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Specification of Spatial-Dynamic Externalities and Implications for Strategic Behavior in Disease Control

Shady S. Atallah, **Department of Natural Resources and the Environment,
University of New Hampshire, Durham NH 03824, USA
E-mail: shady.atallah@unh.edu**

Miguel I. Gómez, **Dyson School of Applied Economics and Management,
Cornell University, Ithaca NY 14853, USA
E-mail: mig7@cornell.edu**

Jon M. Conrad, **Dyson School of Applied Economics and Management,
Cornell University, Ithaca NY 14853, USA
E-mail: jmc16@cornell.edu**

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ABSTRACT

We propose a novel, distance- and density-dependent specification of externalities that captures spatial dynamics within and between neighboring land parcels. We apply the problem to the short- and long-distance diffusion and control of an infectious disease in two privately-owned and ecologically-connected vineyards. Using computational experiments to generate individual and aggregate payoffs, we show how strategic behavior affects diffusion of the disease and the expected present value of the resulting externality. Our results suggest that ignoring the within-parcel spatial dynamics in the model overestimates the social cost of an externality compared to a model that focuses on inter-parcel spatial dynamics only. We find a U-shaped relationship between manager heterogeneity and aggregate payoffs in the presence of an externality, suggesting both positive and negative impacts of increased heterogeneity on strategic behavior and welfare.

Keywords: Bioeconomic models; Computational methods; Disease control; Grapevine Leafroll Disease; Noncooperative games; Spatial-dynamic externalities.

1. Introduction

The economic research on externalities in natural resource problems has increasingly paid attention to the dynamic and spatial characteristics of the biophysical processes generating these externalities. Such processes often cause damages thanks to their ability to cross the boundaries of privately-owned properties. Consequently, a natural assumption is that space matters in that it

defines exposure to risk and private incentives to manage externalities based on location with respect to property boundaries. For instance, the spatial heterogeneity driving the generation of externalities and the strategic choices to control them can be defined by a land parcel's position on the boundary or the interior of a grid (Rich, Winter-Nelson, and Brozovíc 2005a, 2005b; Albers, Fischer, and Sanchirico 2010; Epanchin-Niell and Wilen 2012, 2015; Aadland, Sims, and Finnoff 2015). However, spatial modeling of externalities often assumes that externalities only matter at the boundaries between private properties (i.e., where one parcel ends and another parcel begins). We argue that spatial considerations within a land parcel may also affect how externalities are generated and the private incentives to manage them. Recent advancements in computational methods and processing allow researchers to investigate within-parcel spatial dynamics to shed light on the individual incentives that might trigger the generation of externalities.

We propose a novel, distance- and density-dependent specification of externalities that captures spatial dynamics within and between neighboring land parcels. We apply the problem to the diffusion and control of an infectious disease in two privately-owned and ecologically-connected vineyards. In our model, two vineyard managers maximize the expected net present values of their vineyards by choosing a disease control strategy from a discrete set of strategies. We use computational experiments to generate payoffs and show how strategic behavior affects diffusion of the disease and the expected present value of the resulting externality. Our results suggest that an externality model that focuses on inter-parcel spatial dynamics overestimates the social cost of an externality compared to a model that accounts for within-parcel spatial dynamics as well. We take advantage of our model's specification to explore the relationship between manager heterogeneity and welfare in the presence of an externality. We find that the

4

relationship is U-shaped, suggesting both positive and negative impacts of increased heterogeneity on strategic behavior and aggregate payoffs.

2. Contributions to the literature

There is a considerable amount of recent work on spatial dynamic externalities using different theories and models. Most studies use metapopulation models to allow for spatial interaction between adjacent 'grids' representing habitat patches, forest stands, or land parcels, without considering the within-grid population spatial dynamics (Brown and Roughgarden, 1997; Swallow and Wear 1993; Konoshima et al. 2009; Bhat and Huffaker 2007; Horan et al. 2005; Sanchirico and Wilen 1999). Other studies employ grid-based models, and also ignore within-grid spatial dynamics (Rich, Winter-Nelson, and Brozovíc, 2005a, 2005b; Epanchin-Niell and Wilen, 2012, 2015; Aadland, Sims, and Finnof, 2015). Throughout this literature, one trend has involved representing externality problems on ever larger grids by progressing from two-patch models to NxN grid models. However, throughout this progression, spatial exposure risk remains affected by border considerations only, and not by within-parcel spatial heterogeneity and within-parcel spatially heterogeneous control. These models exclude situations where bio-economic spatial dynamics contribute to the tradeoffs a manager faces within his parcel, and consequently determine his private strategic behavior and the ensuing generation of externalities over the entire landscape. For example, strategic disease control choices in Rich, Winter-Nelson, and Brozovíc (2005a, 2005b) are conditioned by a manager's position on a grid's border or a grid's interior but not on other measures of spatial disease dynamics within the grid. In Epanchin-Niell and Wilen (2012, 2015), the value of containing a biological invasion differs across parcels based on their location in space only, which is defined in relation to the landscape

5

boundaries. Similarly, in Aadland, Sims, and Finnoff (2015)'s forest grid, the spatial heterogeneity driving the generation of pest externalities is defined by a cell's position on either the boundary or the interior of the grid. Likewise, exposure risk to a biological invasion in Albers, Fischer, and Sanchirico (2010) depends on whether a region is located inland or in a port.

While these binary considerations of space are adequate to study essential aspects of the private and collective management of externalities, they do not allow for understanding the private behavior, within a parcel, that might initially generate the externality or hinder its collective management. In the models cited above, managers do not face spatial-dynamic temporal trade-offs in effort allocation within their parcels. Examining the impact of both within-parcel and inter-parcel spatial dynamics on private behavior and the generation of externalities requires new distance- and density-dependent specifications that build on the features of metapopulation models, cellular automata, and spatial games. Such specifications can help test whether within-parcel spatial dynamics, with measures of spatial heterogeneity that go beyond border considerations, are also important for the production of externalities and for the incentives to manage them.

The first contribution of this paper is to propose a novel, distance- and density-dependent specification of externalities that includes short and long-distance dispersal mechanisms capable of modeling a manager's risk spatial endogeneity beyond the adjacent parcel. This specification is derived by explicitly modeling the biophysical processes generating the spatial dynamics using an approach that combines metapopulation and cellular automata models. Definitions of spatial connectivity in some of the models in the literature allow managers to take into account the implications of their actions on the adjacent land, thereby allowing for spatial-endogenous risk (Aadland et al. 2015; Epanchin-Niell and Wilen 2015; Konoshima et al. 2008). However, due to

the focus on inter-parcel spatial dynamics and concerns over model tractability and computational complexity, in these models, a manager's endogeneity of spatial risk is limited to adjacent cells and cannot span the entire landscape. That is, in such models, a manager ignores how current management affects payoffs through multi-cell dispersal (Aadland, Sims, and Finnoff, 2015), or views his site's state as exogenous and solves for temporally and spatially myopic optimal strategies (Epanchin-Niell and Wilen 2015). Aadland, Sims, and Finnoff (2015) characterize this modeling challenge as one of accurately representing the scale mismatch between management and dispersal. Representing this scale mismatch can be done by (1) combining metapopulation and cellular automata models; and (2) adding a power-law, long-distance dispersal (LDD) (Marco, Montemurro, and Cannas 2011) to the more common short-distance dispersal (SDD) mechanism representing the biophysical process in question. Such specification of the distance- and density-dependent externality with SDD and LDD, allows endogenizing spatial risk over the entire landscape. Managers can then take into account how their individual, within-grid control decisions might affect the generation of an externality and the resulting damages at the landscape level.

The second contribution is to examine the relationship among manager heterogeneity, strategic behavior, and aggregate payoffs. Previous literature has addressed some combination of these three elements. Kovacs et al. (2014) introduce heterogeneity in municipal jurisdiction access to the resource at risk, resource value, budgets, and costs. Albers, Fisher, and Sanchirico (2010) compare spatially heterogeneous and spatially uniform policies of invasive species control. Fenichel, Richards, and Shanafelt (2014) consider heterogeneity in managers' property values. Their model predicts that managers of more valuable properties will be more aggressive in their pest control. They note that control in their case is a strategic complement and is

7

therefore not likely to be characterized by free-riding. Bhat and Huffaker (2007) consider strategic interaction among managers that is driven by the possibility of free riding, breach, and the potential need for cooperative agreement renegotiation over time. Free-riding is inherent to their population dynamics where nuisance wildlife moves from the unmanaged to the managed land. Rich, Winter-Nelson, and Brozović (2005a) consider two types of agents in their models, *High* and *Low*, which are heterogeneous in terms of production technology endowments and whose strategic choices are conditioned by their position in space. They find that heterogeneity among neighboring agents accelerates the progression to the less socially desirable outcome (low disease control effort), in contrast to more socially-desirable outcomes that are achieved when agents are homogenous. In this paper, we consider heterogeneity in resource value and its effect on strategic behavior and welfare. We use mean-preserving expansions and contractions in the natural resource value to explore a wider range of heterogeneity, as opposed to two heterogeneity levels. We re-solve the problem for seven values of heterogeneity. For each level of heterogeneity, we study the noncooperative strategic behavior of managers under simultaneous and sequential move settings. We also consider how cooperation might affect the relationship between heterogeneity and welfare.

