International Review of Public Policy

5:2 | 2023
Special Issue

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INTERNATIONAL REVIEW OF PUBLIC POLICY,
VOL. 5, N°2, 203-235, 2023, HTTPS://DOI.ORG/10.4000/IRPP.3550

Understanding the Effects of Social Value Orientations in Shaping Regulatory Outcomes through Agent-Based Modeling: An Application in Organic Farming

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Abstract

Within existing regulatory scholarship, limited attention is given to whether and how meso-level, or group, characteristics shape compliance. We advance understanding of meso-level regulatory dynamics by assessing how the composition of regulated groups shapes overall compliance levels within a regulated system, as well as compliance trends among system participants. Specifically, we employ agent-based modeling as a tool suited to understanding emergent behaviors to assess how variation in the social value orientations of farmers participating in the United States' voluntary organic farming regulatory program may shape aggregate and subgroup compliance. We also assess how variation in sanctioning shapes compliance outcomes, shedding light on the interaction between participant motivation and sanctioning mechanisms. We conclude that, for compliance outcomes, the former is more decisive than the latter. The modeling exercise draws on an institutional grammar coding of regulatory design, survey, and interview data. In addition to reporting findings from the modeling exercise in the context of the organic farming regulatory domain, the paper offers insights about leveraging diverse forms of data to inform agent-based modeling, which is particularly appropriate for studying institutional (e.g., policy) and related behavioral dynamics in any governed setting.

Keywords

agent-based modeling, organic farming certification, compliance motivations, regulatory design, regulatory effectiveness, institutional grammar

Introduction

Over the last several decades, a rich body of scholarship has emerged that addresses regulation design, implementation, and effectiveness of (e.g., Koski, 2007; May, 1993). Chief among the interests of scholars interested in regulatory effectiveness is whether a regulation alters conditions in a given domain in ways that accord with policy objectives. Another complementary focus is regulatory compliance, which is viewed both as a measure of regulatory effectiveness and as a critical intermediary outcome for achieving other measures of regulatory effectiveness. Compliance is typically conceived of as behavioral conformance with regulatory directives (Siddiki et al., 2018).

Studies of regulatory compliance focus predominantly on factors that motivate compliance by individuals and organizations. Scholars consistently observe a linkage between various factors relating to individuals, features of the regulatory context, and characteristics of regulatory design and compliance outcomes. Generally, individually-focused factors can be characterized as micro-level factors, and contextual and regulatory design features as macro-level factors. Limited within extant regulatory scholarship is attention to meso-level (i.e., group) factors, such as the aggregate characteristics of monitoring, enforcement, or other administrative personnel, or features of groups whose behavior is targeted through regulation (Sabatier & Mazmanian, 1980).

We respond to this limitation by examining how regulatee composition with respect to social value orientations influences regulatory compliance. We investigate how variation in the social value orientations (individualistic, mimetic, or prosocial) of farmers participating in the United States' voluntary organic farming regulatory context shapes aggregate emergent compliance outcomes and compliance trends among farmers with the three different value orientations. Agent-based modeling is used to support this investigation (Gilbert, 2008). The model parameterization is informed by a descriptive assessment of regulatory design parsed using the Institutional Grammar (Crawford & Ostrom, 1995), and interview and survey data collected among organic farmers, certifiers, and inspectors.

Leveraging agent-based modeling that is grounded in regulatory design, interview, and survey data allows us to analyze how simulated interactions among agents with different social value orientations shape our regulatory outcomes of interest, which fundamentally orient toward understanding how profiles of regulated agents affect how policy directives take shape in practice. Further, it allows us to determine the effects of experimental conditions on regulatory compliance outcomes. Our analysis explores the effect of two experimental conditions: (i) variation in the composition of regulated agents in terms of their social value orientations; and (ii) variation in the frequency of monitoring and intensity of sanctioning. Drawing on analytical possibilities from the application of agent-based modeling toward our overall research objective, we respond to the following research questions in this paper: How does variation in (i) regulatee composition in terms of social value orientations and (ii) monitoring and sanctioning intensity influence aggregate and sub-group compliance outcomes?

Organic farming is regulated in the United States under the National Organic Program (NOP) Regulation, administered by the United States Department of Agriculture (USDA). Originally urged by farmers critical of traditional farming inputs, methods, and environmental impacts, the NOP is a voluntary regulatory program that permits farmers who opt-in to display a "USDA Organic" seal on their products in exchange for compliance with regulatory standards. NOP regulatory standards pertain to allowable inputs and processes in organic farming and specify protocols for seeking organic certification and penalties for non-compliance. The NOP relies heavily on third party inspectors and certifiers in its administration. As such, the regulation also identifies protocols that allow one to be certified to bean inspector and certifier of organic farming operations, and penalties for acting non-compliantly in these roles.

The organic farming regulatory context is suitable for grounding our modeling exercise for several reasons. First, the voluntary nature of the program elicits inquiry into rationales for program participation and presents an opportunity for investigating outcomes associated with variation among them across organic farmers. Because the NOP was originally established as part of a social movement among farmers resisting conventional farming as regulated under the USDA, contrasting the implications of varying social value orientations toward organic farming is particularly appropriate. Second, recent trends in the composition of the organic farming industry also make investigating our research objectives in this domain relevant. In recognition of consumer demand and a sizeable price premium attached to organic products, the organic industry has seen an influx of traditional agricultural producers seeking the financial benefits associated with organic food production. Thus, assessing the effects of variable composition of organic farmers in terms of whether they participate in the NOP for prosocial reasons or for profit (what we refer to in this paper as "individualistic" motives) is practically appealing. Third, the unique third-party inspection and certifier structure upon which the NOP is based introduces a heightened potential for variation in personnel composition and practices relative to traditional regulatory programs typically implemented entirely by agency personnel, thus warranting consideration of whether and how this variation might influence program outcomes.

Literature Review

Regulation is one of the dominant tools that governments use to achieve their policy objectives. Scholars of public policy and cognate fields have engaged in numerous studies of regulation across governance scales and domains to understand how regulations are designed, how they are interpreted and applied in the process of implementation, and whether they work to alter conditions of the domains in which they are applied in accordance with policy objectives (Koski, 2007; May, 1993). A necessary precondition of the latter is regulatory compliance. To see altered conditions in regulatory domains, regulatory targets -- those whose behavior is compelled through regulatory directives -- must alter their behavior to conform with regulatory directives. Recognizing the critical role of regulatory compliance as a necessary intermediate outcome for achieving other measures of regulatory effectiveness, scholars have dedicated substantial attention to identifying determinants of regulatory compliance relating to characteristics of regulators and regulatees, characteristics of the broader policy and administrative contexts in which regulations are implemented, as well as features of regulatory design. In this brief literature review, we review scholarship on determinants of regulatory compliance, organizing determinants by level of analysis – the micro-level, the macro-level, and the meso-level.

At the micro-level of analysis, the focus is on individuals, including their characteristics and activities. Scholars have found various types of individual level factors to be salient in shaping regulatory compliance. Some of these factors can be characterized as psychological in nature, and include, for example, perceived costs of sanctions relative to benefits of non-compliance, attitudes about rules, attitudes about compliance, and perceptions of regulatory monitoring and enforcement apparati (Siddiki et al., 2018). Among the various types of attitudes about rules that scholars have posited and/or verified matter in shaping compliance is the perceived appropriateness of rules to the domains in which they are applied (Siddiki, 2014; Young, 2002), in both physical (Young 2002) and social or cultural dimensions (DeCaro, 2018). Attitudes about compliance capture, for example, whether rule compliance is viewed by individuals as the "right thing to do," irrespective of their perceived appropriateness. Some individuals perceive a strong sense of duty to comply with rules, that can crowd out specific attitudes about regulations in their compliance decision making. Other individual level factors found to associate with compliance can be characterized as capacity oriented, for example, physical resources, or relevant knowledge or experience, that enables compliance decision making and behavior (Winter & May, 2001).

In contrast to the micro-level of analysis that, in this case, relates to characteristics and behaviors of individuals within a regulatory system, the macro-level of analysis relates to characteristics of the system itself. Encompassed within macro-level factors are the design of monitoring and enforcement mechanisms set in place to support the implementation of regulations, as well as features of the designs of regulations themselves (Jilke et al., unpublished data). Examples of the former found to shape compliance are degree and type of monitoring and enforcement (Gunningham et al., 2003; May & Wood, 2003; Burby & Patterson, 1993). Degree refers to the frequency with which these activities occur. Type of enforcement reflects whether the enforcement style used by administrative personnel within a particular regulatory system would be characterized as formalistic or facilitative (May & Burby, 1998). Formalistic enforcement is characterized by generally rigid interpretation and application of regulatory standards and inflexible administration of sanctions in observed instances of non-compliance. In contrast, facilitative enforcement is marked by more lenient, forgiving regulatory interpretation and application, as well as by the impression that regulators are willing to work with regulatees to maintain, or regain, compliance (May & Wood, 2003). Importantly, where enforcement styles are a deliberate feature of the regulatory system, they are considered macro-level factors. When examining the specific enforcement practices of individual personnel, however, enforcement is treated as a micro-level factor.

Despite extensive research on micro- and macro-level determinants of regulatory compliance, little attention has been paid to meso-level factors, or group characteristics, or dynamics within compliance studies. Siddiki et al. (2018), however, suggest the value of assessing meso-level factors. They posit, within their compliance framework, that attributes of regulated communities can shape compliance outcomes, as well as intermediate outputs and outcomes that may have a bearing on compliance outcomes.

