Received: 2 December 2020 | Accepted: 8 February 2022

DOI: 10.1111/ajae.12308

ARTICLE

When does voluntary coordination work? Evidence from area-wide pest management

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Abstract

We introduce the "coordination frontier" (CF), a simple practical tool to assess the likelihood of success of voluntary coordination in situations where, ex ante, the collective action solution provides an appealing alternative (e.g., for pest and disease control). We demonstrate the value of information conveyed by the CF, explain how to construct the CF from experimental data, and show how to apply the CF in practice. We illustrate the concept with an application to data from a framed field economic experiment, which was designed to elicit the preferences of Florida's citrus growers regarding their willingness to coordinate actions to combat citrus greening disease. This is a highly relevant case study not only because of the significant impact caused by citrus greening on Florida's citrus industry but also because a voluntary area-wide pest management program to control it had been established in 2010 and eventually failed; a similar program is now in place in California, where the disease spread is at an earlier stage. Had the CF been available in Florida, estimates of the (aggregate) chances of successful coordination could have been shared with growers to update their beliefs regarding the chances of successful coordination to help reduce strategic uncertainty. Policymakers in California could use the CF in such way and devise ways to encourage participation to increase the chances of reaching a desired coordination threshold.

KEYWORDS

area-wide pest management, citrus greening, coordination, pest management

JEL CLASSIFICATION
D7, Q1, Q18

1 | INTRODUCTION

During the last 70 years, synthetic pesticides have allowed farmers to control many pests within their farms cheaply, effectively, and without regard for their neighbors' opinions and actions (Hendrichs et al., 2007; Smith et al., 1976). Thus, individual chemical pest management has become the most widely used strategy for pest control (Klassen, 2000). But despite the efforts, invasive species still pose a significant problem to agricultural producers worldwide; in fact, it is estimated that invasive insects alone cost US$70 billion annually (Bradshaw et al., 2016).

One of the major shortcomings of uncoordinated pest control is that its effectiveness is compromised by the mobility of pests (Hendrichs et al., 2007). Using site-specific pest control does not take into account that neighboring farmers share such pests. Hence, individual actions have little effect on the density of the pest within the farm in future periods if there is re-infestation from neighboring farms (Lazarus & Dixon, 1984). As entomologists put it, "[u]niform suppressive pressure applied against the total population of the pest over a period of generations will achieve greater suppression than a high level of control on most, but not all of the population" (Knipling, 1972, p. 155). Therefore, crop damage is dependent not only on the individual farm pest population but also on the pest population within the region. The problem is compounded when the pest is vector of disease, particularly, if there is no cure or management strategy for the disease they transmit. Thus, following site-specific pest management ignores the collective nature of the problem; the ability of individual farmers to control mobile pests depends critically on the actions of neighboring farmers, which characterizes the problem as a collective action dilemma.

Collective action dilemmas are typically dealt with using top-down regulation or a bottom-up approach. However, a bottom-up approach is more attractive given the financial constraints of governments, the resistance that top-down regulation typically encounters, as well as the high cost and the difficulties of enforcing a top-down regulation in agricultural settings (Ayer, 1997; Ervin & Frisvold, 2016; Olmstead & Rhode, 2004). A community-based approach to deal with collective-action problems can not only be more effective but also result in lower transaction costs relative to command-and-control or payment-based approaches (Ostrom, 1990, 2009, 2010). However, cooperative solutions may not be adopted without the appropriate institutions (Loehman & Dinar, 1994). But building such institutional capacity takes time and maintenance (Ervin & Frisvold, 2016; Frisvold, 2019a). Almeida (2016) emphasizes that rapid reaction time is key to address the threat posed by a plant pathogen, but building trust among stakeholders often requires years. The challenge posed by the time required to design, establish, and implement community-based institutions to deal with invasive species is compounded by growers' preferences for control measures over prevention, as well as growers not facing all the costs of their decisions. This is so because the risk of pest invasions depends on the human response to such threat (Perrings et al., 2002). It then seems evident that there is a need for a quicker, albeit temporary, first (voluntary) coordination approach for dealing with invasive species until the appropriate community-based institutions are put in place. This is particularly so for the case of plant diseases, which unlike animal diseases are not transmitted to humans and, therefore, are more likely to be dealt with a slower policy response.

Voluntary coordination does present challenges analogous to those of contributing to the provision of a public good, namely, stakeholder participation. The challenge that stakeholder participation poses to the success of an area-wide pest management (AWPM) program has been widely recognized in the agronomic literature (see, for example, Mumford, 2000; Klassen, 2000; Hendrichs et al., 2007). In fact, according to Hendrichs et al. (2007), feasibility studies are key not only for identifying the most appropriate strategy and technology, and for designing the technical aspects of a program, but also for obtaining the commitment of stakeholders. We have not been able to find any studies focused specifically on determining a minimum threshold of participation for coordination to be successful. However, as Dawes and Thaler (1988, p. 197) put it, "the strong free rider prediction is clearly wrong—not everyone free rides all of the time"; the authors then continue, "there is a big territory between universal free riding and universal contributing at the optimal rate." In fact, in cases in which less than 100% participation is needed, there is some evidence that cooperation may provide a significant benefit (Epanchin-Niell & Wilen, 2015; Singerman et al., 2017).

Previous work on farmers' participation in a regional pest control group includes, for example, the pioneering article of Rook and Carlson (1985), who argue that farmers should participate in AWPM if the benefits of doing so outweigh the costs. However, Hurley and Frisvold (2016) point out that economic factors are not farmers' only incentive regarding weed and insect management decisions. Moreover, gains from cooperation do not always result in a cooperative outcome (Loehman & Dinar, 1994); behavioral and socioeconomic factors may challenge rational economic behavior (Miranowski, 2016). In this regard, Singerman et al. (2017) present a case study that quantifies the benefit of adopting AWPM to farmers, but find that strategic uncertainty—defined as the uncertainty regarding the actions and beliefs of others—hinders cooperation. Following such finding, Singerman and Useche (2019) explore how strategic uncertainty, among other variables, influences farmers' actual decisions to participate in AWPM. Their study extends the literature available evaluating the determinants of individual farmers' willingness to cooperate to control pests (Stallman & James Jr., 2015).

More recently, Xu et al. (2021) find that participation in a farmer organization is conducive to collective action in pest and disease control among Chinese farmers; in particular, they find organizational support, learning, and norms have mediating effects on farmers' decisions for joint pests and disease control. Although there is a need for creating networks of farmers to incentivize cooperation in pest and disease management in the United States (Hurley & Sun, 2019), according to Xu et al. (2021), Chinese farmers can use collective land and other production resources to grow and manage crops; such a program is quite different from the AWPM programs that could be designed in the United States.[1] In addition, as mentioned above, time and effort would be required to develop any formal farmer organization that could impact the joint control of pests and disease.

There is also a growing literature on the spatial-dynamic externalities that arise in transboundary species invasions among adjacent neighbors. For example, Liu and Sims (2016) argue that invasions will spread more quickly in landscapes with many smaller producers, because larger producers have greater incentives to control the invasion. Similarly, Epanchin-Niell et al. (2010) point out that collective action becomes more challenging as the number of land managers in a region increases. Epanchin-Niell and Wilen (2015) develop a model of invasion spread and human behavior, and find that small amounts of cooperation can provide large social benefits under most circumstances. Ahouissoussi (1995), however, uses a principal-agent model to explain why some cotton farmers were dissatisfied with the cooperation resulting from the Boll Weevil eradication program; farmers who had invested effort in determining the optimal combination of inputs felt the program reduced the competitive edge they had gained.

In the present study, we build particularly upon the work of Singerman et al. (2017) and Singerman and Useche (2019) by using some of their data and findings. Unlike all of the cited references above, we examine the aggregate probability of success of a voluntary AWPM and use farm-level experimental data for such purpose. The ability to predict the aggregate outcome of a coordination effort should be of major interest to both stakeholders and policymakers. Moreover, the higher the accuracy of prediction of such an outcome, the lower the strategic uncertainty involved (Heinemann et al., 2009).

[1]Other significant differences with agriculture in the United States include the role of the country's government and the support farmers' organizations provide.

We propose the "coordination frontier" (CF), a simple practical tool to assess the likelihood of success of voluntary coordination in situations where, ex ante, the collective action solution provides an appealing alternative. Such a tool would allow policymakers to determine the likelihood of success of implementing a quick and preliminary voluntary approach for pest and disease control, allowing, in turn, to "buy" time while the necessary (and more formal) institutions to incentivize cooperation in pest and disease management are put in place. Importantly, the CF can help reduce the strategic uncertainty involved in a voluntary program. Providing public information can be helpful to align growers' beliefs, reduce strategic uncertainty, and enhance coordination. Singerman and Useche (2019) test the influence of public information on choices under strategic uncertainty and find that approximately 30% of the growers choose to coordinate more. Morris and Shin (2006) illustrate that public information conveys more information than its face value, even if merely stating the obvious; it can convey important strategic information on the likely beliefs of others and, thus, contribute to coordinating outcomes. The CF also represents a step toward filling the gap in the literature regarding the ex-ante aggregate probability of success of a regional pest control program.

We contribute to the literature by introducing the CF. We demonstrate the value of information conveyed by the CF, explain how to apply the CF in practice, and show how to construct the CF from experimental data. We illustrate the concept with an application to data from a framed field economic experiment, which was designed to elicit the preferences of Florida's citrus growers regarding their willingness to coordinate actions to combat citrus greening disease. This is a highly relevant case study, not only because of the significant impact caused by citrus greening on Florida's citrus industry but also because a voluntary AWPM program to control it had been established in 2010 and eventually failed; a similar voluntary program is now in place in California, where the disease spread is at an earlier stage.