The remainder of the paper is organized as follows. Section 3 introduces the spatial structure, the detailed biophysical process, and the economic model depicting the problem facing each vineyard manager. In addition, it specifies the cell-level diffusion model as a Markov Chain process generating the externality within and between two grids (vineyard plots) constituting a network (the landscape). Section 4 describes the computational experiments, the spatial and nonspatial control strategies available to each manager, and the solution frameworks and concepts. Section 5 presents the solutions to social planner, cooperative, and noncooperative

8

settings and highlights the welfare implications of the proposed externality specification. This section also presents dynamic sensitivity analyses and a discussion of the effect of manager heterogeneity on strategic behavior and total payoffs. Section 6 presents conclusions and highlights the value of distance- and density-dependent specifications when modeling the generation and management of spatial-dynamic externalities.

3. A model of externality diffusion and control

Our model considers two managers whose production processes are spatially connected on a network, composed of the combination of two independently managed sub-networks, or grids. In particular, we consider the case of two vineyard managers whose vines are linked through the short- and long-distance diffusion of the grapevine leafroll disease. This is a vector-transmitted viral disease that reduces the yield and quality of grapes and threatens vineyards worldwide. For notation purposes, vineyard H produces high-valued wine grapes while vineyard L produces low-valued wine grapes. Thus the manager of vineyard L has lower private incentives to control the disease. Each manager's action to control the disease determines his payoffs and the payoffs of the other manager because they are connected through a biophysical network; the actions of each of them have spatial and dynamic consequences for the neighboring vineyard.

Grid G_H represents vineyard H and is the set of $I*J$ cells denoted by their row and column position (i, j). Each cell (i, j) represents a grapevine. Similarly, grid G_L represents vineyard L and consists of $M*N$ cells denoted by their row and column position (m, n). Each grapevine is modeled as a cellular automaton that updates its age and infection states in discrete time steps (t) based on the infection state of its immediate neighbors and on the long-distance dispersal from the neighboring vineyard. Each vine's infection state transitions are governed by a Markov Chain

model. An externality emerges when the privately optimal management strategy in one vineyard causes the disease to spread to the neighboring vineyard. We first describe the managers' private maximization problem; and subsequently we explore a Nash bargaining game.

3.1. Economic model

Each manager's objective is to maximize the expected net present value (*ENPV*) of his vineyard by choosing a disease control strategy from a discrete set of strategies, $\mathcal{W}$, available to manage the disease.[1] According to each strategy, the manager decides, for each vine (i, j) in each period t of T discrete periods of time, whether or not to remove and replant ($u_{w_{i,j,t}} = 1$ if removal and replanting takes place, 0 otherwise), test for the virus ($v_{w_{i,j,t}} = 1$ if virus testing takes place, 0 otherwise), or remove without replanting ($z_{w_{i,j,t}} = 1$, if removal without replanting take place, 0 otherwise). The manager's disease control decisions are based on a vine's age state $\boldsymbol{a}_{i,j,t}$ and its infection state $\boldsymbol{s}_{i,j,t}$, or equivalently, its composite age-infection state $\boldsymbol{w}_{i,j,t}$. In the case of within-grid (i.e., in the same vineyard), spatial disease control strategies, the manager's decisions are also based on the state of vines in neighboring cells.

The optimal strategy $\mathcal{W}^*$ is the sequence of cell-level control variables $\{u_{w_{i,j,t}}, v_{w_{i,j,t}}, z_{w_{i,j,t}}\}$ that allocates disease control effort over space and time so as to yield the maximum *ENPV*. Let E be the expectation operator over the random cell-level (i.e., vine), revenue $r_{w_{i,j,t}}$, and ρ^t the discount factor, where $t \in \{0, 1, 2,\ldots, 600 \text{ months}\}$. The objective of a vineyard manager is to

$$\max_{\mathcal{W}} \mathrm{E} \ \textstyle\sum_{t \in T} \rho^t \sum_{(i,j) \in G} \left\{ \begin{array}{c} r_{w_{i,j,t}} * \left(1 - \sum_{\tau=0}^{\tau_{max}} u_{w_{i,j,t-\tau}}\right) * \left(1 - z_{w_{i,j,t}}\right) \\ -\sum_{\tau=0}^{\tau_{max}} \left(u_{w_{i,j,t-\tau}} * c_{u_{i,j}}\right) - \left(v_{w_{i,j,t}} * c_{v_{i,j}}\right) - \left(z_{w_{i,j,t}} * c_{z_{w_{i,j,t}}}\right) - c_{i,j} \end{array} \right\} \quad (1)$$

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[1] The problems faced by the two managers differ only in their initial conditions and bioeconomic parameters. We therefore describe the model using the notation of one of them only, namely G_H.

subject to

$$E(\boldsymbol{s}_{i,j,t+1}) = \boldsymbol{P}^{\mathrm{T}} \boldsymbol{s}_{i,j,t}, \tag{2}$$

where Eq. (2) is the cell-level infection state transition equation and $\boldsymbol{P}^{\mathrm{T}}$ is the transpose of the infection state transition matrix $\boldsymbol{P}.$

The objective function accounts for the total amount, the timing and the location of control effort. If a vineyard manager decides to remove and replant a vine in cell (i, j) in period t - τ_{max}, then $u_{w_{i,j,t-\tau}}$ is equal to 1 and the revenue (first expression in Eq. 1) is multiplied by zero for periods $t - \tau + 1, t - \tau + 2,\ldots, t - \tau + \tau_{max}$, where τ_{max} is the time it takes from planting to fruit bearing . If a vineyard manager decides to remove a vine without replanting ($z_{w_{i,j,t}} = 1$), the revenue from the cell corresponding to this vine equals zero from t to T. The second expression in Eq. (1) has the cost of removal-and-replanting ($c_{u_{i,j}}$), the cost of testing ($c_{v_{i,j}}$), and the cost of removal-without-replanting ($c_{z_{i,j}}$), all pre-multiplied by their corresponding binary decision variables. The expression also includes vine-level operating costs ($c_{i,j}$), which are grid-level operating costs divided by the number of cells.

Per-vine revenue, $r_{w_{i,j,t}}$, depends on the infection and age states of each cell. Revenue is zero if the vine's age $a_{i,j,t}$ is below τ_{max} (Eq. 3). Beyond that age, $r_{w_{i,j,t}}$, depends on the vine's infection state $\boldsymbol{s}_{i,j,t}$. The disease causes a yield reduction of $\widetilde{y_{S_{i,j,t}}}$, compared to the yield of a healthy vine ($y_{S_{i,j,t}=Healthy}$) with different levels of yield reduction depending on the infection state.[2] In addition, grapes from disease-affected vines are subject to a price penalty $\widetilde{p_{S_{i,j,t}}}$ (Eq. 4)

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[2] Yield from a vine in the *Healthy* state ($y_{S_{i,j,t}=Healthy}$) is obtained by dividing per-acre yield in plot H over the planting density.

when compared to the price paid for grapes harvested from healthy vines ($p_{S_{i,j,t}=Healthy}$). The same description applies to cells (*m, n*) in grid (vineyard) G_L.

$$r_{w_{i,j,t}} = 0 \; if \; a_{i,j,t} < \tau_{max} \tag{3}$$

$$= r_{S_{i,j,t}} \left(y_{S_{i,j,t=H}}, \widetilde{y_{S_{\iota,J,t}}}, p_{S_{i,j,t=H}}, \widetilde{p_{S_{\iota,J,t}}} \right) \; if \; a_{i,j,t} \geq \tau_{max}$$

$$r_{S_{i,j,t}} = y_{(s_{i,j,t}=Healthy)} * \left(1 - \widetilde{y_{S_{\iota,J,t}}} \right) * p_{(s_{i,j,t}=Healthy)} * (1 - \widetilde{p_{S_{\iota,J,t}}}) \tag{4}$$

