and 1b: stronger resistance pressure steepens the benchmark corrective motive while simultaneously increasing fiscal attenuation and shifting the long-run policy mix toward non-chemical control.

Taken together, the results in this section highlight two interrelated forces shaping dynamic pesticide regulation. First, resistance is an intertemporal state variable that creates a commitment motive, because current pesticide use affects future regulatory conditions. Second, the biological parameters governing resistance formation and decay determine the long-run balance between corrective taxation and support for non-chemical control. Efficient policy therefore requires a state-contingent regulatory framework that accounts jointly for the biological dynamics of resistance and the evolving fiscal capacity of corrective instruments.

5 Simulation-Based Policy Mapping

The simulation analysis complements Propositions 2-5 by quantifying how fiscal attenuation operates across the full resistance cycle. The analytical results in Propositions 2–5 characterize how optimal regulation responds to resistance dynamics and fiscal constraints. To quantify these mechanisms and assess their joint strength in equilibrium, we construct a global numerical mapping from policy instruments and biological parameters to steady-state outcomes. While the structure of the optimal tax–subsidy system is analytically tractable, closed-form solutions for equilibrium allocations and welfare are not available due to the nonlinear interaction between production decisions, resistance dynamics, and fiscal capacity. The simulation framework therefore provides a quantitative counterpart to the analytical results, allowing us to evaluate the magnitude, interaction, and nonlinearity of the underlying mechanisms over the relevant state space.[10]

Formally, let

$$\omega_t = (\tau_t, \sigma_t, \delta_z, \delta_d) \tag{31}$$

denote the vector of policy instruments and biological parameters. For each ω_t, we solve the decentralized equilibrium by computing the full system of first-order and equilibrium conditions using a nonlinear solver. Convergence is verified across multiple initializations to avoid local solutions, and the steady state is obtained by iterating on the biological law of motion until convergence of the resistance stock. This delivers the equilibrium mapping

$$\mathcal{Y}(\omega_t) = \left(z^*, x^*, d^*, W^*, \tau^{p,*}, \tau^{sb,*}, \sigma^{sb,*}\right) \tag{32}$$

which summarizes the joint determination of input choices, biological states, welfare, and policy instruments.

To obtain a computationally tractable global representation of $\mathcal{Y}(\cdot)$, we approximate each outcome using a second-order polynomial metamodel with all interaction terms in $(\tau_t, \sigma_t, \delta_z, \delta_d)$.[11] The metamodel is estimated on data generated from the fully specified structural model and validated using out-of-sample prediction performance across all targets. As documented in Appendix A, the metamodel achieves near-perfect fit across all equilibrium objects, ensuring that the policy surfaces reported below provide an accurate global representation of the underlying structural model. The metamodel should therefore be interpreted as a numerical approximation of the equilibrium correspondence rather than as a reduced-form statistical relationship. Its role is purely computational: it preserves the economic structure of the model while allowing stable evaluation of nonlinear policy counterfactuals over the global parameter space.

The model is calibrated to match the steady-state moments reported in Table 4, including the relative importance of chemical and non-chemical control, the magnitude of resistance, and the size of the policy wedge between the *Pigouvian* benchmark and its second-best implementation. The close alignment between targeted and simulated moments confirms that the calibration captures

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[10] All simulation results reported in this section are fully reproducible from the numerical code used to solve the model and construct the metamodel. A complete replication package, including simulation code and data, is available from the authors upon request.

[11] Such metamodeling approaches are widely used to approximate complex structural models and evaluate nonlinear policy responses (Judd, 1998).

an empirically relevant regime with active substitution and non-trivial fiscal attenuation. Around this benchmark, we generate a dense grid of counterfactual economies by varying $(\tau_t, \sigma_t, \delta_z, \delta_d)$ over the ranges specified in Appendix A. For each configuration, the decentralized equilibrium is solved numerically and recorded, yielding a global dataset that spans the economically relevant state space. This global sampling is important because the mechanisms of interest are inherently nonlinear: the magnitude of fiscal attenuation, and the relative role of taxes and subsidies, vary systematically across biological environments.