2 | STRATEGIC INTERACTION IN VOLUNTARY COLLECTIVE PEST CONTROL DECISIONS

Collective pest control decisions can be viewed as a problem analogous to that of contributing to the provision of a public good, in which the public good is the regional level of pest control. The key underlying issue is that farmers' payoffs depend not only on their own actions but also on those of neighboring farmers. Thus, the actions of individual farmers are motivated by their beliefs about what other farmers will do. Such strategic uncertainty is a key consideration in growers' pest-control decision making (Singerman & Useche, 2019). Therefore, each farmer chooses whether to coordinate as the best response to their beliefs regarding the behavior of other farmers.

Mathematically, consider a group of N farmers, each of them deciding whether to coordinate sprays to combat a pest, and suppose that success of the collective effort requires a minimum share or threshold T of the farmers to coordinate. Let farmer i's profits from successful coordination be Π_i^{SC}, from failed coordination be Π_i^{FC}, and from not coordinating be Π_i^{NC}. Assuming for simplicity that the farmer's objective is to maximize expected profits conditional on what other farmers do, her optimal decision to coordinate ($W_i = 1$) or not ($W_i = 0$) can be written as[2]

$$W_i{}^* = \begin{cases} 1 & \text{if } L_i\left(1 + \sum_{n \neq i} W_n, T, N\right) \geq R\Pi_i \equiv \dfrac{\Pi_i^{NC} - \Pi_i^{FC}}{\Pi_i^{SC} - \Pi_i^{FC}}, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

[2]The farmer would be indifferent between coordinating and not coordinating if $L_i\ (1 + \Sigma_{n\neq i}\ W_n,\ T,\ N) = R\Pi_i$. Hence, in general, the decision rule would be $W_i^* = 1$ with probability $\phi_i \in [0, 1]$ and $W_i^* = 0$ with probability $(1 - \phi_i)$ when $L_i\ (1 + \Sigma_{n\neq i}\ W_n,\ T,\ N) = R\Pi_i$. Equation (1) represents the special case where $\phi_i = 1$.

In the expression above, $L_i\ (1 + \Sigma_{n \neq i}\ W_n,\ T,\ N)$ is farmer i's subjective probability of successful coordination (conditional on her decision to coordinate, i.e., $W_i = 1$), and $R\Pi_i$ is the amount by which profits from not coordinating exceed profits from failed coordination, expressed as a percentage of the profit difference between successful and failed coordination, or "relative profits" for short. Each farmer has to decide whether to coordinate sprays, which she would only do if she believed that enough of her fellow farmers would coordinate as well, because she benefits only if the threshold is met (i.e., $\left(\sum_{n=1}^{N} W_n\right)/N \geq T$). If the threshold is not met, coordination fails, and those who coordinated obtain lower payoffs compared to those who did not $\left(\Pi_i^{NC} > \Pi_i^{FC}\right)$. However, if the critical mass requirement is met, the payoff will be higher $\left(\Pi_i^{SC} > \Pi_i^{NC}\right)$. Thus, not coordinating sprays provides a safer option for an individual, but the social outcome may be suboptimal.

The solution to this game depends on T, N, and the vector $\underline{R\Pi} \equiv [R\Pi_1, \ldots, R\Pi_N]$. For any given equilibrium solution, it is conceptually possible to evaluate the aggregate probability of successful coordination among farmers $\lambda\ (\underline{R\Pi},\ T,\ N) \equiv Prob_{F(\underline{W}|\underline{R\Pi},T,N)}\ \left[\left(\sum_{n=1}^{N} W_n\right)/N\ \geq T\right]$, where $\underline{W} \equiv [W_1, \ldots, W_N]$ is the vector of farmers' equilibrium decisions (based on their subjective beliefs), and $F\ (\underline{W}|\underline{R\Pi},\ T,\ N)$ is the corresponding joint distribution. For the case where $R\Pi_1 = \ldots = R\Pi_N = R\Pi$, the probability of successful coordination can be expressed as the function $\lambda\ (R\Pi,\ T,\ N)$. In this instance, another parameter that will prove useful in later sections is the individual coordination probability (ICP) function $\pi\ (R\Pi,\ T,\ N) \equiv E_{F(W|R\Pi,T,N)}\ \left[\left(\sum_{n=1}^{N} W_n\right)/N\right]$, where $E_F\ (\cdot)$ denotes the expectation operator under probability measure F. For a given relative profit value $R\Pi$, function $\pi\ (R\Pi,\ T,\ N)$ gives the probability that a randomly drawn individual from the relevant population will coordinate when she belongs to a group of size N and the threshold for success is T.

3 | THE COORDINATION FRONTIER (CF)

We propose the CF as a way to guide decision making in regard to the ability to establish successful voluntary coordination among individuals interested in meeting a particular goal, such as the control of pests and disease. The CF shows the maximum feasible participation threshold $\left(\overline{T}\right)$ as a function of the relative profits of the no-coordination alternative ($R\Pi$) for a probability of successful coordination λ greater than or equal to some target level $\underline{\lambda}$. Figure 1 depicts an example of a CF, labeled $\overline{T}(R\Pi,\ \underline{\lambda},\ N)$ to emphasize that it represents the maximum feasible participation threshold as a function of the alternative's relative profits ($R\Pi$) for a probability of successful coordination $\lambda \geq \underline{\lambda}$ by a group of N individuals. Like the schedule shown in Figure 1, CFs are non-differentiable continuous functions with at most N horizontal segments. This property follows from the fact that the number of individuals associated with a maximum feasible participation threshold $\left(\overline{T}\right)$ is an integer. The shaded (unshaded) area in the diagram shows T-$R\Pi$ combinations for which the probability of successful coordination is smaller (larger) than the target $\underline{\lambda}$. Of course, in any practical application it would be critical to define the minimum probability of successful coordination $\underline{\lambda}$ associated with a given CF, as $(1 - \lambda)$ represents the risk that voluntary coordination will fail. That is, $(1 - \lambda)$ is the risk faced by decision makers who attempt to go ahead with the coordination effort.

Figure 1 illustrates the CF and can be used to explain how to apply it for decision making using an example. Consider the situation where a pest is present in a particular geographic area. Farmers can control it either by acting individually without coordination with neighboring farmers in that location, or by establishing a voluntary group to coordinate their actions to combat the pest. Suppose that the profits to farmers are $\Pi^{NC} = \$1800$ if they control the pest individually, whereas their profits amount to $\Pi^{SC} = \$2600$ if they successfully coordinate their actions. Suppose further that successful coordination is defined by having a threshold of at least $T = 70\%$ of individuals in the group combat the pest, that the group under consideration consists of $N = 15$ individuals, and that the probability of success should be at least $\underline{\lambda} = 0.80$. If the collective undertaking fails (i.e., less than $T = 70\%$ of farmers coordinate), each individual receives profits of $\Pi^{FC} = \$600$. According to the CF shown in

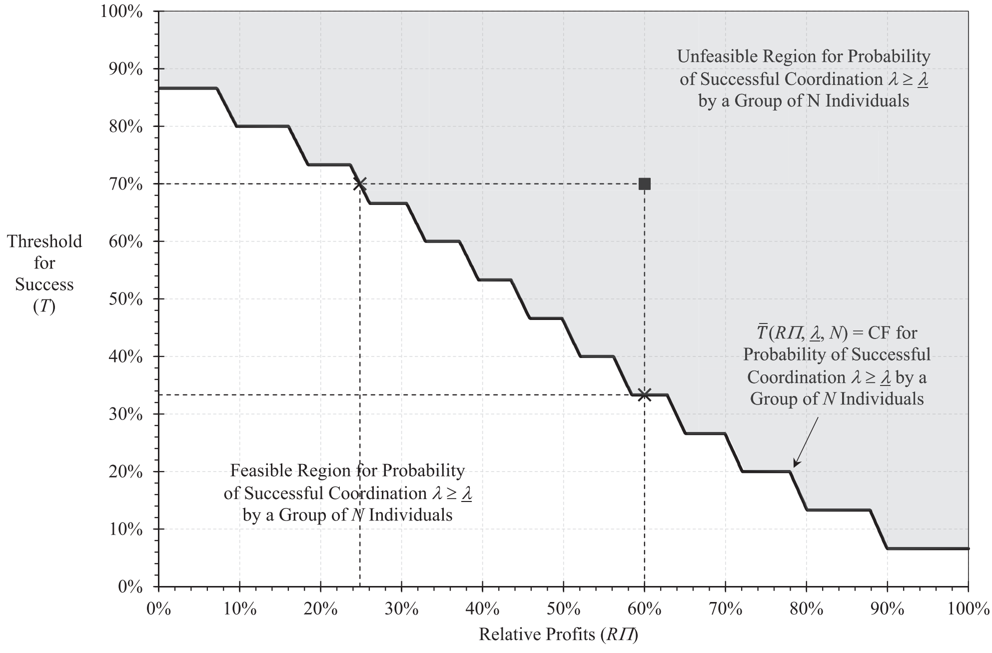

FIGURE 1 A coordination frontier (CF) Note: The CF shown is the $\overline{T}(R\Pi,\ \underline{\lambda} = 0.80,\ N = 15)$ for citrus growers' experimental data depicted in Figure 2

Figure 1, this voluntary coordination project is unlikely to succeed—in the sense that the probability of successful coordination is less than $\underline{\lambda} = 0.80$— because the square in Figure 1 marking the intersection of $R\Pi = 60\%$ (=[\$1800 – \$600]/[\$2600 – \$600]) with the threshold for success $T = 70\%$ lies above the CF; in fact, $\overline{T}(R\Pi = 60\%,\ \underline{\lambda} = 0.80,\ N = 15) = 33.3\%$. Thus, barring a reduction in the threshold for success T, or in the relative profits $R\Pi$, or in both, the CF indicates that voluntary coordination will likely fail, because the probability of successful coordination is below the desired minimum level $\underline{\lambda} = 0.80$. Figure 1 shows that the threshold for success cannot exceed 33.3% if the $R\Pi$ is kept at 60%. Alternatively, the graph indicates that the $R\Pi$ must be less than 24.8% if success requires a threshold of $T = 70\%$ of the group members coordinating. In other words, the threshold and/or alternative payoff needs to be lower or the gains from coordination higher to incentivize individuals to coordinate.