3.2. Model of spatial-dynamic externality diffusion

The disease can spread within and across vineyards in at least three ways (Charles et al. 2009; Grasswitz and James 2008). First, insect vectors crawling on vineyard wires and fruiting canes (i.e., the grid columns) can cause disease transmission to within-column, neighboring vines. Second, vineyard management activities can facilitate vector dispersal to across-column neighboring vines, within the same vineyard. We refer to these two dispersal mechanisms as short-distance diffusion (SDD). Disease spread between neighboring vineyards can take place through aerial dispersal of insect vectors (Le Maguet et al. 2013). We refer to this third dispersal mechanism as a long-distance diffusion (LDD). All external boundaries are reflecting (i.e., when the disease reaches the boundary of a grid, it might be bounced back inside it according to Eq. 2). The boundary between grids (i.e., the sub-networks) is only reflecting for the SDD process. In contrast, according to the LDD process, the disease can move off one grid along the inter-grid boundary in search of a new host. Atallah et al. (2015) analyzed the two short-distance disease diffusion mechanisms in an isolated vineyard. Because the present model is concerned with externalities and strategic behavior, the disease diffusion in Atallah et al. (2015) is extended by allowing for disease diffusion both within and between two neighboring vineyards. That is, a *Healthy* (*H*) vine in one vineyard transitions to state *Exposed-undetectable* (E_u) with a probability *b* that depends on (1) the number and location of *Infective* vines immediately adjacent

to it; and (2) the distance to and number of *Infective* vines in the neighboring vineyard. The distance and density-dependence of this probability captures the impact of a manager's private disease control actions, within a grid, on the spatial damages borne by his neighbor at the border of and within the adjacent grid. A manager cannot distinguish between states H and E_u until the virus population in a vine reaches detectable levels with probability c, at which point the vine transitions to state *Exposed-detectable* (E_d). A manager can detect state E_d by performing a viral vine test.

Vines transition from state E_d to state *Infective-moderate* (I_m) with probability d, which is largest for young vines than for their older counterparts. Once in this state, vines develop visual symptoms and can act as a source of infection to other vines (i.e., they become infective). Symptoms are moderate at first (*Infective-moderate, I_m*) and transition to a high-severity state (*Infective-high, I_h*) with a probability f. The transition matrix $\boldsymbol{P}$ in Eq. (2) governs short- and long-distance disease diffusion and symptom evolution. It can be expressed as follows:[3]

$$\boldsymbol{P} = \begin{pmatrix} (1-b) & b & 0 & 0 & 0 \\ 0 & 1-c & c & 0 & 0 \\ 0 & 0 & (1-d) & d & 0 \\ 0 & 0 & 0 & (1-f) & f \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{5}$$

In Eq. (5), b can be expressed as:

$$b = \Pr\left(s_{i,j,t+1} = E_u \mid s_{i,j,t} = Healthy\right) \tag{6}$$

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[3]$\boldsymbol{P}$ reads from row (states in period t) to column (states in period $t+1$).

$$
= \begin{cases}
1 - e^{-\gamma_{L,H,t}} & \text{if } s_{N_{i,j,t}} = (NI, NI, NI, NI) \\
1 - e^{-(\beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (NI, NI, I, NI) \\
1 - e^{-(\beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (NI, NI, NI, I) \\
1 - e^{-(2\beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (NI, NI, I, I) \\
1 - e^{-(\alpha + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (I, NI, NI, NI) \\
1 - e^{-(\alpha + \beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (I, NI, I, NI) \\
1 - e^{-(\alpha + \beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (I, NI, NI, I) \\
1 - e^{-(\alpha + 2\beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (I, NI, I, I) \\
1 - e^{-(\alpha + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (NI, I, NI, NI) \\
1 - e^{-(\alpha + \beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (NI, I, I, NI) \\
1 - e^{-(\alpha + \beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (NI, I, NI, I) \\
1 - e^{-(\alpha + 2\beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (NI, I, I, I) \\
1 - e^{-(2\alpha + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (I, I, NI, NI) \\
1 - e^{-(2\alpha + \beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (I, I, I, NI) \\
1 - e^{-(2\alpha + \beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (I, I, NI, I) \\
1 - e^{-(2\alpha + 2\beta + \gamma_{L,H,t})} & \text{if } s_{N_{i,j,t}} = (I, I, I, I)
\end{cases}
$$

In Eq. (6), $s_{N_{i,j,t}}$ is the infectivity state of a vine's neighborhood, which is composed of the adjacent neighbors to the north, south, east, and west of vine (i, j). For example, $s_{N_{i,j,t}} = (I, I, I, NI)$ is the state of a neighborhood composed of two *Infective* (*I*) north and south neighbors, one *Infective* east neighbor and one *Noninfective* (*NI*) west neighbor.

Short-distance diffusion. Parameters α and β are the within-column (north-south) and across-column (east-west) transmission rates with $\alpha > \beta > 0$.[4] The period a vine stays in the *Healthy* state before transitioning to the *Exposed-undetectable* state is an exponentially-distributed random variable, with rate α for within-column disease transmission and rate β for across-column disease transmission (Atallah et al. 2015). When two or more transmission types are

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[4] The disease has been shown to spread preferentially along grid columns (Le Maguet et al. 2013).

realized (e.g., one within- and two across-column events), the disease transmission is determined by the shortest of the waiting times (Cox 1959).

Long-distance diffusion. Long-distance, vector-mediated disease diffusion from low-valued vineyard G_L to its high-valued counterpart G_H occurs with rate $\gamma_{L,H,t}$. Here, $\gamma_{L,H,t}$ is a power-law dispersal parameter specified by the following spatial-dynamic, distance- and density-dependent diffusion function:

$$\gamma_{L,H,t} = j^{-\gamma} * \frac{\sum_n^N \sum_m^M ((m,n) | s_{m,n,t} = Infective)*n}{\sum_n^N M*(N-n+1)} , \gamma > 0 \tag{7a}$$

Similarly, long-distance dispersal from G_H to G_L is given by:

$$\gamma_{H,L,t} = (N-n)^{-\gamma} * \frac{\sum_i^I \sum_j^J ((i,j) | s_{i,j,t} = Infective)*j}{\sum_i^j I*(J-j+1)} , \gamma > 0 \tag{7b}$$

In Eq. (7a), for any vine (i, j), $\gamma_{L,H,t}$ is inversely proportional to the distance from the shared boundary (i.e., column j for G_H and column N-n for G_L). We choose a power-law specification because it allows the disease long-distance diffusion to have new infection foci emerging beyond the disease invading front, which is consistent with modeling the wind dispersal of insects (Gibson 1997; Marco, Montemurro, and Cannas 2011). Parameter $\gamma_{L,H,t}$ is also proportional to the total number of *Infective* vines in G_L, weighted by their column position n (numerator in Eq. 7a). Weighting each *Infective* vine by its column position n allows vines closer to the bordering column to contribute more to the externality than vines situated farther from the boundary (i.e., cell-level distance dependence). The denominator in Eq. (7a) allows the multiplier of the power-law expression to vary between 0 and 1 as the number of *Infective* vines in G_L varies between 0 and $M*N$ (i.e., density dependence). In the baseline case, we initialize the disease in G_L and the disease spreads to G_H according to Eq. (7a). Once vines in vineyard G_H become *Infective*, they can act as a source of infection for *Healthy* vines in vineyard G_L according to Eq. (7b), thus

making the externality bidirectional.[5] Note that this power-law specification allows local

management and dispersal to take place at different spatial scales, a modeling challenge

identified by recent bioeconomic studies (Aadland, Sims, and Finnoff 2015). This specification

of dispersal is novel in that it allows private actions of one manager in one management unit (i.e.,

the cell) to have repercussions not only on neighboring units but also on non-neighboring units

that are managed by a different manager. Combined with short-distance dispersal, this distance

and density dependent specification of long-distance dispersal allows testing whether within-

parcel spatial considerations are also important for generating externalities. This is in contrast to

extant resource and environmental economics literature, which assumes that spatial

considerations only matter in that they define the spatial limit to private actions, and that

managers ignore how their management in one cell affects payoffs through multi-cell dispersal.

For descriptions of probabilities c, d, and f, we refer the reader to Atallah et al. (2015). Short-

and long-distance disease diffusion parameters are presented in Table 1a and Figure 1.

[Insert Table 1a here]

[Figure 1]

4. Computational experiments and solution frameworks

We conducted Monte Carlo experiments, each consisting of a set of 1,000 simulations.

Experiments differ based on the strategy pairs employed in both vineyards to control the disease.