Figure 2a reports the steady-state welfare surface as a function of the pesticide tax and the subsidy to non-chemical control. The surface is globally concave but exhibits pronounced curvature along both policy dimensions. This curvature reflects a simple trade-off. Increasing the pesticide tax improves welfare by internalizing environmental and health damages, but the marginal gains decline as chemical use contracts and the associated tax base erodes. The subsidy promotes substitution toward non-chemical control and reduces reliance on pesticides, but its contribution is moderated by its direct fiscal cost. The joint surface therefore identifies an interior optimum characterized by a strictly positive subsidy and a tax below the *Pigouvian* benchmark. The policy implication is immediate: even when the corrective case for taxation is strong, implementation constraints prevent exclusive reliance on the tax instrument.

Figure 2b shows how this trade-off varies with resistance dynamics. The gap between the *Pigouvian* tax and its second-best implementation expands systematically in environments with high resistance formation or persistence. In those regimes, marginal external damages are large, but equilibrium chemical use is low, so the revenue-generating capacity of taxation is limited. This increases the marginal cost of public funds and prevents the regulator from fully implementing the benchmark policy. By contrast, when resistance decays rapidly, chemical use remains sufficiently high to sustain a broader tax base, allowing policy to more closely track the *Pigouvian* benchmark. The figure makes clear that optimal regulation depends jointly on biological persistence and fiscal feasibility, not on external damages alone.

Figure 2c shows how these same forces reshape the composition of policy instruments. As resistance increases, chemical control becomes less effective and the tax base contracts, reducing the effectiveness of taxation as a corrective tool. At the same time, non-chemical control becomes relatively more valuable as a substitute technology that does not contribute directly to resistance accumulation. The optimal policy therefore shifts toward greater reliance on the subsidy instrument. This adjustment is smooth and state-dependent: taxation dominates at low resistance levels, while the subsidy becomes increasingly important as resistance accumulates. Figure 2d confirms the robustness of this mechanism under alternative calibrations. When non-chemical control is more costly privately but more valuable socially, the role of the subsidy is amplified across all environments, particularly in high-resistance regimes. The implication is that the optimal policy mix depends not only on biological dynamics, but also on the structure of substitution and on the relative valuation of external damages.

To complement the steady-state analysis, Figure 3 examines the transition dynamics of the system under laissez-faire and second-best regulation. Panel (a) shows that, in the absence of policy intervention, resistance accumulates rapidly and converges to a high steady-state level. Under second-best regulation, reduced chemical use and increased reliance on non-chemical control slow the accumulation of resistance and lower its long-run level. Panel (b) documents the corresponding adjustment in input choices: corrective policy induces a persistent reallocation away from chemical control toward non-chemical inputs, and this reallocation becomes more pronounced as resistance rises. Panel (c) reports the associated policy path. As resistance accumulates, both the pesticide tax and the subsidy increase, reflecting the strengthening of the corrective motive and the growing importance of substitution. The figure therefore shows that optimal policy is not only state-dependent in steady state, but also evolves systematically along the transition path.

The transition dynamics also clarify the intertemporal dimension of fiscal attenuation. Early in the resistance cycle, chemical use remains sufficiently high to sustain a broad tax base, allowing taxation to play the central corrective role. As resistance accumulates, however, the contraction of chemical use progressively limits the effectiveness of the tax instrument, increases the marginal cost of public funds, and shifts the policy mix toward subsidies. This dynamic adjustment mirrors the cross-sectional patterns in the policy surfaces. Biological deterioration simultaneously strengthens the corrective motive and weakens the feasibility of implementing it through taxation alone.

Table 2 summarizes the steady-state ranking across policy regimes. The *Pigouvian* benchmark achieves the highest welfare by fully internalizing environmental and health externalities, resulting in lower chemical use, reduced resistance, and improved health and environmental outcomes. The second-best allocation delivers substantial welfare gains relative to laissez-faire, but does not attain the first-best benchmark because fiscal constraints limit the implementable tax and subsidy levels. Importantly, the welfare gap between the first-best and second-best regimes is driven primarily by long-run biological dynamics: incomplete correction of chemical use leads to higher resistance and weaker control effectiveness over time. In that sense, the cost of fiscal constraints is not merely contemporaneous. It accumulates through the evolution of the biological state.