Within extant regulatory compliance scholarship, there are several studies that consider the role of group, or social, dynamics, but as perceived by the individual. These studies examine relational factors in connection with compliance, often with the aim of understanding the role of social pressure, social approval/disapproval, peer effects, and the like, in shaping compliance decision making and behavior (Braithwaite & Makkai, 1991, Hatcher et al., 2000; Sutinen & Kuperan, 1999). Much of this research finds an association between social sanctions and influence, social disapproval, and peer effects, generally, in shaping individuals' compliance behavior. Our research extends this scholarship by exploring an alternative way to assess social influence. Assuming a regulatory system comprised of regulatees with distinct behavioral motivations and associated behavioral tendencies, we explore how variation in the compositional profiles of regulated communities impacts compliance outcomes.

Case: U.S. Organic Farming Regulatory Program

According to the USDA, organic farming is defined as "the application of a set of cultural, biological, and mechanical practices that support the cycling of on-farm resources, promote ecological balance, and conserve biodiversity" (USDA, 2015). The production, processing, and handling of organic agriculture is governed by two policies in the United States, the Organic Food Production Act and the accompanying National Organic Program Regulation administered by the USDA. The policies establish a voluntary, certification-based program, which manufacturers and processors can opt into, which confers the right to display on their products a "USDA Organic" seal.

The USDA organic program was established in 1990 in response to demands by farmers committed to organic food production, and as a contrast to traditional, or conventional farming, as regulated by the USDA. A key differentiating characteristic between conventional and organic farming was, and remains, the allowed use of synthetic chemicals and other inputs in the production, processing, and/or handling of agricultural products. Organic farmers urged the creation of a national organic certification system in reaction to the proliferation of numerous independent organic certification schemes during the 1980s that were based on different requirements, and thus did not convey consistent information to consumers about the meaning of "organic". The establishment of a single national level certification program was seen to legitimize the practice of organic food production and processing: instilling confidence among consumers that any product bearing the USDA organic seal was subject to the same standards, monitoring, and enforcement practices.

The NOP is based on a third-party accreditation and certification system, under which government and non-government entities are granted certification to engage in the inspection and/or certifying of organic operations in accordance with regulatory standards. Third-party certifiers are allowed to set their own certification fees and retain in-house or independent USDA accredited inspectors for monitoring organic operations. Certifiers vary in the types of agricultural products that they certify. Organic operators may choose under which certifiers they want to pursue certification irrespective of geographical proximity.

The organic food market has grown rapidly since the passage of the Organic Food Production Act in 1990, with annual growth rates in the double digits throughout the 1990s. The USDA reported that sales of organic products grew by 13% between 2019 and 2021 (USDA, 2022). Over the same period, growth in the organic industry has been coupled and stimulated by growth in the number of suppliers of organic products. While some of these new industry entrants include traditionally organic producers, others are those who have traditionally used conventional farming practices but enter the organic farming industry noting the significant price premium attached to organic products. Organic products are typically more expensive than their conventional counterparts.

The influx into the organic industry of farmers from different farming backgrounds has raised concerns for traditionally organic farmers. Chief among their concerns regarding the participation of traditionally conventional farmers in organic food production is that the latter lack commitment to the underlying humanitarian and environmental principles of organic food production and thus may adopt a relatively relaxed interpretation of regulatory standards, i.e., exhibit a heightened tendency for regulatory non-compliance. Another way of characterizing the difference between farmers espousing different farming traditions, based on which regulatory implications can be assessed, is in terms of their variable motivations for participating in the NOP, with one group of farmers identifying with the NOP based on a prosocial orientation, and the other based on the potential profitability gains accruing from program participation (Carter & Siddiki, 2021).

Given this context, we explore the response of the organic farming sector to prospective changes under the given regulatory framework.

Methods

Data for our study come from multiple sources and collectively inform the agent-based model used to analyze the relationship between regulatee composition and compliance outcomes and associated experimental conditions. We describe our data sources below.

Data Source: Regulation Coding

The NOP regulation coding was conducted in multiple steps. First, the entire regulation was parsed using the Institutional Grammar (Crawford & Ostrom, 1995).[1] The Institutional Grammar has been used for organizing and analyzing the language of institutional statements, or directives, comprising regulatory text in accordance with a generalizable syntax (Siddiki, 2014). Institutional statements, also referred to here as institutional directives, define specific actions that actors can perform within specific contextual constraints, as well as payoffs associated with the compliant performance of these actions. An example of an institutional statement/directive is: "The Program Manager may initiate [certification] suspension or revocation proceedings against a certified operation when the Program Manager has reason to believe that a certified operation has violated or is not in compliance with the [Organic Food Production] Act or regulations of this part."

According to the Institutional Grammar, institutional statements are comprised of some or all of the following syntactic components: (i) Attribute: the person or group of people to whom the institutional statement applies (i.e., the actor carrying out the action identified in the statement); (ii) Aim: the action assigned to the Attribute in the institutional statement; (iii) Object: receiver of the Aim (i.e., statement action); (iv) Condition: a parameter that constrains the Aim; (v) Deontic: a prescriptive operator that indicates whether the Attribute is required, forbidden, or allowed to perform an Aim; and (vi) Or else: a payoff associated with compliance/non-compliance with carrying out the institutional statement as described. Institutional Grammar coding of regulatory text first requires parsing the regulation into individual directives and then further parsing these statements by syntactic component. For the present study, once the NOP regulation was fully parsed according to the Institutional Grammar, we extracted all the directives pertaining to regulatory compliance. These directives specify responsibilities of administrative personnel in enforcing regulatory compliance, details the procedures for conferring notifications of non-compliance to organic operations and the actions operations can pursue in response to non-compliance notices, describes the process of reapplying for organic certification, and identifies sanctions for non-compliance. It also describes the same for certifying agents.

A total of 46 institutional directives on compliance were identified, based on which we parameterized our agent-based model.

1 — The Institutional Grammar parsing undertaken for this study relies on the original version as presented by Crawford and Ostrom (1995) and subsequently modified by Siddiki et al. (2011). Newer versions of the Institutional Grammar – termed IG 2.0 – have been published since the reported study was initially conducted (Frantz & Siddiki, 2022).

Data Source: Online Surveys

Three separate surveys were administered online to organic producers, certifiers, and inspectors (one survey per type of regulatory actor) participating in the NOP as part of a broader research project conducted from 2012-2015 on the regulatory program. The producer survey was administered in the winter of 2013-2014 to all domestic certified operations for which the USDA listed a valid email address (n = 6,273), which represented about half of all operations certified by the USDA under the NOP at the time. Responses were received from 1,055, or 17%[2], of producers contacted with a survey request. The survey asked organic producers to indicate the reasons for practicing organic farming, factors informing their decision to be certified under the NOP, perceptions regarding NOP regulations, perceived impacts of NOP regulations, extent and motivations of regulatory compliance, frequency of interaction with other certified organic producers, perceptions about the certifier through which they seek NOP certification and inspection, and information about their operations and products (e.g., size of operation, how long their operation has been certified, types of agricultural products produced). The inspector survey was administered in the summer of 2014 to 260 organic inspectors, of which 41% responded. These inspectors were identified by soliciting inspector information from the International Organic Inspectors Association and online searches of private certifier and state departments of agriculture websites. The inspector survey asked respondents to indicate their backgrounds and training, information and material resources they utilize in carrying out regulatory responsibilities, certifier oversight of inspectors, inspectors' perceptions of their role, monitoring and enforcement behavior, and trends in compliance among organic producers. The certifier survey was distributed among representatives of the 88 certifiers accredited under the USDA in 2014, when the survey was administered. A total of 43, or 49% of certifiers responded to the survey. The survey asked respondents to indicate information about their organization (e.g., size, type, kinds of organic commodities certified, and services offered to organic operations), perceptions of regulatory directives, perceived difficulty of implementing regulatory activities, and frequency of interaction with organic operations, other certifiers, and administrative personnel.

Data Source: Interviews

Interviews were conducted with 48 organic producers to glean qualitative information on topics covered in the online survey of producers. Most of the questions utilized in the online survey elicited responses from producers on Likert scales, enabling quantitative assessments of the survey data. Interviews were used to capture elaborated narrative responses to questions like those posed in the survey, to aid in the interpretation of survey data.

Data from the regulation coding, surveys of organic producers, inspectors, and certifiers, and interviews with producers, were used to parameterize our agent-based model.

2 — Steps were undertaken to evaluate non-response bias. First, a wave analysis was conducted based on the assumption that the answers of late responders are more likely to approximate the answers of nonrespondents than those of individuals who readily respond to survey requests (Rainey et al., 1995). No statistically significant differences between the dependent variable measure responses of different survey waves were found ($P < 0.05$). Second, 20 nonrespondents were contacted by phone and verbally administered five survey questions. Nonparametric tests (due to the extreme difference in group size) comparing these responses with those of the online sample showed no statistically significant differences ($P < 0.05$). Finally, a comparison of respondents' geographic locations, operation sizes, and production characteristics with available USDA data (NASS, 2014) indicates a fair, but not ideal, representation of the U.S. certified organic producer population. Based on reported operation sizes, products produced, and organic certification scopes, the survey sample characteristics roughly mirrored population trends. See Carter and Siddiki (2021) and Carter (2016) for additional details regarding the non-response bias.

Analysis: Agent-Based Modeling

Agent-based modeling has roots in computer science but builds on analytical traditions from across the social sciences (Schulze et al., 2017; Frantz et al., 2014; Boshuijzen-van Burken et al., 2020; Diallo et al., 2021; Bianchi & Squazzoni, 2015; Mäs & Flache, 2013). A specific feature of agent-based modeling is the focus on a bottom-up interactionist perspective that potentially fosters a wide range of behavioral dynamics that are subject to interpretation by the analyst, in contrast, for instance, to formal approaches (e.g., equation-based modeling). This is operationalized by defining individual agents, where agents can reflect the behavior of entities of interest. The latter can exist on arbitrary abstraction levels, e.g., as individual humans, as groups of individuals, or, for instance, as nations, if those are deemed central with respect to the behavior of interest. In our case, agents map to the individual roles in the organic farming scenario (for which we seek to establish general compliance levels), and as such, involve the farmers, certifiers, and inspectors. Based on their individual decision-making, we can draw insights about hypothetical outcomes at the system level (i.e., the organic farming arrangement governed by the NOP). With its emphasis on emergent behavior, agent-based modeling enables the representation of individuals with respect to their decisions (e.g., operational choices to apply for certification, to comply to regulation), but also priors that influence decision-making, such as the underlying cognitive processes that are based on individual and social preferences and behavioral motivations (e.g., social values based on selfish or prosocial motives). This enables the reflection of both behavioral complexity akin to the one found in the real world, but also mirror socio-structural or behavioral diversity in silico. Implemented as a computational simulation reflecting this 'artificial society', the outcome can be variably analyzed at the micro level (e.g., individual), or the behavioral patterns emerging can be analyzed at the meso (e.g., group) and macro levels (e.g., society at large).