Outcome realizations for a given run within an experiment differ due to random location of

initially infected vines in the grid where the disease is initialized (G_L, for the baseline case), and

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[5] In applications where the externality is asymmetric (e.g., prevailing winds), γ can be given
different values in Eq. 7a and Eq. 7b. Setting $\gamma_{L,H,t}$ and $\gamma_{H,L,t}$ to zero collapses the disease
diffusion model to a case with no externality (Atallah et al. 2015).

stochastic disease diffusion within and between vineyards. Data collected over simulation runs are the NPV realizations under each strategy pair.

4.1. Model initialization

Grapevines are initialized as *Healthy* and of age equal to zero in both vineyards G_H and G_L (high- and low-valued vineyard, respectively). At *t*=1, seven percent of the grapevines in G_L are chosen at random from *U* (0, *M*N*) to transition from state *Healthy* to state *Exposed-undetectable*.[6] Subsequently, the disease spreads to *Healthy* vines within G_L according to the Markov transition process given by Eq. (2) and Eq. (5). The *Infective* vines in G_L act as a primary source of long-distance disease diffusion to the *Healthy* vines in G_H. The disease spreads from G_L to G_H according to the distance- and density-dependent diffusion function $\gamma_{L,H,t}$ (Eq. 7a). Subsequently, *Infective* vines in G_H act as a source of reinfection in G_L according to the distance- and density-dependent diffusion function $\gamma_{H,L,t}$ (Eq. 7b) and so on. Economic parameters are presented in Table 1b.

[Insert Table 1b here]

4.2. Nonspatial, spatial, and fire-break strategies

Nonspatial strategies (strategies 1 to 8, Table 2) consist of removing and replacing vines based on symptoms alone (*Infective-moderate*; *Infective-high*) or based on symptoms and age of individual vines (*Young*: 0-5 years; *Mature*: 6-19 years; *Old*: 20 years and above).[7] In the subset of spatial strategies (strategies 9 to 18, Table 2), the manager removes and replants symptomatic

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[6] This initialization reflects findings indicating that primary infection sources are randomly spatially distributed (Cabaleiro et al. 2008). The disease is initialized in G_L assuming a higher-valued vineyard is not likely to purchase infected plant material. In the sensitivity analysis sections, we consider the opposite case.

[7] A manager might decide to strategically remove younger vines, which exhibit higher risk of transitioning from the *Exposed* to the *Infective* state than their older counterparts (probability *d* in Eq. 5).

vines (*Infective-moderate*) and tests their neighbors. Neighboring vines are removed and replaced if they test positive. In that sense, the manager's spatial disease control decisions are based on a vine's own state and the state of vines in neighboring cells. For example, according to strategy I_mNS (table 2), vines in cells $(i$-$1, j)$ and $(i$+$1; j)$ would be removed and replaced based on the state of vine in cell (i,j); according to strategy I_mNSEW, vines in cells $(i$-$1, j)$, $(i$+$1; j)$, $(i, j$-$1)$ and $(i, j$+$1)$ would be removed and replaced based on the state of vine in cell (i,j), and similarly for all within-grid, spatial strategies.

The third subset of strategies includes fire-break strategies that consist of removing (without replanting) vines in the border columns of a vineyard in order to create 'fire-breaks' or 'buffer zones' that would reduce long-distance disease diffusion between vineyards (Strategy 19 to Strategy 57 in Table 2). Fire-break strategies are intended to decrease the effect of spillovers between vineyards and can give a manager control over their disease risk. All strategies are available to both managers.

[Insert Table 2 here]

4.3. Solution frameworks and game theoretic solution concepts

We employ the objective function (Eq. 1) to rank the vineyard *ENPVs* under the alternative disease control strategy pairs. We first solve the social planner problem and cooperative solution (*C*). The solution to these problems is relevant for situations where one vineyard management firm manages contiguous vineyards that produce wine grapes of different qualities. Second, we solve for the noncooperative solution (*NC*). Third, whenever the cooperative surplus is strictly positive, we find the cooperative solution that satisfies the Nash bargaining framework

Social planner. The social planner chooses the pair of disease management strategies $(\mathcal{W}_H, \mathcal{W}_L)$ that maximizes the total payoff ($ENPV_T$), the sum of the expected net present values of G_L ($ENPV_L$) and G_H ($ENPV_H$). The following maximization problem is solved:

$$\max_{(\mathcal{W}_H, \mathcal{W}_L)} ENPV_H + ENPV_L, \tag{8a}$$

subject to:

$$E(s_{i,j,t+1}) = \boldsymbol{P}^T s_{i,j,t}, \tag{8b}$$

and

$$E(s_{m,n,t+1}) = \boldsymbol{P}^T s_{m,n,t} \tag{8c}$$

where Eq. (8b) and Eq. (8c) are the cell-level infection state transition equations in G_H and G_L, respectively. Note that the managers do not face a common or shared state variable: each manager contends with the stochastic evolution of the disease in his vineyard (Eq. 8b and 8c) while not knowing the status of the disease in the neighboring vineyard. They only observe the control strategy being adopted by the neighboring manager (expect for the simultaneous-move case).

Noncooperative disease control. We use the Nash equilibrium solution concept to solve a simultaneous-move game where the managers do not cooperate and do not share any information about their strategies. We use the subgame perfect Nash equilibrium concept to solve a sequential game with asymmetry of information where one player moves first and the other player makes his choice accordingly (Tirole, 1988). In both simultaneous and sequential move cases, we consider situations where the disease starts in G_L and in G_H.

Cooperative disease control: Nash bargaining game. To solve the cooperative disease control game, we use the static axiomatic approach, specifically the Nash bargaining game (Nash 1953; Binmore, Rubinstein, and Wolinsky 1986). The Nash bargaining game here is similar to the one

used in Munro (1979) to solve for the payoffs in a static, cooperative game with side payments

and fixed disagreement payoffs. The relationship between the two players, as described by Nash

(1953), interpreted by Luce and Raiffa (1967, p. 138), and applied in Munro (1979) and others,

consists of the players entering in a binding agreement at the beginning of the game whereby

each receives the return they would expect without an agreement and half of the cooperative

surplus. If the two vineyards are cooperatively managed, the two managers solve the Nash

bargaining game, the solution to which is the unique pair of cooperative payoffs

$(ENPV_H^C, ENPV_L^C)$ that solves the following maximization problem (Nash 1953; Munro 1979;

Sumaila 1997):

$$\max_{\{ENPV_H, \ ENPV_L\}} (ENPV_H^C - ENPV_H^{NC})(ENPV_L^C - ENPV_L^{NC}), \tag{9}$$

subject to:

$$ENPV^C \geq ENPV^{NC}, \tag{10}$$

and subject to the disease diffusion functions in G_H (Eq. 8b) and G_L (Eq. 8c). The maximand in

Eq. (9), known as the Nash product, is the product of the differences between the cooperative

and noncooperative payoffs from G_H and G_L, and inequality (10) is the incentive compatibility

constraint. Under the standard axioms of bargaining theory, Eq. (9) has the following unique

solution (Muthoo 1999):[8]

$$ENPV_H^C = ENPV_H^{NC} + \frac{1}{2}(ENPV_T^C - ENPV_T^{NC}) \tag{11}$$

$$ENPV_L^C = ENPV_L^{NC} + \frac{1}{2}(ENPV_T^C - ENPV_T^{NC}) \tag{12}$$

In the solution described by Eq. (11) and Eq. (12), $ENPV_H^{NC}$ and $ENPV_L^{NC}$ are the expected

noncooperative payoffs (i.e., the disagreement points) for G_H and G_L, respectively and

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[8] The axioms are individual rationality, invariance to equivalent utility representations, symmetry, and independence of irrelevant alternatives.

$(ENPV_T^C - ENPV_T^{NC})$ is the expected cooperative surplus. The expected cooperative surplus is

defined as the difference between the total expected cooperative payoff $(ENPV_T^C = ENPV_H^C +$

$ENPV_L^C)$ and the total expected noncooperative payoff $(ENPV_T^{NC} = ENPV_H^{NC} + ENPV_L^{NC})$. The

expected cooperative surplus is also a measure of the Pareto-inefficiency caused by

noncooperative disease control.[9]

5. Externality control, heterogeneity and strategic behavior

5.1. Social planner and cooperative control

If the vineyards are managed by a single entity, or a social planner, the total payoff is highest

($122,000/acre) when the disease is managed in both vineyards under strategy I_mNS, which

targets symptomatic vines and their two within-column neighbors (Table 3). If the vineyards are

individually managed and the managers agree to cooperatively control the disease, the Nash

bargaining solution consists of (I_mNS, I_mNS) with payoffs (80, 42) after the managers equally

share the cooperative surplus according to Eq. (11) and Eq. (12) (Table 3).