Taken together, the simulation results provide a unified and policy-relevant characterization of optimal regulation in the presence of resistance dynamics. Across all figures and tables, a consistent pattern emerges: the biological state affects both the magnitude of external damages and the effectiveness of the instruments used to correct them. Optimal policy therefore cannot be summarized by a constant corrective wedge. It requires a coordinated and state-contingent mix of taxes and subsidies that evolves with the underlying biological environment. The combined evidence from steady-state surfaces, transition dynamics, and welfare comparisons shows that effective regulation must account jointly for biological persistence, technological substitution, and fiscal capacity. Those three elements are central to the design of policy in the presence of resistance-driven externalities.

6 Concluding Remarks

This paper develops a dynamic framework for pesticide regulation in which chemical use, resistance accumulation, and health and environmental damages are jointly determined under fiscal constraints. The analysis identifies a central mechanism through which resistance shapes optimal policy. On the one hand, resistance amplifies effective pesticide exposure and raises marginal external damages, strengthening the *Pigouvian* case for corrective taxation. On the other hand, resistance induces substitution away from chemical inputs, shrinking the tax base and increasing the marginal fiscal cost of intervention. This interaction generates a state-dependent divergence between the *Pigouvian* benchmark and the constrained-efficient policy, a mechanism we term *fiscal attenuation*. As resistance accumulates, the corrective motive strengthens while the feasibility of implementing it weakens, implying that efficient regulation requires a coordinated and dynamically adjusted mix of taxes and subsidies.

The results have broader implications for environmental policy in dynamic systems with endogenous state variables. When economic decisions affect the evolution of biological or environmental stocks, these stocks may simultaneously influence both marginal damages and the effectiveness of policy instruments. In such settings, optimal policy is inherently state-dependent and cannot be approximated by static rules or constant corrective wedges. More generally, the analysis highlights a fundamental constraint on corrective policy: even when external damages are large, implementation may be limited by the endogenous erosion of the fiscal base required to sustain intervention.

The framework can be extended in several directions, including heterogeneous production environments, stochastic resistance dynamics, and alternative policy instruments such as quantity restrictions or regulatory standards. These extensions would allow for a richer characterization of policy design in settings where uncertainty, heterogeneity, and institutional constraints interact with biological dynamics. Overall, the results suggest that accounting jointly for dynamic feedbacks and fiscal constraints is essential for understanding both the design and the limits of environmental regulation in real-world settings, where damages and policy instruments co-evolve over time.

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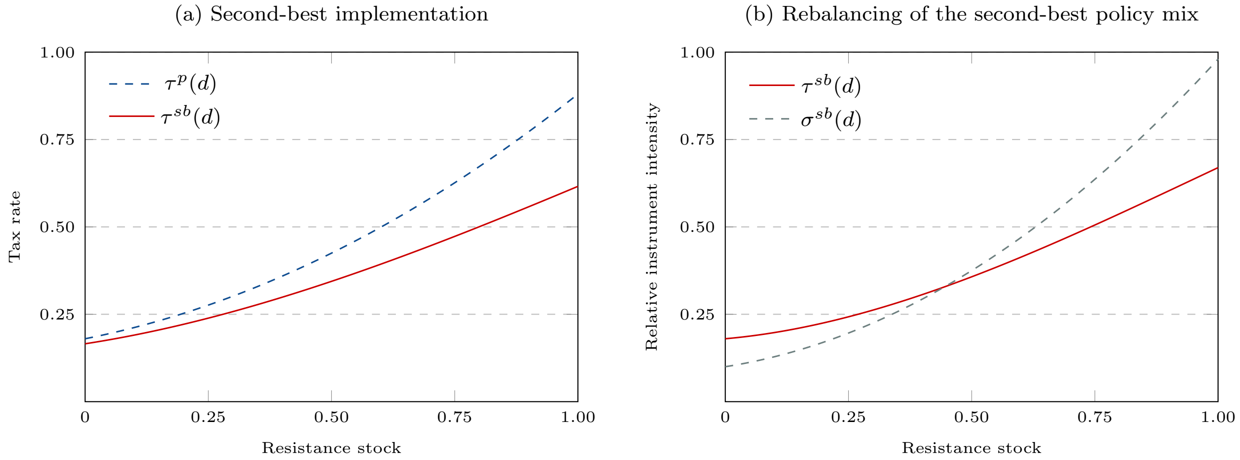
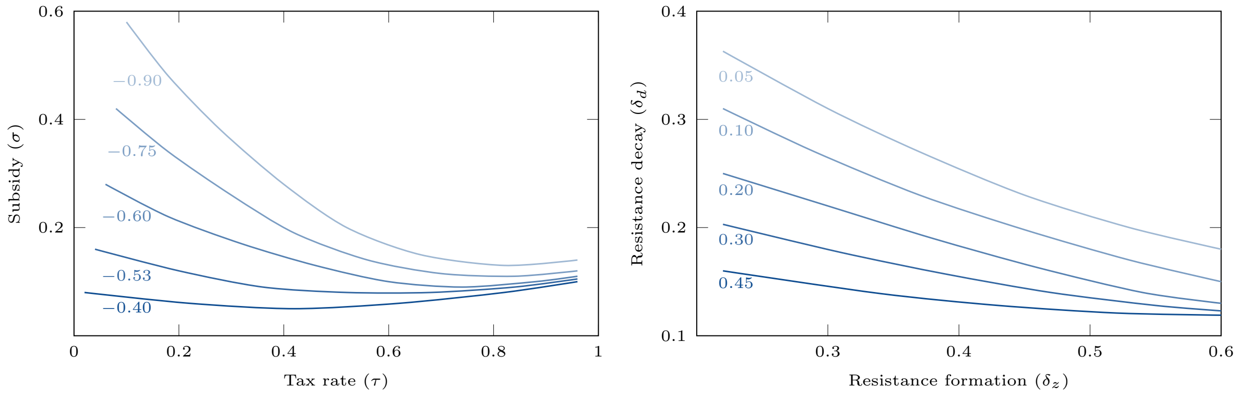