Given the openness of assumptions about what an agent constitutes (e.g., its properties, motivations, and behavior), agent-based modeling endows us with the capability to draw on both theory (e.g., social-psychological insights, compliance theory) and, where it exists, data (see e.g., Tolk, 2015) to reconstruct the scenario of interest. The agent conception can be theoretical and highly abstract or based on both qualitative and quantitative empirical data to capture behavioral complexity more comprehensively (Edmonds & Moss, 2005), but is generally driven by the aspiration to display cognitively plausible behavior (Epstein, 2014). However, to guide the preference and selective inclusion of theoretical and empirical accounts, any agent-based modeling exercise is to be motivated by a purpose, e.g., the intention to leverage an understanding of observed behavior, the explanation of observed social phenomena, or, where the data basis permits, the prediction of future behavior (Edmonds et al., 2019).

A challenge in analyzing regulatory compliance in specific cases through agent-based modeling is the development of a comprehensive representation of different relevant components of a regulatory system. The analyst must develop a sound reconstruction, or representation, of the complex system drawing on theory and diverse forms of data such that simulated actions yield valid insights. This includes, for example, using theory and data to identify the relevant set of agents, attributes of these agents, their choice sets within different decision situations captured in the simulation, and relevant resource, spatial, and temporal constraints. Our process is informed by the purpose of our specific model; to explore compliance outcomes in relation to varying distributions of social value orientations among farmers participating in the organic program, and, in extension, to assess the viability and robustness of the organic farming regime in its current regulatory design against anticipated future shifts in applicant motivation.

Central thereby is to indicate that this exercise emphasizes *understanding* – anticipating the 'effect' – , without attempting to predict outcomes – the 'effect size' – accurately in quantitative terms.

We use coded regulatory data to identify the behavioral choices and related constraints afforded to organic operations, certifiers, and inspectors as relating to operator compliance. We use survey and interview data primarily to identify agent attributes and interaction dynamics. We leverage data from our survey of organic operations to understand, and subsequently assign, the motivational characteristics of operator agents modeled through our simulation. One question from the producer survey asked respondents to indicate on a scale of 1 (Not important at all) to 5 (Extremely important), the importance of the following factors in their decision to be certified USDA organic: (i) to increase profits, (ii) to differentiate products from other products claiming to be "natural" or "sustainable", (iii) to support the organic movement by participating in the NOP, and (iv) to avoid the penalty of marketing non-certified products as "organic." Another survey question asked respondents to indicate on a scale of 1 (Not at all important) to 3 (Extremely important) how important each of the following reasons are to respondents in maintaining compliance with NOP regulations: (i) fear of penalty from certifier, (ii) fear of penalty from the NOP, (iii) a concern for operation's reputation, (iv) a personal sense of duty, and (v) pressure from other producers.

In a separate analysis of these survey data seeking to respond to a distinctive set of research questions pertaining to compliance motivations, Carter and Siddiki (2021) examine correlations between motives for participation in the organic program and motivations for maintaining compliance with NOP regulations. They find that profit-motivated program participation is positively correlated with compliance motivated by a fear of penalties administered by a certifier, whereas socially-motivated participation is not significantly correlated with this factor. They also find that socially-motivated participation is positively correlated with compliance oriented in a sense of duty to comply, whereas a profit motive is not significantly correlated with this factor. Further, reputational concerns and social pressure are found to be positively correlated with profit and socially-motivated program participation. We draw on Carter and Siddiki's research to infer two generalized motivational stereotypes of farmers participating in the organic farming program: the economically-incentivized and the prosocially motivated. We then use these stereotypes to populate characteristics of individual agents included in the separate and original modeling exercise undertaken in this paper to respond to its unique research questions. From a modeling perspective, the generalization of motivational stereotypes provides us opportunities to fill gaps in empirical data, since it allows us to relate the ascribed individual characteristics and regulatory functions selectively (e.g., justifying increased monitoring with an increased sense of duty). Moreover, these theorized prototypical motivations can be used to suggest preferences in specific decision-making scenarios, an aspect that allows us to represent behavior in our proposed model that is not explicitly captured in the considered data sets or collected data.

We further ascribe the following characteristics and regulatory functions to economically-incentivized (which we term "individualistic") and prosocially-motivated participants in the organic farming context based on relevant scholarship, which we then operationalize in our original modeling exercise.

- *Individualistic Participants*: Individualist participants have a low level of intrinsic compliance motivation (duty to comply) in the absence of external monitoring and showcase limited response to informal social pressure by other participants (low social pressure).

The characterization of individualistic participants accords with prior research, which verifies that individuals who are primarily "externally" motivated – i.e., by economic rewards or sanctions – are unlikely to maintain compliance in the absence of consistent external enforcement (Bowles, 2008; DeCaro, 2019). The economically-tied motives of individualistic participants also leads us to infer that they are dually motivated by reputational concerns. Ultimately, the extent of economic benefits that farmers can derive from organic farming – i.e., the price premiums for organic products – is contingent on the reputation of the "organic label." As such, individualistic participants' concern for the reputation of the organic farming industry may motivate their participation in enforcing compliance of other stakeholders, i.e., "defending the organic brand", despite the associated cost. This inference, though specifically cast here in the organic farming context, also generalizes across domains. Within his research on collective sanctioning and cooperative behavior, Heckathorn (1990) highlights the "hypocritical cooperator." This type of actor may not be compliant – or may lack motivation for personal compliance – but nevertheless urges the compliance of others to preserve a broader collective good and associated benefits. Finally, we posit that in alignment with their concern about reputation and economic incentives, individualists fear repercussions by inspectors.

- *Prosocial Participants*: Prosocial participants are strongly motivated to comply with the regulations set out through the organic farming scheme. Their commitment to the "organic farming brand," as well as the underlying principles of organic food production, are central for their motivation. In addition to formal means, these idealistically-motivated participants do not fear the exertion of social pressure to sustain the cooperative outcome of the scheme. The fear of sanctions is naturally low, since the idealistic nature of prosocial participants leaves little motivation to violate the provisions of the regulation in the first place, which is a prerequisite for experiencing penalty.

These posited characterizations of prosocial actors are consistent with previous research. For example, they generally accord with research conducted in other domains that suggests that those who view the actions encouraged by rules to be consistent with their beliefs and values are likely to maintain compliance, with or without the presence of external enforcement. Such individuals are described as having intrinsic or internalized motivations (DeCaro, 2019). The characterization we assign to prosocial actors accords with existing research on cooperation in natural resource management, which shows that sustained cooperation by resource users is greater in cases where individuals have the opportunity to participate in the selection of governing rules that are subsequently enforced (DeCaro et al., 2015). Insofar as voluntary participation in a regulatory program can be treated as a proxy for "voting" to be governed by a set of rules, our expectation that prosocial actors will remain in compliance is consistent with this previous work by DeCaro et al.

To facilitate a basis for differentiated exploration and to explore individuals' motivation characteristics more systematically, we augment the bifurcation into individualistic and prosocial orientation with an additional type of actor, which we tag as *mimetic*. For this stereotype, we seek inspiration from configurations along the conceptual continuum of individualism and altruism in the context of social value orientation (Griesinger & Livingston, 1973). Ascribed characteristics and regulatory functions of mimetic actors, which we operationalize in our model, are described below. Generally, the mimetic stereotype proposed here shares characteristics of the extremal stereotypes, but distinctively differs in that mimetic participants are neither intrinsically nor ideologically motivated. Instead, mimetic actors base their decision-making on the observation of aggregate behavior of other participants, specific aspects of which we discuss at a later stage.

- *Mimetic Participants:* Mimetic participants, in contrast to individualistic and prosocial participants, do not have intrinsic reasons for compliance, but rather tie their motivations to the observed behavior, recognizing opportunities to violate provisions of the regulation if economically and normatively justifiable. Consequently, their concern for reputation of their operation is largely dependent on the socially dominant perspective. The associated exertion of social pressure is implied by the stereotype's social orientation and is sustained for as long as the economic benefits of participation are retained. Similarly, the fear of penalty based on detected violations depends on the socially acceptable level of non-compliance. The ascribed characterization of mimetic participants aligns with Heckathorn's (1990) archetypal actor encountered in the context of public good dilemmas – the "private cooperator." These types of actors cooperate to minimize the risks and sanctions to the larger group to which they belong, associated with their own non-compliance, but do not engage, or have a relatively lower incentive to engage – in the monitoring of others' compliance.

In Table 1, we summarize motivational stereotypes of modeled agents.