[Insert Table 3 here]

5.2. Noncooperative control

In a simultaneous game, we find a unique Nash equilibrium pair of strategies that consists of

no control in either vineyard, with payoffs (60, 22) for the managers of the high, and low-valued

vineyards, respectively (Table 3; see Table A1 in Appendix for the payoff matrix). In a

sequential game where the low-valued vineyard moves first, (*no control*, *no control*) is the

subgame perfect Nash equilibrium. The payoffs from the solution to the Nash bargaining

problem indicate that, if the two vineyard managers cooperate and agree to implement spatial

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[9] Our result is a special case of the solution to the generalized (or asymmetric) Nash bargaining game where players have the same 'bargaining power' (Muthoo 1999, p. 35).

Strategy I_mNS in their respective vineyards, there is a cooperative surplus of $40,000 for the two acres. This surplus is statistically significant at the 1% level and represents a welfare ($ENPV_T$) gain of approximately 47% over the noncooperative outcome. These benefits to cooperation are consistent with previous findings from studies on the cooperative management of fisheries (Sumaila 1997) and nuisance wildlife species (Bhat and Huffaker 2007).

Interestingly, we find that the social planner solution can be achieved, without cooperation, when the high-value manager moves first. In that case, his optimal strategy is spatial control I_mNS. Given G_H's commitment to spatially control the disease, G_L's value of control increases due to the strategic complement nature of disease (or pest) control with neighbor-to-neighbor spillovers (Fenichel, Richards, and Shanafelt 2014). G_L's optimal strategy is spatial control, I_mNS, as well, with payoff $31,000/acre. The strategic complement nature of transboundary disease control also explains why (*no control*, *no control*) is the subgame perfect Nash equilibrium strategy in a sequential game where G_L moves first as well as in a simultaneous game.

5.3. Welfare effects of the externality specification

We measure the welfare implications of including the detailed within-parcel, spatial, biophysical process in our specification of the externality and its control. We do so by comparing the model's outcomes to those obtained from management decisions using strategies that ignore the within-parcel spatial dynamics of the biophysical process. We restrict the set of disease control strategies to those that are nonspatial and those that consist of 'fire-breaks' (1 through 8, and 10 through 57, Table 2). Including the inter-parcel, spatial strategies leads to strategy (I_mNS, I_mNS), with total payoffs of $122,000. Ignoring within-parcel spatial considerations leads to the strategy pair (*no control*, *no control*) and total payoffs of $82,000,

thus overestimating the social cost of the externality in the social planner setting, the Nash bargaining game, and the noncooperative sequential game where G_H moves first. [10] For the settings where (*no control*, *no control*) is the subgame Nash perfect equilibrium strategy pairs – the simultaneous game and the sequential game where G_L moves first – welfare remains (unsurprisingly) the same regardless of whether or not within-parcel spatial considerations are taken into account.

5.4. Dynamic sensitivity analysis

We conduct a dynamic sensitivity analysis to examine the effect of changes in the values of key within-parcel and across-parcel disease diffusion parameters on the externality's welfare impacts. These parameters are the short-distance parameter α in Eq. 6; the long-distance diffusion parameter γ in Eq. (7a) and Eq. (7b); the vineyard size parameters I, J, M, and N in these same equations; and disease initialization.

First, we find that reducing the value of the short-distance parameter α by half (from 4.2 to 2.1) causes aggregate welfare to increase by 52% in a noncooperative, simultaneous game or in a noncooperative, sequential game where G_L moves first and none of the managers controls the disease. The increase in welfare ensuing from a reduction in α is more modest, 3%, in a nooncooperative game where G_H moves first or in a Nash bargaining game where both managers spatially control the disease (percent changes are obtained by comparing payoffs in Table 4 with those in Table A2 of the appendix). Reduction in the value of the short-distance parameter can be achieved by increasing the distance between grapevines within the grid's columns and suggests that individual, within-parcel choices about the physical configuration of the vineyard can directly impact the welfare effects of an externality.

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[10] This welfare increase is for two one-acre vineyards, over 50 years.

Second, we solve the baseline problem for larger and smaller values of the long-distance transmission coefficient γ. [11] For a larger long-distance transmission coefficient (i.e., where disease transmission is characterized by a more rapid decline over space and the vineyards are therefore less ecologically connected), the manager of the lower-value vineyard spatially controls the disease, in which case the G_H does not need to control (Table A3-a of the appendix). The outcome (*no control, I_mNS*) does not depend on the type of game played. If the long-distance transmission coefficient has a smaller value than in the baseline case, none of the managers control the disease in any of the noncooperative game solutions and the strategy pair (I_mNS, *Exit*) is the central planner's solution (Table A3-b of the appendix). These results identify an upper bound for the long-distance diffusion coefficient where the externality does not trigger any control in the neighboring vineyard, and a lower bound where the externality is large enough to warrant removal of the lower-valued vineyard by a central planner. Changes in the value of γ can be achieved by modifying the biophysical environment that affects the extent to which the vineyards are ecologically connected, such as physical barriers or other pest management practices that reduce the flow of insect vectors.

Third, we explore the effect of the relative vineyard size. Recall that in the baseline case, G_H is larger than G_L, the NE strategy pair is (*no control*, *no control*), and the noncooperative payoffs are 32% lower than the cooperative or social planner payoffs, generated by the strategy pair (I_mNS, I_mNS). If the relative size of the vineyards is reversed (G_L larger than G_H) or if both vineyards are large, we obtain the same strategy pair solutions. The noncooperative,

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[11] The ratio of new infections caused by long-distance diffusion between vineyards to total new infection events is 90% for $t=12$ months, and decreases to 69%, 34%, and 21% for $t=100, 300,$ and 600 months, respectively (results are expected values from 1,000 simulations conducted for G_H, under the baseline case and a strategy of no control in both vineyards).

simultaneous game's total payoffs are 31 and 41% lower than the cooperative payoffs, if G_L is

larger or both are large, respectively (Table A4- b and c). However, if both vineyards are smaller,

strategy (I_mNS, I_mNS) is the strategy pair solution in all frameworks and the externality is

minimized (Table A4- c). The results from these three vineyard size scenario analysis are driven

by disease population dynamics: a larger vineyard has a larger population of *Susceptible*

grapevines, which speeds disease diffusion and renders disease control less effective (and less

cost-effective) than a strategy of no control.

Fourth, we explore the implications of the disease beginning in the high-valued vineyard, as

opposed to the most likely case where the disease starts in the low-valued vineyard. Initializing

the disease in G_H instead of G_L leads to the Nash equilibrium (I_mNS, I_mNS) no matter whether the

game is simultaneous or sequential, noncooperative or cooperative (Table A5 of the appendix).

In the baseline case, an uncontrolled lower-valued vineyard provides a reserve for the disease,

affects the incentives for control in G_H, and leads to the Nash equilibrium (*no control*, *no*

control).

5.5. Heterogeneity, strategic behavior, and total payoff

We now turn to addressing whether and how manager heterogeneity affects strategic disease

control decisions and total payoffs. Although our focus is on strategic (noncooperative) behavior,

we also solve the Nash bargaining game to gain insight on the differences between cooperative

and noncooperarive outcomes under increased heterogeneity. To that end, we solve the problem

for five additional price pairs under all noncooperative and cooperative settings: starting with the

baseline price pair (Table 4, case 5), we consider four mean-preserving price gap contractions

(Table 4, cases 1 to 4) and two mean-preserving price gap expansions (Table 4, cases 6 and

25

7).[12],[13] Results in Table 4 show that the price gap has a substantial influence on the managers' strategic behavior and their payoffs. These results can be discussed in terms of three distinct management situations. First, in cases 1 through 4, both managers choose Strategy I_mNS regardless of whether the game is simultaneous or sequential, cooperative or noncooperative. In these cases, prices received for grapes in both vineyards are high enough for the managers to afford Strategy I_mNS and the price gap is small enough for the incentives of both players to be aligned.

[Insert Table 4 here]

In contrast, in cases 5 through 7, the price gap is large enough for the managers to have different privately optimal disease control strategies. In cases 5 and 6, the strategy pair (*no control*, *no control*) constitutes a unique Nash equilibrium in a simultaneous game. In the baseline case 5, G_L opts for *no control* when he moves first, while G_H opts for I_mNS when he moves first. Then, because of strategic complementarity in disease control, the second mover chooses the same strategy as the first mover. The unique subgame perfect Nash equilibrium is therefore (*no control*, *no control*) if G_L moves first and (I_mNS, I_mNS) if G_H moves first. In case 6, however, due to the low price received by G_L, (*no control*, *no control*) is the Nash equilibrium of the simultaneous game and the subgame perfect Nash equilibrium in the sequential game, no matter which manager moves first (Table 4, case 6). The greater heterogeneity in prices in case 6 also causes the cooperative solution to be different compared to case 5. Here, the Nash bargaining solution consists of G_H paying G_L ($\$34,000$/acre) to exit production (Strategy *16Col* or *Exit*), in which case there is no externality and G_H controls the disease in his vineyard through

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[12] Note that the price gap is equal to zero in case 1 and it increases as we move to case 7.