3.1 | The value of the CF

To illustrate how to compute the net benefits of the CF, we use the following equation that, for simplicity of exposition, depicts the problem facing a risk-neutral citrus grower i, whose objective is to maximize expected profits by adopting (or not) AWPM sprays:

$$\max_{W_i} E_{\left(W_{\{-i\}}\right)}\left\{Py(\underline{x}_i)\left[1 - D\left(g, W_i, W_{\{-i\}}\right)\right] - \underline{r}_x\underline{x}_i - (r_W + c)W_i\right\}. \tag{2}$$

Here, P and y (·) are the price and production (in the absence of pest damage), respectively, whereas x_i and r_x represent vectors of all inputs and input prices other than AWPM sprays.[3] The damage function D (·) ∈ [0, 1] denotes the reduction in output due to pest damage (Lichtenberg &

[3]We assume that the individual spray decisions are included in $\underline{x}_i$.

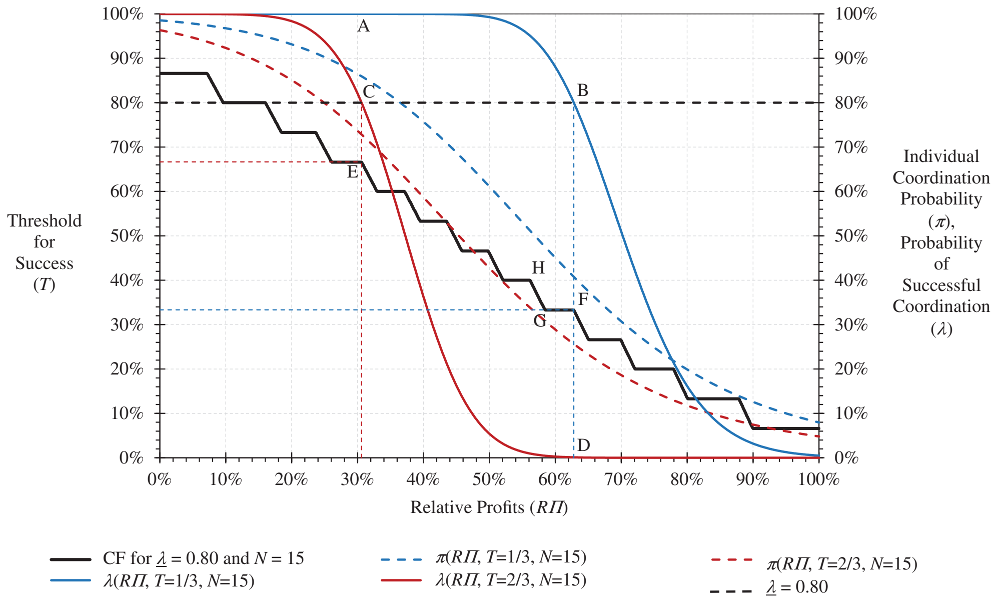

FIGURE 2 Individual coordination probability (ICP) function and probability of successful coordination (λ) for citrus growers' experimental data computed from the ICP estimated model 1, with corresponding coordination frontier (CF) for $\underline{\lambda} = 0.80$ probability of successful coordination and a group of $N = 15$ individuals Note: The CF shown is the $\overline{T}(R\Pi, \underline{\lambda} = 0.80, N = 15)$ for citrus growers' experimental data

Zilberman, 1986) and is increasing in the level of pest population g. The damage function is decreasing in W_i and $W_{\{-i\}}$, which represent the decision to adopt AWPM sprays by the individual grower and her neighboring growers, respectively. The price of inputs associated with W_i is denoted by r_W, and the cost of coordinating sprays is symbolized by c. Although the grower will want to adopt the technology if it yields a higher net benefit, it is not clear, ex-ante, whether AWPM will achieve that goal because the abatement effect involves uncertainty, because with AWPM sprays the expected outcome depends on others $E_{\left(W_{\{-i\}}\right)}(\cdot)$. Coordination is successful when $\Sigma_n \; W_n \geq TN$. In Equation (2), when farmer i adopts AWPM ($W_i = 1$) and the threshold is met ($\Sigma_{n \neq i} \; W_n \geq TN - 1$) we denote it as $W_{\{-i\}} = 1$, otherwise $W_{\{-i\}} = 0$; when farmer i does not adopt AWPM, $W_i = 0$.

To demonstrate the use of Equation (2) empirically, consider the estimates for the costs and benefits of the AWPM program in Florida used by Singerman et al. (2017). By examining data from two groves in different areas within neighboring counties that had comparable management and climatic conditions, they found that the 5-year cumulative gross revenues were \$12,970 and \$9746 per acre for successful and failed AWPM, respectively; yielding a difference in gross revenues from coordinating equal to \$3224 per acre, which had an extra cost of \$1720/acre when using ground applications. The 5-year cumulative cost of cultural programs other than coordinated sprays was \$9405 per acre.[4] More specifically, in the notation of Equation (2), the profits from implementing AWPM to the individual grower are:

$$\text{Successful AWPM}: \Pi_i^{SC} = \underbrace{P\, y(\underline{x}_i)\left[1 - D\left(g, W_i = 1, W_{\{-i\}} = 1\right)\right]}_{\$12{,}970} - \underbrace{\underline{r}_x\, \underline{x}_i}_{\$9{,}405} - \underbrace{(r_W + c)\, W_i}_{\$1{,}720}, \\ = \$1{,}845, \tag{3}$$

[4]Based on publicly available estimates at: https://crec.ifas.ufl.edu/economics/central-florida/

$$\text{Failed AWPM}: \Pi_i^{FC} = \underbrace{P\, y(\underline{x}_i)\, \left[1 - D\left(g, W_i = 1, W_{\{-i\}} = 0\right)\right]}_{\$9{,}746} - \underbrace{\underline{r}_x\, \underline{x}_i}_{\$9{,}405} - \underbrace{(r_W + c)\, W_i}_{\$1{,}720}, \\ = -\$1{,}379. \tag{4}$$

On the other hand, profits without AWPM are[5]:

$$\text{No AWPM}: \Pi_i^{NC} = \underbrace{P\, y(\underline{x}_i)\, \left[1 - D\left(g, W_i = 0, W_{\{-i\}} = 0\right)\right]}_{\$9{,}746} - \underbrace{\underline{r}_x\, \underline{x}_i}_{\$9{,}405}, \\ = \$341. \tag{5}$$

Given the setting just provided, the usefulness and value of the CF can be illustrated as follows. Consider the case in which the policymaker must decide whether to implement an AWPM ($a = AM$) or not ($a = NoAM$). Her net benefits, $B\ (a, s)$, depend on her action a as well as the state of the world s, namely, whether AWPM succeeds ($s = SC$) or fails ($s = FC$). When the CF is not available, the probability of successful coordination is unknown to the policymaker. Therefore, it would be reasonable to assume that she would assign the same probability $\Lambda_s = 1/2$ to each state of the world $s \in \{SC, FC\}$, which satisfies the restriction $\Lambda_{s=SC} + \Lambda_{s=FC} = 1$. Following Bikhchandani, Hirshleifer, and Riley (2013, Chapter 5), the above information is summarized in Table 1 Panel A, which reports the net benefits per acre under the different combinations of actions and states, together with the policymaker's prior beliefs.

If the policymaker must choose her action immediately (i.e., without knowledge of the CF), it would be optimal for her to not implement AWPM, $a_0^* = NoAM$, because doing so maximizes expected net benefits $E_\Lambda[B\ (a, s)]$, that is, $E_\Lambda[B\ (NoAM, s)] = \$341 > \$233 = E_\Lambda[B\ (AM, s)]$:

$$E_\Lambda[B(NoAM, s)] \equiv \Lambda_{s=FC} \times B(NoAM, FC) + \Lambda_{s=SC} \times B(NoAM, SC), \\ = 0.5 \times \$341 + 0.5 \times \$341 = \$341, \tag{6a}$$

$$E_\Lambda[B(AM, s)] \equiv \Lambda_{s=FC} \times B(AM, FC) + \Lambda_{s=SC} \times B(AM, SC), \\ = 0.5 \times (-\$1{,}379) + 0.5 \times \$1{,}845 = \$233. \tag{6b}$$

Suppose instead that the decision maker might be able to use the CF to learn about the likelihood of success of the AWPM before deciding whether to implement it. Under the framework of Bikhchandani, Hirshleifer, and Riley (2013, Chapter 5), the CF is thus a "message service" whose message m conveys information about the likelihood of success of the AWPM. Let us assume that the values reported in Table 1 Panel B represent the decision maker's beliefs about the likelihood of AWPM success that she will learn from the CF. Such a likelihood matrix indicates that the decision maker believes the most likely CF message will be neutral and the least likely message will be favorable.[6] Importantly, the CF is informative about the state, as the likelihood that it conveys a favorable (unfavorable) message is much higher (lower) when coordination is successful than when it fails.

[5]We consider $W_{\{-i\}} = 0$ as opposed to the case in which farmer i would free ride (i.e., $W_{\{-i\}} = 1$), because the former is the case that is relevant because we are trying to establish the value when no CF is available.

[6]Given a scenario like the one discussed in the "Estimating the ICP Function: The Case of Citrus Greening in Florida" section, in which the CF is computed from experimental data and therefore subject to sampling error, a "neutral" message would correspond to the 95% confidence interval around the estimated CF, whereas the favorable and unfavorable messages would correspond to the areas below and above such confidence interval, respectively. The likelihood values reported in Table 1 Panel B are purposely chosen to emphasize that it is not necessary to have $q_{m=Unf|s=FC} = q_{m=Fav|s=SC}$ and $q_{m=Fav|s=FC} = q_{m=Unf|s=SC}$, as one might intuitively expect.