Table 1: Motivational Stereotypes for Operators

Stereotypes/ Motivation	**Duty to Comply**	**Reputation**	**Social Pressure**	**Deterrent Fear**
Individualistic	Low	High	Low	High
Mimetic	Low	Medium	Medium	Medium
Prosocial	High	High	High	Low

Source: The author

Operationalizing Stereotypes

Returning to the certification scheme, we can translate these motives to characterize individuals' decision-making related to their involvement in the certification scheme. When deciding about their participation, individualists are primarily attracted by the perceived sustainability of the scheme (i.e., low levels of non-compliance by others), whereas mimetic individuals seek their motivation from certification levels in their social environment. Idealistically-motivated participants seek certification without regard for external factors based on intrinsic motivation, maintain compliance with the underlying regulations, but furthermore, seek for adherence to the scheme by others, e.g., by promoting idealistic motives. As characterized here, individualists may primarily seek profit motives when deciding about the participation and subsequent compliance behavior once certified, maintaining, as hypocritical cooperators, expectations about the reputation of the scheme that they are involved in. Mimetic participants, as characterized above, reflect a conception of mainstream behavior, both with respect to approaching certification, as well as with respect to the ensuing compliance behavior. The operationalization of the stereotypes with respect to their regulatory functions in the explored scenario is captured in Table 2.

Table 2: Operationalization of Stereotypes with Respect to Institutional Functions in Organic Farming Scenario

Stereotypes/ Motivation	Participation	Compliance	Monitoring
Individualistic	Dependent on economic opportunity	Compliance in response to external monitoring	Dependent on need to defend reputation
Mimetic	Dependent on social environment	Dependent on social environment	Dependent on social environment
Prosocial	Strong motivation to participate	Intrinsically compliant	Strong intrinsic motivation to monitor

Source: The author

Model

The basic model[3] represents a specified number of operators, certifiers and inspectors and captures specific tasks such as: the application process that involves the decision as to whether obtaining a certification is desirable, followed by the subsequent interaction between operators and certifiers; operational processes by operators as well as monitoring and reporting by inspectors; and finally, potential administration of penalty by certifiers.

Before introducing the experimental conditions specifically, we require a refined understanding of the operational semantics of the model more generally, and of the involved role conceptions specifically. An execution cycle represents an individual's role-specific operations for a given simulation round, i.e., all individuals execute their execution order in each round. While the execution of all individuals occurs at any given round, their scheduling order is randomized. For modeling, a simulation round is conceptualized as a day of operation.

Given the orientation of any modeling activity on available theory and data, the execution cycles introduced in the following explicitly focus on an abstract representation of any organic farming certification and operation activity based on a) the stereotypical profiles of agents, b) institutionally relevant events (e.g., application for certification, approval, compliance/violation behavior), and the c) parameterization based on real-world information. Given the analytical focus, the behavioral model thus puts primary emphasis on the emergent dynamics that arise from compliance and violation behavior, as opposed to focusing on a detailed representation of farming activities, for instance.

The Operator Execution Cycle

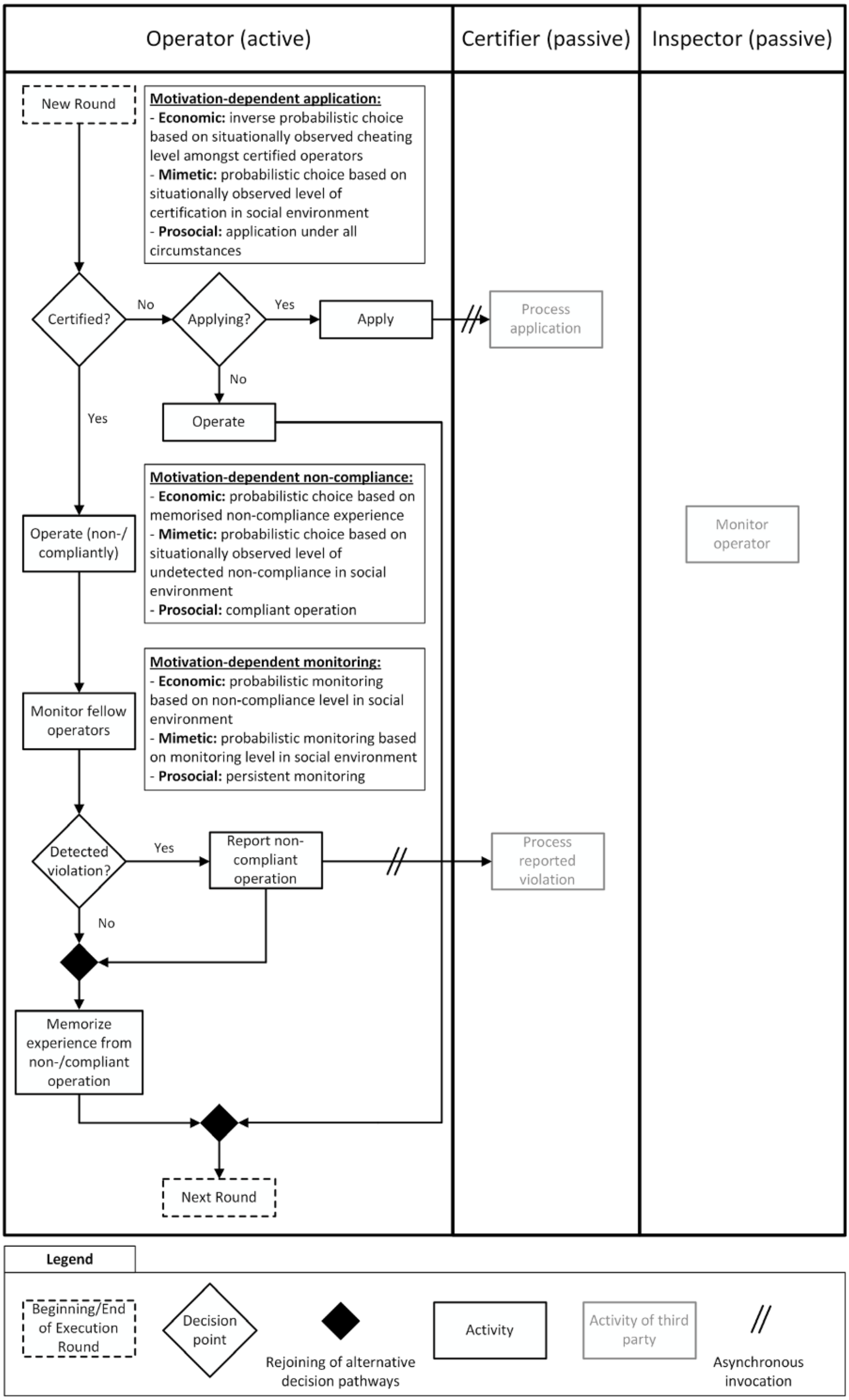
A cornerstone of the developed model is the Operator Execution Cycle. Retracing the procedural steps specified in the USDA regulation, the certification process is initiated by regular

3 — The complete model specification in the ODD+D format (Müller et al., 2013) is provided in Appendix A.

farming operators who seek access to certification to operate under the organic label. Following the initial decision to apply, operators send their application to the certifier and, depending on the outcome, will continue to operate as uncertified (regular) operator or, if the certification is approved, will operate as certified operator, and thus fall under the provisions of the USDA regulation. Once certified under the regulation scheme, participants can engage in the monitoring of fellow participants and report observed non-compliance to certifiers. Independent of this, certified operators are subject to monitoring by inspectors appointed by one or more certifiers, an aspect that is discussed in greater detail after the discussion of the individual roles' execution cycles. This fundamental process – the operator execution cycle – is schematically illustrated in Figure 1. This figure differentiates between involved roles horizontally, whereas time (and the corresponding interactions between those role) progresses vertically. Activities are represented using square boxes, arrows signify the logical progression, and diamond symbols represent alternative logical pathways following explicit decisions.[4]

4 — The notation for the remaining execution cycle figures is described in the legend of Figure.

Figure 1: Operator Execution Cycle



Source: The author

As part of the discussion of the execution cycles, a central modeling decision requires attention: Activities that involve interaction amongst different role types generally operate *asynchronously*[5], that is, requests do not require immediate response, provided that they are addressed eventually. As an example, operators will not receive an immediate decision on their application, but instead, continue to operate as regular (non-certified) operators until their application is eventually processed. This asynchronous operation approximates a realistic representation of the certification process based on its long-running and bureaucratic nature based on a) the extensive requirements for compliance assessment as part of the certification process, and b) the limited number of certifiers relative to the pool of potential applicants.

The motivation of individual behavior is informed by the divergent participation motives. Central decision points in this model include a) the decision to participate in the organic farming scheme, b) the decision whether to act compliantly once certified, and c) the decision whether to engage in monitoring of peers. When deciding whether to act compliantly, individualists, for example, act opportunistically and base their probabilistic decision on their experience, that is, on the number of iterations in which they have acted non-compliantly without being penalized, relative to instances in which they acted in compliance without being monitored. In alignment with the idealistic participation motive, prosocial individuals consistently act in compliance with the provisions of the Organic Farming regulation. Mimetic individuals observe the situational compliance level (between 0, reflecting collective non-compliance, and 1, representing collective compliance) in their social environment and use this as a probabilistic basis for their situational decision-making.

In addition to their operation as certified operators, participants have the option to monitor their fellow operators[6], an ability that is, like the actual operation, mediated by their respective participation motive. Given their focus on economic profit, individualists base their engagement in active monitoring on the perceived non-compliance level amongst fellow participants, both to defend the premium brand of organic farming as well as the competitive advantage that undetected non-compliance bears. However, since monitoring is costly, individualists seek to minimize their involvement in monitoring where avoidable. Mimetic participants, in contrast, base their probability of monitoring on the mean monitoring level in their social environment. Prosocially-oriented individuals will monitor their social environment at every opportunity, which is consistent with their idealistic involvement in organic farming in the first place.

Concluding the discussion of the operator execution cycle, observed instances of non-compliance are reported to the associated certifier, before concluding the execution by memorizing the individual experience, i.e., the choice as to whether one acted compliantly as well as the potentially associated sanction. An overview of all activities involved in the execution cycle, along with the impact of participation motives at central decision points, is provided in Figure 1.