[13] When conducting price expansions, we also increase the quality penalty (linearly with the price) up to an upper bound of 70%.

strategy I_mNS. After this transfer, both managers are better off compared to the noncooperative solution ($97,000 vs. $72,000 for G_H and $28,000 vs. $3,000 for G_L; Table 4, case 6). The Nash bargaining solution improves the aggregate payoffs by 67% when compared with the noncooperative solution (percent difference between $126,000 and $75,000 in Table 4, case 6). In case 7, the price received by G_L is low enough for Strategy *16Col* or *Exit* (exiting production) to be privately optimal, in which case G_H implements spatial control I_mNS regardless of whether the game is simultaneous or sequential, cooperative or noncooperative.

Along the various degrees of manager heterogeneity represented in the six noncooperative setting cases (cases 1 through 6, simultaneous and sequential settings), total payoff is monotonically decreasing in the level of heterogeneity (i.e., the magnitude of price gap) between cases 1 and 6. Cases 6 and 7, on the other hand, represent a range where the relationship between price gap (more generally, heterogeneity) and total payoff (more generally, social welfare) becomes U-shaped (Figure 2, panel a). The shape of the curve is unchanged in a cooperative game but the effect of increased heterogeneity is less pronounced. First, Nash bargaining reduces the magnitude of the decline in total payoffs for cases 5 and 6. Second, it shifts the inflexion point of the U-shaped curve to the left, that is, the curvature takes place at a lower level of heterogeneity (in case 5 instead of case 6) (Figure 2, panel b). Figure 2 shows that there is a critical range of heterogeneity in resource value that substantially reduces welfare and that it is exactly in this range that cooperative control is welfare-improving in comparison to noncooperative control.

[Insert Figure 2 here]

6. Conclusions

In this paper, we examined how metapopulation models and cellular automata can be combined to develop a novel distance- and density-dependent specification of externalities that acknowledges the importance of inter- and intra-parcel spatial dynamics in the generation and control of externalities. Our specification is general in that it can be collapsed to represent metapopulation models only, cellular automata models only, or a combination of the two, with short-distance diffusion only, long-distance diffusion only, or with both, depending on the characteristics of the process generating the externalities.

We used this specification to solve spatial noncooperative and cooperative games that endogenize spatial risk beyond the immediate neighborhood and capture the inter- and intra-parcel private incentives to control. We found that within-parcel spatial decisions can generate the externality and may lead to inefficient outcomes in the decentralized management of public bads. We also showed that noncooperative strategic spatial decisions within the parcel can lead to efficient outcomes even in the absence of Coasian bargaining (Coase 1960). Finally, we have characterized the relationship among resource value heterogeneity, strategic behavior, and total payoffs. Our analysis, with heterogeneity, allows of different, first-move-dependent, noncooperative equilibria ranging from no control to spatial control to entire vineyard removal.

Our work contributes to the growing literature that examines the spatial-dynamic nature of externalities by increasing the spatial dimension of the problem and the number of players making strategic decisions. We show that increased computational power that has allowed researchers to consider larger grids and a greater number of players, can also be used to understand the spatial-dynamics within a parcel that determine the generation of externalities and private incentives to control. Our results suggest that ignoring the complex biophysical details of

the within-parcel spatial dynamics can lead to misleading measures of welfare impacts of externalities.

Our model makes valuable contributions to the literature can be extended to examine other types of spatial-dynamic externalities. Yet, it has several limitations that should be addressed in future research. For instance, the model does not offer clear insights into the cooperative management of externalities in which disagreement payoffs (i.e., noncooperative payoffs) are not fixed, agreement renegotiation is needed and there are more than two players. In such situations, differential games with N players might be appropriate but solution methods for such games require restrictive assumptions about the state equations and game solutions are not guaranteed (Bressan 2011). In parallel to the on-going research on whether stable solutions exist, future research might use evolutionary or learning dynamics to explore whether solutions to spatial-dynamic externalities in N-player bargaining games are achievable (Smead et al. 2014). Such effort might identify reasons why desirable solutions might not be attainable and the mechanisms that might be implemented to increase the likelihood of reaching these solutions.

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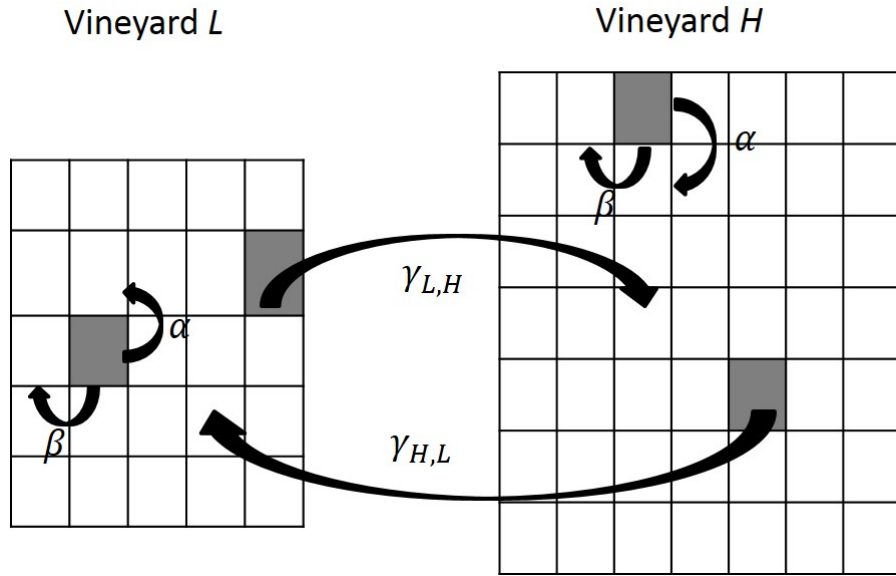Tirole, J., The theory of industrial organization (1988). MIT press.