TABLE 1 Net benefits, prior beliefs, likelihood matrix, and potential posterior matrix for illustrative example of the value of the CF

A. Net benefits per acre under the alternative combinations of actions and states of the world, and policymaker's prior beliefs.			
	State of the world		
Action	**s = AWPM fails (*FC*)**	**s = AWPM succeeds (SC)**	
a = No AWPM (*NoAM*)	B ($a = NoAM$, $s = FC$) = \$341	B ($a = NoAM$, $s = SC$) = \$341	
a = AWPM (*AM*)	B ($a = AM$, $s = FC$) = −\$1379	B ($a = AM$, $s = SC$) = \$1845	
Prior beliefs (Λ_s)	$\Lambda_{s=FC} = 0.5$	$\Lambda_{s=SC} = 0.5$	
B. Likelihood matrix, reporting probabilities of messages conditional on the state of the world.			
CF message	**State of the world**		**Unconditional message probability**
	s = AWPM fails (*FC*)	**s = AWPM succeeds (*SC*)**	$q_m = \Sigma_s \Lambda_s q_{m\vert s}$
m = Unfavorable (*Unf*)	$q_{m=Unf\vert s=FC} = 0.46$	$q_{m=Unf\vert s=SC} = 0.12$	$q_{m=Unf} = 0.290$
m = Neutral (*Neu*)	$q_{m=Neu\vert s=FC} = 0.48$	$q_{m=Neu\vert s=SC} = 0.43$	$q_{m=Neu} = 0.455$
m = Favorable (*Fav*)	$q_{m=Fav\vert s=FC} = 0.06$	$q_{m=Fav\vert s=SC} = 0.45$	$q_{m=Fav} = 0.255$
$\Sigma_m q_{m\vert s}$	1	1	
C. Potential posterior matrix, containing $\Lambda_{s\vert m} \equiv q_{m\vert s} \Lambda_s / (\Sigma_s q_{m\vert s} \Lambda_s)$.			
CF message	**State of the world**		$\Sigma_s \Lambda_{s\vert m}$
	s = AWPM fails (*FC*)	**s = AWPM succeeds (*SC*)**	
m = Unfavorable (*Unf*)	$\Lambda_{s=FC\vert m=Unf} = 0.793$	$\Lambda_{s=SC\vert m=Unf} = 0.207$	1
m = Neutral (*Neu*)	$\Lambda_{s=FC\vert m=Neu} = 0.528$	$\Lambda_{s=SC\vert m=Neu} = 0.472$	1
m = Favorable (*Fav*)	$\Lambda_{s=FC\vert m=Fav} = 0.118$	$\Lambda_{s=SC\vert m=Fav} = 0.882$	1

By application of Bayes' Theorem, knowledge of the CF would allow the decision maker to update her beliefs about the probability of success of the AWPM, as reflected by the potential posterior probabilities reported in Table 1 Panel C. Importantly, the policy maker would be able to choose her optimal action based on the CF message received. For example, if the CF conveyed a favorable message, the potential posterior probabilities imply that the policymaker's optimal action would be to implement AWPM, $a_{m=Fav}^{*} = AM$, as it yields the highest expected net benefits

$$E_{\Lambda|m=Fav}[B(NoAM,s)] \equiv \Lambda_{s=FC|m=Fav} \times B(NoAM,FC) + \Lambda_{s=SC|m=Fav} \times B(NoAM,SC),$$
$$= 0.118 \times \$341 + 0.882 \times \$341 = \$341, \tag{7a}$$

$$E_{\Lambda|m=Fav}[B(AM,s)] \equiv \Lambda_{s=FC|m=Fav} \times B(AM,FC) + \Lambda_{s=SC|m=Fav} \times B(AM,SC),$$
$$= 0.118 \times (-\$1,379) + 0.882 \times \$1,845 = \$1,466. \tag{7b}$$

This means that the favorable CF message has a positive value of $\omega_{m=Fav} = \$1125$, given by the gain in expected net value from implementing AWPM ($a_{m=Fav}^{*} = AM$) instead of not doing so as dictated by the optimal immediate action (a_0^{*}):

$$\omega_{m=Fav} \equiv E_{\Lambda|m=Fav}[B(a_{m=Fav}^{*},s)] - E_{\Lambda|m=Fav}[B(a_0^{*},s)],$$
$$= \$1,466 - \$341 = \$1,125. \tag{8}$$

A similar analysis reveals that if the CF message were either neutral or unfavorable, the policy maker's optimal action would be to not implement AWPM, $a_{m=Neu}{}^{*} = a_{m=Unf}{}^{*} = NoAM$.[7] Hence, such messages would have no value

$$\omega_{m=Neu} \equiv E_{\Lambda|m=Neu}\left[B\left(a_{m=Neu}{}^{*}, s\right)\right] - E_{\Lambda|m=Neu}\left[B\left(a_0{}^{*}, s\right)\right] = \$341 - \$341 = \$0, \tag{9a}$$

$$\omega_{m=Unf} \equiv E_{\Lambda|m=Unf}\left[B\left(a_{m=Unf}{}^{*}, s\right)\right] - E_{\Lambda|m=Unf}\left[B\left(a_0{}^{*}, s\right)\right] = \$341 - \$341 = \$0. \tag{9b}$$

Of course, the CF message is unknown to the policy maker before the CF information is revealed to her. Hence, the value of the CF information to the policy maker, Ω (CF), is equal to the expected gains in net benefits from knowing the CF. That is, the value of the CF equals the expected value of its messages:

$$\begin{aligned} \Omega(CF) &\equiv q_{m=Unf}\,\omega_{m=Unf} + q_{m=Neu}\,\omega_{m=Neu} + q_{m=Fav}\,\omega_{m=Fav}, \\ &= 0.290 \times \$0 + 0.455 \times \$0 + 0.255 \times \$1{,}125 = \$287, \end{aligned} \tag{10}$$

where q_m is the unconditional probability of receiving message m. Combining Ω (CF) = \$287/acre with the 415,169 acres grown in Florida at the time gives an estimate of the 5-year aggregate ex ante value of having the CF of \$119 million. This provides evidence that the information the CF could provide is both actionable and consequential by leading to a nontrivial improvement in the outcome.[8]

Had the CF been available ex-ante, the results could have been shared with growers by extension personnel to reduce growers' strategic uncertainty regarding coordination. Singerman and Useche (2019) find that the average grower displays strategic uncertainty aversion; as T increases, a grower's switching point from coordination to certain payoff decreases, which can be interpreted as the behavioral counterpart to the change in strategic uncertainty facing growers. By providing estimates of the (aggregate) chances of successful coordination at each threshold, the CF could have contributed to reducing the strategic uncertainty by updating growers' beliefs regarding the chances of success. Thus, policy makers in California could potentially make use of the CF to encourage coordination not only by sharing results but also by devising ways to encourage participation to increase the chances of reaching a desired threshold and communicating to stakeholders how the results of the program hinge critically on their individual decisions to coordinate.[9]

3.2 | How to construct the CF

To discuss how to obtain a CF for a specific minimum probability of successful coordination $\underline{\lambda}$ and group size N, $\overline{T}(R\Pi, \underline{\lambda}, N)$, it is helpful to make use of the ICP function π $(R\Pi, T, N)$. ICPs are

[7]This is true because $E_{\Lambda|m=Neu}[B\ (AM, s)] = 0.528 \times (-\$1379) + 0.472 \times \$1845 = \$144 < 341 = E_{\Lambda|m=Neu}[B\ (NoAM, s)]$, and $E_{\Lambda|m=Unf}[B\ (AM, s)] = 0.793 \times (-\$1379) + 0.207 \times \$1845 = -\$712 < \$341 = E_{\Lambda|m=Unf}[B\ (NoAM, s)]$.

[8]It must be noted that, as pointed out by an anonymous reviewer, the value of information about the CF depends critically on the assumptions of the prior probabilities (Λ_s) and the conditional probabilities of CF messages ($q_{m|s}$).

[9]A reviewer raised an interesting issue regarding the unintended consequences of sharing aggregate probabilities of success. Although it is conceivable that some growers would free ride thinking there is a high success probability when, say, $\lambda = 90\%$, two arguments can be made regarding the beneficial consequences of sharing aggregate probabilities of success. First, as mentioned above, there is evidence that public information can convey strategic information on the individuals' beliefs of others; in settings where coordination is important, public signals play a role in coordinating outcomes that exceed the information content of those announcements. Second, Singerman et al. (2017) find that the main reason for growers not to coordinate was their beliefs about others not coordinating. Therefore, making the aggregate outcome public should help reduce such (strategic) uncertainty. The other case that may discourage participation is when $\lambda < 50\%$, because growers might think there is a low probability of success, so they may prefer to do their own spraying instead of participating in AWPM. In such a case, before sharing the results with growers, policy makers and/or extension agents will have to come up with an incentive mechanism to foster cooperation among farmers so as to increase λ.

illustrated in Figure 2, which depicts π ($R\Pi$, $T = 1/3$, $N = 15$) and π ($R\Pi$, $T = 2/3$, $N = 15$), estimated using experimental data discussed in more detail in the next section, together with the corresponding CF for $\underline{\lambda} = 0.80$ and $N = 15$, which is identical to the CF shown in Figure 1.[10] Ceteris paribus, the probability that an individual coordinates falls as $R\Pi$ or T increases. For example, according to the ICPs plotted in the graph, when the group size is $N = 15$ and $R\Pi = 30.6\%$ (62.8%), the probability that an individual randomly drawn from the relevant population coordinates is $\pi = 0.860$ (0.408) when $T = 1/3$, but decreases to $\pi = 0.728$ (0.256) when $T = 2/3$.