The Certifier Execution Cycle

Complementing the operator execution cycle, certifier activities are shown in Figure 2. Given the role distribution characteristics of operators, inspectors and certifiers, a central aspect is the certifiers' role as a bottleneck in the certification process, given the fewer number of certifiers, as well as their dual function as processors of application requests as well as reported violations. We thus model any request to certifiers as a message in a mailbox, from which certifiers retrieve and process one message per round in the order of arrival.

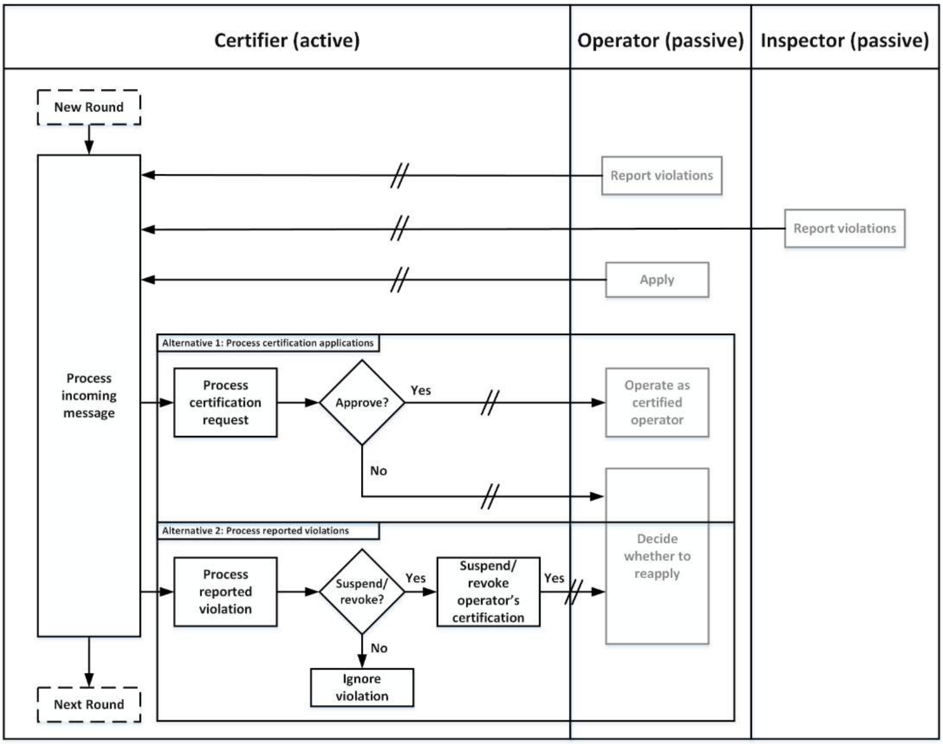
5 — The asynchronous nature of interactions in Figure 1 is symbolized with double dashes across arrows reflecting inter-role communication.

6 — We provide operational details with respect to monitoring behavior in Section IV.

Consequently, during each round certifiers potentially process a certification request (denoted as Alternative 1 in Figure 2). Given the case-specific nature of the assessment and limited availability of empirical data, we model the acceptance of certification requests probabilistically. Following the approval of an operator's certification, the operator will be considered certified in the following round. Alternatively, if not approved, the operator can reapply in future iterations.

If processing a reported violation (Alternative 2 in Figure 2) either by operators or by inspectors, the certifier has the choice to ignore a violation, or alternatively, suspend or revoke an operator's certification. In the latter case, the operator is considered uncertified and tagged as suspended or revoked respectively, but it has the option to reapply for certification in future iterations.

Figure 2: Certifier Execution Cycle

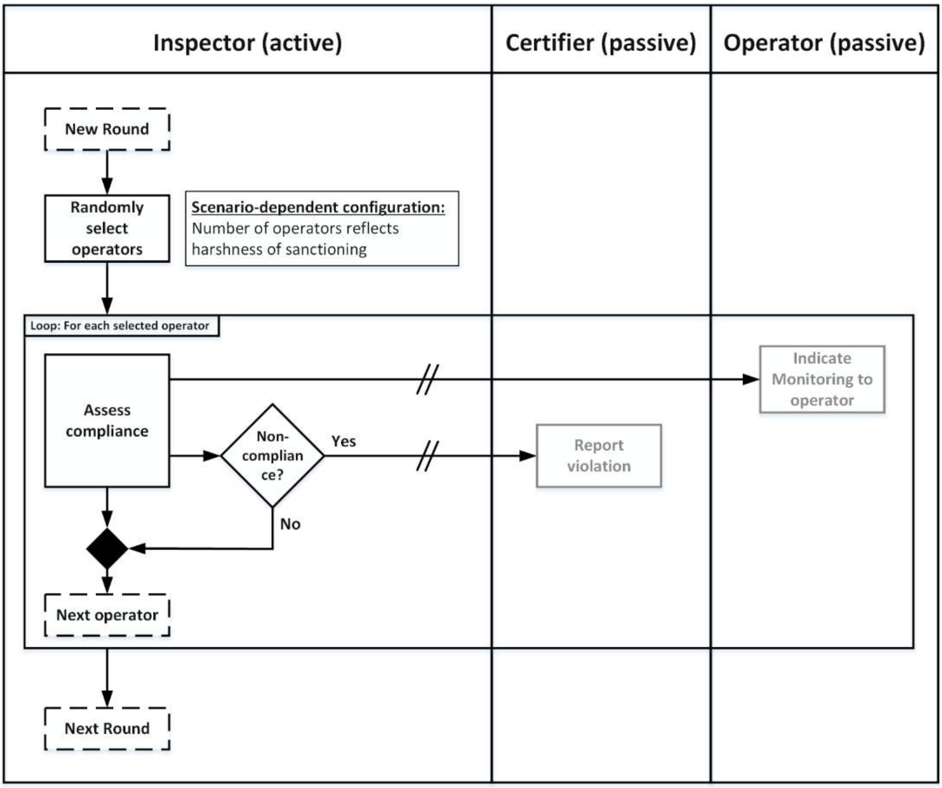


Source: The author

The Inspector Execution Cycle

The final and most simplistic execution cycle – reflecting the emphasis on decision-making around certification and sanctions – is the one of inspectors (see Figure 3). Inspectors merely monitor certified operations for compliance and report eventual violations to the responsible certifier, who then administers sanctions. Depending on the experimental configuration, inspectors can monitor multiple operators in each round as reflected in the Loop construct in Figure 3.

Figure 3: Inspector Execution Cycle



Source: The author

Parameterization of the Base Model

A central aspect of the model, beyond the characterization of the participating roles, is the specification of the structural nature of the regulatory system. This specifically involves the relationships and interaction links between individuals, and furthermore, the number of individuals operating in the previously introduced roles. While role responsibilities and operational details are modeled following coded institutional directives, the empirical information necessary for the parametrization of the model is drawn from surveys. To understand the structural nature of the system, it is important to note that operators who wish to be certified, can, in principle, apply to any certifier of their choice, assuming that they are registered under the USDA organic program. While certifiers are responsible for both the certification and sanctioning of violations, monitoring of operators' compliance is performed by inspectors appointed by certifiers. The inspector-certifier relationship is not exclusive, i.e., inspectors can have an arbitrary number of certifier relationships. To afford a realistic parametrization, we rely on data from the inspector survey, which provides insight into the average number of inspectors that certifiers tend to rely on. The specific question posed to inspectors in the survey was, "How many different organic certifiers have you worked with in the past year?" Responses to this question are summarized in Table 3.

Table 3: Inspector Survey: Response to Question "How many different organic certifiers have you worked with in the past year?"

1	2	3	4	5	6	>8
39.3%	21.3%	10.1%	9%	15.7%	2.2%	2.2%

Source: The author

Similarly, to parametrize the number of operators a certified entity is responsible for, we rely on data from the certifier survey. We specifically focus on responses to a question that asked certifiers how many operations they certify, responses to which are summarized in Table 4.

Table 4: NOP Certifier Survey: Distribution of Certifier Size by Number of Certified Operators

Fewer than 50	20-200	201-400	401-600	601-1000	More than 1000
5%	16%	6%	3%	3%	5%

Source: The author

The distribution of certifiers to operators provides the basis for further modeling assumptions. Since complete visibility amongst operators is unrealistic with respect to compliance assessment in the context of peer-based monitoring, it is important to specify realistic boundaries of the observational scope. While the NOP regulation does not contain provisions that delimit the operational radius of a certifier and/or operators, the USDA database suggests that in practice certifiers frequently operate with regional focus, i.e., single or few operators are responsible for certifying operations in specific regions. We use this regional concentration as a proxy to delineate observational radius of operations, that is, we assume that operators who monitor their peers will only monitor operations that have received certification from the same certifier.

Given these characteristics, we have a foundation to construct the interaction network in the base model. To instantiate a baseline population, we rely on a combination of current information from the USDA database about the number of certified operators (~7,500), along with estimates about the number of involved certifiers (82) as well as inspectors (~400), both of which are estimates based on direct communication with the Accredited Certifiers Association and the International Organic Inspectors Association.

Independent Variables

Building on the baseline model initialized with empirical data, we specify a set of variables that afford the explorative variation in experiments. A parameter set of specific importance is the *distribution of operator participation motives* as either individualist, mimetic or prosocial. Further extensions of the model include hypothetical informal activity beyond the provisions of the regulation. To explore the effect of *peer-based monitoring* on compliance outcomes – in addition to the mandated centralized inspections by inspectors –, we further selectively employ this ability. To accommodate a complementary exploration of centralized monitoring, we selectively allow for the variation of the number of operators an inspector can explore per simulation round.

Given our general interest in exploring the institutional configuration and the absence of empirical grounding, a set of parameters is calibrated by replicating the observed real-world certification levels in the baseline model. Parameters that we assume constant throughout all simulation scenarios are the probability of application approval, the probability for admission in the case of reapplication after suspension, as well as the probability for reapplication following a revocation.