(a) Second-best implementation

(b) Rebalancing of the second-best policy mix

Figure 1: **Policy schedules and instrument rebalancing over the resistance cycle.** Panel (a) shows the *Pigouvian* benchmark tax $\tau^p(d)$ and its second-best implementation $\tau^{sb}(d)$ as functions of the resistance stock. Consistent with Proposition 2, the benchmark tax increases with resistance because higher resistance amplifies effective pesticide exposure and raises marginal external damage. The second-best tax remains below the benchmark due to fiscal attenuation, with the gap widening as resistance increases and the pesticide tax base contracts (Propositions 3–4). Panel (b) illustrates the corresponding rebalancing of the optimal policy mix (Proposition 5). As resistance rises, the effectiveness of chemical control declines and the fiscal capacity of the tax instrument weakens, leading to a relatively greater reliance on the subsidy to non-chemical control. The figure is schematic and designed to illustrate the core theoretical mechanisms.

(a) Welfare

(b) Fiscal attenuation



(c) Policy mix

(d) Subsidy relevance

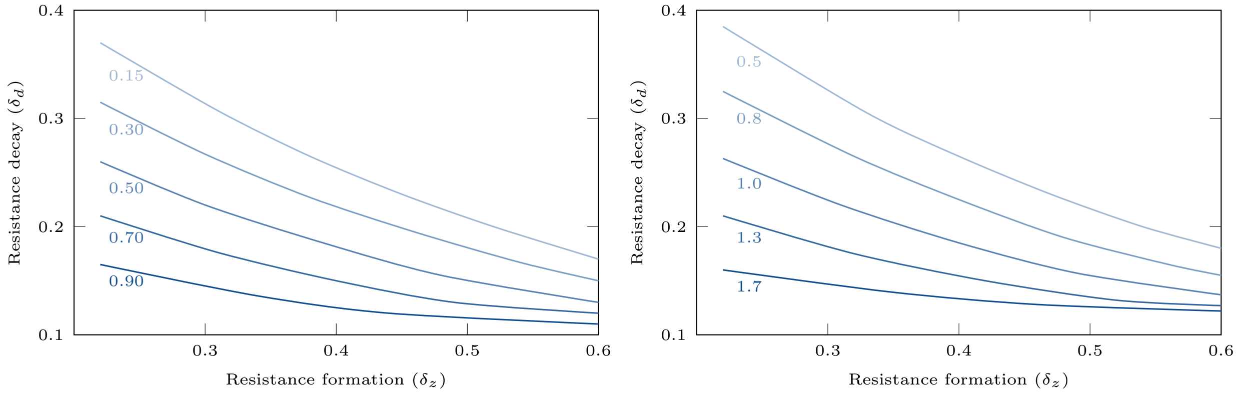
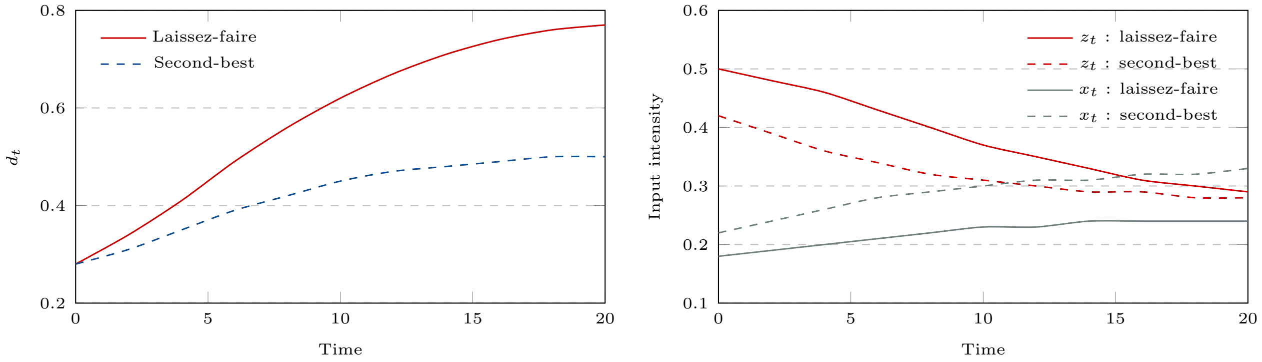