The ICP function π ($R\Pi$, T, N) deserves special attention because it provides the basis to compute the CF for any desired minimum probability of successful coordination $\underline{\lambda}$ and group size N. We propose to estimate the ICP function using data obtained from experiments to elicit the probability that individuals coordinate when being part of a group of a specific size (N) and threshold for success (T). Importantly, in the experiments it is not possible to directly ask individuals whether they would coordinate at a given level of successful coordination (λ), because the latter depends on the individuals' decisions.

The ICP function is estimated from individuals' revealed choices when facing coordination decisions involving $\{R\Pi, T, N\}$. The mechanism by which subjects arrive at such choices can be hypothesized to be based on individuals' subjective beliefs regarding either the probability that a randomly selected player in the group other than herself will coordinate ("π beliefs") or, alternatively, regarding the probability that the group coordination will be successful ("λ beliefs"). As pointed out by Heinemann et al. (2009), one problem of attempting to elicit such beliefs by directly asking subjects about them in an experimental setting (with the provision of adequate incentives for players to reveal their true beliefs) is that doing so may affect their behavior. Such caveat notwithstanding, Heinemann et al. (2009) conducted experimental coordination games similar to ours and asked players for their π and λ beliefs to learn more about how their subjective beliefs were formed. Overall, the authors found no significant differences in the coordination outcomes observed in the games asking for π beliefs compared to the games asking for λ beliefs. In both games, about 40% of the individuals' coordination choices were consistent with their stated beliefs. The authors found no evidence regarding whether individuals asked for their π beliefs tended to make fewer or more mistakes in their coordination choices compared to individuals asked for their λ beliefs. However, they found a very strong correlation between players' actions and their stated π and λ beliefs.

A noteworthy finding from the study by Heinemann et al. (2009) is that subjects state almost the same probabilities whether asked for π or λ beliefs, because individuals seem to ignore the effect of the binomial function that relates the two probabilities. This finding suggests that extension programs may incentivize coordination by making the CF available, which would allow subjects to update their (underestimated) λ beliefs. In this regard, Singerman and Useche (2019) found that approximately 30% of the growers chose to coordinate more after receiving information on a well-performing AWPM area. The authors hypothesized that one explanation for such a result was that those growers changed their beliefs regarding the chances of achieving successful coordination, which suggests that providing public information can be helpful to increase the expected payoff and decrease the uncertainty about others' behavior.

To explain how to draw the CF $\overline{T}(R\Pi, \underline{\lambda}, N)$ from the ICP function π ($R\Pi$, T, N), it is necessary to be more specific about the size of the coordinating group, N, and the number of individuals who coordinate. In particular, if the threshold for success is T, then at least $K \equiv \lceil TN \rceil$ of the N individuals in the group must coordinate, where $\lceil x \rceil$ denotes the closest integer greater than or equal to x. Then, the corresponding probability of successful coordination conditional on each individual coordinating with probability π ($R\Pi$, T, N), λ ($R\Pi$, T, N), is given by the complement of the binomial distribution function

[10]For simplicity of exposition, for the time being it is assumed that ICPs only depend on $R\Pi$, T, and N. As noted in the "Estimating the ICP Function: The Case of Citrus Greening in Florida" section, however, ICPs may be functions of other variables, such as the demographics (e.g., age or gender) of the individuals in the group.

$$\lambda(R\Pi,T,N) \equiv 1 - \text{CumBinom}[\lceil TN \rceil - 1, N, \pi(R\Pi,T,N)], \tag{11a}$$

$$= \text{CumBinom}[N - \lceil TN \rceil, N, 1 - \pi(R\Pi,T,N)]. \tag{11b}$$

In expressions (11a) and (11b), CumBinom (k, n, φ) denotes the cumulative binomial distribution function of k successes in n independent trials with replacement, when the probability of success in each trial is φ. According to (11b), the probability of successful coordination λ ($R\Pi$, T, N) is equal to the probability that at most ($N - \lceil T\,N \rceil$) = ($N - K$) out of N individuals do not coordinate, where the probability of an individual not coordinating is [$1 - \pi$ ($R\Pi$, T, N)].

Expression (11b) makes it straightforward to calculate the probability of successful coordination λ corresponding to any $R\Pi$, because the ICP function establishes the link between $R\Pi$ and the individual coordination probability π. For example, for the ICPs shown in Figure 2, the probability of successful coordination for $R\Pi = 30.6\%$, $N = 15$, and $T = 1/3$ is

$$\begin{aligned}\lambda(R\Pi = 30.6\%, T = 1/3, N = 15) &= \text{CumBinom}(N - \lceil T\,N \rceil, N, 1 - \pi(R\Pi,T,N)) \\ &= 1.00,\end{aligned} \tag{12}$$

because π ($R\Pi = 30.6\%$, $T = 1/3$, $N = 15$) = 0.860. However, the probability of successful coordination drops to $\lambda = 0.800$ when $R\Pi$ increases to $R\Pi = 62.8\%$, because the probability that an individual coordinates decreases to π ($R\Pi = 62.8\%$, $T = 1/3$, $N = 15$) = 0.408. These probabilities of successful coordination at $R\Pi = 30.6\%$ and $R\Pi = 62.8\%$ are labeled as points A and B along the probability of successful coordination function λ ($R\Pi$, $T = 1/3$, $N = 15$), which traces all such points for $R\Pi \in [0\%, 100\%]$.

Increasing the threshold for success to $T = 2/3$ reduces the probability of successful coordination at any given level of $R\Pi$, as illustrated in Figure 2 by the fact that λ ($R\Pi$, $T = 2/3$, $N = 15$) lies below λ [$R\Pi$, $T = 1/3$, $N = 15$]. At $R\Pi = 30.6\%$ (62.8%), π ($R\Pi = 30.6\%$, $T = 2/3$, $N = 15$) = 0.728 (π [$R\Pi = 62.8\%$, $T = 2/3$, $N = 15$] = 0.256); hence, the probability of successful coordination is $\lambda = 0.800$ (0.001), which is depicted as point C (D) on the graph of function λ ($R\Pi$, $T = 2/3$, $N = 15$).

The fact that the probability of success, λ ($R\Pi$, T, N), can be computed from the ICP function as indicated above makes it straightforward to calculate the CF for any desired probability of successful coordination λ and group size N, $\overline{T}$($R\Pi$, λ, N). More concretely, the CF is defined as

$$\overline{T}(R\Pi,\underline{\lambda},N) \equiv \max\{T \mid \lambda(R\Pi,T,N) \geq \underline{\lambda}\} \tag{13a}$$

$$= \max\{T \mid \text{CumBinom}[N - \lceil TN \rceil, N, 1 - \pi(R\Pi,T,N)] \geq \underline{\lambda}\}. \tag{13b}$$

To illustrate how the CF is obtained, consider points E and F on the CF in Figure 2, which depicts $\overline{T}$($R\Pi$, $\underline{\lambda} = 0.80$, $N = 15$). The two points denote the maximum feasible thresholds $\overline{T} = 2/3$ and $\overline{T} = 1/3$, respectively. In the case of point E, it can be observed that π ($R\Pi = 30.6\%$, $T = 2/3$, $N = 15$) = 0.728, which yields a probability of successful coordination of λ ($R\Pi = 30.6\%$, $T = 2/3$, $N = 15$) = 0.800 (designated as point C in the graph). A lower threshold T would increase the probability of successful coordination (e.g., π ($R\Pi = 30.6\%$, $T = 1/3$, $N = 15$) = 0.860, for which λ ($R\Pi = 30.6\%$, $T = 1/3$, $N = 15$) = 1.00), and vice versa. Therefore, the highest threshold for $R\Pi = 30.6\%$ resulting in a probability of successful coordination equal to or exceeding $\underline{\lambda} = 0.80$ is $T = 2/3$. Analogously, at point F, where $\overline{T} = 1/3$ and $R\Pi = 62.8\%$, the probability of successful coordination λ ($R\Pi = 62.8\%$, $T = 1/3$, $N = 15$) = 0.800 (because π ($R\Pi = 62.8\%$, $T = 1/3$, $N = 15$) = 0.408). Thus, a threshold above $T = 1/3$ results in a probability of success below the constraint $\underline{\lambda} \geq 0.80$ (e.g., π ($R\Pi$ = 62.8%, $T = 2/3$, $N = 15$) = 0.256 and λ ($R\Pi$ = 62.8%, $T = 2/3$, $N = 15$) = 0.001).

The segment HGF in the CF depicted in Figure 2 can be used to explain why $\overline{T}(R\Pi, \underline{\lambda}, N)$ as a function of $R\Pi$ is characterized by a combination of horizontal and downward-sloping segments. All points along the GF segment are such that $\overline{T} = 1/3$. The probabilities of successful coordination corresponding to this segment increase monotonically from λ ($R\Pi$ = 62.8%, $T = 1/3$, $N = 15$) = 0.800 to λ ($R\Pi$ = 58.5%, $T = 1/3$, $N = 15$) = 0.914 as one moves from F to G, because the associated ICPs increase from π ($R\Pi$ = 62.8%, $T = 1/3$, $N = 15$) = 0.408 to π ($R\Pi$ = 58.5%, $T = 1/3$, $N = 15$) = 0.474. Thus, the probability of successful coordination over $R\Pi \in$ [58.5%, 62.8%) strictly exceeds the required minimum level of $\underline{\lambda} = 0.80$, that is, the constraint is only binding at the right-most extreme of the GF segment. Despite the $\underline{\lambda}$ constraint not being binding over $R\Pi \in$ [58.5%, 62.8%), however, increasing the threshold above $T = 1/3$ by an infinitesimal amount leads to a violation of the constraint. The reason why the constraint violation happens is that such an increase in T causes a discrete jump in the number of coordinating individuals required for success from $\lceil TN \rceil = 5$ to $\lceil TN \rceil = 6$, which in turn reduces the associated probability of successful coordination to a level below $\underline{\lambda} = 0.80$ (see the role of the term $\lceil TN \rceil$ in Equation [13b]).