Table 5 provides an overview of all independent variables, their default parameterization and exploration boundaries and steps, as well as the reference to the experimental condition (see following section) in which the corresponding parameter is used.

Table 5: Independent Variables

Parameter	**Boundary Values and Step Size** **[Distribution Specification]**	**Relevant Experiment(s)**
Distribution of social value orientations by individualistic, mimetic, and prosocial agents/ [Distribution permutations]	Distributions: 0.33 individualistic 0.33 mimetic 0.33 prosocial [Distribution permutations of 0.75, 0.125, 0.125 0.5, 0.25, 0.25 1, 0, 0]	Experiment 1
Peer-based monitoring	Activated, deactivated	Experiment 1
Inspection intensity (inspections per round)	1-3 Step size: 1, default: 1	Experiment 2
Distribution of inspection intensity (low: 1; medium: 2; high: 3) [Distribution permutations]	Distributions: 0.33 0.33 0.33 [Distribution permutations of 0.75, 0.125, 0.125 0.5, 0.25, 0.25 1, 0, 0]	Experiment 2

Probability of suspension vs. revocation of operator certification for medium sanctioning by certifiers; probability of suspending operator certification (as an alternative to ignoring the reported non-compliance) for soft sanctioning by certifiers	0.5	Experiment 2
Probability of approving certification	0.75	All experiments
Probability of approving certification after suspension	0.4	All experiments
Probability of approving certification after revocation	0.2	All experiments

Source: The author

Dependent Variables

To assess the effect of parameter variations, the simulation model collects information on a set of variables that we use as a basis for verification as well as quantitative assessments of the simulation outcome for given parameter configurations. The dependent variables can be grouped by categories, with specific metrics that include:

- The certification status of all operators, including:
    • non-certified regular operators
    • certified operators
    • operators whose certification request has been rejected
    • operators whose certification has been revoked
    • operators whose certification has been suspended
- level of non-compliance across all operators
- level of non-compliance amongst regular operators
- level of non-compliance per participation motive, such as:
    • level of non-compliant individualistic operators
    • level of non-compliant mimetic operators
    • level of non-compliant prosocial operators[7]

In addition to these direct metrics, we rely on two derived metrics to not only capture discretized compliance *outcomes* of simulation runs, but also to capture the simulation *dynamics* to gain insights into the overall performance of a given configuration in terms of the achieved level of compliant operations, as well as how quickly this convergence level is reached.

7 — While the last non-compliance metric (non-compliance by prosocial operators) is purely theoretical, given the persistently compliant behavior of prosocially motivated participants (as discussed in the context of the operator lifecycle), we nevertheless used the metric for the sake of comprehensive assessment as well as a verification means.

To determine the compliance outcome, we determine the strongest compliance level of a simulation run. For the operationalization we relied on preliminary observations of simulation runs[8] that indicated strong levels of fluctuation during the bootstrapping phase before showing stable convergence trends, hence measuring convergence only after an initial fraction of simulation rounds, denoted as $threshold_{Start}$. The maximum convergence level (*maxConvergence*) is thus the highest fraction of compliant operators throughout a simulation run (*max(complianceLevel(r))*) within the range of rounds following the initial number of rounds dismissed from measurement ($threshold_{Start}$ * *max(r)*, with *r* representing a given simulation round and *max(r)* the maximum number of simulation rounds), which is formalized as

$$maxConvergence := max(complianceLevel(r))|threshold_{start} * max(r) < r < max(r)$$

Values for the convergence level for a given simulation run thus range between 0 (for exclusively non-compliant operators) to 1 (comprehensive compliance amongst certified operators).

In addition to the maximum convergence level, we further require the simulation round (r) during which the highest convergence level was observed (maxConvergenceRound):

$$maxConvergenceRound := argmax(complianceLevel(r))|threshold_{start} * max(r) < r < max(r)$$

Based on those metrics, we can determine the fraction of rounds necessary to reach convergence, with values closer to 0 indicating no or slow convergence throughout the simulation run, and conversely, 1 indicating immediate convergence, which we operationalize as:

$$convergenceRate := 1 - \frac{maxConvergenceRound}{max(r)}$$

Using these metrics, we can thus capture both substantive outcomes of individual simulation runs, while also providing richer insights into the dynamics underlying the simulation configurations, aspects we will explore in the upcoming section.

Experiments

In this section, we describe the experiments performed using the agent-based model, as well as their respective results. The first experiment responds to our central research aim, to explore variation in compliance outcomes based on variation in the composition of organic operators with respect to social value orientations. The second experiment assesses effects of variation in the intensity of monitoring and sanctioning activity.

For both experiments, we relied on the baseline configurations as specified in Table 5, and systematically explored parameters relevant for a given experiment within the specified value range. All simulations ran for 10,000 rounds. This value was chosen based on preliminary tests that indicated convergence within the given number of rounds. The sufficiently long timeframe furthermore allows for a differentiated treatment of convergence dynamics as operationalized in the previous section. Since the agents' decision-making is probabilistic, outcomes for a single experiment inherently depend on the associated seed value for the random number generator (from which probabilities are drawn), the experiments have been run across a set of ten random number seeds in order to ensure the reliability of the established results.

8 — A simulation run is the execution of a simulation configuration over a given number of execution cycle iterations for all agents (rounds).

Experiment 1: Composition of Participation Motive

For our first experiment, we systematically vary the distribution of social value orientations as described in Table 5 and observe correlations between this primary independent variable and aggregate behavior dynamics. These correlations are shown in Table 6.

Table 6: Results of Experiment 1: Participation Motive Composition

	Non-Compliance (All Agents)	**Non-Compliance (Individualistic Agents)**	**Non-Compliance (Mimetic Agents)**	**maxConvergence**	**convergenceRate**
Individualistic	0.87	0.57	0.46	-0.37	0.33
Mimetic	-0.19	-0.06	0.21	-0.25	-0.40
Prosocial	-0.41	-0.16	0.00	0.83	0.53

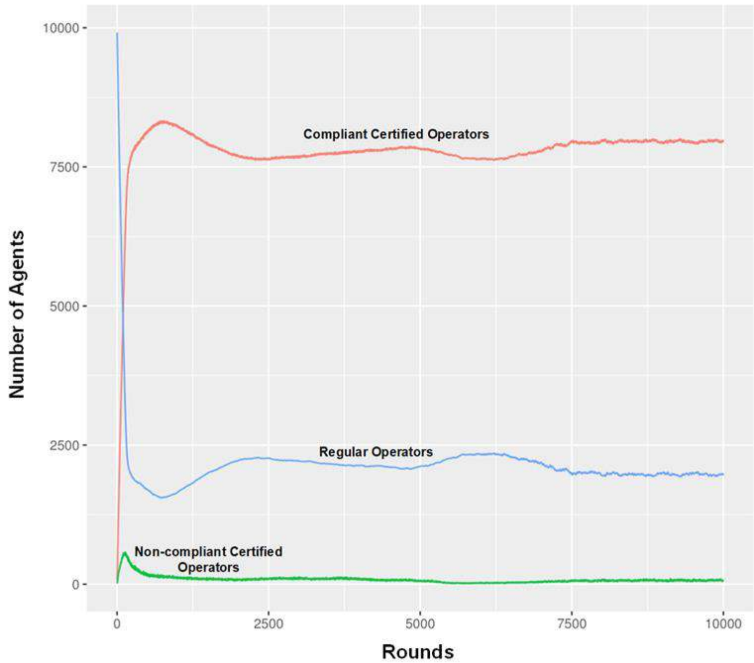
Source: The author

In this table, the independent variable *participation motive* (i.e., relative increase in representation for individualistic, mimetic and prosocial participation motivations in certified operators) is shown in the first column. Dependent variables, such as the resulting level of non-compliance across all participation motives, the level of non-compliance for individualistic agents, and the level of non-compliance for mimetic ones are displayed in the corresponding columns. Additionally, we capture the correlations of participation motives with the previously operationalized maximum convergence level (*maxConvergence*) and rate of convergence (*convergenceRate*). Given the non-parametric nature of result distribution for the selected output variables, all correlation values are reported using Spearman's Rho (significance level: 0.05).

Exploring the individual participation motives, we can observe a dominating effect of individualistic participation motives on the level of non-compliance (0.87). Taken in isolation, both alternative orientations, mimetic and prosocial, drive a reduction in global levels of non-compliance, leading to the suggestion that fostering participation of mainstream operators (i.e., those without a distinctive social value orientation) and idealistically motivated operators drive compliance within the regulatory setting, albeit to varying extents – and certainly with more moderate effect compared to individualists' bias towards non-compliance.

Exploring the compliance behavior for specific participation motives further, we can observe insightful interaction effects. Observing the direct relationship between an increased fraction of individualists and the cheating level, we can see that individualistically-motivated agents are only moderately responsible for an overall increase in non-compliance levels (0.57). Instead, the interaction with increasing levels of mimetic participants drives overall cheating levels, which can be explained based on the sensitivity of mimetic agents to their social environment. Here, we can clearly observe an amplification effect produced by injecting agents into the scenario that are neither primarily committed to profit orientation nor follow idealistic motives when applying for certification. Another interaction effect that warrants explanation is the moderately decreasing non-compliance of individualists with the increasing number of prosocial agents (-0.16). Since individualistic agents are primarily opportunistically-oriented, they do not display direct reaction to a changing composition in social value orientations. However, the reduction in non-compliance is associated with the higher prevalence of monitoring amongst prosocial agents, reflecting their policing role to sustain compliance. This is exemplified for a single simulation run in Figure 4, which displays the compliance behavior over time for 75% of prosocial agents, the remainder being equally split between individualistic and mimetic agents. In this figure (as for all following figures), the x axis reflects time steps, and the y axis showcases the corresponding non-/compliance behavior for specific operator groups (i.e., respective compliance for certified and regular operators) at a given point in time. As observable in this specific simulation run, the dominating prosocially-oriented operators sustain high levels of compliance over the course of the simulation run.