Fig. 1 Short-distance diffusion is governed by α for within-column dispersal and β for across-column dispersal; Long-distance diffusion between H (right) and L (left) is governed by $\gamma_{H,L}$ (from H to L) and $\gamma_{L,H}$ (from L to H). Shaded cell represents Infective vine.
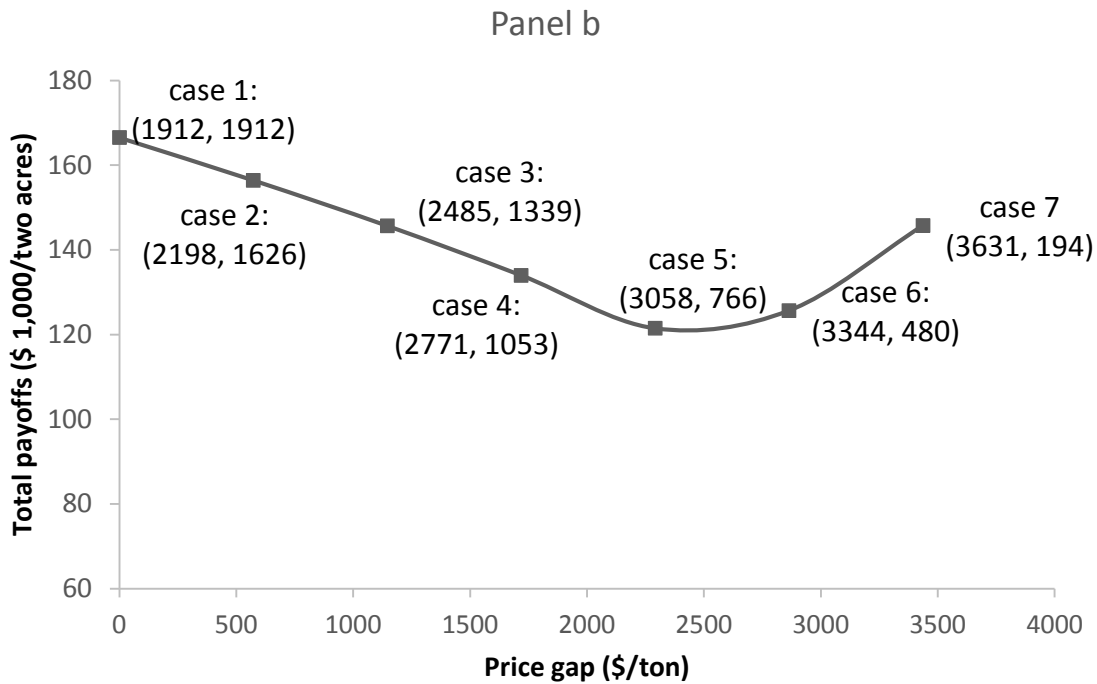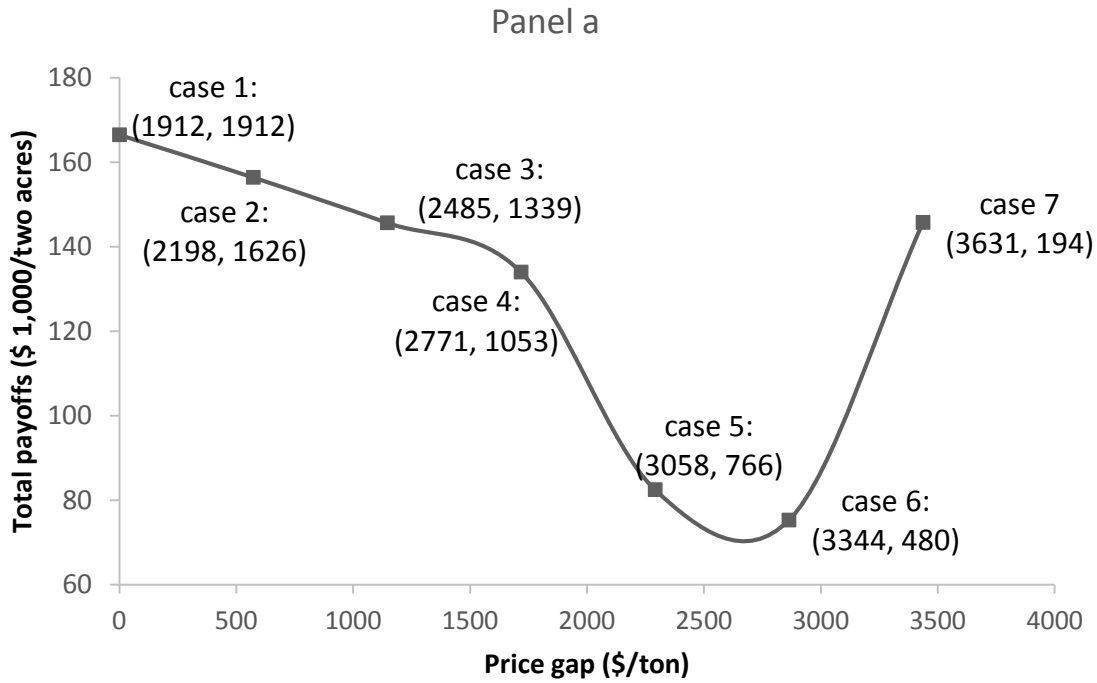
Fig. 2 Total payoffs for each of the seven price differential cases, in a noncooperative, sequential game where G_L moves first (panel a), and in a cooperative, Nash bargaining game (panel b). Each data point is an expected value obtained from 1,000 simulations.

Table 1 a
Disease diffusion parameters

Parameter	Description	Value	Unit
α	Within-column H to E_u transition rate	4.2	month^{-1}
β	Across-column H to E_u transition rate	0.014	month^{-1}
γ	Distance-dependence, power-law parameter	3	unitless
τ_{max}	Period from planting until fruit bearing	36	months

Sources: Values of parameters α and β are obtained from model calibration in Atallah et al. (2014) using data in Charles et al. (2009) with validation using data in Cabaleiro and Segura (2006) and Cabaleiro et al. (2008). The value of parameter value γ is obtained from Cabaleiro and Segura (1997). Parameter value for τ_{max} is from White (2008).

Table 1 b
Economic parameters faced by managers of vineyards G_H and G_L

		Vineyard G_H		Vineyard G_H
Vineyard layout				
Grid dimensions (rows*columns)	$I*J$	68*23=1,564	$M*N$	49*16=784
Grid row (vine) spacing (ft.)		4		5
Grid column spacing (ft.)		7		11
Revenue parameters				
Per-vine revenue	$r_{w_{i,j,t}}$	Random	$r_{w_{m,n,t}}$	Random
Grapes price ($/ton)	$p_{S_{i,j,t}}$	5,058	$p_{S_{m,n,t}}$	726
Price penalty (%)	$\widetilde{p_{s_{i,j,t}}}$	70	$\widetilde{p_{s_{m,n,t}}}$	0
Yield (tons/acre)	y_{G_H}	4.5	y_{G_L}	10
Yield (tons/acre/month)		0.375		0.834
Planting density (vines/acre)	d_{G_H}	1,564	d_{G_L}	784
Yield (tons/vine/year)	$y_{i,j}$	0.0029	$y_{m,n}$	0.0128
Yield (tons/vine/month)		0.0002		0.0011
Yield reduction (%)[a]	$\widetilde{y_{S_{i,j,t}}}$	Depends on $S_{i,j,t}$	$\widetilde{y_{S_{m,n,t}}}$	Depends on $S_{m,nj,t}$
$s = Exposed$	$\widetilde{y_{S_{i,j,t=E}}}$	30	$\widetilde{y_{S_{m,n,t=E}}}$	30
$s = Infectious, moderate$	$\widetilde{y_{S_{i,j,t=I_m}}}$	50	$\widetilde{y_{S_{m,n,t=I_m}}}$	50
$s = Infectious, high$	$\widetilde{y_{S_{i,j,t=I_h}}}$	75	$\widetilde{y_{S_{m,n,t=I_h}}}$	75
Cost parameters				
Roguing and replanting ($/vine)	$c_{u_{i,j}}$	14.6	$c_{u_{m,n}}$	14.6
Roguing ($/vine)	$c_{z_{i,j}}$	8	$c_{z_{m,n}}$	8
Testing ($/vine)	$c_{v_{i,j}}$	2.6	$c_{v_{m,n}}$	2.6
Operating costs ($/vine)	$c_{i,j}$	3.6	$c_{m,n}$	2.8
Discount factor (month $^{-1}$) [b]	ρ	0.9959	ρ	0.9959

[a] Note that managers are unable to observe yield reduction for each grapevine; instead they observe average yield.

[b] The discount factor is equivalent to an annual discount rate of 5%.

Sources: Values for vineyard *H*'s parameters are from Cooper, Klonsky, and De Moura (2012) and values for vineyard *L*'s parameters are from Verdegaal, Klonsky, and De Moura (2012). Grape prices are from the California Department of Food and Agriculture (2014). Removal and replanting costs are from Klonsky and Livingston (2009).

Table 2
Disease control strategies: definitions and acronyms

Strategies	Acronym
Nonspatial strategies	
1 Removing and replacing all vines that are *Infective*.	I
2 Removing and replacing all vines that are *Infective-moderate*.	I_m
3 Removing and replacing all vines that are *Infective-high*.	I_h
4 Removing and replacing vines that are *Infective-moderate* and *Young*.	I_mY
5 Removing and replacing vines that are *Infective-moderate* and *Mature*.	I_mM
6 Removing and replacing vines that are *Infective-moderate* and *Old*.	I_mO
7 Removing and replacing vines that are *Infective-high* and *Mature*.	I_hM
8 Removing and replacing vines that are *Infective-high* and *Old*.	I_hO
Spatial strategies	
9 Removing and replacing *Infective-moderate* vines in addition to testing their two within-column neighbors then removing and replacing those that test positive.	I_mNS
10 Removing and replacing *Infective-moderate* vines in addition to testing their two across-column neighbors and two-within column neighbors then removing and replacing those that test positive.	I_mNSEW
11 Removing and replacing *Infective-moderate* vines in addition to testing their four within-column neighbors and two across-column neighbors then removing and replacing those that test positive.	I_mNS2EW
12 Removing and replacing *Infective-moderate* vines in addition to testing their four within-column and four within-row neighbors then removing and replacing those that test positive.	$I_mNS2EW2$
13 Removing and replacing *Young*, *Infective-moderate* vines in addition to testing their two within-column neighbors then removing and replacing those that test positive.	I_mY-NS
14 Removing and replacing *Mature*, *Infective-moderate* vines in addition to testing their two within-column neighbors then removing and replacing those that test positive.	I_mM-NS
15 Removing and replacing *Old*, *Infective-moderate* vines in addition to testing their two within-column neighbors then removing and replacing those that test positive.	I_mO-NS
16 Removing and replacing *Young*, *Infective-moderate* vines in addition to testing their two across-column neighbors and two-within column neighbors then removing and replacing those that test positive.	I_mY-NSEW
17 Removing and replacing *Mature*, *Infective-moderate* vines in addition to testing their two across-column neighbors and two-within column neighbors then removing and testing those that test positive.	I_mM-NSEW
18 Removing and replacing *Old*, *Infective-moderate* vines in addition to testing their two across-column neighbors and two-within column neighbors then removing and replacing those that test positive.	I_mO-NSEW
'Fire-break' strategies	
19 Removing all the vines in the bordering column in G_L.	*1Col*
20 Removing all the vines in two bordering columns in G_L.	*2Col*
… …	…
34 Removing all the vines in all 16 columns G_L.	*16Col* or *Exit*
35 Removing all the vines in the bordering column in G_H.	*1Col*
36 Removing all the vines in two bordering columns in G_H.	*2Col*
… …	…
57 Removing all the vines in all 23 columns G_H.	*23Col* or *Exit*