Turning attention to the HG segment, where $R\Pi \in$ [56.1%, 58.5%), the maximum threshold increases monotonically from an infinitesimal amount above $\overline{T} = 1/3$ at point G to $\overline{T} = 6/15$ at point H, but the levels of the respective ICPs stay constant at π ($R\Pi$ = 58.4%, $T = 0.334$, $N = 15$) = π ($R\Pi$ = 56.1%, $T = 6/15$, $N = 15$) = 0.475. The reason for the constant ICP levels is that the increase in ICP due to a reduction in $R\Pi$ is exactly compensated by the reduction in ICP due to the increase in T.[11] Therefore, the probability of successful coordination equals the constraint $\underline{\lambda} = 0.80$ over the entire segment, despite T increasing from G to H while the ICP levels remain unchanged at $\pi = 0.475$.[12]

In summary, the CF for a desired minimum probability of successful coordination $\underline{\lambda}$ and group size N is calculated by means of expression (13b). Further, from the example just presented it is straightforward to infer some regularities that apply to CFs estimated from experimental data. First, a ceteris paribus increase in the minimum probability of successful coordination $\underline{\lambda}$ shifts the corresponding CF down and to the left. Second, the vertical distance between a CF's successive horizontal segments equals $1/N$. Third, all else the same, augmenting the group size N increases the number of horizontal segments in the CF.

3.3 | The approximate CF for $\underline{\lambda} = 0.50$ (ACF50)

The lack of smoothness of the CFs may be unappealing for some purposes, for instance, when the intended use of the CF is to assess whether an extension program aimed at improving the probability of successful coordination is achieving its goal. In such circumstances, the approximate CF for $\underline{\lambda} = 0.50$ (ACF50) described next may prove more attractive than the CFs.

The ACF50 is postulated based on the intuitive notion that the chance of successful coordination should be approximately $\lambda \cong 50\%$ if successful coordination requires a threshold of $T = p$ and each individual coordinates with probability π = p. Formally, the ACF50 is defined as the implicit function determined by

$$p = \pi(R\Pi, T = p, \mathrm{N}). \tag{14}$$

[11]The ICPs π ($R\Pi$, T, $N = 15$) and the successful coordination probabilities λ ($R\Pi$, T, $N = 15$) for $T \in$ [0.334, 0.40] are not depicted in Figure 2 to avoid cluttering. However, as it may be inferred from the schedules shown, they would lay immediately to the left of π ($R\Pi$, $T = 1/3$, $N = 15$) and λ ($R\Pi$, $T = 1/3$, $N = 15$), respectively.

[12]The increase in T does not cause a reduction in the probability of successful coordination, as one might expect with the ICP fixed at $\pi = 0.475$, because the number of coordinating individuals required for success is $\lceil T\,N \rceil = 6$ over this CF segment where $T \in (1/3, 6/15)$.

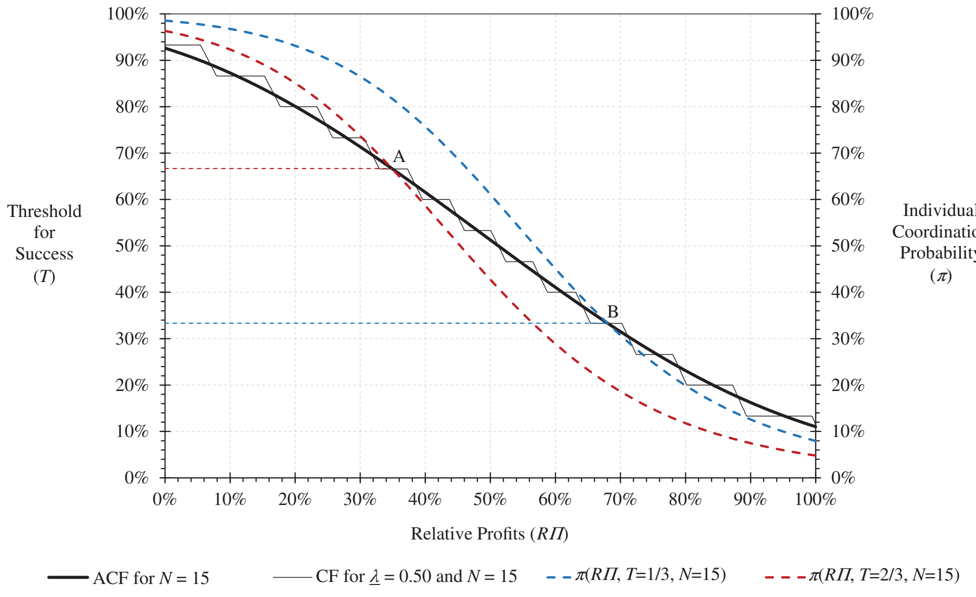

FIGURE 3 Individual coordination probability (ICP) function for citrus growers' experimental data, with corresponding coordination frontier (CF) for $\underline{\lambda} = 0.50$ probability of successful coordination and a group of $N = 15$ individuals, and ACF50 for $N = 15$ computed from the ICP estimated Model 2 Note: The CF shown is the $\overline{T}(R\Pi, \underline{\lambda} = 0.50, N = 15)$ for citrus growers' experimental data

The ACF50 yields the threshold T as a decreasing function of $R\Pi$ if the ICP function π $(R\Pi, T, N)$ is monotonically decreasing in both $R\Pi$ and T, as supported by the experimental evidence. An interesting feature of the ACF50 is that, as discussed in the online supplementary Appendix S1A, the ACF50 is a good approximation to the CF for $\underline{\lambda} = 0.50$. In fact, the online supplementary Appendix S1A also demonstrates that the ACF50 equals

$$\tilde{\overline{T}}(R\Pi,N) \equiv \lim_{n\to\infty} \max\{T \mid \mathrm{CumBinom}[n - \lceil Tn \rceil, n, 1 - \pi(R\Pi,T,N)] \geq \underline{\lambda} = 0.50\} \tag{15}$$

when the ICP function π $(R\Pi, T, N)$ is monotonically decreasing in both $R\Pi$ and T. Despite the ACF50 equivalence between (14) and (15), the solution to the fixed-point problem (14) is favored to compute the ACF50 in practice, as it is simpler to solve than the optimization problem (15).

The ACF50 for the ICPs shown in Figure 2 is depicted in Figure 3. Consistent with equality (14), the points π $(R\Pi = 34.9\%, T = 2/3, N = 15) = 2/3$ and π $(R\Pi = 68.0\%, T = 1/3, N = 15) = 1/3$, labeled respectively as points A and B, are on the ACF50.[13] In general, if π $(R\Pi, T = t, N) = t$ when evaluated at $R\Pi = \rho$, then it must be the case that $\tilde{\overline{T}}(R\Pi = \rho, N) = t$. In other words, the ACF50 is such that $\pi\left[\mathrm{R\Pi} = \rho, T = \tilde{\overline{T}}(R\Pi = \rho, N), N\right] = \tilde{\overline{T}}(R\Pi = \rho, N)$.

The CF for $\underline{\lambda} = 0.50$ is also included in Figure 3 to demonstrate how it is approximated by the ACF50 function. In general, as the group size N increases, the ACF50 exhibits an even closer approximation to the corresponding CF for $\underline{\lambda} = 0.50$.

[13]The $\tilde{\overline{T}}(R\Pi, N = 15)$ values for the plot were obtained by employing the bisection routine in Miranda and Fackler's (2002) COMPECON computer package to solve the root-finding problem (14) using MATLAB. Succinctly, for a given N, the bisection routine takes the function π $(R\Pi, T, N)$ and a vector of $R\Pi$ values as inputs, and yields as output the vector of $\tilde{\overline{T}}(R\Pi, N)$ values associated with the inputted $R\Pi$ vector.

4 | ESTIMATING THE ICP FUNCTION: THE CASE OF CITRUS GREENING IN FLORIDA

The premise underlying the efforts to coordinate pest and disease management is that they can be more effective relative to farmers acting individually (Klassen, 2000). By computing the maximum feasible participation threshold of a voluntary effort for different levels of *RΠ*, we provide policymakers with a valuable tool to assess the merits of establishing a voluntary program to coordinate farmers' actions to combat pest and disease. We illustrate the application and usefulness of the CF concept using the case of citrus greening in Florida.

Citrus greening or Huanglongbing (HLB) is a devastating disease caused by the bacterium *Candidatus* Liberibacter asiaticus and transmitted by a highly mobile insect, the Asian citrus psyllid. The disease affects major commercial citrus production areas worldwide and was first found in Florida in 2005. HLB spread rapidly throughout the state, where it is now endemic. Given the lack of treatment or management strategy to cure the disease, citrus production in Florida has decreased by 80% since 2004.[14] As a consequence, Florida is no longer the largest citrus-producing state in the United States, although it is still the largest orange-producing state (U.S. Department of Agriculture. National Agricultural Statistics Service [USDA-NASS], 2021).

As part of the strategic plan for the Florida citrus industry to address HLB, a voluntary AWPM program to control the psyllid was established in 2010. The program's objective was not to eradicate the pest or disease but to limit its impact. In either case, still today there is no entomological study establishing what percentage of coordination is needed for such a program to be effective. However, had the CF been available at the time, it would have been valuable for providing reasonable estimates of successful coordination for different combinations of conjectural participation thresholds and *RΠ*. Thus, having the CF could have been beneficial for policymakers working with scientists not only to determine the likely outcome of the program, but also —because they would have been more aware of the issues that coordination entails— to devise ways to encourage participation to reach a desired threshold. In addition, having the CF could have been valuable to communicate to industry stakeholders how the results of the program hinged on their individual decisions to coordinate. Only in 2017, Singerman, Lence, and Useche provided empirical evidence regarding not only the key question of whether the program contributed to mitigate the impact of HLB but also the type of participation needed for the program to be effective. The authors found a significant differential yield and profitability in areas with higher (but not unanimous) coordination.