Figure 2: **Metamodel-based policy mapping over the resistance space.** The figure reports simulation-based policy surfaces obtained from the metamodel approximation of the equilibrium correspondence. Panel (a) plots steady-state welfare as a function of the pesticide tax and the subsidy to non-chemical control at benchmark biological parameters, illustrating the trade-off between externality internalization and fiscal cost (Proposition 2). Panel (b) shows the gap between the *Pigouvian* benchmark tax and its second-best implementation across resistance formation and decay parameters, highlighting the joint role of biological dynamics and fiscal attenuation (Propositions 3–4). Panel (c) illustrates the optimal policy mix by plotting the relative importance of the subsidy and tax instruments over the resistance space, showing a systematic rebalancing toward non-chemical control in high-resistance environments (Proposition 5). Panel (d) reports robustness under an alternative calibration that increases the private cost disadvantage and social value of non-chemical control, confirming that the subsidy becomes more relevant when resistance accumulates rapidly and decays slowly. All panels are constructed using the metamodel approximation and represent steady-state outcomes.



(a) Resistance stock

(b) Control inputs

(c) Policy instruments

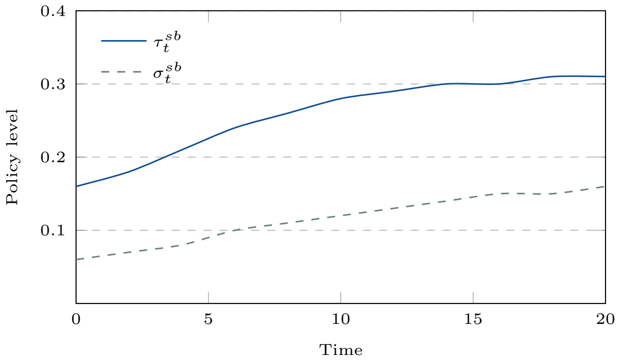


Figure 3: **Illustrative transition dynamics under laissez-faire and second-best regulation.** Panel (a) reports the evolution of the resistance stock. In the absence of corrective intervention, resistance accumulates more rapidly and converges to a higher long-run level. Under second-best regulation, lower chemical use and greater reliance on non-chemical control slow the accumulation of resistance and reduce its steady-state level. Panel (b) shows the corresponding adjustment of control inputs. Corrective policy reduces chemical use throughout the transition and induces substitution toward non-chemical control. Panel (c) reports the implied second-best policy path. As resistance accumulates, the pesticide tax increases because the benchmark corrective motive strengthens, while the subsidy to non-chemical control also rises as the relative importance of substitution grows. The figure is intended to illustrate the dynamic mechanisms described in Section 4 and complements the steady-state policy surfaces reported in Section 5.