Note: Strategies are assumed to be implemented at $t=24$, which corresponds to the moment when initially infected vines in G_L develop visual symptoms. Note that strategies 25 and 42 correspond to total vineyard removal for the smaller and larger vineyards, respectively.
Source: Nonspatial and spatial strategies are from Atallah et al. (2014).

Table 3

Expected payoffs under the social planner, noncooperative, and cooperative solutions

Strategies (G_H, G_L)	Expected Payoffs [a] ($1,000/acre over 50 years)					
	Payoff to G_H	Payoff to G_L	Total payoff	Surplus [b]	Cooperative Payoff to G_H	Cooperative Payoff to G_L
Social planner solution (I_mNS, I_mNS)	91 (3)[c]	31 (5)	122	N/A	N/A	N/A
Cooperative solution (I_mNS, I_mNS)	91 (3)	31 (5)	122	40[***]	80	42
Simultaneous game or sequential game, G_L moves first $(no\ control,\ no\ control)$	60 (3)	22 (1)	82	N/A	N/A	N/A
Sequential game, G_H moves first (I_mNS, I_mNS)	91 (3)	31 (5)	122	N/A	N/A	N/A

N/A is not applicable.

[a] Expectations are obtained from 1,000 simulations; payoffs are computed for the baseline prices p_H=$5,058/ton and p_L=$726/ton.

[b] Cooperative Surplus= Total payoff (Cooperative)-Total payoff (Noncooperative)

[c] Standard deviations in parentheses.

*** Statistically significant at the 1% level.

Table 4
Solution strategy pairs and expected payoffs; disease starts in G_L.

Case	Prices [a] p_H, p_L ($/ton)	Setting	Solution strategy pairs G_H, G_L	Expected payoffs $ENPV_H, ENPV_L$ ($1,000/acre)	$ENPV_T$
1	1912, 1912	Simultaneous	I_mNS, I_mNS	17, 150	167
		Sequential-G_L moves first	I_mNS, I_mNS	17, 150	167
		Sequential-G_H moves first	I_mNS, I_mNS	17, 150	167
2	2198, 1626	Simultaneous	I_mNS, I_mNS	35, 121	156
		Sequential-G_L moves first	I_mNS, I_mNS	35, 121	156
		Sequential-G_H moves first	I_mNS, I_mNS	35, 121	156
3	2485, 1339	Simultaneous	I_mNS, I_mNS	54, 92	146
		Sequential-G_L moves first	I_mNS, I_mNS	54, 92	146
		Sequential-G_H moves first	I_mNS, I_mNS	54, 92	146
4	2771, 1053	Simultaneous	I_mNS, I_mNS	72, 62	134
		Sequential-G_L moves first	I_mNS, I_mNS	72, 62	134
		Sequential-G_H moves first	I_mNS, I_mNS	72, 62	134
5	3058, 766 (baseline)	Social planner [b]	I_mNS, I_mNS	91, 31	121
		Simultaneous	*no control, no control*	60, 22	82
		Sequential-G_L moves first	*no control, no control*	60, 22	82
		Sequential-G_H moves first	I_mNS, I_mNS	91, 31	121
		Nash bargaining [b]	I_mNS, I_mNS	80, 42	121
6	3344, 480	Social planner [b]	I_mNS, Exit	131, -5	126
		Simultaneous	*no control, no control*	72, 3	75
		Sequential-G_L moves first	*no control, no control*	72, 3	75
		Sequential-G_H moves first	*no control, no control*	72, 3	75
		Nash bargaining [b]	I_mNS, Exit	97, 28	126
7	3631, 194	Simultaneous	I_mNS, Exit	151, -5	146
		Sequential-G_L moves first	I_mNS, Exit	151, -5	146
		Sequential-G_H moves first	I_mNS, Exit	151, -5	146

[a] Recall that prices in cases 1 through 6, and prices in cases 6 and 7 are obtained through a mean-preserving contraction and a mean-preserving expansion of prices in the baseline case (case 5), respectively.
[b] We only report the social planner and Nash bargaining solutions when they are different from the noncooperative solutions.

Appendix

Table A1
Normal form game payoff matrix for the baseline case (payoffs in $1,000)

		G_L					
		no control [a]		I_mY		I_mNS	
	no control	60 [b]	22	81	-11	98	-5
G_H	I_mY	41	1	81	-11	93	-5
	I_mNS	-20	1	25	-11	**91**	**31**

[a] Underbars indicate a player's payoff of dominant strategy, given the strategy of the other player.
[b] Payoffs of the welfare-maximizing solution pair are in bold.

Table A2
Effect of a smaller short-distance diffusion parameter ($\alpha=2.1$): normal form game payoff matrix (payoffs in $1,000)

		G_L			
		no control		I_mNS	
G_H	no control	60	23	98	27
	I_mNS	-14	23	**93**	**32**

[a] Underbars indicate a player's payoff of dominant strategy, given the strategy of the other player.
[b] Payoffs of the welfare-maximizing solution pair are in bold.

Table A3
Effect of (a) larger ($\gamma=3.5$) and (b) smaller ($\gamma=1.5$) long-distance diffusion parameter: normal form game payoff matrix (payoffs in $1,000).

(a) $\gamma=3.5$

		G_L					
		no control		I_mNS		Exit	
	no control	78 [a]	23	**103**	**29** [b]	93	-5
G_H	I_mNS	12	23	95	31	110	-5
	Exit	-11	23	-11	31	-11	-5

(b) $\gamma=1.5$

		G_L					
		no control		I_mNS		Exit	
	no control	-13	19	34	-77	52	-5
G_H	I_mNS	-316	21	13	14	**94**	**-5**
	Exit	-11	23	-11	30	-11	-5

[a] Underbars indicate a player's payoff of dominant strategy, given the strategy of the other player. Two underbars indicate the payoffs of the Nash equilibrium strategy pair.
[b] Payoffs of the welfare-maximizing solution pair are in bold.

Table A4
Effect of vineyard relative size: normal form game payoff matrix;
(a) G_L is larger than G_H; (b) vineyards are both big; (c) vineyards
are both small (payoffs in $1,000)

(a)	G_L larger		G_L		
		no control		*I_mNS*	
G_H	*no control*	<u>-59</u> [a]	<u>298</u>	<u>-59</u>	285
	I_mNS	-84	384	**-65**	**<u>414</u>** [b]

(b)	*Both large*		G_L		
		no control		*I_mNS*	
G_H	*no control*	<u>71</u>	-37	<u>104</u>	-44
	I_mNS	10	<u>-37</u>	**103**	**-44**

(c)	*Both small*		G_L		
		no control		*I_mNS*	
G_H	*no control*	<u>243</u>	22	345	<u>24</u>
	I_mNS	208	23	**<u>368</u>**	**32**

[a] Underbars indicate a player's payoff of dominant strategy, given the strategy of the other player. Two underbars indicate the payoffs of the Nash equilibrium strategy pair.
[b] Payoffs of the welfare-maximizing solution pair are in bold.

Table A5

Expected payoffs under the social planner, noncooperative, and cooperative solutions, case where disease starts in G_H

Setting	Solution strategy pairs G_H, G_L	Expected Payoffs [a] $ENPV_H; ENPV_L$	$ENPV_T$
Simultaneous	I_mNS, I_mNS	5, 76	81
Sequential-G_L moves first	I_mNS, I_mNS	5, 76	81
Sequential-G_H moves first	I_mNS, I_mNS	5, 76	81

[a] Expectations are obtained from 1,000 simulations over 50 years; payoffs are in $1,000/acre and are computed for the baseline prices p_H=$5,058/ton and p_L=$726/ton.

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