Figure 4: Simulation run for 75% prosocially-motivated agents and 12.5% individualistic and mimetic participation

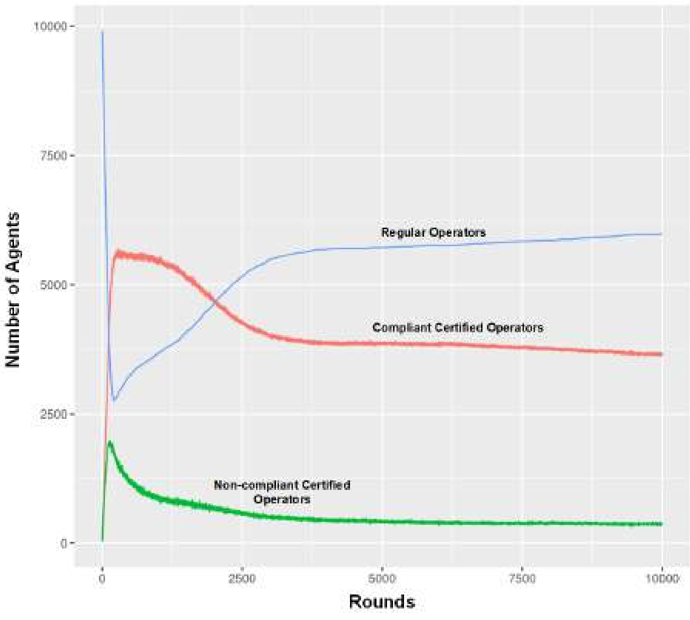


Source: The author

Metrics that provide insights into the dynamics of compliance levels are *maxConvergence* and the *convergenceRate*. While *maxConvergence* indicates the effect size at large, *convergenceRate* indicates how quickly the system converges. We can observe that the focus on individualistic participants moderates the overall level of convergence, an observation that appears counterintuitive at face value. Given their opportunistic nature, intuition would suggest dominating defection from regulation. While this is indeed the case, the very characteristics of individualists moderate this trend. We modeled individualists not only to reflect opportunistic behavior, but also to seek and maintain reputation as part of their association with the organic farming label. As such, the compliance behavior is controlled by two aspects. Firstly, prior to committing, individualists observe the fraction of non-compliant operators in their social environment who could challenge the reputation of the institution. A second level of enforcement is driven by individualistic members themselves. Despite potentially exercising non-compliance (defection on the operational level), individualistic operators observe their social environment and make their decision to monitor and denunciate peers contingent on the overall cheating level, leaving them to display cooperation on the enforcement level, i.e., to *defend the institution* – reflecting Heckathorn's (1990) conception of hypocritical cooperation. In consequence, increasing fractions of individualists have a self-moderating effect on the institutional outcomes at large. However, the consequence of this behavior is not a desirable convergence on compliance, but instead, the pool of certified but non-compliant operators is reduced over time.

Prosocial individuals stylized as ideologically committed, in contrast, drive high convergence levels, and do so efficiently. In such cases, the regulatory system effectively converges towards complete compliance within a few rounds of execution. More interesting is the role of the mimetic participants with respect to convergence dynamics. Their reactive nature, given the absence of strong conviction for or against compliance, moderates convergence levels. Specifically pronounced is their negative influence on the convergenceRate, since mimetic individuals rely on external stimuli for motivational activation. In effect, the introduction of mimetic agents reflects the conception of mainstream participants who moderate the interaction dynamics between players that would otherwise drive extremal outcomes (here compliance for prosocial individuals or non-compliance for individualistic agents), with an exemplary simulation run that showcases this phenomenon (see Figure 5).

Figure 5: Simulation run for equally distributed fractions of operators with individualistic, mimetic and prosocial participation motives



Source: The author

Summarizing the insights of this initial experiment, we suggest that the composition of participants in the organic farming regulatory program can have a decisive influence on its long-term sustainability. While these insights are intuitively retraceable, the interaction effects between individual behavioral stereotypes warrant careful exploration, which includes the amplifying effect on mimetic agents, as well as their role in delaying the convergence of the system -- independent of the convergence towards compliance or non-compliance. While the behavioral convergence towards compliance for prosocially-motivated operators is expected, the more complex behavior of individualists shows self-moderating interaction effects, pointing at the significant impact of monitoring as part of the simulation. At this stage, it is important to recall that while the modeled role stereotypes are synthetic and complemented with additional assumptions, the specific behavioral characteristics are derived from empirical insights and thus lend themselves for experimental exploration of inter-stereotype interactions.

Having observed the effect of self-monitoring, specifically for the case of individualists, little light has been shed on the role of regulatory monitoring. Given the presumed influence of monitoring on the compliance outcome in the regulatory system, especially in conjunction with prosocial orientation, we are left with the question as to how varying levels of monitoring by inspectors and corresponding sanctioning by certifiers interacts with varying compositions of participants. We explore this aspect in the following experiment.

Experiment 2: Variation of Monitoring Frequency and Sanctioning Intensity

The first experiment offers us isolated insight into the cooperation outcome with varying participant composition, assuming a static response of inspectors and certifiers to violation of the regulation. Given the discretion the organic farming regulation affords to inspectors (as observers) and certifiers (as sanctioners), it appears sensible to explore interaction effects of participation motive and variable sanctioning behavior. Recalling the functional characteristics of the explored participation motives, we find that those vary with respect to their observational behavior. Individualists explore the compliance level in their social environment as part of their decision-making, and mimetic agents are highly responsive to dominant compliance behavior.

The second experiment thus extends the initial experiment with variable monitoring behavior by inspectors, and consequently, variable sanctioning behavior by certifiers based on the reported violations. Since the administration of sanctions under the NOP relies on the cooperation of two roles, we provide a differentiated model that reflects behavioral modifications both for inspectors, who exercise the monitoring task, and certifiers, who react to reported non-compliances and administer sanctions. In the absence of empirically grounded penalty information for discretionary behavior of inspectors, we use the monitoring frequency as a proxy to model the probability of sanctioning in the first place. We thus vary the number of operators an inspector can observe per simulation round in a value range from 1 (used as the default setting for Experiment 1) to 3. Certifiers stratify their sanctioning behavior based on parameterization and initialize those either to favor:

- revocation as representing hard sanctions
- probabilistically (random) choosing between certification revocation and suspension for moderate (medium) sanctions
- probabilistically (random) suspending operators or simply foregoing any consequences for non-compliance (soft sanctioning)

The explored value ranges and experimental configurations used for the systematic variation are specified in Table 5. The results of associated simulation runs, presented in Table 7, effectively show the absence of any relationship between monitoring frequency, and consequently sanctioning frequency, and cheating level. In extension (and excluded from the tabular overview), varying levels of monitoring thus influence neither the extent of convergence (*maxConvergence*) nor the rate of convergence (*convergenceRate*). However, while the relative differences in monitoring/sanctioning have a largely insignificant impact, monitoring per se (see Row "Any sanctioning") impacts the outcomes of interest.

Table 7: Results of Experiment 2: Variation of Monitoring Frequency and Sanctioning Intensity

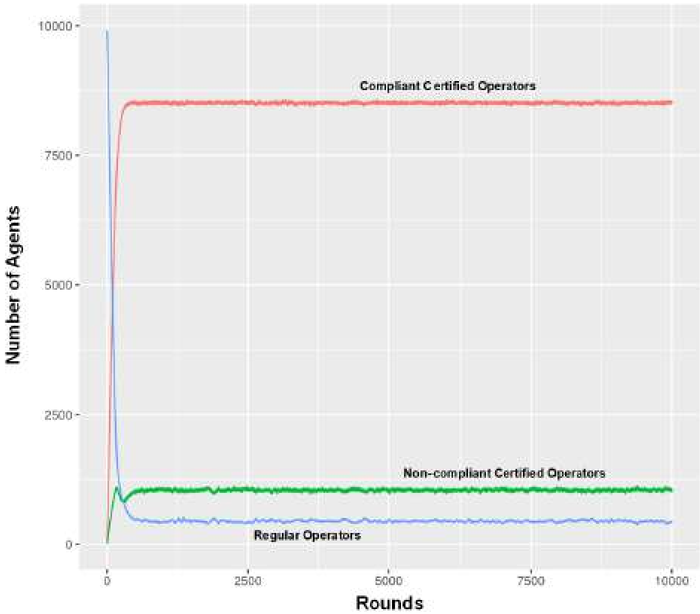
	Cheating Level	Suspended License	Revoked License
Hard sanctioning	0.00	-0.36	0.23
Medium sanctioning	0.00	0.11	0.09
Soft sanctioning	0.00	0.32	-0.21
Any sanctioning	-0.05	0.26	0.23

Source: The author

Observing the effectively insignificant influence of monitoring on compliance levels in the overall system is surprising, given the observational learning capabilities of individualistic and mimetic agents. While monitoring does not affect the overall cheating level, if detected, non-compliances are sanctioned harsher by certifiers, as shown in the relative shifts between operators whose certification has been suspended or revoked for different forms of sanctioning, respectively.

To recall: while our modeling did not rely on explicit empirical information about the frequency of inspections, we approximated the inspector-operations network distribution based on empirical information and suggest that the modeled extreme case of three inspections per iteration (read 'day of operation') is extremely optimistic. To contextualize our results, we need to highlight that the influence of varying levels of sanctioning on the compliance outcomes is insignificant relative to other influence factors, such as social value orientation. However, for specific configurations, varying sanctioning levels indeed produce substantive differences in outcomes. To highlight the effects of varying sanctioning levels, we show individual simulation runs to illustrate the principal effect of differentiated sanctioning in specific scenarios in Figures 6 and 7.