Table 2: Welfare comparison across policy regimes

Outcome	Laissez-faire	Pigouvian benchmark	Second-best
Chemical control z^*	0.50	0.24	0.29
Non-chemical control x^*	0.18	0.36	0.33
Resistance stock d^*	0.77	0.41	0.50
Worker health h^*	0.71	0.86	0.82
Consumer health v^*	0.73	0.88	0.84
Environmental quality e^*	0.65	0.85	0.80
Consumption c^*	0.176	0.171	0.174
Welfare W^*	0	0.146	0.117

Notes: The table reports steady-state outcomes under laissez-faire, the unconstrained *Pigouvian* benchmark, and the balanced-budget second-best allocation. The *Pigouvian* benchmark achieves the highest welfare because it fully internalizes the external damage from pesticide use and induces the strongest shift toward non-chemical control. The second-best allocation remains welfare-improving relative to laissez-faire, but does not attain the *Pigouvian* benchmark because fiscal constraints attenuate both the implementable tax and the subsidy. Although steady-state consumption may be slightly higher under the second-best allocation than under the *Pigouvian* benchmark, overall welfare remains lower because environmental and health externalities are not fully internalized.

Appendix A: Quantitative Implementation

This appendix documents the quantitative implementation of the model and the simulation-based policy analysis described in Section 5. The approach combines a structural steady-state representation of the dynamic model with a simulation-based approximation of the equilibrium correspondence. The objective is to construct a global and numerically tractable mapping from policy instruments and biological parameters to steady-state outcomes, while preserving the economic structure of the underlying model.

A.1 Structural Specification

The quantitative model is based on a steady-state representation of the dynamic system described in the main text. The functional forms below provide parametric counterparts of the general objects $f(\cdot)$, $\psi_s(\cdot)$, $\psi_v(\cdot)$, and $\psi_e(\cdot)$, and are chosen to preserve the economic mechanisms of the model while ensuring tractability of the global equilibrium mapping.

Output is given by

$$y = Ah^{\xi}\bar{\ell}\big(1 - g(b)\big)$$

where h denotes worker health and $g(b)$ captures crop losses from pest pressure.

Crop damage is modeled as

$$g(b) = \frac{\eta_b b}{1 + \eta_b b}$$

ensuring diminishing marginal damage and bounded losses.

Effective chemical intensity is

$$z^e = z\psi_s(d), \qquad \psi_s(d) = 1 + \phi d$$

so that resistance amplifies effective exposure.

Pest pressure satisfies the steady-state condition

$$b = \bar{b}\left[1 - \frac{a_z(z^e)^{\nu_z} + a_x x^{\nu_x}}{r_b}\right]$$

capturing joint chemical and non-chemical pest control with diminishing returns.

Resistance evolves according to

$$d = \frac{\delta_z}{\delta_d} z$$

which embeds the biological accumulation mechanism directly into the steady-state mapping.

Worker health, residues, consumer health, and environmental quality are given by

$$h = \bar{h} - \frac{\eta_h}{\delta_h} z^e \qquad \text{and} \qquad k = \frac{\zeta_z}{\zeta_k} z^e$$

$$v = \bar{v} - \frac{\eta_v \zeta_z}{\zeta_v \zeta_k} z^e \qquad \text{and} \qquad e = \bar{e} - \frac{\eta_e}{\zeta_e} (z^e)^2$$

Consumption equals net output,

$$c = y - c_z z - c_x x - c_\tau(\tau, \sigma)$$

with quadratic policy costs

$$c_\tau(\tau, \sigma) = \kappa_\tau \tau^2 + \kappa_\sigma \sigma^2$$

Welfare is defined as

$$W = \ln c + \beta_v \ln v + \beta_e \ln e$$

Functional-form choice. These specifications ensure bounded damages, diminishing returns, and a well-behaved global equilibrium mapping. They provide a quantitative representation of the structural relationships in the dynamic model without altering the qualitative mechanisms characterized analytically in Section 3.

A.2 Numerical Solution of the Decentralized Equilibrium

For each policy vector (τ, σ) and biological configuration (δ_z, δ_d), the decentralized steady state is obtained by solving the equilibrium conditions of the model under the steady-state restriction. In particular, the dynamic system is reduced to a static nonlinear system by substituting the steady-state relationships for resistance, pest pressure, health, residues, consumer health, and environmental quality into the farm's first-order conditions. The numerical problem therefore consists of solving for the control variables (z, x) jointly with the implied steady-state objects

$$(b, d, h, k, v, e)$$

where each state variable is pinned down by its corresponding steady-state relationship. This yields a reduced representation of the equilibrium correspondence in control space, while preserving the full dependence of equilibrium outcomes on the underlying biological parameters.