4.1 | Data

The data we use to estimate the ICP for the case of HLB in Florida were collected by conducting an experimental game during a meeting of Florida citrus growers in April 2016, which was organized by the University of Florida Cooperative Extension. During the meeting, scientists from different disciplines (horticulture, entomology, soil science, etc.) summarized the advances for managing HLB. One of the authors was part of the program as a speaker and made a presentation on AWPM during which he collected the data. These data have been previously used by Singerman and Useche (2019) to analyze the role that strategic uncertainty played in Florida citrus growers' decisions for participating in AWPM. In that study, the authors examined individual grower's choices and behavior. Unlike them, here we focus on aggregate behavior; as mentioned in the introduction, we aim at providing a practical tool that will allow inferring whether group coordination is feasible under specific conditions.

[14]Even though HLB was first found in Florida in 2005, the initial figures we use to illustrate its impact on the industry correspond to 2004 because they provide a better estimate of the scale of the industry prior to HLB. Florida was hit by four hurricanes between August and September of 2004. A little over a year later, in October 2005, another hurricane hit the state. Those hurricanes had a significant negative impact on yield and, therefore, the production of oranges statewide in 2005, 2006, and 2007.

As growers entered the room, they were provided with game forms and randomly assigned into three different (hypothetical) coordinating groups, with $N = 15$, 30, or 45 growers; that is, we had three different versions of the coordinating games. The set $N = \{15, 30, 45\}$ was chosen so as to be representative of the actual AWPMs around the state based on the recommendation of the entomologist at the University of Florida who was in charge of the program. Such setting allowed examining whether the size of the coordinating group was a relevant variable for growers to decide whether to coordinate, as it had been found in previous studies (Carlson & Wetzstein, 1993; Olson, 1965; Ostrom, 2010; Sandler, 2015).

At the beginning of the presentation, the speaker explained that the talk was going to be divided into two parts. In the first part, he was going to conduct the experimental game, and in the second part, he was going to share some results on AWPM performance. Before starting the experiment, and to align growers' responses with their actual preferences, the speaker announced that one of the participants would have the chance to win up to \$150 (10% of the maximum payoff) in a raffle at the end of the session based on that individual's responses. The speaker then had growers play four games, two of which furnished the data used to estimate the ICP.[15] In these two games, referred to as strategic Games 1 and 2 from now on, growers had to choose between Options A and B (see online supplementary Appendix S1C). Option A consisted of a certain payout starting at \$150 in the first binary choice, which increased by \$150 in each of the following choices, reaching \$1500 in Choice 10. Option B was framed as an AWPM participation decision, where the expected payoff depended on the grower's belief about the number of individuals who were willing to coordinate sprays. The objective was to find the individual's relative profits ($R\Pi$) up to which each grower was willing to coordinate.

To identify the change in individual behavior related to strategic uncertainty, all factors were kept fixed between strategic Games 1 and 2, but the coordination requirement was changed. In strategic Game 1, Option B offered a payout of \$1500 if at least one-third of the growers in the area coordinated sprays and zero otherwise. In strategic Game 2, Option B offered a payout of \$1500 if at least two-thirds of the growers in the area coordinated sprays and zero otherwise. That is, the threshold was $T = 1/3$ for the first strategic game, and $T = 2/3$ for the second one. The maximum amount of \$1500 was based on the estimated cumulative difference in profits of a well-performing AWPM group relative to a not so well performing group (Singerman et al., 2017). After finishing the games, the raffle was conducted, and participants returned the forms at the end of the session.

We collected 123 questionnaires out of the 140 growers who attended the event and took the survey, for a response rate of 88%. The growers who responded to the survey cultivated 153,278 acres, or approximately one-third of the area planted with citrus in Florida at the time. Twelve of the collected questionnaires were discarded due to missing information. An additional 28 questionnaires were also disregarded for the present analysis, because growers did not play threshold strategies.[16] In total, we obtained 1660 Yes/No responses from 83 growers regarding AWPM participation at different $R\Pi$ levels, thresholds T, and group sizes N presented in the strategic games. This set of responses and $\{R\Pi \times T \times N\}$ combinations provided the basic data for the ICP estimation.

[15]The experiment also included a non-strategic game, in which the uncertain alternative was a simple lottery, whose data were used by Singerman and Useche (2019) to study farmers' individual behavior. For the simple lottery, farmers faced a similar setting to that of the strategic games, but Option B simply consisted of the chance to obtain \$1500 with a 67% probability, and \$0 otherwise. Thus, the expected payout was \$1000 throughout the 10 B choices. The entire experiment (including both non-strategic and strategic games) resembles the one conducted by Heinemann et al. (2009). The difference, however, is that in our case it was applied to capture specific features of a real and current (agricultural) issue and the participants were farmers (instead of students), who actually make the type of participation decisions featured by the experiments and, therefore, directly face consequences from those decisions. Nevertheless, in the online supplementary Appendix S1B we also make use of the data collected by Heinemann et al. (2009).

[16]Following Heinemann et al. (2009), threshold strategies are defined as those in which the grower (a) chose the uncertain Option B at least once in any of the games; (b) switched from Option B to Option A during that game; and (c) after switching to Option A, did not switch back to Option B. The percentage of participants playing threshold strategies was considerably larger in the study conducted by Heinemann et al. (2009) than in our experiment. We attribute this difference to the time constraints we faced to properly explain and perform the experiment, which may have caused some individuals to not choose threshold strategies due to not completely understanding the game. Thus, by using data only for participants who adopted threshold strategies, we are implicitly assuming that the other participants would have behaved similarly if only they had had a better understanding of the game.

4.2 | Estimation

The experimental data allow us to directly estimate the probability that a grower in the sample coordinates sprays at different $R\Pi$ levels, thresholds T, and group sizes N. We conduct this estimation by fitting the following logit model to the data[17]

$$\ln[\pi/(1-\pi)] = \beta_0 + \beta_R R\Pi + \beta_T T + \beta_N N + \beta_{RR} R\Pi^2 + \beta_{NN} N^2 + \beta_{RT} R\Pi T + \beta_{RN} R\Pi N + \beta_{TN} TN. \tag{16}$$

Hence, the estimated ICP function consists of

$$\pi(R\Pi, T, N) = \frac{\exp(\boldsymbol{\beta}^{\mathrm{T}} \boldsymbol{X})}{1 + \exp(\boldsymbol{\beta}^{\mathrm{T}} \boldsymbol{X})}, \tag{17}$$

where $\boldsymbol{\beta}^{\mathrm{T}} \equiv [\beta_0\ \beta_R\ \beta_T\ \beta_N\ \beta_{RR}\ \beta_{NN}\ \beta_{RT}\ \beta_{RN}\ \beta_{TN}]$ is the row vector of coefficients and $\boldsymbol{X} \equiv [1, R\Pi, T, N, R\Pi^2, N^2, R\Pi\ T, R\Pi\ N, T\ N]$ is the column vector of explanatory variables. Other regressors, such as individual's demographics, are omitted from our estimated regression because, for simplicity of exposition, we assume that the individuals in the experiment are representative of the coordination group for which the CF is being considered. However, such regressors would be worth including if their values for the group are known.[18]

To account for the potential correlation among each grower's responses, we cluster the responses by grower and make statistical inferences using cluster-robust standard errors. Such estimation method does not require specification of a model for within-cluster error correlation (Cameron & Miller, 2015). The estimates of the logit regression (17) are reported in Table 2 under the column Model 1, along with the more parsimonious specification Model 2, which only includes the variables that are simultaneously statistically significant at the 5% level. Although Model 1 shows that only variable $R\Pi$ is negative and statistically significant, Model 2 shows that the variables $R\Pi$ and threshold T are both negative and statistically significant at the 1% level.[19]

The graphs of the estimated π ($R\Pi$, T, N) obtained from Model 2 by using the AWPM experimental data for $T = \{1/3, 2/3\}$ and $N = 15$ are shown in Figures 2 and 3. Figure 3 depicts the graph of the ACF50 obtained from Model 2. Figure 4 shows the same ACF50, as well as its 95% confidence interval. This figure helps illustrate how one could use the ACF50 to test whether an extension program designed to improve attitudes toward coordination is performing as planned.

4.3 | Significance of the ICP function and the CF

Given that the ICPs and the CF depicted in Figure 2 are based on data collected from a framed field economic experiment of growers facing a real-world social dilemma, the relevance of the information they portray specifically for the case of voluntary coordination to deal with HLB —and, more importantly, for any future application involving similar collective action dilemmas— cannot be overstated. Figure 2 not only illustrates but also quantifies two key aspects that are at the heart of

[17]Variable T^2 cannot be included as a regressor in the logit model due to collinearity because the experiment involved only $T = \{1/3, 2/3\}$.
[18]For example, suppose that the coefficient of a gender dummy is significantly different from zero when included in the logit (16), so that $\pi(R\Pi, T, N|female) \neq \pi(R\Pi, T, N|male)$. Then, if one knows that the group for which the CF is being drawn consists of N_F women and $(N - N_F)$ men, the appropriate ICP to use in the CF computation (13′) should be $\pi(R\Pi, T, N) = N_F/N\ \pi(R\Pi, T, N|female) + (1 - N_F/N)\ \pi(R\Pi, T, N|male)$.
[19]We also estimated models 1 and 2 in Table 2 using Generalized Estimated Equations (GEE). The results are very similar to those presented for the clustered logit model.