Figure 6: Exemplified simulation execution for soft sanctioning level

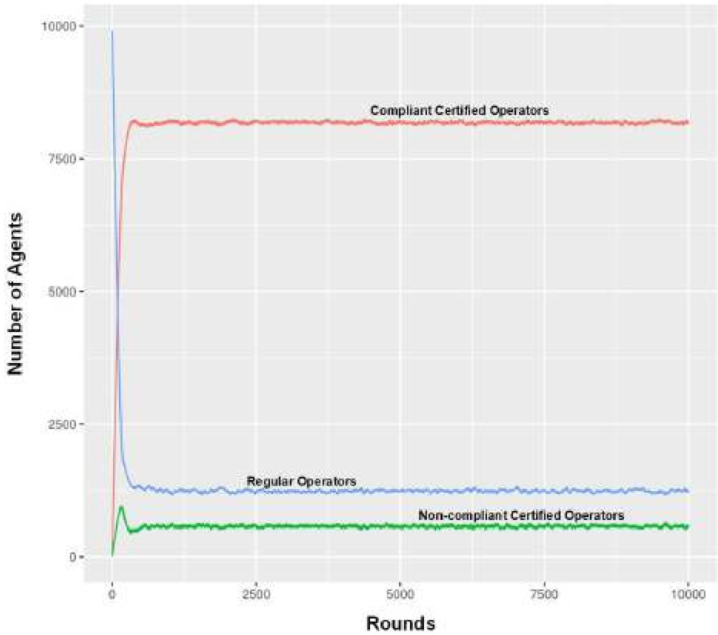


Source: The author

Figure 6 shows the time series reflecting the number of (compliant) certified, non-compliant certified and regular operators (i.e., operators not bound by the organic farming regulation). In this specific simulation configuration, inspectors are initialized with low monitoring levels and participants are primarily composed of prosocial participants (75%), with the remainder being equally split amongst individualist and mimetic operators. Putting specific focus on the number of certified non-compliant operators, we can observe a continued operation of ~1000 of such operators in the regulatory system.

Exploring how higher levels of monitoring and sanctioning manifest themselves in the emerging dynamics of the simulation, Figure 7 – showcasing an exemplary simulation run for a moderate level of monitoring and sanctioning – reflects a reduction of the non-compliant certified operators to around 500, with the balance identified as non-compliant and released into the pool of regular operators. As such, while of moderate impact at large (i.e., across all explored participation motive compositions), varying sanctioning levels can influence regulatory outcomes for specific scenarios.

Figure 7: Exemplified simulation execution for medium sanctioning level



Source: The author

Looking at the regulatory system more generally, analytically we are left with the impression that the monitoring levels, as far as represented in this model, are insufficient to drive and maintain compliance. Instead, specifically prosocial orientation, combined with status preservation of profit-oriented operators (previously characterized as self-monitoring of individualistic operators) appear as essential drivers for the success of the regulatory system.

Discussion

We use an agent-based model to understand the effects of regulatee composition in terms of social value orientations in shaping emergent regulatory compliance outcomes in the context of U.S. organic farming regulation. Our central experiment assesses whether and how variation in the relative shares of individualist, mimetic, and prosocial farmers in the regulatory community effects aggregate compliance outcomes. We introduce an additional experimental condition to ascertain its effects on compliance and related regulatory outcomes: variation in monitoring and sanctioning intensity. Our research advances regulatory scholarship by drawing attention to meso-level determinants of regulatory compliance. Part of the contribution of our research stems from merely evaluating outcomes linked to a meso-level factor (i.e., group composition) to complement existing research, which has tended to focus on micro- and macro-level factors. Additionally, the way we assess our meso-level factor of interest offers a novel way to conceive of interpersonal influence.

Overt results from the first experiment highlight individualists as drivers of non-compliance, and conversely, of prosocially motivated individuals as efficiency drivers. More insightful aspects of the analysis relate to the effect of individualists' self-monitoring capacity emerging from the synthesis of opportunistic profit orientation motives and sustainability focus, operationalized as reputation concern for one's operation. A further insight gained from the analysis suggests that while individualists and prosocial individuals drive high rates of convergence towards compliance or non-compliance, a relative increase in mimetic participants negatively affects the convergence performance. While not empirically grounded at this stage, the modeled 'follower conception' emphasizes motivational dynamics as the idiosyncratic counterpart to the static motivation models represented by individualistic and prosocial participants – a pragmatic conception of mainstream participants.

Our second experiment expands our focus beyond the role of operators and sheds light on the role of inspectors and certifiers as moderators of regulatory compliance. Results from the experiment, modeled based on primary data, and complemented with optimistic estimates of inspection frequencies, suggest that monitoring alone is insufficient to sustain high levels of compliance. Instead, the functioning of the regulatory system crucially relies on the good will of the participants, both to self-monitor as well as to engage in social monitoring, an aspect that accords with the concepts of prosocial and the behaviorally more complex individualistic orientation. This observation presents opportunities to investigate centralized and decentralized enforcement. Insights regarding such can inform the regulatory refinement of the National Organic Program with respect to participation incentive structures as well as organizational structure. However, while the current results open this path of inquiry, they are insufficient to make tangible recommendations.

Beyond the insights gained for the organic farming regulatory context, the application of an agent-based model grounded both in regulation data and corresponding real-world data offers novel analytical opportunities that include the assessment of the extent to which regulation influences emergent behavior, but furthermore, how such analysis can explicate the interaction between regulation and possible futures, i.e., behavior not (yet) observed in real-world settings. This ability to assess behavioral dynamics within regulation-imposed parameters can specifically extend to selective foci on different levels of analysis in social systems. In our analysis, we put specific focus on the meso-level participation motives – and explore hypothetical scenarios, such as sensitivity to growth, and enforcement mechanisms. However, analysts can equally focus on macro-level phenomena on society level that may include and go beyond the exploration of behavioral attribution to macro-level outcomes (e.g., sustainability impact of the organic farming regime at societal level).

While applicable in this specific case, the opportunities associated with agent-based modeling naturally hinge on the availability of theory and data [here both understood quantitatively (e.g., resource levels) as well as qualitatively (e.g., behavior patterns)] to substantiate and parameterize the modeled behavior. Associated with this is the need to afford internal validation, or verification, as well as external validation. The internal validity of agent-based models relies on the assessment of a designed model against its computational implementation as a simulation. This, for instance, relies on stepwise retracing of the simulation progression and assessment of the performed calculation. With focus on parameterization, this further relies on performing sensitivity analyses to assess the model's reaction to systematically explored parameter constellations (e.g., variation in applicant compositions based on participation motive), especially where precise parameters remain unknown (i.e., cannot be established based on empirical data) (David et al., 2017). This aids the identification of pivotal configurations that indicate behavior shifts, and hence support the identification of parameters with central influence on model outcomes, and more specifically, parameter ranges that reliably reproduce observed outcomes. Insofar as external validation – the assessment of models against reality

– is concerned, this critically relies on the purpose of the model and, naturally, the available corresponding data. Coarse, sparse, or unreliable data only invites for a coarse-grained assessment. In the context of our model, for instance, we can rely on participation data, as well as on the broad insight into the connectedness of individual actors (e.g., average number of certifier-inspector relationships). In as far as the motivation of individual participants is concerned, the reliance on survey and interview data naturally reflects uncertainty with respect to selective reporting by involved farmers as well as potentially unknown cognitive biases (e.g., responses accommodating the purpose of the interview). Further data that is challenging to precisely assess is the operational aspects of certification processes, an aspect we hence abstract from by merely accounting for events of operational relevance for compliance assessment (e.g., approved/rejected certification requests, observed violations). In consequence, the model can thus leverage general understanding about the effect, or trend, a particular intervention has (e.g., changing participant composition leading to change in group-level and general compliance outcomes), which can serve as a general guidance and basis for policy adjustments to mitigate observed trends (e.g., adjustment of incentives or monitoring to counteract anticipated non-compliance behavior). Counteracting the illusion of precision based on the numerical output produced by the computer simulation, reporting on central insights produced by models that focus on establishing an understanding of the phenomenon of interest can occur in terms of correlation strength to signal the general interaction between identified variables of concern – as done in this case. Conversely, where modelers can rely on a detailed information basis (e.g., comprehensive capturing of behavior based on observation), the analyst can draw on a more precise quantitative characterization of the outcome (e.g., in terms of distributions or specific numeric values) to aim toward reliable prediction of unknowns.[9]

Directions for future work are twofold. On the one hand, the developed model provides a robust basis for investigation into selected aspects of the regulatory arrangement by informing empirical studies that provide targeted insights to inform concrete policy recommendations. Selected aspects include the extended exploration of enforcement and organizational characteristics, as well as the nature and impact of the social network structure. A specific aspect is the dynamicity of the network structure, that is, the variation of participant composition over time. As posited by Melamed et al. (2017), while dynamicity of networks fosters cooperation, it only effectively does so if network nodes are predominantly prosocial; notions of mimetic agents, however, are not explored in their work. A further direction is to exploit the method agent-based modeling, specifically its generative nature, by gaining qualitative insights into the decision-making processes of individual agents or groups thereof (Frantz, 2020). To date, however, the granularity of the available data (that form the behavioral foundation of individuals) limits meaningful observation to meso- (i.e., inter-group) and macro- (i.e., society) level characteristics. Despite such limitations, agent-based modeling, with its heritage in artificial intelligence, provides us with a unique untapped resource: the ability to leverage a conception of systemic understanding on the micro-level to explain emergent phenomena on both meso- and macro-level, offering novel pathways to evaluate policy aspects on multiple levels of analysis. Moving beyond a descriptive analysis of real-world phenomena, it instead enables us to test hypotheses and explore alternative futures in an artificial society that is grounded in, but “fast forwards”, reality.

9 — A detailed account on verification and validation in agent-based models can be found in David et al. (2017).

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Appendix A

The implemented simulation model, including the model specification following the ODD+D protocol, is provided under the following URL:
https://github.com/chrfrantz/OrganicFarmingSocialValuesSimulation