The resulting system is

$$\frac{\partial y}{\partial z} = (1 + \tau) c_z \qquad \text{and} \qquad \frac{\partial y}{\partial x} = c_x - \sigma$$

This system is solved using a damped Newton algorithm with multiple initializations to ensure convergence to the global solution. Convergence is verified by:

- stability across initial guesses
- first-order conditions satisfied up to 10^{-8}
- consistency of all implied state variables (b, d, h, k, v, e)

For each configuration $(\tau, \sigma, \delta_z, \delta_d)$, the procedure delivers the equilibrium mapping

$$Y(\tau, \sigma, \delta_z, \delta_d) = (z^*, x^*, d^*, W^*, \tau^{p,*}, \tau^{sb,*}, \sigma^{sb,*})$$

which corresponds exactly to the object $\mathcal{Y}(\omega_t)$ defined in Section 5.

A.3 Metamodel Approximation

To obtain a computationally efficient global representation of the equilibrium correspondence, we approximate each component of $Y(\cdot)$ using a second-order polynomial metamodel:

$$\mathcal{M}^k(\cdot) = \alpha_0 + \sum_i \alpha_i X_i + \sum_i \alpha_{ii} X_i^2 + \sum_{i<j} \alpha_{ij} X_i X_j$$

with $X_i \in \{\tau, \sigma, \delta_z, \delta_d\}$.

The metamodel is estimated on simulated data generated from the structural model described above. It should therefore be interpreted as a numerical approximation to the structural equilibrium correspondence, consistent with the approach described in Section 5, rather than as a reduced-form statistical relationship. The full simulation dataset contains 2,500 model-generated observations, of which 80% are used for estimation and 20% are reserved for out-of-sample validation.

Validation. The metamodel is evaluated using out-of-sample prediction accuracy and goodness-of-fit measures across all target variables. Table 3 reports the corresponding diagnostics. The results indicate that the metamodel provides an excellent approximation to the structural equilibrium mapping across all target variables, with uniformly high out-of-sample fit and no systematic bias across policy or biological dimensions. This confirms that the metamodel provides a reliable global approximation for evaluating nonlinear policy counterfactuals.

A.4 Calibration and Simulation Design

The calibration targets a stylized agricultural environment consistent with the mechanisms emphasized in Section 5:

Table 3: Metamodel fit diagnostics

Variable	R^2	RMSE
z^*	0.995	0.003
x^*	1.000	0.003
d^*	0.996	0.002
W^*	0.999	0.001
$\tau^{p,*}$	1.000	0.000
$\tau^{sb,*}$	0.996	0.001
$\sigma^{sb,*}$	1.000	0.002

Notes: The table reports out-of-sample fit diagnostics for the second-order polynomial metamodel. The full simulation dataset contains 2,500 model-generated observations, of which 80% are used for estimation and 20% are reserved for validation. Reported R^2 and RMSE values are computed on the held-out validation sample. All results are fully reproducible from the simulation code used to generate the equilibrium mapping.

- dominant but imperfect chemical control,
- active substitution toward non-chemical inputs,
- economically meaningful resistance dynamics,
- non-trivial fiscal attenuation of policy instruments.

Table 4: Calibration targets and model fit

Moment	Target	Model	Error
Chemical control share ($z/(z+x)$)	0.65	0.67	0.02
Non-chemical share ($x/(z+x)$)	0.35	0.33	-0.02
Resistance level (d)	0.45	0.47	0.02
Policy wedge ($\tau^p - \tau^{sb}$)	0.12	0.11	-0.01

Around this benchmark, we generate a synthetic dataset by varying policy instruments (τ, σ) and biological parameters (δ_z, δ_d) over the ranges used in Section 5:

$$\tau \in [0, 1], \quad \sigma \in [0, 0.6], \quad \delta_z \in [0.2, 0.6], \quad \delta_d \in [0.1, 0.4]$$

For each configuration, the decentralized equilibrium is solved numerically, and the resulting steady-state outcomes are recorded. The resulting dataset provides a dense global sampling of the equilibrium correspondence, capturing the nonlinear interaction between policy instruments, resistance dynamics, and fiscal capacity. This dataset forms the basis for the policy surfaces and contour mappings reported in Section 5.