TABLE 2 Cluster-robust logit estimates of the probability that a grower coordinates insecticide sprays with others[a]

Variable	Model 1[b]	Model 2
Constant	4.988***	5.086***
	(1.325)	(0.476)
$R\Pi$	−7.917***	−7.058***
	(2.343)	(0.623)
T	−1.759	−3.098***
	(1.678)	(0.513)
N	−0.00425	
	(0.103)	
$R\Pi^2$	1.738	
	(1.541)	
N^2	0.00110	
	(0.00177)	
$R\Pi \times T$	1.238	
	(2.215)	
$R\Pi \times N$	−0.0602	
	(0.0499)	
$T \times N$	−0.0729	
	(0.0446)	
Pseudo R^2	0.403	0.396
Observations	1660	1660

Note: $^{***}p < 0.01$. Robust standard errors within parentheses.
[a]Data from Singerman and Useche (2019).
[b]Variable T^2 cannot be included in Model 1 because of collinearity.

strategic uncertainty; namely, the magnitude of the aggregate change in the probability of successful coordination (λ) due to a change in threshold and the magnitude of the change in the probability of successful coordination as the (opportunity) cost of coordinating increases. The impact from a change in either the threshold or the opportunity cost, or both, on successful coordination is a consequence of the underlying change in the individuals' beliefs about the (coordinating) behavior of others.

Coordinating efforts to combat invasive species typically require high participation. In fact, in some cases, the effort needed is characterized as a weakest-link public good problem (Ervin & Frisvold, 2016; Perrings et al., 2002). Frisvold (2019b) argues that if participation of small-scale producers—for whom farming is not a main source of economic livelihood—is necessary, the need of near-universal participation is far more daunting than, say, a threshold of $T = 75\%$. Even without taking the specifics of growers' heterogeneity into account, the CF in Figure 2 illustrates the challenges of meeting near-universal participation. For example, the CF shows that for $\lambda = 0.80$ and $N = 15$, the maximum feasible participation threshold is 86.6%. Importantly, such threshold is feasible only as long as $R\Pi \leq 7.1\%$. Comparatively, a threshold of $T = 75\%$ requires $R\Pi \leq 17.8\%$ if the probability of successful coordination needs to be at least $\lambda = 0.80$ with $N = 15$. Increasing the probability of successful coordination would require a reduction in the maximum participation threshold. The CFs could be used not only to understand the conditions under which different levels of voluntary coordination can be successful but also to establish the magnitude of the economic incentives needed to make it work.

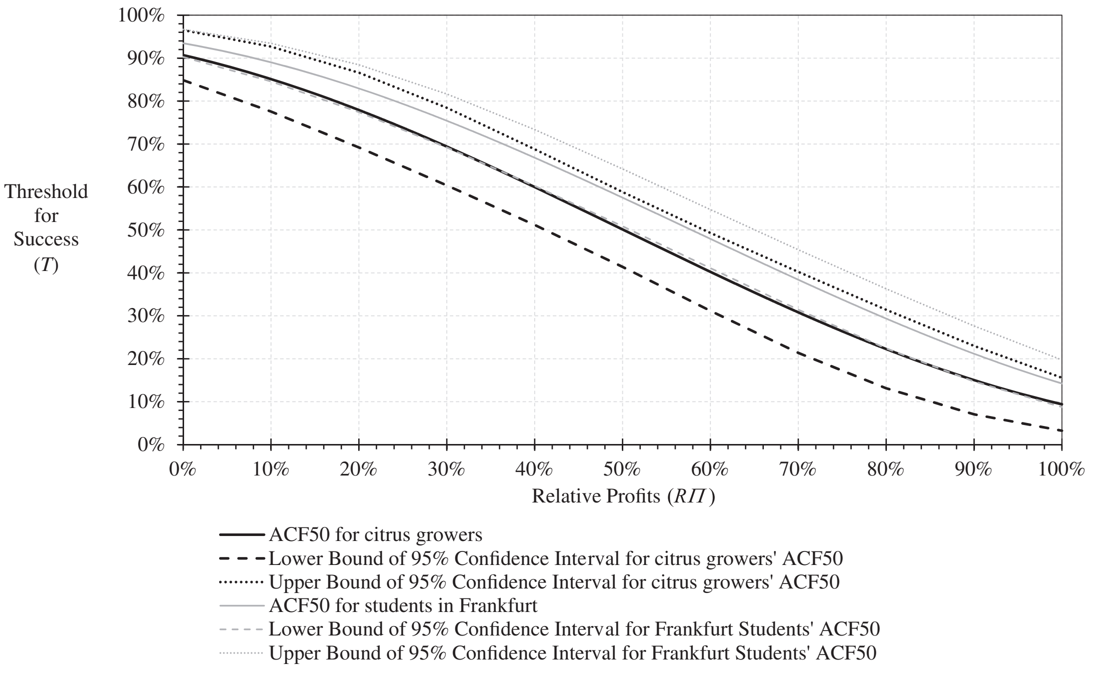

FIGURE 4 ACF50s computed from the estimated ICP Model 2 for the citrus growers' experimental data, and the estimated ICP Model 4 for the Frankfurt students' data from Heinemann, Nagel, and Ockenfels (2009). *Note:* The ACF50s shown are computed from the estimated ICP Model 2 for the citrus growers' experimental data, and the estimated ICP Model 4 for the Frankfurt student data from Heinemann et al. (2009)

5 | DISCUSSION AND CONCLUSIONS

Collective action would be an optimal solution to tackle the challenges posed by invasive species. But building the appropriate institutions necessary for implementing such an action takes time. A quicker first approach for dealing with invasive species is to use voluntary coordination. However, a key question is: What level of voluntary coordination could be achieved (given the strategic uncertainty involved)? To answer such a question, we propose the CF as a practical tool to assess the likelihood of success of a voluntary coordination program. As such, our framework allows quantifying the impact of two variables that are at the heart of the strategic uncertainty that such a program involves: first, the magnitude of the aggregate change in the probability of successful coordination due to a change in threshold and, second, the magnitude of the change in the probability of successful coordination as the (opportunity) cost of coordinating increases. The CF could be used not only to understand the conditions under which different levels of voluntary coordination can be successful but also to establish the magnitude of the economic incentives needed to make it work. Thus, the CF proposed here has at least three possible applications.

The first application would be to evaluate the initial feasibility of AWPM. The CF would allow researchers and policymakers to determine, ex ante, the conditions under which voluntary coordination can be successful. The second application would be to assist in devising incentives that would foster cooperation, such as the magnitude of spraying subsidies to small growers to increase the chances of reaching a desired threshold. Caplat et al. (2012) argue that subsidizing the control efforts of the players with the least incentive to control increases the confidence of the whole group regarding the usefulness of their efforts, and this becomes a self-fulfilling belief. Finally, a third application of the CF would be as a tool for assessing the impact of the extension program designed to affect grower cooperation through time. Arguably, cooperative extension specialists should work to shift farmers' attitudes about the voluntary adoption of cooperative solutions. A few recent studies provide evidence regarding the importance and effectiveness of cooperative extension in encouraging grower cooperation on pest control (Ervin et al., 2019; Singerman & Useche, 2019; Stallman & James Jr., 2015), as well as the malleability and role of social norms in coordination decisions (Brown, 2018). If the extension program is successful, the CF will move up and right through time.

A limitation to our analysis is the implicit assumption that growers are homogenous in size. However, similarly to the commonly made assumption of perfectly competitive markets, this assumption not only makes the CF tractable but also allows us to obtain insights regarding the conditions for successful coordination under strategic uncertainty. Anecdotal evidence based on knowledge of the citrus industry suggests that even a very large grower will very likely benefit from coordination with small-scale "lifestyle" or "hobby" farmers, who could be less motivated by profit incentives and may be a challenge for the sustained success of AWPM.[20] However, more research is needed to better understand the extent to which farmer heterogeneity can hinder the application of the CF concept.

Another limitation of the present study is that the games for which we had data consisted of one-shot coordination games. Voluntary coordination of growers typically involves repeated interaction. To the extent that voluntary coordination has been found to deteriorate over time (Fischbacher & Gachter, 2010; Isaac et al., 1984; Isaac et al., 1985; Kim & Walker, 1984), our findings would denote the first interaction with the highest coordination possible. However, given that (a) discussion among players has been found to enhance cooperation (Orbell et al., 1988), (b) cooperation has been found to be reciprocated, and (c) cooperation is positively related to the investment return on the public good (Dawes & Thaler, 1988), extension can play a critical role in reducing strategic uncertainty and fostering collective action. In fact, extension has already been found to encourage grower dialogue and cooperation on pest control (Ervin et al., 2019; Stallman & James Jr., 2015).

ACKNOWLEDGMENTS

The authors contributed equally to this article. The authors are grateful to editor Terry Hurley for his thoughtful suggestions, as well as to three anonymous reviewers for their valuable comments.

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[20]One of the authors visited a farm in Brazil that has approximately 30,000 contiguous acres of citrus (no citrus farm in Florida has that amount of contiguous acreage). One would expect that a farm so large would not have a strong interest in coordinating because it could be viewed as an AWPM in itself. However, the farm manager in Brazil had recruited a group of 14 employees (at a total annual cost of $120,000) whose only job was to detect neighboring "lifestyle" or "hobby" farmers who were not spraying their trees. Using traps placed every 150 meters within the perimeter of the farm, the manager was able to trace the direction the psyllids were coming from. The employees then looked for the neighboring source of psyllids and, when found, offered the neighboring small grower or backyard citrus homeowner to spray the trees on a monthly basis. Alternatively, homeowners were offered replacement fruit trees other than citrus. The manager calculated that the prevented loss in production offset the cost of such a program.

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How to cite this article: Lence, Sergio H., and Ariel Singerman. 2022. "When Does Voluntary Coordination Work? Evidence from Area-Wide Pest Management." *American Journal of Agricultural Economics* 1–22. https://doi.org/10.1111/ajae.12308